Stigmergy-based Load Scheduling in a Demand Side Management Context

Zur Erlangung des akademischen Grades eines
Doktors der Ingenieurwissenschaften
(Dr.-Ing.)

bei der Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte
DISSERTATION

von

Ing. Civil Inf. Fredy H. Rios S.

Karlsruhe, 2016

Datum der mündlichen Prüfung:	09. Juni 2016
Referent:	Prof. Dr. Hartmut Schmeck
Korreferent:	Prof. Dr. Wolf Fichtner

Abstract

The power grid is composed of thousands of autonomous entities, which form intricate networks and feedback loops. In addition, the power grid is robust to perturbations and failure of some of its components. It is adaptable, being able to increase or decrease generation to maintain load balance and cope with sudden changes in the consumption of customers. Furthermore, it is in continuous evolution, through the incorporation of new technologies, both on the supply and demand side. These features are characteristic of self-organized systems.

Nevertheless, the future context of the power grid may push these features to their limits. For political and environmental reasons, most industrialized countries aim to increase the shares of renewable energy sources (RES), such as wind and solar power, in their power grids. RES have fundamental differences with traditional forms of electricity generation. RES depend on weather conditions, therefore, the supply is intermittent and hard-to-predict. Since power generation from these technologies cannot be fully controlled, increasing shares of RES may drastically increase the risks of load imbalances within the power grid, endangering the system operation and power supply.

In this context, the demand could be influenced to match the RES supply, such that the balance in the power grid can be maintained by increasing RES utilization. To this end, intelligent devices are introduced. These devices have the ability to autonomously select their operating times, within a user defined flexibility interval. Hence, these devices may be influenced to select operation times, which maximize RES usage and, therefore, reduce load imbalances. Nevertheless, incentives should be carefully designed, such that a desired global consumption behavior is obtained without generating avalanche effects of uncoordinated response to stimuli.

This work proposes an approach, based on a fundamental coordination mechanism from nature, namely stigmergy. Stigmergic systems are characterized by exhibiting coordination and cooperation in the process of achieving global objectives. This state of coordination emerges spontaneously as participants indirectly communicate through untraceable alterations on a shared environment. Stigmergic systems are inherently self-organized, therefore they exhibit the previously mentioned features of these systems. The proposed meta-heuristic is utilized to distributively calculate global schedules for a population of customers provided with intelligent devices. These schedules maximize RES utilization, allowing the power grid to maintain a balance between supply and consumption. Results show that the approach is able to produce global schedules, which derives into a micro-grid load profile that closely resembles a given RES output.

Furthermore, this approach is adapted and utilized as a coordination mechanism in a real-time optimization context. In this case, participants correspond to individual autonomous customers, which are influenced by a control signal to modify their consumption behavior. Results show that the approach is able to guide the global consumption behavior of a simulated micro-grid in real-time to increase RES usage. Moreover, desirable features of the future power grid are enhanced, such as privacy of customers, autonomy and anonymity of participants, among others.

This work contributes to the field of energy informatics by providing a meta-heuristic for calculating schedules that increase usage of a given RES output. In addition, this meta-heuristic is adapted for real-time coordination of autonomous consumers. Further contributions regard the field of self-organizing systems, by providing additional insights for the study of stigmergy.

Acknowledgments

> *The effort of the today, is the success of the tomorrow.*
>
> Cristián Alarcón, *Informal conversations*, 2003

In the process of pursuing this dream, I had the pleasure to share my journey with wonderful people. Hence, I would like to express my gratitude to those who have provided me with criticism, support, advice, patience and company during this process. First, I would like to thank my supervisor Prof. Dr. Hartmut Schmeck for welcoming to his group, his guidance and the freedom he provided me to develop my ideas. Furthermore, I am utterly grateful to Prof. Dr. Wolf Fichtner, Prof. Dr. Nora Szech and Prof. Dr. Kay Mitusch for their time, advice and valuable comments as members of my thesis committee.

In addition, I would like to express my gratitude to my colleagues at KIT and FZI. The experiences and discussion that I participated in were essential for the successful termination of my doctoral project, and allowed me to understand this wonderful culture and its subtleties. Although each one of them was essential in this adventure of mine, I would like to address some word in particular to the following colleagues: To Dr. Florian Allerding for displaying his cooking abilities and always welcoming me to enjoy them. To Kaibin Bao for being an amazing and caring person. To Marlon Braun without whom this thesis might have never been finished, and for all the discussion, advice, drinks and friendship. To Christian Gitte for all the advice on how Germany works. To Sebastian Gottwalt for his permanent support from beginning to end and aiding me in feeling like a peninsula, rather than an island in this foreign country. To Christian Hirsch for sharing a cup of rum and some interesting stories. To Fabian Kern for the positive attitude towards every situation. To Sebastian Kochanneck for his educated opinion on everything. To Dr. Lukas König for the intense discussions on science, research, economy and politics, and for (un)gracefully escaping from these discussions. To Manuel Lösch for the relentless good vibe and that loud, loud laugh. To Ingo Mauser for his commitment to science. To Jan Müller for his amazing advice and willingness to discussion. To Friederike Pfeiffer-Bohnen for listening to my doubts and worries. To Fabian Rigoll for his pragmatism and humor. To PD. Dr. Pradyumn

Shukla for permanently having an open door and provide constructive (and destructive) criticism. To Sebastian Steuer for all the continuous help and interest on my research. To Huiwen Xu for her courage on pursuing her goals in a foreign country.

Furthermore, I would like to thank my friends for their support and the time we shared, on which they listened to my worries, defeats and successes. Especially I would like to thank Ana María, Bettina, Billy, Janina, Julia, Lidia, Lucas, Marie, Martin, Patrick, Peña, Reiner, Richard, Roberto, Ruth, Thomas, and Zaza. In this context, I would also like to express my gratitude to Dr. Victor Martinez and Mr. Achim Niessen without whom this journey would have never commenced.

I would also like to give my greatest thanks to my parents, Alicia and Wladimir, for their permanent care and support throughout these years and to my siblings, Mirtha and Eduardo, for being there through all my life, during the good, the bad and the ugly. Also, special thanks to my pets, Kuky, Motita and Wikilin.

Finally, I would like to thank Andrea, for being the light at the end of the tunnel in my life. For all that has been, for all that it is and for all that will be.

Contents

List of Figures

List of Tables

1. Introduction

> *The story of civilization is, in a sense, the story of engineering - that long and arduous struggle to make the forces of nature work for man's good.*
>
> Lyon Sprague DeCamp, *The Ancient Engineers*, 1963

Since it was discovered that electric current produces a magnetic field and vice versa, to contemporary times, where we are surrounded by an endless sea of technology and information, electricity has shaped every single aspect of our lives. Today, electricity is the primary fuel of every thriving and competitive economy. In the age of information and communication technologies, a reliable and abundant power supply enables innovation to flourish, and new markets to establish and develop. Furthermore, the power supply, which is usually taken for granted, enables end-customers to enjoy new devices that allow access to knowledge and discoveries in every corner of the world.

The power grid has grown relentlessly to cope with the increasing energy requirements of industries, commerce and residential customers. As a consequence of this growth, its complexity has drastically increased [BMM14]. Participants, which are counted by millions, influence each other, forming convoluted relations and feedback loops, while system operators aim to achieve system stability and provide electrical services [Blu07]. This stability is determined by the permanent balance between supply and demand. This means, power generation has to match the demand at any time [Str08, Got15]. If this requirement is not met, the power system stability can be compromised, electric supply could be interrupted, large economic losses might be experienced and even lives may be put to risk.

Considering this context, during the last few decades the power grid has been experiencing dramatic changes. The dependency on fossil fuels is promoted to be reduced due to their diminishing availability, to achieve security of energy supply, and for environmental reasons [BMM14, Got15]. To this end, distributed generation and renewable energy sources (RES), such as wind and solar power, arise as an alternative to complement and eventually replace large centralized fossil fuel-based power generation. From a state and government perspective RES are highly desirable, since their utilization implies increasing the security of the energy supply [BMM14, USD+13]. From an environmental perspective, RES usage does not only reduce dangerous emissions but prevents highly contaminant processes like fuel refinement and waste disposal [Got15, Blu07]. From an energy efficiency perspective, utilizing RES to generate electricity implies increasing utilization of resources that, otherwise, are stationary and which can promote local growth and economic development. In addition, increasing distributiveness of the power grid brings customers closer to the RES generation, reducing power transportation costs and energy losses [BMM14].

Nevertheless, RES power generation imposes serious challenges. RES energy output is intermittent and uncertain, since, particularly in the case of wind and solar power generation, it depends on weather conditions. Therefore, we cannot rely on a permanent supply [RKS16, SGC+13]. Furthermore, RES output is not dispatchable, this is, it cannot be controlled on demand [SGDG+12]. As a consequence, this power output should ideally be utilized immediately after its generation, otherwise, the power is lost or the system might reach an imbalanced state, endangering its operation.

In addition to this type of generation, from the demand side perspective, customers increasingly change their load composition. The introduction of intelligent devices has drastically increased the flexibility of customers, by enabling the autonomous selection of their own operation times [BF12, IA09]. To further reduce the dependency on fossil fuels, electric vechiles (EV) are promoted to play a major role in future transportation systems and, as a consequence, in the electric system. This will connect two traditionally separated sectors [Got15]. EVs, however, are intensive power consumers and their connection to the power grid implies an important change in the consumption profile of customers [GZA10, MAS12].

These new conditions increase the complexity and fragility of the power system functioning [GKB+11, FIG+13]. The power grid has not been designed to include large amounts of intermittent RES supply nor highly flexible customers. In the past, the introduction of load-intensive applications and elements which produced large load peaks has led to outages and overloads, which have propagated throughout the system, resulting in partial or total blackouts [BMM14, Gla09, Dob14]. Hence, in the future power grid the requirements for techniques and approaches to achieve system stability will be an essential issue.

Nevertheless, although in this new scenario the demand and the supply side might compromise the operation of the power system, they can also complement each other to bring load balance and system stability. To this end, utilities can implement different demand response (DR) programs. DR corresponds to technologies that enable interaction between end-customers and utilities, such that the consumption of the former can be modified to achieve specific load objectives of the latter [BMM14, Str08]. On the one hand, these programs can consider the implementation of incentives, such that customers autonomously modify their consumption. On the other hand, utilities can achieve contracts with customers, which implies that the former will have full control over the appliances within the domain of a customer. DR programs have pros and cons, from the perspective of computational complexity, privacy preservation, robustness and flexibility, among others [Got15].

Hence, given the future context of the power grid: How can we efficiently complement the increasing shares of intermittent generation with the additional flexibility of consumers, such that the power grid remains flexible, robust, and safe for its users, while providing a reliable electrical service? Furthermore, how can we guide or control the *global behavior* of autonomous customers, such that their aggregated consumption fulfills specific load objectives?

1.1. Motivation

Many man-made systems, such as world wide web, stock exchange markets, or traffic systems, both require and establish complex networks. In these systems, self-organizing behavior arises as a consequence of the interaction and relations between participants, formed in the process of providing and receiving a service [Ger07, Ric09, SMSc$^+$11]. These systems tend to be highly distributed, respond in real-time to cope with the necessities of customers and adapt to disturbances [MSS10, BMMS$^+$06]. Their operation adapts and evolves to serve their respective purposes. From a global perspective, these adaptations, their overall organized state and their stability is achieved in an autonomous manner [PB11, Ger07].

The power system can also be considered to self-organize. It adapts its network range and installed generation capacity to provide electricity services to an increasing number of customers [BMM14]. It is able to cope with uncertainty of demand and adapt its generation in real-time to maintain load balance in the power grid [Blu07]. The power system is also able to tolerate perturbations, such as failure of some of its components [USD$^+$13]. Furthermore, from an overall perspective it depicts emergent behavior [Got15, Blu07, Dob14].

From the study of self-organizing systems several questions arise: What enables these systems to adapt to uncertain circumstances? How do specific properties of self-organized systems emerge? Where are the limits of self-organization?

Furthermore, can specific features of self-organizing systems be provided or enforced in other systems? Finally, can the behavior of self-organizing system be guided to achieve specific objectives?

Stigmergic systems are a special type of these systems [Ger07]. In conjunction with other features from self-organizing systems, they achieve remarkable coordination and cooperation from a global perspective. This state is reached as a consequence of the indirect interaction between participants, through non-traceable alterations in a shared environment [TB99]. On the one hand, these systems show typical self-organizing features, such as flexibility, adaptability, or robustness. On the other hand, in stigmergy, a single participant can trigger the auto-catalytic process which gives rise to coordination and cooperation, and the achievement of self-organized behavior. Participants do not interact directly, reducing the complexity of the network and increasing flexibility to include additional individuals. Moreover, as a consequence of this feature, the identity of participants is not a requirement to achieve coordination. Hence, autonomy is enhanced.

Many of these features are desirable for the power grid. From the perspective of utility companies, achieving load balance between supply and demand, in an autonomous manner, through cooperative behavior, can drastically reduce operating costs [Blu07, VST13]. From the perspective of end-customers, the enhancement of privacy and preservation of autonomy might by a deciding factor in the selection of electricity providers, in the future power grid. Hence, considering the relation between the power grid, self-organizing systems and stigmergy, a question arises: Is it possible to utilize stigmergy in some form or capacity to achieve the balancing objectives of the power grid?

1.2. Scope and Objectives

As previously outlined, the first motivation of this work, regards understanding special features of self-organizing systems to address the described problems of the future power grid. Specifically, the spontaneous emergence of global behavior, which achieves specific high level objectives. In this context, the investigation of stigmergy corresponds to a step in that direction, given that stigmergic systems are a type of self-organizing systems. Moreover, the interest in researching stigmergy, comes from the desire in understanding how autonomous participants which do not interact directly, can coordinate and cooperate to perform global actions which are beyond their individual abilities.

The second motivator of this thesis, regards the applicability of concepts from self-organizing systems to the power grid scenario. More specifically, how can traditional features of self-organization, some of which may be traditionally present in the power system, be utilized to provide stability to the future power grid. In this context, the main objective would be to promote self-organized behavior to maximize the utilization of RES generation and reduce load imbalances. The challenges of this objective have been previously mentioned. Hence, features such as flexibility, adaptability and robustness might be enhanced through the incorporation of concepts related to self-organizing systems. In addition, issues which might become relevant, such as privacy and autonomy of customers, may also be addressed through the implementation of these ideas.

To address these inquires, the following research questions are stated:

> **Research Question 1:** *How can the global behavior of a stigmergic system be guided?*

In stigmergy, coordination and cooperation naturally arise as a consequence of indirect interactions between participants. Hence, the means in which global behavior can be guided, while respecting the autonomy of individual participants, will allow the understanding of the boundaries of self-organization in this context. To answer this question, a comprehensive analysis is performed on the meaning of guiding and controlling behavior in the context of self-organization [SD97, Joh00, SMSc$^+$10]. Furthermore, the main features of stigmergy in natural and artificial systems are investigated [TB99]. In addition, the different elements and stages that define the raising and diffusion of cooperation and coordination in these systems are investigated.

> **Research Question 2:** *How can artificial stigmergic systems be utilized to distributively generate schedules which can maximize a given RES output utilization?*

The most well-known artificial stigmergic system corresponds to ant colony optimization (ACO - [DBT00]). This meta-heuristic requires a special representation of the load scheduling problem, in the form of a graph, before it can be used to solve it [FH13, SMCO15]. This certainly carries some disadvantages in terms of scalability, flexibility and efficiency. In this context, other stigmergy-based approaches may be able to represent the optimization problem in more intuitive manners, which improve flexibility in the inclusion of additional loads and do not reduce the performance when the network size increases. To answer this question, a meta-heuristic for stigmergy-based load control is proposed. This meta-heuristic is experimentally evaluated to assess the problem of generating global schedules which maximize usage of a given RES output.

> **Research Question 3:** *How can artificial stigmergic systems be utilized to guide the global consumption behavior of autonomous customers in real-time and in a dynamic environment, such that RES usage is increased?*

A major challenge of the DR programs is the compliance of customer restrictions, while achieving a specific global behavior and load objectives [Got15]. Additionally, they should be able to influence the system to respond adequately to unforeseen events and reduce the impact of potentially dangerous load oscillations [BMM14, SMSc$^+$11]. In this context, considering the inherent properties of stigmergy in natural systems and multi-agent coordination contexts [TB99, DBT00], the assessment of its ability to manage a system composed of many autonomous customers is of relevance. For this, the proposed meta-heuristic is adapted and utilized as a mechanism for guiding the global behavior of autonomous customers in compliance with the requirements of stigmergy. This approach is experimentally evaluated in a dynamic environment, represented by a changing RES forecast.

1.3. Major Contributions

The main contributions of this thesis refer to the extension of the current body of science on the research fields of artificial stigmergic systems, nature inspired algorithms and energy informatics.

An adequate understanding of the opportunities and limitations of stigmergy, as a mechanism for managing the global consumption behavior of a micro-grid is required. To this end, a literature review provides insights on the fundamental features of stigmergic systems in nature. This overview serves to provide the first contributions of this thesis (Chapter 3 and 7). Firstly, an improvement of the current taxonomy for stigmergic systems is proposed. Moreover, the stages in the stigmergic coordination process are defined in detail. Furthermore, a set of requirements that systems should comply with, in order to be called stigmergic, and therefore, depict the features of this type of self-organizing systems, is proposed.

The comprehensive analysis of stigmergy enabled the design of a stigmergy-based load control approach for distributively calculating global schedules for a population, such that the usage of a given RES is maximized. The approach, considers the utilization of sematectonic stimuli to guide the behavior of simulated households. These households perform a probabilistic scheduling process of their appliances in consideration of the received stimuli. A formal model for this meta-heuristic is presented and the algorithm is experimentally evaluated in Chapter 4 and 5, respectively. The evaluation scenario considers a simulation of an isolated subsection of a balancing group, populated with households with different types of flexible loads. The RES supply is scaled from real generation from two balancing zones in Germany. The analysis provides information regarding the limits and possibilities of the meta-heuristic to be applied to other optimization problems.

As previously outlined, the power grid operates in an uncertain scenario under dynamic conditions. In this context, the proposed meta-heuristic is adapted, such that it can be utilized as a multi-agent coordination mechanism for real-time optimization (Chapter 4). RES forecasts which deviate from the final RES outputs are considered as a source of uncertainty and dynamism. The ability of the approach to reschedule flexible loads in real-time, such that the utilization of the RES output is increased, without generating imbalances, is evaluated in simulations (Chapter 6). Furthermore, different shares of load coverage from the demand side are considered in conjunction with different shares of flexibility of the end-customers loads.

1.4. Structure and Overview

To begin the reading of this thesis and obtain an overall perspective of the issues to be addressed, a description of the content of each chapter is provided. This description should guide the reader to his or her main points of interest and enhance the enjoyment of reading this work.

- Chapter 2 describes the traditional power grid operation and the importance of maintaining a balance between power supply and consumption for the stability of the power system. Furthermore, the challenges of increasing the shares of RES and including new technologies (such as intelligent appliances or electric vehicles) for the future power grid operation, are discussed. In this context, the importance of demand side management and demand response is mentioned, and some approaches for maintaining load balance in this new scenario are reviewed.

- In Chapter 3, argumentation is provided to support the consideration of the power grid as a complex and self-organizing system. Furthermore, through the revision of examples from nature, the implications of guiding the behavior in self-organizing systems are discussed. In addition, the concept of stigmergy is comprehensively analyzed. Results from this analysis are used to enhance the existing taxonomy for stigmergy systems and specify a set of requirements for constructing artificial stigmergic systems.

- Chapter 4 provides an argument for supporting the utilization of stigmergy as a coordination mechanism for load balancing in the power grid. In this context, the optimization problem to be addressed is described. An architecture for the proposed stigmergy-based management mechanism, in conjunction with its formal description applied to static optimization and real-time optimization, is presented.
- Chapter 5 provides the results of the stigmergy-based meta-heuristic proposed in Chapter 4, for distributively generating global schedules maximizing the usage of RES generation. For this, an isolated idealized micro-grid is simulated, which is considered to be powered by solar and wind generation. From the demand side, different flexible devices are considered, such as intelligent washing machines and electric vehicles. The internal functioning and solution construction process is analyzed in depth and improvements to the original approach are proposed and implemented. The approach is further compared to a synchronized closed-loop pricing approach. Results from this chapter are also utilized for argumentation about the possibilities of extending the approach to solve other combinatorial optimization problems.
- In consideration of the dynamic and uncertain nature of the power grid operation and RES power generation, in Chapter 6 the proposed meta-heuristic is also experimentally evaluated in a real-time optimization context. For this, a similar scenario, from the supply and demand perspective, as in Chapter 5 is considered. Nevertheless, RES forecasts are also considered, which represent the dynamic factor in the scheduling process of autonomous participants. The approach is compared with a synchronized closed-loop pricing approach, and relevant issues, such as robustness, simplicity of implementation and privacy of customers are emphasized.
- The obtained results are comprehensively discussed in Chapter 7. Furthermore, an extensive comparison with another well-known stigmergy-based meta-heuristic, namely ACO, is performed. Additional conceptual issues regarding stigmergy are discussed, emphasizing on the importance of the design of incentives to obtain desirable and stable emergent behavior. Furthermore, limitations and future opportunities for the proposed meta-heuristic are presented and discussed.
- Finally, Chapter 8 summarizes the main findings of this thesis and addresses the fulfillment of the stated research questions.

Some paragraphs and sections in this thesis are extensions or reproductions of own publications or working papers. Their use is mentioned explicitly at the beginning of the corresponding chapter, section or subsection.

2. Power Systems and the Power Grid

> *Why, sir, there is every probability that you will soon be able to tax it!*
>
> Michael Faraday to William Gladstone, Chancellor of the Exchequer, when the latter asked about the practical worth of electricity, quoted by R. A. Gregory, *Discovery, Or The Spirit and Service of Science*, 1916

The primary engine of a thriving and competitive economy is energy. This has been true throughout history. In ancient times, the efficient utilization of energy from the wind was essential in the exploration, establishment and exploitation of commercial routes. Further in the future, the same occurred with steam engines, powering trains and ships that connected different parts of the world faster than ever. Currently, that role is mostly fulfilled by fossil fuels. Nevertheless, in the age of information, when the exchange of physical goods conforms only one aspect of the economic activity, another type of fuel is essential. This is obviously electricity.

In the same ways as different fuels and their uses have evolved, currently the way electricity is supplied and consumed is also evolving. As a consequence of political and environmental decisions, the relevance of renewable energy sources (RES) in the power grid is promoted to be dramatically increased [BF12, GKB$^+$11]. In conjunction with this tendency, customers continuously increase their flexibility and autonomy, through residential generation and intelligent appliances [AMS14, VST13, GlBK11]. This enables the development of new market models and innovation opportunities, in which information and communication technologies (ICT) should have a preponderant role for the efficient management of the different components that compose these futuristic power system, namely the smart grid. In this context, the European Technology Platform (ETP) defines the smart grid as [USD$^+$13]:

> *[...] an electricity network that can intelligently integrate the actions of all users connected to it (generators, consumers, and those that do both),*

> *in order to efficiently deliver sustainable, economic and secure electricity supplies.*

From this definition, it can be drawn that the future of the power grid lies in how the new features of the participants can be complemented with each other, such that new forms of power supply can be efficiently utilized while enabling and promoting the incorporation of new technologies.

In this chapter, the operation of the power grid and the current and future challenges it undergoes, are described. Afterwards, the problem of load balancing between supply and demand is described. Then, the challenges of the future power grid are mentioned, emphasizing the impact of increasing shares of RES and flexibility of customers. In this context, different strategies for managing flexible loads to increase RES usage are discussed. Moreover, a short revision of algorithms and specific approaches for load balancing is performed. Finally, a short summary and conclusion regarding the presented scenario is provided. At the end of the chapter, the reader should have a general understanding of the problem to be addressed in this thesis. This is, the coordination of flexible loads to increase RES usage and load imbalances reduction in the power grid.

2.1. Current Power Grid Operation

In this section, an overall description of the traditional operation of the power grid is provided. The case of the German power grid is used as a model of reference. Afterwards, the problem of balancing the supply and the demand in the power system is described.

2.1.1. An Overview

The physical structure and the operation of the power grid have been experiencing a dramatic evolution, specially in the last decades. A simplified representation of the different levels of the power system can be observed in Fig. 2.1.

Originally, the electric system was designed for deploying energy from large centralized power plants in a unidirectional manner [BMM14]. These power stations have been located far away from the consumption centers. In this configuration, an *extra high voltage* transmission system is utilized for transporting power from large scale power stations, such as nuclear power plants, hydroelectric power plants, or off-shore wind power stations, through long distances to the main consumption center [Blu07, Got15]. In the German scenario, this

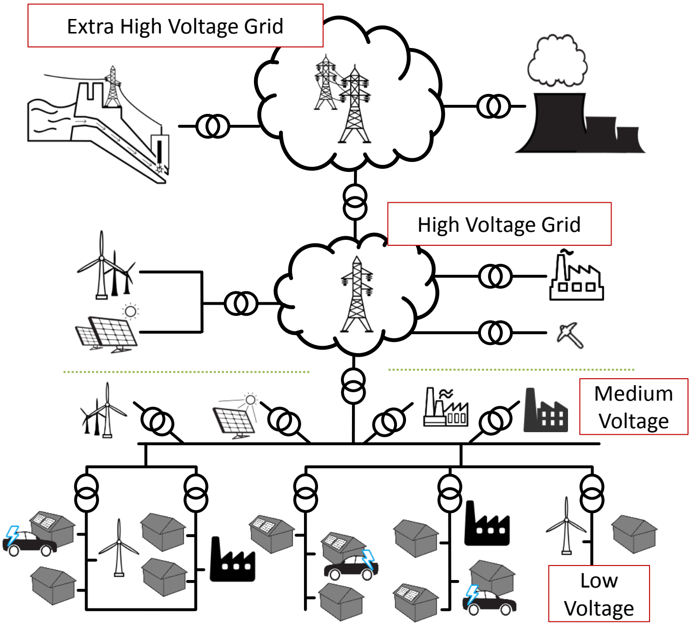


Figure 2.1.: Simplified power grid diagram. Levels above the dotted line correspond to the transmission system, whereas levels below correspond to the distribution system. Based on [Blu07] and [Got15].

grid operates at 220 kV or 380 kV. Medium dispatch power plants operate at a *high voltage grid* level, with voltage usage ranging from 60 kV to 220 kV. At this level, supply from large-scale PV power plants and on-shore wind power generation is fed to the network. From a demand side perspective, very large electrical consumers, such as steel factories, mining industries or oil refineries, are directly connected to this level and provided with electric services. These customers usually establish contractual agreements regarding their supply directly with the transmission system operators (TSO) due to the volume of their power consumption, and have their own infrastructure to reduce power voltage, such that it can be safely utilized [Blu07]. The high voltage distribution grid also transports energy to substations in population centers. At a *medium voltage grid* level (from 6 kV to 60 kV), small power plants can provide their supply and, if necessary, balancing power for achieving load balance in the power grid (this issue is further discussed in the following subsection). This grid level includes small wind and solar farms. Moreover, industries and commercial enterprises usually connect directly to this network. The medium voltage distribution grid is also traditionally utilized to illuminate rural areas or isolated customers. Finally, the *low voltage power grid* distributes power to residential customers, commerce, service-based enterprises and small industries. At this level (230 V to 400 V), combined-heat and power plants, district heating and residential PV also operate [Blu07, Got15, Sta08].

Different technologies are utilized for power generation. Their implementation depends on operational features, costs, scalibility, power grid requirements, geographical features and internal policies. As a consequence, power grids can have a heterogeneous composition of the fuels utilized, e.g. the German scenario, or power generation highly concentrated on a single type of technology, e.g. the French power grid, in which roughly 75% of the total domestic generation comes from nuclear power [IEA09].

The power grid is designed to function as a real-time energy delivery system [Blu07]. This means that power is generated, transported and supplied the moment the consumer desires to make use of it, e.g., to turn on the light of a room. Hence, it can be said that generators produce energy to satisfy an immediate demand. This is very different from what occurs on other systems, such as the water utility network [Blu07]. If a continuous flow of power between generation and consumption is not met at every instant, the system stability might be compromised and supply can be disrupted [Got15].

2.1.2. Power Balancing

As outlined, in the power system generation must be constantly adapted to follow the electricity demand. This implies that a permanent balance between power generation and consumption needs to be met, to prevent the power system from suffering instability and failure, including damaged equipment. *Transmission system operators* (TSOs) are responsible for the secure and reliable operation of the electricity network. This considers the management of the balance between generation and consumption at every moment and power trading within the underlying networks. This way, each TSO is in charge of an established *control zone* [BS14].

In this context, *balancing groups* (BGs) correspond to a structure which joins operators from the energy market in order to achieve economic and accountable objectives. BGs consolidate consumers and providers in a virtual group where demand and supply are balanced [KML$^+$15, MOP14, DE13]. Achieving this balanced state implies costs to the entity responsible of managing the BG. This way, TSOs and *balancing responsible parties* (BRPs) achieve contracts to guarantee power balance within a control zone [BS14].

Control zones of a TSO can consist of an arbitrary number of BGs. These control zones contain power injection nodes, for supplying power to the BGs, and

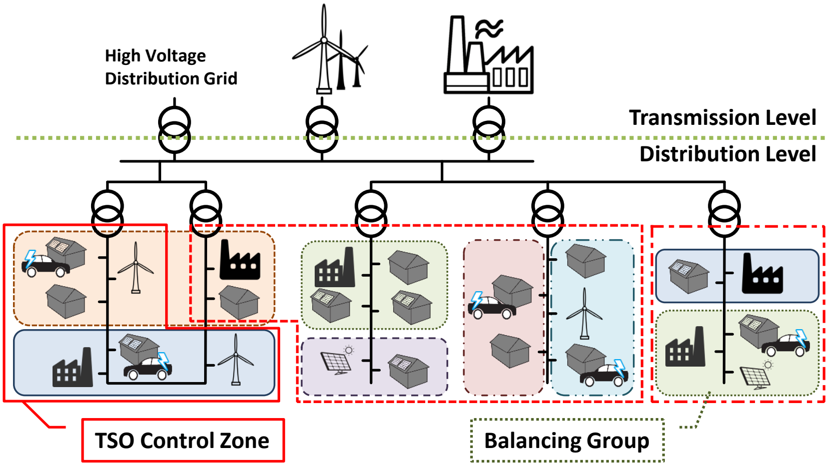


Figure 2.2.: Virtual and physical structures for the power management in the power grid. Based on [BS14, USD$^+$13].

withdrawal nodes, which represent the demand. In the context of a liberalized market, customers are not geographically restricted to a specific power supplier. Hence, supply companies can serve customers in different territories. Furthermore, balancing groups are not restricted by the distribution network [BS14], and injection points can supply power to many BGs. A simplified diagram of the structures for power grid management can be observed in Fig. 2.2.

From a BRP perspective, typical responsibilities include providing a balanced planned schedule, with a specific time resolution [MOP14]. The required generation and consumption are estimated through probabilistic methods. In this context, the use of balancing energy to cover loads should only take place in order to compensate unpredictable deviations [DE13, MOP14]. As a consequence, BRPs invest to manage the deviations in energy load, both from the supply and demand side, in order to avoid fines and economical repercussions when unforeseen events occur [MOP14].

To face potential deviations from the generated schedules, balancing power products are considered and traded in the market. These products are categorized into primary control, secondary control, and tertiary reserve (Fig. 2.3). Each system operator must guarantee a certain amount of balancing capacity of each of these products [MOP14]. Primary reserves are activated to face small imbalances, drops or increases of frequency, and prevent large errors. Secondary reserves are utilized to control the zones where the imbalances have occurred. They are able to balance large errors, such as ramping, demand

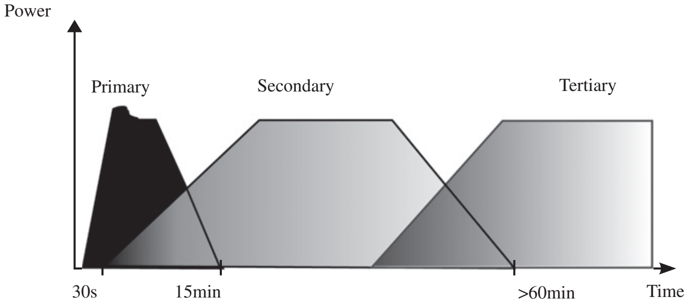


Figure 2.3.: Timescales of frequency regulation control. From [GZA10].

forecast or renewable energy in-feed forecast inaccuracies. Both, primary and secondary reserves are triggered automatically. Tertiary reserves, are rarely used, and are manually activated to face large and long lasting disturbances [GZA10][1].

Currently, the stability of the system and load balance within BGs mainly depends on the accuracy of the consumption and generation schedules. Nevertheless, issues will be accentuated by the generalized demand of increasing penetration of RES in current power grids. Fluctuations on the declared schedules from solar and wind power generation require special consideration, due to the stochastic nature of their generation profiles. Moreover, load flexibility in the demand side will increase unpredictability of the consumption schedules. Hence, the relevance of mechanisms for addressing unbalances generated from the supply side is justified.

2.2. Challenges of the Future Power Grid

The future power grid is expected to dramatically change the traditional structure and operation of the power grid. The main drivers of this change are, from the supply side, the increasing shares of RES and, from the demand side, the increasing flexibility of end-customers. In this section, these challenges are described and strategies to maintain load balance in the power grid, in consideration of the new scenario, are discussed.

---

[1] In the German scenario, the balancing control products are referred to as primary control, secondary control, and minutes reserve [MOP14].

2.2.1. Renewable Energy and Autonomy of Customers

An exemplary case of and increase in the utilization of RES in the last decade is Germany. After the environmental disaster of the Fukushima nuclear power station, the country has stepped up its efforts to reduce the dependency on this type of fuel [GKB^{+}11]. The Federal Government aims to achieve a share of 18 % of renewables in the gross final energy consumption by 2020, going up to 40% in 2025 and at least 80% in 2050 [Gov14]. Moreover, according to the Federal Statistical Office ([Bun]), 30 % of the gross electricity production in Germany in 2015 corresponded to RES, representing an increase of almost 7 percentage points from 2013. In addition, wind and solar power represent roughly 20% from the total generation.

Although these numbers are positive for achieving the objectives of the country, regarding the reduction of CO_2 emissions and dependency on nuclear power, they certainly present a major challenge to the power grid operation. RES, such as wind and solar power, are characterized by being: *(i)* hard-to-predict, it cannot be known exactly how much power is generated at any given moment, *(ii)* intermittent, meaning that one cannot rely on a constant supply generated by these means, and *(iii)* not dispatchable, specifically, one cannot intentionally increase the supply to fulfill the demand ([SGDG^{+}12]). An example of this can be observed in Fig. 2.4, which depicts the large variations between three consecutive days for wind and PV generation. Moreover, large differences can be recognized between the predicted generation and the real generation for the same days.

As explained, the power grid has not been designed to include large amounts of non-controlled generation. From the BGs perspective, increasing levels of RES will lead to deviations from the scheduled power supply. As a consequence, BRPs will require to adopt measures to continue procuring the balancing of supply and demand, such as repeatedly shutting and starting power plants, accelerating technical wear. From an operational perspective, it is reasonable to assume that increasing PV and wind penetration will increase the costs of purchasing balancing energy [DE13]. Moreover, the consequences of insufficient balancing supply will eventually be suffered by all grid users.

An alternative to improve the ability of the power grid to maintain load balance comes from the demand side, in the form of the so-called intelligent appliances and electric vehicles [Sta08, GKB^{+}11, VST13]. These devices have the ability to autonomously select, within a user-defined flexibility interval, their operation time according to some external or internal criteria. Then, from a load balancing perspective, it would be desirable that these appliances begin their operation when forecasts predict larger RES generation, which otherwise would generate load imbalances. On the contrary, if forecasts predict that RES supply will

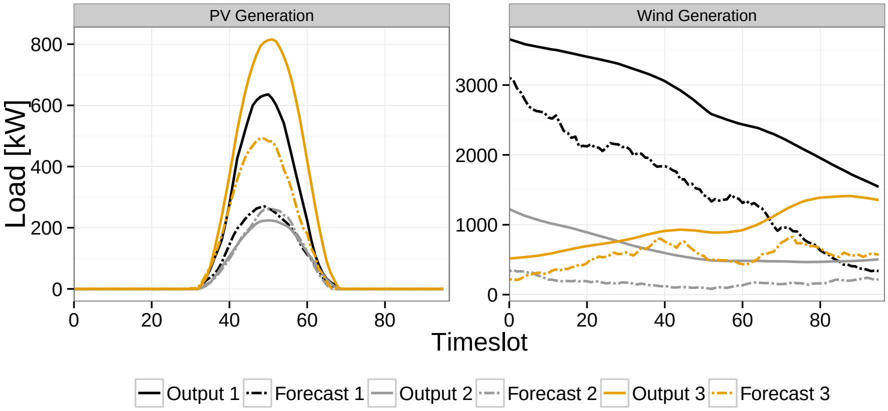


Figure 2.4.: Differences between forecast and RES output of three consecutive days of January, 2014. The balancing zones correspond to 50Hertzs for wind generation and TransnetBW for PV generation.

be reduced or non-existent, it would be desirable that these devices shift their operation times to other hours. This way, the shape of balancing group demand curve would flatten, reducing the requirement of balancing power and increasing the efficiency of power usage [SYH12].

Additional actors in the future power grid are battery electric vehicles (BEVs), in vehicle-to-grid configurations (i.e., the feed-in to the grid from the batteries of vehicles) and micro-combined heat and power plants (μCHP) [MAS12, AMS14]. These technologies are characterized by being able to consume and produce energy. Hence, they can absorb imbalances from too much generation, by charging in the case BEVs, or negative imbalances from shortage of supply, by feeding-in power to the electric system or beginning operation in the case of the μCHP. Nevertheless, these technologies also increase complexity of the operation of the power grid and its management[2].

In this context, the main challenges for the future power grid come from the features of the new elements within it and the increasing complexity they impose on system operation. On the supply side, the main challenge corresponds to the absorption of inevitable imbalances generated by RES. On the demand side, the main challenges come from the increasing flexibility and autonomy of

---

[2] Although these technologies are promising, they are not addressed in the present work. Nevertheless, an outlook on the integration of them into the approach presented in this thesis is presented in Chapter 7, Section 7.3.

customers, which will make the predictability of global schedules and aggregated load profiles much more difficult. Furthermore, customers will be able to supply themselves or exchange electricity products, dramatically increasing the complexity of the system operation. In this sense, both sides of the power grid can operate to compensate each other weaknesses and increase power grid efficiency. If this is not the case, objectives, such as increasing RES penetration, reducing dependence on fossil fuels, or achieving energy security, will not be met and the power grid stability might be compromised.

2.2.2. Demand Response and Load Balancing

Although intelligent appliances might help in reducing load imbalances in BGs, their autonomy represents a challenge for the power grid operation. Let's assume an intelligent washing machine is given a user-defined flexibility interval of six hours, after being charged with a load. Now let's assume that the washing machine operates within a BG with $10,000$ additional intelligent washing machines, with similar flexibility interval. Theoretically, a wrongly designed incentive mechanism might influence all washing machines to select the same operation time, generating large imbalances in the BG and threatening power grid stability[3]. Hence, the utilization of intelligent devices to absorb RES generation, would further increase imbalances in the power grid. Therefore, some mechanism is required to organize the operation times of these devices, such that they do not generate additional imbalances.

To coordinate the demand of flexible loads, such that the load balance in the BGs is achieved, different mechanisms or measures can be utilized. In the context of the energy market, the planning and implementation of the activities of utilities to modify the consumption of customers, such that specific global load profiles are achieved, is referred to as demand side management (DSM - [Gel85]). These mechanisms can range from different types of incentives, to directly controlling the load shifting process of individual devices. The active coordination of loads to achieve specific consumption objectives, is referred to as demand response (DR) and specific measures are referred to as DR programs. DR programs consider advanced forms of interaction between utilities and customers to achieve the desired global consumption behavior. Hence, means that enable these forms of communication are required [BMM14]. In this thesis, in concordance with [Got15], DR programs are categorized into two groups:

- In **centralized load control**, strategies are characterized by customers ceding control to an external entity, which calculates adequate operation times

---

[3] It has to be noticed that this situation could also occur with the current power grid operation. Nevertheless, the stability of the power grid is maintained due to the randomized execution times of these appliances, when no incentives are performed on costumers.

for the appliances of customers, such that balance within a BG is achieved and RES usage is maximized [TAMU14]. Under this paradigm, approaches such as direct load control and optimal schedulers can be found [SYH12, SGC$^+$13, TAMU14]. Nevertheless, if the size of the network is too large, this type of approach may not be computationally affordable [TAMU14]. Moreover, to achieve optimal results, centralized schedulers usually require full information of the load composition of customers and full control over loads defined as *flexible*. This certainly implies major privacy concerns for end-customers and for some users, such an approach might be considered unacceptable. In connection to this issue, centralized approaches might not be adaptable when new devices are incorporated, requiring a permanent update regarding the load composition of customers.

- In **decentralized load control**, incentives are given to customers, such that they modify their consumption behavior. In this case, computational complexity is dramatically reduced, since the decisions involved in the scheduling of appliances are performed in a distributed manner, among participants. Privacy concerns are also reduced, since no external entity has control over what occurs within the domain of the customer. Typically, pricing approaches (such as real-time pricing or time-of-use pricing [Str08]) fall into this category. In this case however, since the behavior is guided, not commanded, misplaced incentives can trigger *avalanche effects* [GKB$^+$11]. If all customers respond in the same way to pricing incentives large imbalances will be obtained. To mitigate this effect, some authors have proposed different forms of randomization [Got15, VST13, GWT$^+$13]. Additionally, some approaches propose communication between participants, such that their aggregated actions minimize individual costs while achieving balance within BGs [HVS11, MRWJ$^+$10]. In the latter, however, privacy concerns might increase far more than with centralized approaches, since communication channels to achieve the required coordination might be utilized to corrupt the behavior of participants. On the other hand, the decision making process to achieve consensus through communication and negotiation in larger networks, might be unacceptably long.

This way, the challenge of any load management mechanism is how to maximize RES usage in a computationally affordable manner, while respecting customers autonomy and privacy, and without increasing load imbalances in the power grid.

2.2.3. Some Load Balancing Strategies

Many alternatives have been proposed for load balancing. In [MRWJ$^+$10], an autonomous distributed algorithm, based on pricing incentives for energy consumption scheduling, is proposed. This approach minimizes costs and balances the total residential load of customers sharing a common energy source. The algorithm focuses on small interactions between participants, where each one tries to maximize their own benefit in a game-theoretical setting, which leads to a Nash equilibrium. This approach is proven to converge and reach an optimum. Nevertheless, the requirement for direct interaction implies security risks. Furthermore, in larger networks, achieving the Nash equilibrium might not be possible in a reasonable amount of time and might lead to a high communication overhead.

A distributed approach for scheduling smart appliances, named randomized load control, is presented in [VST13]. In this case, a utility transmits the ideal shiftable load to each smart meter in a micro-grid. This device derives a probability distribution from the profile and randomly reschedules the household appliances execution times. They conclude that quality solutions depend on the coincidence between micro-grid load composition and RES output. In this approach, however, a feedback mechanism between smart meters and the utility is not considered and the utilization of RES forecasts is not mentioned. Additionally, this alternative is mostly reactive and it does not consider the impact of imprecise of RES forecasts and uncertainty.

Another probability-based scheduling alternative is proposed in [SYH12]. In this case, a water-filling approach is utilized to distributively schedule the execution time of appliances. The main objective is to obtain a flat micro-grid load profile, such that the efficiency in the utilization of conventional generation is maximized. Participants reschedule probabilistically their appliances, according to a centrally computed distribution. Hence, no direct communication occurs between participants. In this case, however, the increase of RES, whose shape is irregular, is not addressed and the utilization of RES forecasts is not considered.

A real-time algorithm for decentralized deferrable load control under uncertain RES is proposed in [GWT$^+$13]. In this case, each individual appliance, such as a washing machine, receives an average aggregated load, which considers all participants. Then, according to the authors, each individual load solves a convex optimization problem and calculates its own schedule. The schedules of all participants are aggregated by a central entity. In this algorithm, the central entity requires knowledge regarding the total number of deferrable loads and their schedules, once generated. As explained, this can imply security risks for individual participants.

In [SGDG+12], three policy designs are proposed for real-time load scheduling, with a receding horizon control approach outperforming the other policies. The main proposal of the approach is a new evaluation function, which incorporates prices and RES forecasts, for the centralized scheduling operation times of multiple EVs. In this approach, a centralized scheduler has full control over the devices. Furthermore, the validity of this approach with less flexible devices is not empirically demonstrated.

[HVS11] proposes a so-called stigmergy-based approach for load balancing. Here, a coordination mechanism to address the supply and demand matching large numbers of distributed actors, is presented. This approach considers achieving an equilibrium state through alterations on a definition of a shared environment space. Nevertheless, in this approach, the identity of participants is required for coordination to occur. Moreover, a direct communication channel between actors is necessary to cooperatively construct solutions. As mentioned, this implies potential privacy and security risks for end-customers. From a conceptual perspective, this approach does not qualify as stigmergy, in the strict sense of the concept, since requirements like anonymity and indirect communication are not met. These issues are further discussed in Chapter 3.

Approaches for demand side management based on ant colony optimization (ACO) have also been developed. On the one hand, [SMCO15] proposes an algorithm to calculate efficient schedules for flexible appliances within a household. The approach considers a graph representation of the load scheduling problem. The objective is the minimization of the electricity costs of a household while complying with load restrictions. This approach obtained competitive results when compared with a genetic algorithm. On the other hand, [DPR14] presents an architecture for distributed load scheduling in an isolated population of the power grid powered by wind turbines. The scheduling problem is also modeled as a graph, in which the arcs represent the operational prices of the loads to schedule. The objective of the problem is to minimize the costs of the whole system by increasing wind power usage. An ACO-based algorithm is used to generate schedules for all participants. Results show that, with this approach, customers are able to direct their demand such that wind power usage is increased. Although both approaches present a novel perspective of the problem, some elements undermine their real applicability. Firstly, the required graph representation of the problem is constructed through the combination of possible load schedules. Hence, with larger networks, the size of the graph to be constructed, before the solution construction process begins, will grow exponentially. Secondly, both approaches require detail knowledge of the load composition of consumers to construct this graph. As discussed, this represents a major privacy issue for end-customers.

These are some of the many approaches to face load balancing in the power grid. As it can be observed, the focus in each scenario is quite clear and defines the strengths and weaknesses of each alternative, regarding user autonomy, privacy, flexibility and optimality of the performance, among others. Hence, in the described scenario for the future power grid, a BG manager must be aware of the trade offs and benefits of each alternative, in order to decide which approach is more suitable in each scenario.

The load balancing approach proposed in the present thesis puts the emphasis on autonomy, simplicity and privacy of customers. Additional issues emphasized are robustness of the global behavior, flexibility for the inclusion of new loads and customers, and coordinated behavior for achieving load balancing and increasing RES usage.

2.3. The Power Grid as a Complex System

Throughout this chapter, some of the many components of the power system have been discussed. These components connect and interact in non-linear ways, forming intricate networks and feedback loops. The power grid is in continuous adaption to provide electrical services to thousands of autonomous customers. The system is robust to perturbations, being able to, within reasonable boundaries, increase or decrease generation in order to maintain balance of the load. The power grid is also in permanent evolution through the incorporation of new technologies. These features are characteristic of complex systems [BMMS+06, MSS10].

The increase in RES shares in conjunction with the implementation of EVs and intelligent appliances, although increases flexibility, implies a major change in the way the power grid operates. Unpredictability of the supply and demand schedules increases, due to the new features of the participants. Nevertheless, this opens the alternative for the development of new business models in which BRPs can cooperate with residential customers to guarantee local stability of the power grid. Hence, the main challenge for managing such a complex system is: How to guide a system composed of potentially thousands of autonomous entities such that a coherent global behavior is achieved, which complies with restrictions of customers while balancing the power grid and increasing RES usage?

2.4. Discussion and Summary

The power grid is experiencing a dramatic change from its traditional design, based on centralized large power plants transporting power through long distances in a unidirectional manner, to a highly distributed system with large flexibility of customer and RES penetration. In this new scenario, access to the internal architecture of participants should be limited in order to reduce privacy risks. Moreover, there will be no guarantee of benevolent behavior of end-customers, regardless of their potential flexibility. Furthermore, the behavior and interactions between customers will be less predictable. Hence, load management mechanisms should consider these restrictions when assessing load balancing and increasing RES usage.

From a load balancing perspective, the increasing shares of RES represent a major challenge for maintaining balance between power supply and demand. Since supply cannot anymore be freely adapted to the demand, the increasing flexibility of customers could be utilized to cover the supply and achieve load balance. Traditionally, only large consumers participate in DR programs. Hence, market models which promote residential customers participation in DR programs should be designed and implemented [Got15].

Once the participation of customers is achieved, the challenge becomes the utilization of the residential flexible loads to achieve load balancing. In this case, load management mechanisms should aim to achieve robust behavior, adaptability to perturbations and deviation from RES, effective utilization of the distributed nature of the future power grid, and cooperation and coordination in the achievement of balancing objectives.

These features may be conflicting with basic requirements of customer. From this perspective, traditionally end-customers are anonymous within a population. In the future scenario, communication channels will open, which might be utilized for malicious activities and could threaten privacy and autonomy of customers. Hence, load management mechanisms must take account of the global and individual perspectives.

In the following chapter, a detailed description of a coordination and cooperation mechanism from nature, which depicts many of these features, is presented. This mechanism is characterized by indirect and anonymous communication between participants of a system, which depicts self-organized behavior and is called *stigmergy*.

3. Stigmergy and Self-Organization

> *What are you bitching about? In case you haven't noticed, we ants are running the show. We're the Lords of the Earth.*
>
> Weaver, *Antz*, 1998

The intricate relationships and feedback loops between the different elements within complex systems make them hard to manage. In case of the power grid, the growing autonomy of customers and the requirement of expanding the penetration of *hard-to-predict* supply from renewable energy sources such as wind and solar power, are increasing the complexity of its operation and its efficient management.

Nevertheless, it is quite interesting to observe that the power grid has self-organizing features. It is resilient to the failure of single components, as long as they are not essential, such as individual consumers or small power plants. Moreover, it has the ability to moderately adapt its generation, in order to supply energy to large amounts of autonomous customers. Additionally, it is in permanent evolution, incorporating new technologies both on the demand and supply side, changing its features and limitations. In this context, it is reasonable to consider that the power grid behaves similarly as a living organism with a defined purpose which can improve the efficiency of its operation.

To understand how to manage this complex system, first, some fundamental issues regarding self-organization and life-alike systems need to be discussed. Furthermore, the relation between stigmergy and self-organization needs to be understood, since the approach for managing autonomous customers in the power grid presented in this thesis, is based on the former one.

In this chapter a discussion of the relation between organic systems and self-organization is presented. Furthermore, different strategies for managing self-organizing systems while preserving desirable self-organizing features are discussed. This discussion is essential for justifying the power grid as a life-alike system and understand how it can be efficiently guided, given its features. In the context of managing self-organizing systems, a comprehensive analysis of stigmergy is performed. Results of this analysis are utilized for supporting stigmergy as a valuable alternative for managing the power grid, given the requirements and characteristics of the future power system (Chapter 2). Furthermore, this analysis is utilized in Chapter 4, for the design of a stigmergy-based management mechanism for the power grid.

Contributions in this chapter regard the enhancement of the taxonomy for stigmergy, the specification of the stigmergic coordination process, and the definition of the requirements for artificial stigmergic systems.

3.1. Organic Systems and Self-Organization

Which features do *organic systems* have that make them capable to cope with uncertainty? How do these features relate self-organization and organic systems? Can artificial systems be called organic ? Which are the conceptual implications of designing management mechanisms for self-organized systems?

In this section, some of the features that allow to reference some artificial systems as *organic* are discussed. Furthermore, the relation between organic systems and the concept of self-organization is studied. Through the revision of two definitions of self-organized systems, the importance of autonomy and the relation between individuals for the spontaneous rise of global coherent behavior is emphasized. Finally, the boundaries of the management mechanisms for self-organized systems are discussed.

3.1.1. An Overview of Organic Systems

Increasingly, the presence of autonomous devices which are able to exchange information, build intricate networks and influence each other, becomes ubiquitous [MSS10]. Systems composed of these kinds of devices are complex, in the sense that minor alterations in the way local interactions take place might trigger large changes from a global perspective. These devices should be able to organize themselves in order to achieve objectives and provide services specified by the users. This implies that users will define an acceptable behavior for these devices, and they autonomously will have to find solutions that fulfill those requirements in the best possible manner. Then: How can a system composed of autonomous entities which can influence each other be managed, in order to coherently achieve clear objectives defined by a user? To answer this question first these systems should be acknowledged as life-like entities, or *organic systems*, and the notion that full control over them cannot be obtained, should be understood.

This notion implies that the performance of individual components of the system is not required to be perfect, and that the system itself is not required to perform as an orary, where every state and result are completely predictable. On the contrary, what matters in organic systems is that the final global objective is achieved within acceptable boundaries, acknowledging the possibility that some final results within these boundaries might be better than others. Therefore, in this context the failure of specific components of the system is acceptable as long as this does not prevents it from achieving its global objectives.

These features can be observed in living systems. The human brain is composed of billions of neurons interacting and coordinating automatic behavior, such as breathing, and voluntary behavior, such as walking. The brain autonomously directs attention to objects that are relevant for the current task, and neglects others that are not [MCS11]. Additionally, if one suffers an accident (especially in early stages of its development) the brain is able to reconfigure the connections between neurons in order to perform these tasks in the best possible way, given the new context. However, there is a breaking point where the brain cannot reconfigure or repair itself anymore. This can be observed with individuals that have suffered dramatic accidents or are afflicted by degenerative illnesses, which are never able to fully recover their autonomy and, in many cases, loose consistency of their own personalities.

Other type of complex living systems are schools of fish. These systems can be composed of thousands of elements. It can be assumed that the school has a unique systemic objective, e. g., to move from one place to another. However, all elements in the school are autonomous, interact and can influence one another, since the route of each fish depends on its distance to other fish and the proximity to predators such as a shark. If a shark attacks a single fish, the escaping individual will influence its neighbors and change the shape of the school, making it impossible for the shark to focus on a single prey to hunt. As a consequence, it can be observed that the school behaves in a similar way as a single organism which has the ability to avoid obstacles and reorganize itself in order to continue its journey. Interestingly though, this system can be *managed* to perform in a certain way, while still depicting self-organizing features and respecting the autonomy of individual fish. A strategy of orca whales when hunting schools of herring is building, through cooperative work, a wall of bursting bubbles in order to guide the position of the school to the surface. Individual fish escape from the bubbles, identifying them as threats and, as a consequence, influence the position of their neighbors modifying the global behavior of the school. Once the school is forced into a tight sphere by an ever smaller wall of bubbles, the whales slap the school with their tail flukes, killing or stunning small numbers of herring. Then, the herring are devoured one at a time by the whales, which take turns to maintain the wall of bubbles. The process continues until all whales have fed, which usually implies that the school exists no more [SD97, Sim97].

Given these examples, some essential features of these systems that can be observed, either natural or artificial, are adaptability to uncertainty, tolerance to failure of individual components, interaction between components, autonomy and emergent global behavior. Hence, organic systems are systems which dynamically adapt, through the interaction between their components, to alterations on their environment while aiming to achieve an objective [MSS10].

Furthermore, it can be observed that given the correct stimulus, organic self-organized systems can be influenced to achieve a specific global behavior or perform in a certain way, which serves a clearly defined purpose. In the case of the herring school, the purpose is defined externally, incidentally implying the destruction of the system, and the stimuli is the wall of bubbles. Moreover, the process of influencing this system is only possible because whales exploit the global behavior of the school, unlike the shark, which focuses on individual components. Something similar occurs with patients in physiotherapy recovering from limbs amputation. In early stages, they are influenced through massages and electric impulses in order to recover sensibility on severed limbs. Afterwards, patients are provided with prosthetics which they have to learn how to utilize. During the whole process, the brain autonomously creates and enforces new neuronal connections in order to achieve high level objectives [CYKD13, Joh00]. The stimuli correspond to the training process that the patient undergoes.

3.1.2. A Brief Discussion of Self-Organization

A central topic in the discussion is that artificial systems which behave organically also exhibit self-organizing features. From a global perspective, they reorganize their individual components and the way they perform, to protect, heal and even improve themselves in order to cope with uncertainty. Abstracted from the philosophical discussion and referred exclusively to the practical applications of self-organization, these features can be regarded as the so-called *self-x properties*: self-configuration, self-optimization, self-healing, self-protection, and self-explanation, among others. A system provided with self-healing properties is able to detect malfunction in its operation and to correct it autonomously, without external assistance. A self-protecting network is able to proactively detect and defend itself against attacks or cascading failure, while autonomously improving the knowledge of potentially dangerous activities that might impair its operation. These features allow self-organizing systems to learn from their environments and respond intelligently to unexpected scenarios. For complementary insights and extended discussion on the self-x properties, cf. [SMSc$^+$11, BMMS$^+$06, MSS10].

These features might raise the perception that self-organized systems are too complicated and not the adequate alternative for specific tasks, which might permanently require optimal responses[1]. Self-organized systems, like organic systems, are designed to operate in changing environments, which require flexibility. Moreover, they are designed for situations where achieving the optimal solution might not be as important as achieving any solution which will allow the system to survive and improve in future stages.

In this context, and in order to understand essential issues of self-organization in practical scenarios, two definitions are reviewed. The first definition, from [Ger07], goes as follows:

> *A system described as self-organizing is one, in which elements interact in order to dynamically achieve a global function or behavior.*

The main idea behind this definition is clear. Nevertheless, in the context of this thesis a more precise definition of the term *interaction* is required, together with a clear perspective on the importance of individual autonomy. Indeed, a centralized controller could *interact* with subordinated entities and still have full control over the system. Certainly, this is not the case in self-organization as it was observed in the previous examples. Self-organized systems should be guided to move into or within a target space [SMSc$^+$11].

Moreover, a question rises regarding the self-x properties: Can these properties individually be provided to a system or do they spontaneously emerge as a consequence of the interaction and feedback between the components of the system? This issue is addressed in the definition from [EdM08]:

> *A self-organizing system (SOS) consists of a set of entities that obtains an emerging global system behavior via local interactions without centralized control.*

The importance of this definition is that it explicitly recognizes the importance of a non-existent centralized control. Furthermore, it clearly connects the spontaneous emergence of global behavior to the local interaction of individual components. These are relevant distinctions to be made. From this definition it can be concluded that the self-x properties emerge spontaneously from the interaction between components and that they are a sub-product of the system behaving in an organic manner. This unveils a relevant requirement for designing

---

[1] In this specific case a difference is stated between *optimal* and *acceptable* behavior or performance.

self-organized systems. The system design should promote or disrupt the interaction between individual entities such that a desired global behavior arises. Hence, specific systemic properties should emerge and be visible from a global perspective as a consequence of specific design features.

The previous conclusions bring to light the importance of the *micro-macro effect* for self-organized systems. The relevance of the link between micro-levels and macro-levels is obvious when it is understood that the relations, interactions and behaviors at a micro-level define the global properties and behavior of the system. Therefore, in self-organized systems, the way behavior is designed at a micro-level is vital. A wrong design might not only prevent the system from achieving a desired global behavior, but might also trigger *avalanche-effects* or uncontrolled chaotic behavior in a negative feedback spiral.

Nevertheless, at this stage, the role of the user continues to be vague. In the context of artificial stigmergic systems, the system should autonomously reconfigure and operate to achieve user-defined objectives which might change in real-time. This is fundamentally different for natural stigmergic systems. Hence, in consideration of the previous ideas, for the remainder of this thesis the following tentative definition of self-organization for artificial systems is considered:

> *A system is described as self-organizing if it consists of a set of autonomous entities that proactively interact giving rise to and modifying the global systemic behavior in order to fulfill user requirements regarding the system operation and its output.*

With this definition, a final piece in the puzzle of artificial self-organizing systems can be recognized. These systems should serve a purpose. Therefore, the local interactions should be oriented such that the emerging global behavior can fulfill the desired objectives. Furthermore, this definition recognizes that self-organizing systems can face dynamic and uncertain scenarios. Hence, the requirement of modifying the global behavior to move the performance of the system into a desired target space becomes essential. This is the final challenge for artificial self-organizing systems: Designing individual autonomous components such that through their interaction, which cannot be explicitly controlled, a global behavior can emerge that fulfills the objectives of the system.

3.1.3. Guiding Behavior in Self-Organized Systems

A relevant issue in artificial self-organized systems is that individual behavior at micro-levels of the system should not be directly controlled but only induced, so that the user-defined objectives are achieved autonomously by the system as a whole [Ger07]. However, in real world applications it might be required that some form of control over the performance of these systems is available. Then, it is important to identify how control over a self-organizing system can be increased, without depriving it of its desired features.

From literature ([SMSc$^+$11]), two main strategies can be identified for guiding the global behavior of these systems in order to increase control without affecting the self-organizing features.

In the first strategy, the guidance mechanism can be distributed among the different components of the system. The objective is to modify the interactions and feedback loops that give rise to global behavior. No explicit control is performed over the system, nor explicit commands sent to individuals. On the contrary, the global behavior is influenced through the alteration of the rules and mechanisms that define the interaction between individuals. Hence, since the interactions which give rise to a global behavior are modified, a different global behavior will be achieved [SMSc$^+$11, Ger07]. This strategy can be illustrated by a cellular automaton. Cellular automata are mathematical idealizations of physical systems which consist of a grid of *cells*, each having one out of a finite number of states, such as *on* or *off* [Wol83]. At each point t in time, the state of each cell is determined according to rules which consider the state of the neighboring cells at the previous point in time $t - 1$. In this case, the modification of the rules that define the change of state of the cells, will change the way they interact among themselves, and therefore the global behavior. This strategy is referred to as *strong self-organization*, since no central entity is actively modifying the behavior of the system. On the contrary, control is distributed among all entities and the rules that define emergent behavior are modified, giving rise to different global behavior.

In the other basic strategy, a central entity performs controlling actions that drive the system behavior into a desired target zone [DBT00, SMSc$^+$11]. These actions influence the system, or sub-groups of it, directly to perform their tasks in a different way or at a different location, while complying with the autonomy requirements of the individual components. *Ant Systems* (AS)[DBT00] can be considered as a typical example of this strategy. Specifically, regarding an AS solving a Traveling Salesman Problem (TSP) instance, a central entity enforces a specific route at the end of each iteration with extra pheromone deposition, directing the search to specific sections of the search space (Details of this example are discussed in Subsection 3.2.4). Nevertheless, the solution construction process continues to be performed in a distributed and self-organized manner. This approach is referred to as *weak self-organization*, since controlling actions are performed by a central entity [FD11].

Variations and combinations of these strategies are possible in order to comply with specific problem instances. Hence, these two strategies define the boundaries in the range of alternatives, which can be utilized to include controlling actions over self-organized systems. Nevertheless, the common denominator is that no direct command is performed over individual elements of the system. Conversely, they are only influenced to perform in a different way.

It can be seen that the key feature in self-organization is autonomy of individuals, since it is this autonomy which enables emergent behavior to arise and fulfill the objectives defined for the system. Therefore, once the autonomy of individuals is acknowledged, the existence of a centralized controller, as an entity which has full control over the system, becomes a conceptual contradiction. Then, in this context, the objective of a management mechanism is to modify and guide the global behavior, which is a consequence of individual autonomous actions, in a coherent and consistent way.

3.2. The Stigmergy Mechanism

The concept of stigmergy was introduced by the French entomologist Pierre Paul Grassé in 1959 and it explains how large collections of insects coordinate, giving rise to global behavior that largely exceeds in complexity the abilities and scope of individual insects. Stigmergy enabled researchers to understand the paradox of coordination in social insects (like ants, wasps or termites) which from a system perspective look surprisingly organized and well coordinated to achieve clear systemic objectives. However from an individual perspective, it seems as if each insect pursues its own agenda, without much awareness of the activities of other nestmates ([TB99, ROV$^+$07]). Furthermore, the stigmergy mechanism explains how self-organization emerges, maintains and dissolves in insects societies.

From a self-organizing systems perspective, stigmergy conforms a viable alternative for the coherent guidance of emergent global behavior. For the remainder of this thesis the following definition of the concept will be utilized, which comprises the main ideas and perspectives in literature ([TB99, HRJ08, MO08, Hey11]):

> *The concept of stigmergy explains the processes and self-organized behavior which results from the indirect communication between individuals through anonymous alterations on the environment. As a consequence of these alterations cooperation and coordination emerge spontaneously which enables the system to achieve global objectives in a self-organized manner.*

To understand the internal functioning of this mechanism and the different aspects of it, in this section different examples of stigmergy in nature are analyzed. Then, a taxonomy of the so-called *stigmergic variables*, which enable indirect communication in these systems, is provided. Afterwards, a discussion regarding the best known artificial stigmergic system is performed. Finally, the cycle of the stigmergic coordination process and the requirements for a system to be classified as *stigmergic* are provided.

3.2.1. Stigmergy in Nature

Stigmergy presents itself in nature in many forms. Each form implies different types of responses from the engaged individuals, different features of the coordination process and different global behavior. The following examples enable the identification of the common features in stigmergic systems and determine the requirements of this coordination mechanism.

Foraging Ants

The typical example of stigmergy in nature is ants foraging. Ants are able to, incrementally, reveal the most adequate path between each food source and the nest, in terms of distance, food source quality, and accessibility, among others. Given that there are millions of possible paths and that each individual ant is an extremely simple organism unable to find the path by itself, how are they able to reveal a fairly optimal one? Ants randomly explore the area surrounding the nest, and while moving they leave a chemical pheromone trail on the ground, which all ants can perceive and evaporates at a certain rate. When an ant finds a food source, the ant evaluates the quality and quantity of it. While the ant returns to the nest, it deposits additional pheromone on the path according to the quality of the food source. Ants select probabilistically their path, tending to follow the path with the largest pheromone concentration [BL08, DBT00]. Additionally, considering that pheromones evaporate over time, the shortest or most visited path will achieve a larger probability of being visited, thus in turn raising it's pheromone concentration and becoming more attractive for ants to follow. The evolution of the search can be seen in Fig. 3.1. The stimulus that triggers this auto-catalytic process ([TB99, DBT00]) which gives rise to coordination in solving the problem is called *stigmergic stimulus*. In the according terminology, ants coordinate through a signal or mark embedded in the environment, with a continuous value.

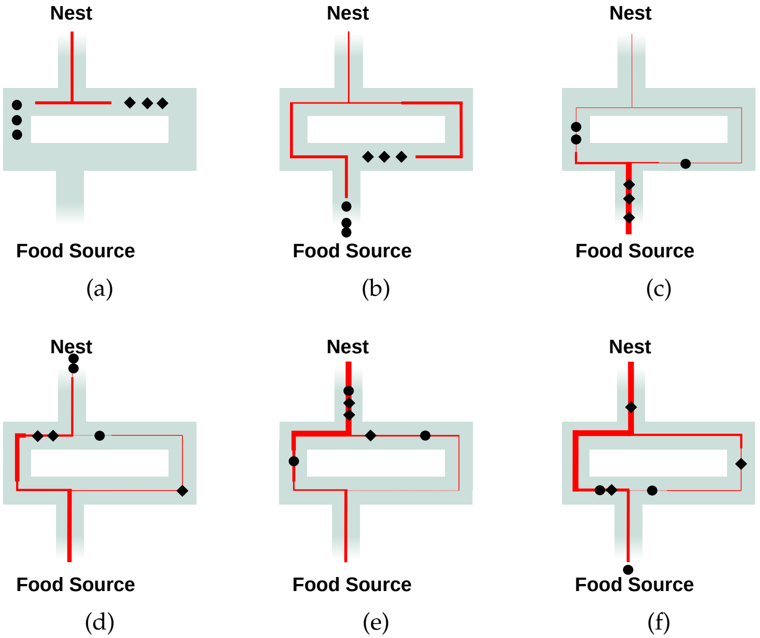


Figure 3.1.: Idealized setting explaining the foraging behavior of ants. Pheromone is characterized as a red line which increases or reduces its width according to the level of pheromone concentration. (a) foraging starts. 50% of the ants take the short path (circles), and 50% the long path (rhombus). (b) ants which have taken the short path arrive earlier. Pheromones evaporate in the first sections of the routes. (c) Pheromone has less time to evaporate on the short path. Hence, it has more pheromone concentration and is more likely to be visited. On the long path, pheromone has more time to evaporate. Therefore, the path becomes less attractive as pheromone concentration diminishes. (d), (e) and (f) the shortest path is visited regularly receiving constant pheromone deposition. The search converges.

Wasps Funnel

The experiments performed by Dr. Andrew P. Smith ([Smi78]) unfold other aspects of stigmergy. He examined the construction of a solitary wasp shed, specifically of a funnel above the entrance made from mud pellets. The process corresponds to a *stimulus-response* sequence, on which the completion of each well characterized stage constitutes a stimulus to perform the next stage of con-

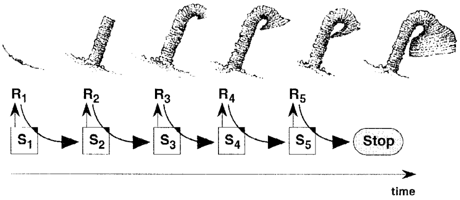


Figure 3.2.: Stimuli-response sequence in the funnel construction process of the Eumenid wasp Paralastor sp. Each stage in the process is triggered by an stimulus S_n, $n \in [1, 5]$, which stimulates the wasps to begin a new set of actions R_n. The completion of each stage conforms the stimuli which triggers the beginning of the next stage. When the last stage is finished, there are no more stimuli triggering additional actions. Therefore, the construction process stops ([TB99]).

struction process. This way, the funnel is built in five distinct stages, which can be observed in Fig. 3.2. Stage 1 considers building the stem of the shed up to a specific height. In Stage 2, the wasps cease to construct uniformly upwards and begin to build a uniform mud curve on one side of the stem. In Stage 3, when the mud curve is finished, the construction of a bell begins by splaying the stem to create a flange. In Stage 4, the flange is widened in the direction of the stem, giving it a characteristic asymmetry in one direction. Finally in Stage 5 the bell is completed by building downward from the edge of the flange [TB99, Smi78]. After identifying each stage, Dr. Smith made holes in the funnels at different stages of the construction, specifically when the funnel was almost completed. When wasps returned to their nests they soon discovered the holes. After some minutes of careful examination, one wasp began to work: A second funnel was built on top of the first one [Smi78] (see Fig. 3.3). These results reveal that in solitary circumstances, the process of indirect coordination of behavior through previous consequences or stimuli, results in sequential-like behavior [TB99]. Furthermore, if the stimuli are conflicting or incoherent redundant behavior can be obtained and in larger populations, *avalanche effects* may appear ([Fro05, GKB$^+$11]). However, the most interesting conclusion of these experiments is that if individuals are not able to distinguish the results of their own labor from those of others, then indirect cooperation between individuals can occur. Moreover, in this case the behavior of individuals could be influenced without directly commanding them to perform any task, as it was shown by the previous experiments. This is a fundamental concept in stigmergy (See discussion in Section 3.2.5). Finally, the stigmergic stimulus corresponds to the level of completion of the funnel, this is, the level of completion of the task that the wasp performs. This way, wasps would coordinate through a physical alteration of the environment with a discrete value.

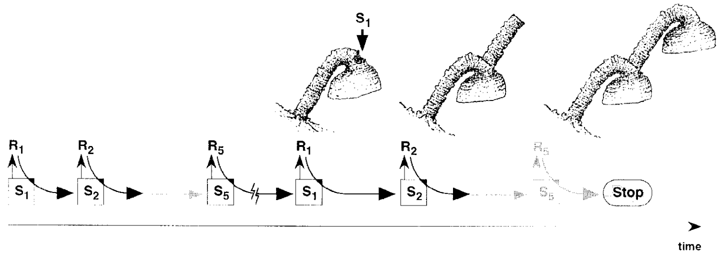


Figure 3.3.: Construction of an abnormal funnel of the Eumenid wasp Paralastor sp. When the funnel is almost finished (end of Stage 5), a spherical hole is made. This hole emulates stimulus S_1, which triggers a new funnel construction. The wasp identifies this stimulus and begins the construction of a new funnel on top of the previous one ([TB99].

Another conclusion that can be drawn from this example, is that a fundamental concept of stigmergy is the role of identity of participants. According to [TB99], if a wasp is not able to distinguish the product of its own labor from that of another, then two wasps can in principle work at completing the same nest structure, without awareness that other workers perform the task cooperatively. Furthermore, it is elaborated that this is precisely the mechanism that Grassé had in mind when he presented stigmergy. This implies that the identity of the author of the alterations is not relevant for the coordination process. Individuals do not trace the origin of the alterations, they are only guided by them, never mind their origin. As a consequence, the coordination mechanism allows anonymity of its participants.

Ants Cemetery Formation and Clustering Behavior

Another example of stigmergy corresponds to the process in which some species of ants, and other insects, collect and sort their corpses (from now on *items*), spontaneously building cemeteries without previous knowledge of their final location. When a large number of items is located over a surface, ants begin to relocate them such that a single cemetery eventually forms in what appears to be a collective well coordinated effort. Nevertheless, each ant seems to perform as if it was not aware of other individuals, ignoring their strategies or behavior [MCA02]. To understand the process the model proposed by J. L. Deneubourg is utilized, which relies on biologically plausible assumptions ([DGF$^+$91]). Here, a single ant is located in a bounded surface with a large number of items randomly located over the surface. The only task of this ant is

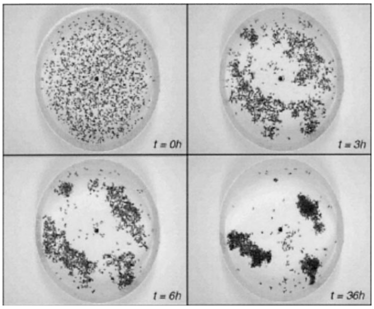


Figure 3.4.: Clustering behavior of real ants. The figure shows spontaneous raise of clusters throughout several hours ([DGF+91, DBT00]). Small, evenly spaced clusters form, which eventually merge into larger clusters.

to transport the items from one location to another. Then, how does a unique cemetery raises? The process of transporting an item is framed within two decisions: which item to pick up, and where to deposit it. The key is that both decisions are performed based on a probability, and the definition of the probabilities depends on *environmental information* which is modified every time the ant relocates an item. Deciding which item to pick up depends on how many items have been observed in the close vicinity (also referred to as *immediate environment* in [DGF+91]). Deciding on which pile of items (or cemetery in formation) to deposit the one being transported depends on the size of the pile, which the ant is able to estimate [MCA02]. The larger the pile, the larger the probability for the ant to deposit an additional item on it. Following this decision process, the ant is able to, incrementally, group the items and eventually form a unique cemetery, as depicted in Fig. 3.4. This example, as well as the wasp funnel example, shows that a stigmergic system composed by one single individual stimulating itself and achieving complex global behavior can exists. In this case, the stigmergic stimuli correspond to the size of the pile of items, and the location of the items over the surface. This stimulus constitutes a physical alteration of the environment interpreted as a continuous value.

Other remarkable examples of stigmergy in nature are termites utilizing soil pellets impregnated with pheromones to build their nests and wasps building combs in successive stages ([TB99]).

3.2.2. Features of Stigmergic Systems

The analyzed natural systems help to understand some characteristics of stigmergy. Firstly, it is clear that stigmergic systems are self-organized. Global behavior arises spontaneously as a consequence of the interaction (indirect communication) between individual components, and the global results obtained through this aggregated behavior clearly overcomes the isolated abilities of those individuals. Hence, stigmergic systems depict desirable properties of self-organizing systems such as robustness, adaptability to uncertain scenarios, flexibility, etc. In addition, the coordination and cooperation process is framed within an exceptionally simple interaction process. This simplicity enables many of the positive features of the approach.

From a conceptual perspective these features provide stigmergy with some advantages for the management of the behavior of groups of agents, in comparison to traditional coordination mechanisms for multi-agent systems (MAS):

- It is a light weighted mechanism, unlike others like direct negotiation between agents, which imply the definition of complex rules, settlement of priorities and extremely specific guidelines to each individual situation ([VKV04]).
- Since participants are not required to engage into direct forms of interaction, their identity is not a requirement for the coordination and cooperation to arise in the system. Moreover, as it was previously discussed it is this very property which enables stigmergic systems to depict self-organizing features.
- The information encapsulated within the stigmergic variables is determined by the designer. This enables flexibility to explore a wide range of design alternatives for the stigmergic variables, and implicitly, for inducing agent behavior ([VKV04]).
- Participants are not exposed to the overall model. They do not need to be conscious of the complexity and dynamics of the global perspective, as their behavior is guided by local modifications. Moreover, individuals only need to address their inherent labor, while the global objectives are being accomplished without them being obvious to individuals.
- Stigmergic systems do not have a single point of failure. Nevertheless, a minimum number of participants is required for the coordination process to occur (one single participant stimulating itself). In general, malfunction of individuals does not affect the coordination and cooperation process. Furthermore, these systems are dynamically opened ([She01,

WM15]), in the sense that they do not require special stages to incorporate or remove individual participants from the process.

- Stigmergy provides a frame which enhances modularity and separation of responsibilities within the model ([VKV04]). This way, it is easy to optimize independent elements and assess separately matters like robustness, feasibility, etc.

On the other hand, the concept of stigmergy also carries disadvantages. Specifically:

- Cooperation emerges as a natural consequence of the continuous modifications of stigmergic variables and the behavior they induce. Nevertheless, in the case of occasional decisions with profound implications the stigmergic process may fail in providing an acceptable solution [VKV04]. This is particularly true when agents perform a probabilistic response to stimuli. In this case, combination of stimuli could be implemented in order to deal with specific situations.
- Depending on the type of the stigmergic variables, the observable consequences and dynamics of agent behavior might be exposed with delay [VKV04]. As a consequence, in some scenarios, drastic reorganization or redirection of the system, may not be achieved within the require time limits to prevent system failure.
- Stigmergic systems fully depend on the stigmergic variable. If the design of the variable is not appropriate the system might not achieve coordination (This issue is later discussed in Subsection 3.2.3). Moreover, corruption of the stimuli may redirect the coordination process towards irrelevant tasks, compromising the achievement of objectives.

Limits of the approach could be palliated by combining techniques and tools from MAS. In this case, however, the desirable features of stigmergy should remain when combining it with other approaches. This way, the importance of identifying a system as *stigmergic* is that this system should depict the previously mentioned features. Furthermore, as discussed in Chapter 2, these features are desirable for the power grid.

3.2.3. The Stigmergic Variable and Enhanced Taxonomy

As discussed, in stigmergy the achievement of system objectives is performed without an entity delivering commands of explicit action. In general, the individual behavior and abilities are quite simple. In the absence of any stimulus, individuals perform their inherent behavior in a randomized manner. Once the stimuli take effect, individuals are influenced to perform their inherent behavior in some specific way, e. g., choosing a concrete path to follow or deposit items on a precise location. They do not have detailed knowledge of the final results of their actions and how their actions will contribute to the system objective, although they might have a notion of it (wasps building a funnel example).

Since the origin of the alterations is irrelevant, a single individual can be the source of stimuli of itself, which implies that it *collaborates with itself*. Then, it can be said that it is not required that individuals are aware of others in order to cooperate, coordinate, and achieve global objectives. This makes stigmergic systems tolerant to failure of some components. For example, if a foraging ant suffers an accident and it is not able to smell pheromones anymore, the process will continue without that ant. Obviously, as it happens in organic systems, there is a breaking point: At least one individual is required to trigger the process of coordination. This raises the question: If it is not a requirement that individuals are aware of each other, even more, if it is not required that many individuals exist (as it was shown by the wasp funnel and ant cemetery examples), how can they coordinate and cooperate? They may not be aware of others, however, they are aware of the alterations on the stigmergic stimuli.

Hence, a fundamental element in stigmergic systems is the existence of a *stigmergic variable*, which is printed or embedded in the environment. The alterations on this variable trigger the auto-catalytic effect which gives rise to coordination and cooperation in the system. Therefore, coordination process and activities are defined by the stigmergic variable, and with it, the relation between the environment and the individuals. Stigmergic variables can be of different forms, relating the components of the system in different manners and triggering different forms of stigmergic coordination. Two types of stigmergic variables can be defined ([HRJ08, MO08, Hey11]) according to how they are embedded into the environment:

- **Sign or Marker-Based Variable**: Refers to indirect communication through a signal mechanism. An element external to the environment (a sign) is located on it, and the alterations of this element guide the coordination of individuals. The signs correspond to special markers that agents deposit in the environment, guiding the system behavior. From the previous examples, pheromones utilized by ants foraging correspond to this variant of stigmergic variable.

- **Sematectonic Variable**: Corresponds to indirect communication through physical modifications of the environment. Unlike marker-based stigmergy, the modification of the variable implies a contribution to the given task, expressing the current progress or state in the fulfillment of the global objective. Hence the variable becomes an active part of the problem and its modification does not only determine how solutions are constructed, but also imply an alteration of the solution itself. Ants cemetery construction process and wasps building a funnel, which utilize the level of fulfillment of the system objective as an incitement of action, correspond to this variant of variable.

In order to clearly understand the difference between marker-based and sematectonic variables lets assume a hypothetical scenario: An agent is situated in a room which has a number of tables. The agent calculates its trajectory through the room based on information *embedded* in the tables, which in this scenario is considered the environment. If a bottle is left on a table and the agent utilizes it as an indicator of its future trajectory, this would correspond to a marker-based variable, since the stimulus is something external to the environment. On the other hand, if the table is destroyed, or its shape is modified, and the agent utilizes this information (the shape of the table) to calculate its trajectory, this would correspond to a sematectonic variable, since the stimulus is a physical alteration of the environment.

In addition, the definition of the stigmergic variable and how it is interpreted has repercussions on the kind of stigmergic process that takes place. Accordingly, two kinds of stigmergic mechanisms corresponding to the variable and the response it triggers from individuals ([TB99, Van06]) can be defined:

- **Qualitative Stigmergy**: The interaction between individuals is determined through alterations on discrete stimuli. Hence, a qualitative stimulus generally generates qualitatively different responses. For example, an individual I_1 responds to a stimulus type-1 with an action-A, and action-A transforms stimulus type-1 into a stimulus type-2, which triggers an action-B from individual I_2 ([TB99]). From previous examples, wasps building a funnel correspond to qualitative stigmergy.

- **Quantitative Stigmergy**: The stimuli response does not vary qualitatively. Conversely, modifications on the value of the stimuli imply that the probability to react to it, is modified. Regarding the previous examples, ants foraging and ants cemetery construction correspond to quantitative stigmergy. In the former, the stronger the pheromone trail, the larger the probability of an specific response.

Considering how the stigmergic variable is imprinted on the environment (variety of the variable), how it is modified, and which stigmergic process it triggers (stigmergic mechanism) a taxonomy was defined by [Van06]. Nevertheless, this taxonomy might not be precise enough for the specific design and

Table 3.1.: Improved taxonomy of stigmergy, based on [Van06]. Values in the cells describe agent responses to the correspondent stimuli.

	Marker-Based	**Sematectonic**	**Mixed-Variety**
Quantitative	Stochastic response to signs embedded in the environment	Stochastic response to physical alterations of the environment	Stochastic responses to combinations of physical alterations and signs
Qualitative	Deterministic decision based on a combination of signs	Deterministic decision based on physical alterations of the environment	Deterministic decisions based on combinations of physical alterations and signs
Mixed-Responses	Deterministic and stochastic responses to combinations of signs	Deterministic and stochastic responses to physical alterations	Combinations of responses to combinations of stimuli

implementation of artificial stigmergic systems. Therefore, in this thesis an improved version of the taxonomy for applied scenarios is provided. This improved version clearly specifies the type of response of the individuals to the different kinds of stigmergic variables. Moreover, the range of possible alternatives has been extended to include additional responses to different combinations of stimuli. This increases the possibilities and versatility of the approach for its implementation as a multi-agent coordination mechanism for applied problems. The improved taxonomy is listed in Table 3.1.

The discovery of stigmergy was an important step forward for entomology in improving the understanding of how social insects achieve their complex social structure and coordinate to perform complex tasks which require collaboration. However, it also inspired the study and development of a whole new line of research in problem optimization and MAS.

3.2.4. Artificial Stigmergic Systems: Ant Colony Optimization

The best known implementation of stigmergy in artificial systems is *Ant Colony Optimization* (ACO), which corresponds to an improved version of the *Ant System* (AS) algorithm ([DMC91]). Its implementation will be described for solving the Traveling Salesperson Problem (TSP). This problem is a *combinatorial optimization problem* (COP), and in its most simple version it can be informally described as follows: a salesperson needs to find the shortest possible route through a given set of cities, beginning and ending the trip in his or her hometown.

In its most basic form, the TSP can be formally defined to be a fully connected weighted graph $G = (C, E)$, along with the optimization criterion to find a closed path in G which contains each node exactly once and whose summed-up weights are not higher than for any other closed path. The cities correspond to the nodes (C) and the edges to the connections between cities (E). The search space S corresponds to all possible tours (i.e., closed paths as described) in G. In COP terms, a function f evaluates each solution $s \in S$ by adding the weight of all edges in s, this is, the distance between cities, hence calculating the length of each tour. Thus, a solution s would be a tour connecting all nodes in G and back to the starting node. The evaluation of this solution will be length of that route. Furthermore, each edge $e_{ij} \in E$, which connects cities i and j with $i, j \in C$ is a component of solution s.

ACO is an approach to approximately solve the TSP for a given graph by utilizing basic mechanisms known from ant behavior in nature. Solutions are incrementally improved over time in a concurrent and asynchronous manner by simulating a population of artificial agents with ant-like behavioral patterns. The algorithm is iterative and in each iteration, each artificial ant a builds a solution s to the problem. For each solution component e_{ij} a pheromone value τ_{ij} (emulating the artificial pheromones utilized by ants foraging) is introduced. Furthermore, each ant has a small memory $J^a\left(i\right)$ that allows it to know which nodes remain to be visited when a is at node i. Then, the solution construction process in each iteration for an ant a goes as follows:

1. The ant is located on a randomly selected node.
2. The ant selects the node to visit from set $J^a\left(i\right)$ according to a probability. This probability is defined as:

   $$p_{ij}^{a}\left(t\right)=\begin{cases}\frac{\tau_{ij}^{\alpha}\cdot\eta_{ij}^{\beta}}{\sum_{l\in J^{a}(i)}\tau_{il}^{\alpha}\cdot\eta_{il}^{\beta}} & \text{if } j\in J^{a}\left(i\right)\\ 0 & \text{if } j\notin J^{a}\left(i\right),\end{cases} \tag{3.1}$$

   where τ_{ij} is the pheromone concentration on the arc that connects i and j, η_{ij} is a heuristic value which corresponds to the inverse of the distance or weight of the arc that connects i and j, α and β are parameters that define the relative weight between the pheromone concentration and the heuristic value. Then, a has a larger probability to visit cities following edges that have lower weight and with a larger pheromone concentration.
3. The ant moves to the selected node and removes it from J^a. If J^a is empty, the ant has constructed a solution. If not, step 2 is repeated. It is worth to notice, that artificial ants are able to construct feasible solutions only. The utilization of a memory by each ants has this purpose: Prevent the construction of sub-tours.

At the end of each iteration t, when all ants have finished their solution construction process, each ant a deposits a quantity of pheromone $\Delta\tau^{a}\left(t\right) = {}^{1}/_{J_{\Psi}^{a}\left(t\right)}$ on each arc of the tour $\Psi^{a}\left(t\right)$, of length $J_{\Psi}^{a}\left(t\right)$, they have constructed[2]. The rule for this local pheromone deposition is:

$$\tau_{ij}\left(t+1\right) = \tau_{ij}\left(t\right) + \Delta\tau^{k}\left(t\right),\ \forall e_{ij} \in \Psi^{k}\left(t\right),\ k = 1,\ldots,m \tag{3.2}$$

where m is the number of ants. The deposition of pheromones of ant a, $\Delta\tau^{a}\left(t\right)$, depends on the performance of the ant in the following way: The shorter the route, the greater the amount of deposited pheromone.

After each individual ant has deposited pheromones over their tours, evaporation of the pheromones is triggered according to:

$$\tau_{ij}\left(t+1\right) = \left(1-\delta\right)\cdot\tau_{ij}\left(t\right) \tag{3.3}$$

where $\delta \in (0,1]$ is a parameter called *pheromone decay coefficient*, which regulates the evaporation rate of the pheromones ([DD99, BL08, DBT00]).

Variations of this approach usually modify the pheromone updating rules in order to balance exploration and exploitation of the search. However, the general concept remains: pheromone evaporation and deposition is performed in order to efficiently direct the collective search of good candidate solutions throughout a number of iterations.

As it occurs with ants in nature, the global behavior arises spontaneously as a consequence of the indirect communication through the anonymous alterations on the environment (Graph G). The system is tolerant to failure of some of its components (diminished number of ants in between iterations) and it can adapt when the problem definition changes ([DBT00, Blu05]).

Since individual ants decide according to a probability, they can still choose different paths from the one with the largest pheromone concentration. This enables the algorithm to explore additional alternatives to the currently best solution. This is a relevant aspect of the algorithm, and directly connects with what was previously discussed in Subsection 3.1.3. From a self-organizing and organic systems perspective, a similar situation can be observed with the orca whales hunting herring. In both situations, individuals are guided in a way such that a desired global behavior emerges. This guidance is performed through a stimuli (wall of bubbles in the case of the whales, and artificial pheromones, in the case of ACO) to which individuals respond. Hence,

---

[2] It has to be mentioned, that in many versions ACO, only the ant which finds the best route in the current iteration is allowed to deposit pheromone.

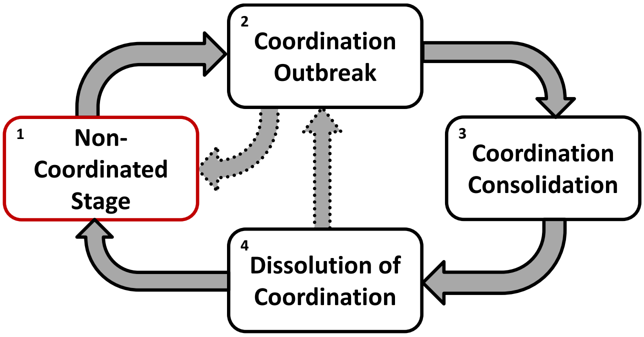


Figure 3.5.: Stages in the stigmergic coordination process. Dotted arrows represent a possible return to a previous stage.

it can be said that the global behavior is guided and no explicit command is sent to individuals.

Other examples of artificial stigmergy utilize the concept to coordinate swarms of robots to perform complex tasks which require collaboration and team work. For a detailed explanation of those implementations, cf. [WN06, PR10, VGVV07].

3.2.5. Stigmergic Process and Requirements for Stigmergy

After discussing the previous examples from nature and artificial systems, the stigmergic coordination process can be considered to be comprised of a series of loops of actions, composed by some general steps. These steps are the result of the aggregated behavior of the individuals within the system, which are the entities that actually engage in the coordination and cooperation process. In order to provide a generalized description for artificial systems, these entities are referred to as *agents*.

Stigmergic Coordination Process

The stages in the *stigmergic coordination process* can be found dispersed throughout literature, usually described in an informal manner, and, to the knowledge of the author, not specified in detail. Therefore, in the following, a general description of the stigmergic coordination process is proposed:

1. Agents perform or are beginning to perform an activity. This activity could correspond to the inherent behavior of the agent. A global objective

exists but no collaboration between agent's to fulfill it. This could be considered a **non-coordinated stage**, as described by [TB99], where agents operate in a random uncoordinated manner, fulfilling their inherent tasks and modifying the environment. However, the stigmergic stimuli concentration is not enough to enforce a coherent global behavior. Considering an ACO solving an instance of a TSP, this stage corresponds to the first iterations. Ants select their routes in a randomized way based only on the heuristic value, since the pheromone concentration on every arc is the same and does not influence the selection process. Regarding cemetery construction by ants, this stage corresponds to ants moving and depositing items without clearly identifiable piles/cemeteries.

2. The concentration of stimuli surpasses a certain threshold or manifests itself in a clear and observable manner becoming relevant in the decision making process of the ants. As a consequence, the **coordination has an outbreak**. Agents continue to perform their inherent tasks, but now they do it while being guided by the stimuli. Moreover, the execution of their tasks implies additional alterations on the stimuli value enforcing the process. Nevertheless, at this stage the coordination is still vulnerable and can be broken by some event or circumstance. In the context of ACO and TSP, this corresponds to the stage in which many good candidate solutions have a relevant amount of pheromone concentration.

3. Agents operate in a fully coordinated manner guided by the stimuli concentration. Exploration of alternative solutions has been reduced. While they operate, they further increase the stimuli concentration providing **consistency and cohesion to the coordination**. At this stage, the system and its level of coordination is resilient to events which could disrupt it from its current behavior, exhibiting *self-x properties*. Moreover, the effect of stimuli diffusion, such as evaporation, becomes minimal. In the context of ACO and TSP, this would correspond to the stage where the algorithm has converged to a solution. In the context of ants constructing cemeteries, this corresponds to the stage in which a single pile is clearly bigger than competing piles.

4. The global objective has been fulfilled. Hence, agents cannot execute their tasks in the current form or location. Individuals can be attracted by residual stimuli. However, they cannot increase the stimuli concentration significantly since there is no more labor to be done in that location or it is physically impossible to perform anymore. Hence, they continue to work on other locations. As a consequence, the stimuli concentration decreases until it becomes irrelevant, **dissolving coordination**. With foraging ants, this corresponds to the stage in which the food source is consumed. Ants will continue to visit the route due to the residual stimuli. Eventually,

however, evaporation will diffuse the pheromones and ants will not follow that path anymore. In the case of cemetery construction by ants, this stage corresponds to the achievement of a single pile of items. Ants may continue relocating items. However, since there is only one single pile, items will be relocated on different places of the perimeter of that cemetery.

It has to be noted that, depending on the type (marker-based or sematectonic) and mechanism (qualitative or quantitative stigmergy) the separation between stages can be less clear. For instance, regarding the wasp funnel construction, the rise of coordination is much more direct, almost omitting Stage 2. This is generally the case when structures are built through quantitative stigmergy. Moreover, in artificial systems Stage 4 does not occur unless the system operates in dynamic environments. In this case a feedback loop from Stage 4 to Stage 1 or 2 would be present, depending on the level of disruption. Additionally, in COPs fast convergence to solutions is a desirable feature. Therefore, Stage 2 becomes harder to identify.

Requirements for Stigmergy

Now that the stigmergic process has been identified, the requirements that each stigmergic system should fulfill in order to depict the previously defined features (Subsection 3.2.2) can be specified as:

- A **stigmergic variable** that can be imprinted on the environment by means of a sign or a physical alteration of it. The stigmergic variables should be **perceivable by the agents** of the system and the origins of the alterations of these variables are not traceable.
- An **environment** to be used as a means to transmit information through signals embedded in it, or by its actual physical alteration. The environment corresponds to an abstraction within the context of the global objective that is being faced. In ACO, the environment is modeled as a graph on which the stigmergic variables (pheromones) can be deposited as an external entity. In ants cemetery construction, the environment corresponds to a surface on which a specific amount of items (dead ants) are located, and where the alteration of the size of these piles implies an alteration of the physical description of the environment.
- A **population of autonomous agents** which are not capable of exchanging information directly. The only way they can share their knowledge is through the stigmergic variable. In stigmergy, a fundamental issue for the spontaneous rise of coordination is the inability of agents to identify labor of other agents from their own ([TB99]). Therefore, if it is known

who modified the stigmergic variable, and this information is utilized in the decision making process, we do not call it stigmergy. The way flocks of birds or schools of fishes coordinate to migrate does not qualify as stigmergy. In those cases, individuals calculate and adjust their trajectories considering the position of neighboring entities. As a consequence, communication can be traced to specific individuals, violating the rule of anonymity.

- Each stimulus corresponds to an action performed by another individual and the response corresponds to an action triggered by a previous one, making each individual a source of stimuli for another. Therefore, the design of the system should allow the **response-stimuli sequence** to take place. Furthermore, the message being transmitted through the alteration of the environment must be modifiable by other agents. With ants foraging, this happens through the updating of the pheromone trail by each ant when they move from one place to another. In the construction process of an ants cemetery, this occurs by relocating items and increasing or reducing the size of the piles. On the other hand, orca whales hunting school of herring does not qualify as stigmergy. Although there are similarities (self-organization, emergent behavior as a consequence of individual interactions, and reaction to stimuli, among others), herring do not have the ability to modify the wall of bubbles. Hence, the response-stimuli sequence does not take place, and the bubbles do not conform to a valid stigmergic variable.

- Agents should have an **inherent behavior**. This behavior is guided by the stigmergic stimuli, such that the agent performs it in a different way or a different location. In the case of ACO, the inherent behavior or labor of the artificial ants is to travel from one node of the graph to another, which has not yet been visited, until a solution has been built. In ants cemetery construction, the inherent behavior is to move items from one location to another. In both cases, the stimuli guides the way these tasks are performed.

- Modifications can only be done on the **local environment**. Agents should not have the capabilities to modify the global values of the variables, just their local neighborhood. Hence, the behavior of agents that get into contact with this local environment is guided. This raises an interesting issue. In the context of ACO a global pheromone update rule is performed. This task does not correspond to the inherent behavior of any agent. It rather aims to emulate the natural process of pheromone evaporation and direct the search of solutions. In any case, if an agent has the ability to modify the global values of the stigmergic stimuli, the system should be able to respond intelligently. However, this specific agent could not be considered as part of the production system within the stigmergy paradigm. Instead, this agent would correspond to an external entity to the system, which can coexist with the agent population but is not in the same domain. In this sense, stigmergy describes the coordination process between agents in the same domain.

- The stigmergic system is characterized by not having a single point of failure. This means that the system is able to continue performing in a cooperative and cohesive manner even when individual agents break down or leave the ensemble. Moreover, if additional participants join the process, the system should be able to incorporate them without requiring special stages or a restart of the system, in conjunction with the stigmergic coordination process (Fig. 3.5). In literature, this is referred to as **dynamic openness** [WM15, She01].

With these requirements, stigmergy can be distinguished from other coordination mechanisms. Finally, stigmergy constitutes a light weighted mechanism for coordinating autonomous entities and achieving self-organized behavior through indirect communication. Individuals coordinate themselves as a response to stimuli variations, and perform their tasks induced by these stimuli. As a consequence, there is no need for developing complex structures to support negotiation, argumentation, or other communication tools usually found for managing complex autonomous systems.

3.3. Summary

In this chapter, relevant features of organic systems are discussed, including their relation to self-organization. Through the review of examples in nature and their relation to artificial systems, the importance of individuals autonomy, influence between individuals, emergent global behavior, and guidance of this global behavior has been emphasized. In this context, conceptual implications and strategies for managing self-organizing systems have been discussed. The results of this first discussion, in conjunction with the arguments exposed in Chapter 2, further justify the characterization of the power grid as an organic system, and the requirement of advanced techniques for its management. In the context of management mechanisms for self-organized systems, a comprehensive analysis of stigmergy is performed. Typical examples of stigmergy in nature are analyzed, with the purpose of understanding the extension and different forms of this coordination mechanism. Moreover, desirable features of stigmergy, as a multi-agent coordination mechanism, have been identified. The results and discussion of this analysis are utilized in Chapter 4, for argumentation of stigmergy as an adequate alternative for managing the power grid. Additionally, a classification of the different kinds of stigmergic variables is provided. Moreover, the stigmergic coordination cycle was identified, and requirements for stigmergy are specified. Results of this second analysis will be utilized in Chapter 4, for the design of a management mechanism based on stigmergy for the management of a simulated power grid. Stigmergy is later revisited in Chapter 7 to discuss general aspects of the concept after the proposed coordination mechanism is evaluated.

Novel scientific results included in this chapter correspond to the improvement of the taxonomy of stigmergy for practical scenarios (3.2.3), the description of the stigmergic coordination process, and the specifications of the requirements for stigmergy (3.2.5).

4. The Power Grid and Stigmergy

> “ *We are continually faced by great opportunities brilliantly disguised as insoluble problems.* ”
>
> John W. Gardner, *US Administrator*, 1912 - 2002

The main challenges of the future power grid relate to the increasing penetration of renewable energy sources (RES) in the power supply. Due to its characteristics, it is desirable that RES generation is consumed as soon as it is generated (Chapter 2).

Traditionally, the power grid depicts properties such as tolerance to failure and perturbations, adaptability to real-time requirements, flexibility to include new technologies and emergent behavior. Such features, as discussed in Chapter 2, are typically found in organic and self-organized systems. In the power grid, these properties emerge in the process of fulfilling the requirement of permanent balance between supply and demand. Nevertheless, larger shares of RES might overcome the ability of the power grid to maintain this balance and, as a consequence, reliable supply. Therefore, it can be said that the adaptability of this *organic system* would be exceeded.

To enhance the self-organizing properties of the power grid such that the balance between supply and demand is maintained, new approaches and techniques will be required (Chapter 2). In this sense, RES usage can be increased by integrating intelligent devices ([Sta08, GKB$^+$11, VST13]). For example, these devices may be able to autonomously select their operation times on hours of the day with less RES usage[1]. Nevertheless, these devices need to be managed, such that balancing objectives are achieved and *avalanche effects* of uncoordinated response to incentives do not occur. Meanwhile, the management of these flexible loads should also comply with scalability requirements, adaptability and preservation of the privacy of customers. In this context, the increasing flexibility of end-customers and RES penetration will drastically increase the complexity the future power grid operation.

---

[1] This issue was previously discussed in Chapter 2, Section 2.2.

From the perspective of a load management mechanism, the challenge is to increase RES usage, either through incentives or direct control of intelligent devices, in a computationally affordable manner, while preserving the privacy of customers and preventing appearance of additional load imbalances. In this context, stigmergy has been described as a coordination mechanism of autonomous agents characterized for providing systems with robustness, adaptability to uncertainty and self-organizing features in the achievement of global objectives (Chapter 3). Moreover, in stigmergic systems, the communication process is indirect and anonymous. Therefore, privacy of participants is preserved while global coherent behavior naturally emerges. These features support the selection of stigmergy as a potential candidate for managing the scheduling of flexible loads in the power grid. This way, through a stigmergy-based mechanism, load balancing objectives may be achieved in a flexible and adaptable manner, while privacy and autonomy of participants is preserved.

In this chapter, a load management approach, inspired by nature's fundamental cooperation mechanism named stigmergy, is presented. This approach is referred to as stigmergy-based load control. The approach corresponds to a metaheuristic for generating schedules for the load balancing problem in the power grid (Chapter 5). Moreover, this approach can also be utilized in a real-time optimization scenario, for coordinating consumption of distributed flexible loads and increase RES usage (Chapter 6). In Section 4.1, an overall description of the load balancing problem is provided. In Section 4.2, a basic architecture for implementing the approach is proposed. Afterwards, in Section 4.3 the formal models for the approach are presented, including the required adaptations for real-time optimization. Later, this formalization is generalized to extend the range of possible applications for stigmergy-based load control. Moreover, the pseudo-code of the algorithm is presented. Section 4.4 presents the model utilized to artificially generate forecasts. These forecasts are considered in a real-time optimization context and, from a conceptual perspective, as a source of dynamism of the problem. In Section 4.5, the fulfillment of the requirements for artificial stigmergic systems (Chapter 3, Section 3.2.5) by the approach is assessed. This section provides a theoretical ground for stigmergy-based load control to exhibit the desirable features of stigmergy. The models from this chapter are later utilized for evaluating the approach in a simulated scenario in Chapter 5 and 6, and later for conceptual discussion in Chapter 7. From now on, the approach in the context of real-time optimization will be referred to as **SLC**, while in the context of static optimization, as **SLC-FK**.

Core sections of this chapter have been submitted for publication. The architecture for SLC (Section 4.2) is a refinement of the work presented [RS15]. On the other hand, the formal model for static optimization is the basis for the paper [RKS16].

4.1. Problem Description

In the load scheduling problem presented in this thesis, a balancing group, which represents an isolated sub-section of the distribution grid, is assumed. From now on, this balancing group is referred to as the *micro-grid*. The micro-grid is populated with buildings which will be referred to as *prosumers*, for their ability to consume and shift their load according to different incentives or criteria. Prosumers are provided with intelligent devices, such as washing machines, dishwashers or electric vehicles (EV). With the exception of the EV, which is only power and energy restricted, once devices have begun their execution they cannot interrupt it. These devices have specific load profiles, therefore, their aggregated load profiles in conjunction with their times of execution shape the load profile of the prosumer. The load profile of every prosumer is aggregated, and together they constitute the micro-grid load profile.

The micro-grid is considered to be powered by wind and solar power generation. The distribution throughout the day of this generation is irregular. Therefore, there might be hours of the day when much RES generation is supplied, and hours of the day when no RES generation is supplied to the micro-grid. In addition, it might occur that the RES generation does not cover the totality of the micro-grid power demands. This means that the amount of RES generation fed to the micro-grid is less than its actual energy requirements. In those cases, it is assumed that the required extra power is supplied by conventional generation, through the delivery of the corresponding balancing product (Chapter 2, Subsection 2.1.2). In addition, depending on the scenario, RES forecasts can be considered. These forecasts provide information regarding possible future availability of RES generation. Nevertheless, it is possible that these forecasts diverge from the real RES generation which will be produced.

Hence, the objective of the problem, is to calculate the execution time for each intelligent device, such that the aggregated load profiles of the prosumers, the micro-grid load profile, matches a given RES output as closely as possible, therefore maximizing RES utilization. Two main optimization scenarios are identified: *(i)* The optimization of the schedules such that the RES generation usage is maximized considering full-knowledge of the future generation. *(ii)* The optimization of the schedules is performed in consideration of RES forecasts, which, as hours pass by, increasingly resemble the real RES generation. Scenario *(i)* implies a static optimization problem and corresponds to an idealized scenario which serves as a proof of concept for the approach. Scenario *(ii)* implies the adaptation of the scheduling process in execution time to achieve a desired and dynamic target performance, as a consequence of the modification of the RES forecast. In this context, the concept is utilized as a MAS coordination mechanism.

4.2. An Architecture for Stigmergy-Based Load Control

In SLC, a centralized entity called the *micro grid manager* (MGM) influences flexible intelligent devices within a balancing group (Chapter 2, Subsection 2.1.2), to shift their loads and make use of available RES generation. These devices belong to buildings which can be commercial or residential. These buildings have been previously referred to as prosumers, and the balancing group as the micro-grid.

The overall functioning of the SLC in real-time optimization is informally described as follows: The optimization period is discretized into timeslots. For the ease of exposition, this period will be considered to be a single day. Nevertheless, it can be extended indefinitely. In every timeslot a rescheduling round takes place. Additionally, in every round the MGM receives an RES forecast with more accurate information regarding future RES availability. In the first rescheduling round, the MGM transforms the RES forecast into a control signal and broadcasts it asynchronously to each prosumer within the micro-grid. This signal represents RES availability for future timeslots.

The control signal is considered by prosumers as an indicator of desirability, regarding which timeslots are preferred for them to reschedule their intelligent devices, from a global perspective. These devices run within a user-defined flexibility interval. Prosumers include the signal into a probabilistic decision process for the selection of new operation times for their devices. As a consequence, the load profile of each prosumer is modified for the remaining of the day. Then, the updated profile is then sent to the MGM.

The MGM aggregates all profiles and builds a micro-grid load profile for the current rescheduling round. In every following round after the first one, the MGM considers the last broadcast signal, the micro-grid load profile, and the updated RES forecast to build a new control signal. This updated signal reflects the distance between the current state of the micro-grid and the desired state. Once again the signal is broadcast and the process repeats.

Thus, the micro-grid is influenced, such that participants shift their loads and, as a consequence, the load profile of the micro-grid resembles the current RES forecast. In addition, the control signal is a function of the actions of the prosumers. Hence, prosumers influence and are influenced by the activities of other participants indirectly through this signal and without the ability to identify individual participants.

A consequence of optimizing in real-time is that only the future is available for optimization. Therefore, devices which have already begun their operation in

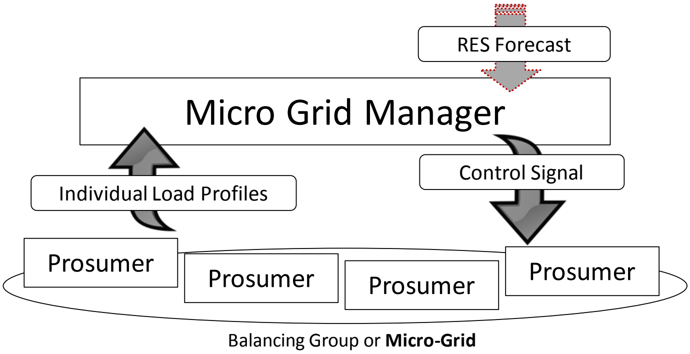


Figure 4.1.: Information flow in SLC and SLC-FK, between the MGM and the prosumers within an idealized micro-grid. The MGM broadcasts a signal to all prosumers, which asynchronously return their load profiles. The RES forecast is not considered for SLC-FK.

the current timeslot in evaluation are not available for rescheduling anymore. The information flow for SLC can be observed in Fig. 4.1.

In the case of SLC-FK, full knowledge of the RES output is assumed. This is expressed in Fig. 4.1 by the red dotted arrow on the received forecast. As a consequence, instead of calculating the new signal with an ever updating forecast, the final RES output is directly utilized. Moreover, in SLC-FK the algorithm remains static in the first timeslot and continuously optimizes the current global schedule for the whole day. In this scenario, the MGM evaluates the quality of the generated global schedule in each rescheduling round and preserves the best performing one, while the process continues until a stopping criteria is met. This way, SLC-FK functions as a decentralized meta-heuristic to generate a good quality schedule for all participants. In the following, the essential components for the implementation of SLC are described.

4.2.1. Components of the Architecture

The approach considers the existence of a bi-directional communication channel between prosumers and the MGM. For this, prosumers can utilize smart meters with the ability to receive a signal from the MGM and deliver load profiles to the same entity [BMM14, FB14, Jin11]. The architecture remains constant for both, SLC and SLC-FK.

In Figure 4.2 the internal architecture of a generic prosumer and the components required to respond to the control signal within the SLC paradigm can

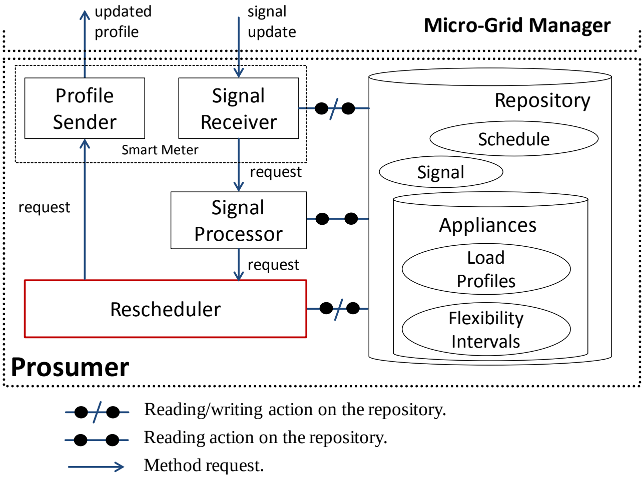


Figure 4.2.: Generic prosumer architecture in SLC and SLC-FK. The decision process takes place in the *Rescheduler* module.

be observed. The *Repository* stores all relevant information to the prosumer, including the currently active schedule and the last received signal. Additionally, details related to the appliances, like their load profiles and user-defined flexibility intervals are stored. Once the control signal is received (*signal update* request), the module *Signal Receiver*, which corresponds to a smart meter, stores it in the *Repository*. Then, the *Signal Receiver* requests the processing of this signal to the *Signal Processor* module. The latter module reads the updated signal and transforms it into a vector. Afterwards, this module requests the update of the current schedule to the *Rescheduler* module, in consideration of the current state of the micro-grid, expressed in the signal vector. This module proceeds to calculate a new time of execution (ToE) for each appliance which is available to be rescheduled, ergo, has not begun its execution. To calculate this new ToE, the *Rescheduler* considers the user defined flexibility intervals and the load profiles of the appliances, stored in the *Repository*, in conjunction with the processed signal from the *Signal Processor* module. With this information, the *Rescheduler* constructs a probability distribution for available timeslots for rescheduling of each device. From this distribution, the *Rescheduler* obtains a new ToE for every appliance. Finally, the *Rescheduler* stores the updated schedule in the *Repository* and requests the *Profile Sender* module to send the updated load profile of the prosumer to the MGM. This module would also correspond to the smart meter.

The internal architecture of the MGM for SLC is shown in Figure 4.3. The MGM also utilizes a *Repository*. In this case, it stores the historic information of

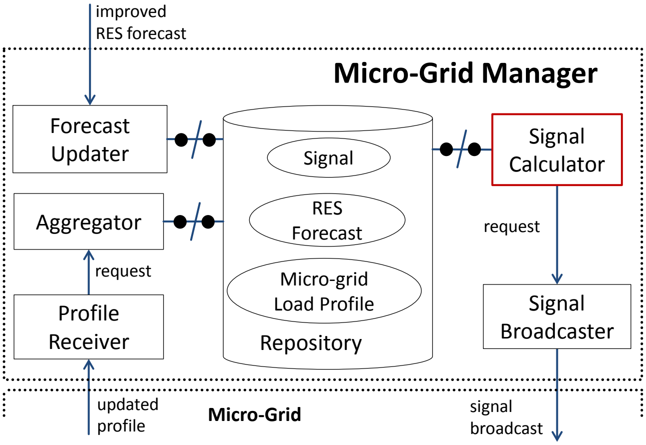


Figure 4.3.: Generic architecture for an MGM in SLC and SLC-FK. The control signal construction process occurs in the *Signal Calculator* module.

the broadcast signals, the current RES forecast and the current micro-grid load profile. As mentioned, the MGM continuously receives RES forecasts from the *Forecast Updater* module, which are stored in the *Repository*. At the same time, the MGM also receives the updated load profiles of the prosumers through the *Profile Receiver* module. These profiles are aggregated through the *Aggregator* module to build the current micro-grid load profile. Then, the *Signal Calculator* module utilizes a function to construct an updated control signal considering the current RES forecast, the micro-grid load profile, and the last broadcast signal. Then, the updated control signal is broadcast to every prosumer in the micro-grid through the *Signal Broadcaster* module and the process repeats in the following rescheduling round.

It can be observed that both, prosumer and MGM, perform as a signal receiver-processor. The elements which allow the system to perform in a self-organized manner are, in the case of prosumers, the decision making process of prosumers which takes place in the *Rescheduler* module, and in the case of the MGM, the construction process of the control signal that influences the system, which is performed in the *Signal Calculator* module.

The iterative feedback loop that takes place between prosumers and MGM allows the system to search for individual load schedules which, once aggregated, will achieve the global load objectives of the system. Additionally, this feedback enables the system to make use of new information, the updated RES forecasts, and adapt its behavior to the new scenario. Hence, SLC should have the ability to respond reasonably to a changing objective, represented by the changing RES forecast.

4.2.2. Communication with End-Customers

The current communication infrastructure in the power grid is not designed to support advanced demand response (DR) programs for increasing the usage of RES. Currently, the communication between customers and utilities refers mostly to the transmission, either manual or automatic, of the aggregated consumption of consumers [BMM14]. This does not allow end-customers to obtain advanced information regarding potential incentives to change their behavior or details of their own consumption. In this sense, future technologies require advanced forms of monitoring and communication, such that new load balancing techniques can be utilized in the future energy market [Jin11, DRWA11].

The future of metering envisions the implementation of Advanced Metering Infrastructure (AMI), typically represented by smart meter [BMM14, FB14, Jin11]. These technologies enable a two way communication channel between customers and utilities. Therefore, incentives can be designed and broadcast to users, while end-customers can access detailed information regarding their own consumption and automatically deliver it to utilities.

In the case of stigmergy-based load control, such AMI would be essential for the functioning of the approach. From the perspective of the broadcast stimuli, the control signal would not be different from a pricing signal in a real-time pricing scheme. In this context, the communication infrastructure would require the means to broadcast a signal in 15-minute intervals to, potentially, thousands of customers. Nevertheless, the main challenge would be the asynchronous response from customers. In this case, the MGM corresponds to a bottleneck for the reception of thousands of load profiles, where each load profile is a vector of real numbers, within a restricted time frame. Approaches to reduce the communication overheads and enhance its reliability include the implementation of Neighbor Area Networks (NAN). Such networks are formed around data collectors for groups of smart meters and allow the reliable deployment and reception of information to and from electric utilities[2].

These communication requirements for stigmergy-based load control are shared with other DR programs, which consider a close-loop communication between utilities and customers [Got15]. In this sense, DR programs where customers are only reactive reduce complexity of the communication. Nevertheless, it has to be mentioned that many of the required technologies for assessing these issues have experienced a fast recent development [Jin11, KP11, BMM14].

---

[2] For a detailed explanation of such approaches to improve efficiency and reliability of communication between utilities and customers, the interested reader is referred to [BMM14].

4.3. Formalization of Stigmergy-Based Load Control

In this section, stigmergy-based load control is formally described for two application scenarios. The first scenario, considers the formalization of the approach as a load scheduling mechanism for decentrally calculating global schedules for all participants to maximize RES usage in a micro-grid. This scenario is referred to as **SLC-FK**, standing for **S**tigmergy-based **L**oad **C**ontrol (SLC) with **F**ull-**K**nowledge of the RES output. The second scenario corresponds to the utilization of the approach for real-time optimization, in order to guide the consumption behavior of autonomous agents to a desired target zone in a dynamic environment. This target zone is characterized by the increase in the utilization of an RES forecast by the aggregated loads of the autonomous agents. The dynamism in the environment is given by the permanent update of the forecast. The approach in this context is referred to as **SLC**. In addition, the pseudo-code of the algorithm for both scenarios, is presented (Subsection 4.3.5). Furthermore, the formal model of SLC is generalized in order to include additional stimuli, external and internal, in the decision making process (Subsection 4.3.4). These formal models are later utilized to evaluate the approach in Chapter 5 and 6. The formal model for SLC-FK is a direct transcription from [RKS16], which has been previously submitted for publication.

4.3.1. Control Signal Determination

In this Subsection, the formalization of the signal construction process is described. Firstly, the formal model for the meta-heuristic in a static context is presented. Then, the required adaptations for the implementation of the approach in real-time optimization are described.

Decentralized Optimization of Schedules

In SLC-FK, full-knowledge is considered. Hence, the RES forecast reception from Fig. 4.1 does not occur in this scenario, since the RES output is known from the beginning. Moreover, a discrete time horizon is assumed, indexed by $t \in [T]$, with $[T] = \{0, \dots, T\}$. An RES output vector $\mathbf{g} = (g_0, \dots, g_T)$ is considered, where $g_t \geq 0$ for all $t \in [T]$. The signal in each rescheduling round i is given by the vector $\mathbf{s}^i = \left(s_0^i, \dots, s_T^i\right)$, with $s_t^i \in [0, 1]$. In the first round ($i = 0$) the values in $\mathbf{s}^i$ are given by $s_t^0 = \frac{g_t}{\max \mathbf{g}}$.

In the following rounds, the MGM receives the schedules that the prosumers generated in the previous round. These schedules are derived into load profiles and aggregated to obtain the overall system load, which corresponds to vector $\mathbf{l}^i = \left(l_0^i, \ldots, l_T^i\right)$ with $l_t^i \geq 0$. This way, the control signal (stigmergic stimulus) is updated in each rescheduling round $i > 0$. The values of the updated signal $\tilde{\mathbf{s}}^i$ are given by:

$$\tilde{s}_t^i = s_t^{i-1} + \alpha \cdot b_t^i, \; i > 0, \; t \in [T] \tag{4.1}$$

where $\mathbf{b}^i = \left(b_0^i, \ldots, b_T^i\right)$ is the vector that defines the adaptation of the signal. The value $\alpha \in [0,1]$ specifies the weight of this vector for signal updating. The larger the value of α the larger the effect of $\mathbf{b}^i$ and vice versa. It can be said that α regulates the level of exploration and exploitation in the search for an adequate global schedule. As previously mentioned, the values in $\mathbf{b}^i$ are calculated considering the micro-grid load and the RES output:

$$b_t^i = \frac{g_t - l_t^i}{\max\left\{\max \mathbf{g}, \max \mathbf{l}^i\right\}} \tag{4.2}$$

Since the signal which guides the rescheduling process of the prosumers requires values in the interval $[0,1]$, the updated control signal $\tilde{\mathbf{s}}^i$ has to be normalized:

$$\hat{s}_t^i = \frac{\tilde{s}_t^i + \left|\min \tilde{\mathbf{s}}^i\right|}{\max \tilde{\mathbf{s}}^i + \left|\min \tilde{\mathbf{s}}^i\right|} \tag{4.3}$$

To prevent step responses and oscillating behavior, a final filtering of the stimuli is performed. Hence, the broadcast signal is defined as:

$$s_t^i = \begin{cases} \frac{s_t^{i-1} + \hat{s}_t^i}{2} & \text{if } i < 2, \\ \frac{s_t^{i-2} + s_t^{i-1} + \hat{s}_t^i}{3} & \text{if } i \geq 2. \end{cases} \tag{4.4}$$

A schedule for each appliance in the micro-grid at the end of each rescheduling round is received. The performance of this global schedule is evaluated according to the difference of the areas between the RES output and the micro-grid load profile. Hence, at the end of each round, the new schedule is compared with the current best performing schedule. If the new schedule has a better performance, it replaces the old one as the new current best.

Therefore, the evaluation function, which assesses the optimization objective of the system, is the minimization of the difference between RES output and micro-grid load profile. By utilizing a function of the distance between current load profile and desired load profile as a mean to stimulate individual behavior, SLC is able to search for solutions that increase RES utilization in a static optimization context.

Real-Time Optimization

Some modifications are required to the data structures in order to adapt the approach for real-time optimization. Nevertheless, the overall definition of the signal remains the same.

To model the passing of timeslots, SLC considers a receding horizon approach. In this approach, at each rescheduling round an optimization problem with a finite horizon is solved [SGC$^+$13]. The size of the optimization horizon is reduced in each progressive round, until the last timeslot of the simulated day passes by. Hence, rescheduling takes place once per timeslot. The reduction of the optimization horizon in every rescheduling round i, is given by $T - i$.

Instead of a fixed RES output, a RES generation forecast is required in this context. Moreover, the reduction of the optimization horizon needs to be considered in the definition of the utilized vectors. Hence, the definition of vector $\mathbf{g}$ now includes a sub-index which specifies the current rescheduling round, and implicitly, the current size of the optimization horizon. Therefore, $\mathbf{g}$ becomes $\mathbf{g}^i = \left(g_i^i, \ldots, g_T^i\right)$, where $g_t^i \geq 0$. This forecast is updated in every rescheduling round i, as more accurate RES information becomes available. A similar redefinition is required for the control signal to represent the reduction of the horizon. Hence, $\mathbf{s}^i$ becomes $\mathbf{s}^i = \left(s_i^i, \ldots, s_T^i\right)$. In the same way, the vector that contains the micro-grid load profile $\mathbf{l}^i$ becomes $\mathbf{l}^i = \left(l_i^i, \ldots, l_T^i\right)$ with $l_t^i \geq 0$, and $\mathbf{b}^i$ becomes $\mathbf{b}^i = \left(b_i^i, \ldots, b_T^i\right)$. Moreover, the calculation of this vector is adapted to:

$$b_t^i = \frac{g_t^i - l_t^i}{\max\left\{\max \mathbf{g}^i, \max \mathbf{l}^i\right\}} \tag{4.5}$$

4.3.2. Prosumer Response

In SLC-FK, after receiving the signal, each prosumer decides where to schedule its devices in compliance with the user-defined flexibility intervals. For this, each prosumer processes the signal and obtains a vector $\mathbf{r}^i = \left(r_0^i, \ldots, r_T^i\right)$. The values in $\mathbf{r}^i$ are interpreted as an indicator of where it is more desirable to schedule the execution times of its devices in rescheduling round i.

In principle, the additional hierarchical level conformed by the prosumer could be omitted by directly delivering the signal to the intelligent devices. However, the detour of the signal over this abstract concept called prosumer has a direct correlation with reality. Prosumers can be categorized according to their device composition, allowing more advanced forms of interpretation of the signal. Nevertheless, in this thesis all prosumers utilize the same transformation function $\mathbf{r}^i = \mathbf{s}^i$.

In the following, the scheduling process is described for one exemplary appliance. Given an appliance a which runs once a day, we want to schedule this run. Let t_s^a be the time where the appliance is ready for operation and t_e^a the latest possible starting time. In real world applications both values can either be defined by the user or automatically derived to meet appliance constraints. For ease of exposition in the following we drop the appliance index a. The flexibility interval for appliance a is defined as $F = [t_s, t_e]$, with $t_s, t_e \in T$ and $t_s \leq t_e$. Additionally, let δ be the duration of one execution of a. The load profile of this appliance is a static vector defined as: $\tau = (\tau_0, \ldots, \tau_\delta)$ where $\tau_j \geq 0$ for all $j \in [\delta]$.

The process of selecting a time of execution for the appliances is performed sequentially within each prosumer. For this, the control signal $\mathbf{r}^i$ is utilized to build a vector which defines a *probability distribution* for the execution time of a: $\mathbf{p}^i = \left(p_0^i, \ldots, p_T^i\right)$. For the construction of $\mathbf{p}^i$, the consumption profile τ and the flexibility interval F are considered. Through this distribution a new starting time for a is probabilistically selected. Values in $\mathbf{p}^i$ are given by:

$$p_t^i = \begin{cases} \frac{\sum_{m=0}^{\delta} r_{t+m}^i \cdot \tau_m}{\sum_{k=t_s}^{t_e} \sum_{m=0}^{\delta} r_{k+m}^i \cdot \tau_m} & \text{if } t \in F, \\ 0 & \text{otherwise.} \end{cases} \tag{4.6}$$

Vector $\mathbf{p}^i$ can be different for each appliance. Furthermore, $\mathbf{p}^i$ can change in each rescheduling round for the same appliance, as the processed signal $\mathbf{r}^i$ changes. Devices such as electric-vehicles are only power and energy constrained, and require a specific energy level during their flexibility interval. In this case, the consumption on each individual time slot is rescheduled as an appliance with a load profile with one timeslot of length ($\delta = 1$) by Eq. 4.6. As a consequence, the load profile of an EV does not need to have a fixed shape, and can change in the progressive rounds. After all devices in the prosumer have been rescheduled through this process, a new schedule is obtained and, implicitly, a new load profile for the prosumer as well.

Small adaptations are required for implementing the prosumer to a real-time optimization scenario. Firstly, vector $\mathbf{r}^i = \left(r_i^i, \ldots, r_T^i\right)$ reduces its size in progressive rounds, in concordance with the reduction of the optimization horizon. Additionally, the user-defined flexibility interval changes its size throughout the execution of SLC. At the first rescheduling round the entire flexibility interval $F^0 = [t_s, t_e]$ is available for scheduling. For later rounds, if $i > t_s$ the interval may decrease its size, according to $F^i = [i, t_e]$.

At the end of each round i, each prosumer sends its updated schedule to the MGM. The schedules are aggregated and derived into a new micro-grid load profile $\mathbf{l}^i$. With this information the MGM calculates the updated control signal for the next round and the process repeats.

4.3.3. Summary of Static and Real-Time Optimization

In the scenario presented for SLC-FK, which throughout this thesis is also referred to as static optimization, the objective is to generate an individual schedule for each participant, such that the aggregated loads maximize the usage of a given RES output. This combinatorial optimization problem can be solved with meta-heuristics, such as evolutionary algorithms or ant colony optimization[3]. In the case of SLC-FK, as discussed, in each rescheduling round the generated global schedule is compared with the currently best solution, and the best performing one is selected as current best for the following rounds. The level of exploration and exploitation in the solution searching process is regulated by parameter α. Finally, good quality schedules for every participant are obtained, which derives into a micro-grid load profile that increases the usage of a given RES output.

On the other hand, SLC requires to adapt the consumption behavior of the micro-grid from one rescheduling round to the next one, while the optimization horizon reduces. The reason for this is that, in each rescheduling round, a new RES forecast is received. Hence, the problem objective is continuously modified. As a consequence, the global behavior of the swarm needs to be adapted to the new problem and the best solutions cannot be preserved for improvement. Therefore, this scenario is referred to as real-time coordination of the consumption of prosumers. The control signal contains historic information regarding the previous state of the system. The balance between new information in the adaptation process of SLC to the changing RES forecasts is regulated through parameter α. Hence, conceptually α has different functions according to the application scenario. Global behavior, which in this case corresponds to the micro-grid load profile, emerges as a consequence of the aggregated individual behavior of the participants. Moreover, prosumers correspond to real autonomous entities in the real world. As such, throughout different rescheduling rounds they might reschedule deviating from an optimal into a sub-optimal

---

[3] For the latter, additional discussion is presented in Chapter 7, Section 7.1.1.

micro-grid profile, and vice-versa. Hence, the objective of the mechanism is to guide individual behavior such that the aggregated behavior of individual prosumers remains within a desired target space and results in increased RES usage.

A relevant point of difference is that, in real-time coordination, to create the micro-grid load profile, the MGM only requires the aggregated load profile of participants. Hence, personal information regarding their individual schedules, load profiles and even identities remain private. In addition, in SLC-FK schedules are generated for each prosumer. These schedules are received by them and have to be followed in order to increase the usage of the RES output. Therefore, conceptually SLC-FK corresponds to a centralized demand response program. In SLC, prosumers are only guided by the control signal. Their scheduling decisions are completely autonomous. As a consequence, SLC operates as a decentralized demand response program (Subsection 2.2.2).

4.3.4. Generalization of Algorithmic Approach

The formalization of stigmergy-based load scheduling can be considered as a specific instance of a more general model. From the perspective of the MGM, many signals could be broadcast, each referencing different behavioral requirements of the problem. This multi-leveled signal could trigger localized self-organized behavior of prosumers with specific features. Formally, the generalized form of the signal corresponds to: $\mathbf{S}^i = \left\{ \left(\mathbf{s}^{1,i}, \ldots, \mathbf{s}^{J,i} \right) \mid \mathbf{s}^{j,i} \in \mathbb{R}^T, 1 \leq j \leq J \right\}$, where J is the number of *sub-signals* comprised in the message.

From a prosumers perspective, the decision making process described in Eq. 4.6 can be generalized and the signal interpretation mechanism enhanced. Regarding the later, the received message, now signal $\mathbf{S}^i$, could be filtered such that only useful information to the individual customer is utilized in decision making process. This means $\mathbf{R}^i = h\left(\mathbf{S}^i\right)$, where $h : \mathbf{S}^i \mapsto \mathbf{R}^i$, $\mathbf{R}^i = \left\{ \left(\mathbf{r}^{1,i}, \ldots, \mathbf{r}^{N,i} \right) \mid \mathbf{r}^{n,i} \in \mathbb{R}^T, 1 \leq n \leq N \right\}$ and $N \leq J$.

Regarding the former, the only internal features of prosumers which are currently considered for building new schedules are the user-defined flexibility intervals and the load profile of each appliance. This way, for constructing the probability distribution, additional specific internal preferences and restrictions, relative to individual customers, could be considered in conjunction with the interpreted signal. Hence, devices with different features, like feed-in power, could be included. Therefore, the set of vectors which express the internal state of the prosumer utilized for rescheduling a single appliance a in rescheduling round i, is described as: $\beta^i = \left\{ \left(\tau^{1,i}, \ldots, \tau^{D,i} \right) \mid \tau^{1,i} \in \mathbb{R}^{T_1}, \ldots, \tau^{D,i} \in \mathbb{R}^{T_D} \right\}$ with $T_1, \ldots, T_D \subseteq T$ and $D \leq J$. Hence, the generalized form of Eq. 4.6 for calculating each element in the probability distribution for a single appliance corresponds to:

$$p_t^i = \begin{cases} \frac{f(\mathbf{R}^i,\beta^i)}{\sum_k f(\mathbf{R}^i,\beta^i)} & \text{if } t \in F^i, \\ 0 & \text{otherwise.} \end{cases} \tag{4.7}$$

where $f : \mathbf{R}^i \times \beta^i \mapsto \mathbb{R}^+$ and F^i is a vector which conditions the timeslots on which appliance a can be scheduled in rescheduling round i. This way, through Eq. 4.7 different kinds of stimuli can be considered, either external or internal to the prosumer, which influence the rescheduling of devices. Furthermore, some stimuli might be specific and unique to each prosumer depending on the features of the intelligent devices. In this context, the micro-grid would be fully heterogeneous in regard to the prosumers load composition and their range of responses.

This generalization clearly enhanced the flexibility of the approach and allows the consideration of a number of additional scenarios for evaluation. Moreover, this generalization facilitates the application of stigmergy-based load scheduling for other COPs. Additional implications of this generalization are further discussed in Chapter 7, Section 7.3.

4.3.5. Pseudo Code and Complexity of the Approach

In the following the pseudo-code for the operation of the MGM and the prosumer, in real-time coordination and static optimization, is described.

In Algorithm 1 the elements and processes previously described which regard the MGM in a real-time coordination context (SLC) can be found. At line 5, the RES forecast for the current rescheduling round i is stored in vector $forecast$. This update occurs in every rescheduling round. At line 9, the control signal s in the current round is built according to Eq. 4.1, 4.5, 4.3 and 4.4. Additionally, at line 12 the MGM waits until all prosumers profiles have been received, or a user defined time limit is reached (the later is not considered in a simulation scenario for obvious reasons). The profiles are aggregated at line 13.

In the case of the prosumer (Algorithm 2), aspects to stand out consider the initial schedule for each prosumer. As mentioned, appliances perform within a user-defined flexibility interval. Hence, an initial schedule is constructed by uniformly distributing the execution times of the appliances within this interval. This operation takes place in line 2. Lines 4 and 5 refer to the reception and processing of the control signal. As mentioned, in the current thesis, the values within the signal are directly utilized for the rescheduling process without

Algorithm 1 Pseudo-code for MGM operation in real-time optimization.

```
1:  $i \leftarrow 0$
2:  $mgProfile \leftarrow null$
3:  $s \leftarrow null$
4:  while $i < T$ do
5:      $forecast \leftarrow getForecast\,(i)$
6:      if $i = 0$ then
7:          $s \leftarrow buildControlSignal(forecast, null, null, i)$
8:      else
9:          $s \leftarrow buildControlSignal(forecast, mgProfile, s, i)$
10:     end if
11:     $broadcastSignal(s)$
12:     $waitForProfiles()$
13:     $mgProfile \leftarrow aggregateReceivedProfiles()$
14:     $i \leftarrow i + 1$
15: end while
```

any processing. At line 6, a list containing all devices available to be scheduled in the current rescheduling round i is constructed. Devices which have begun their operation are not considered. Only the appliances in this list go through the rescheduling process. Rescheduling of devices is performed for each individual appliance between lines 8 and 12. Here, the construction of the probability distribution is performed at line 9, according to Eq. 4.6. Moreover, the probabilistic selection of the new operation time for the correspondent appliance is performed at line 10. The active schedule is updated with the rescheduled device. Finally, the new schedule is derived into a load profile and delivered to the MGM at line 14.

For both, Algorithm 1 and 2, the number of rescheduling rounds is limited by the number of timeslots into which the day is discretized (Line 4 in Algorithm 1, and line 3 in 2).

Regarding SLC-FK, minor differences exist regarding the operation of the MGM, in order to select and preserve the current best performing solution (Algorithm 3). A vector with the current best micro-grid load profile and a list with the current best global schedule are defined (Line 3 and 4 correspondingly). In addition, the termination time is not defined by the number of timeslots in the simulation, but by a user-defined parameter R. Instead of receiving only the load profile of prosumers, the MGM receives the actual schedule, since the objective is to generate a global schedule that maximizes RES usage. This is performed at line 15. Then, the performance of the constructed solution is compared with the current best performing schedule, between lines 16 and 23.

Algorithm 2 Pseudo-code for prosumer operation

```
1:  $i \leftarrow 0$
2:  $schedule \leftarrow getRandomSchedule()$
3:  while $i < T$ do
4:      $s \leftarrow receiveSignal\,(i)$
5:      $r \leftarrow processSignal\,(s)$
6:      $availableDevices \leftarrow getAvailableDevices\,(i)$
7:      if $availableDevices \neq null$ then
8:          for each $device$ in $availableDevices$ do
9:              $p \leftarrow getProbabilityDist(r, device, i)$
10:             $opTime \leftarrow selectOperationTime(p)$
11:             $schedule \leftarrow updateSchedule(device, opTime)$
12:         end for
13:     end if
14:     $sendLoadProfile(schedule)$
15:     $i \leftarrow i + 1$
16: end while
```

In addition to these alterations of the MGM, minor adjustments have to be made to the pseudo-code of the prosumer when utilizing SLC-FK. Specifically, at line 3, instead of T the limit is defined by a user-defined parameter R, and at line 14, instead of delivering the profile, the actual schedule of the prosumer is sent. Both alteration regard Algorithm 2.

With this information, the complexity of the algorithm can be addressed. The complexity of the approach in real-time optimization and static optimization is the same. Regarding the MGM, the complexity is $O\left(T\right)$. In the signal construction process (Line 7 and 9, Algorithm 1), the execution time increases linearly with the number of timeslots in which the day is discretized. For the control signal broadcast and the reception of the load profiles from the prosumers (Line 11, Algorithm 1), the execution time increases linearly with the number of prosumers in the micro-grid.

Regarding the response of the prosumer to the stimuli, the most computationally expensive procedure is the rescheduling of the appliances (Line 11, Algorithm 2). In this case, the execution time increases linearly with the number of appliances in the corresponding prosumer, and to the square of the number of timeslots in which the day is discretized. Hence, the complexity of the prosumer is $O\left(T^2\right)$ and, implicitly, the complexity of stigmergy-based load scheduling is also $O\left(T^2\right)$.

Algorithm 3 Pseudo-code for MGM operation in static optimization.

```
$i \leftarrow 0$
$currentSchedule \leftarrow null$
$bestProfile \leftarrow null$
$bestSchedule \leftarrow null$
$s \leftarrow null$
while $i < R$ do
    $forecast \leftarrow getForecast\,(i)$
    if $i = 0$ then
        $s \leftarrow buildControlSignal(forecast, null, null, i)$
    else
        $s \leftarrow buildControlSignal(forecast, mgProfile, s, i)$
    end if
    $broadcastSignal(s)$
    $waitForSchedules()$
    $currentSchedule \leftarrow aggregateReceivedSchedules()$
    if $bestProfile = null$ then
        $bestSchedule \leftarrow currentSchedule$
        $bestProfile \leftarrow unusedRES(bestSchedule)$
    end if
    if $unusedRES(currentSchedule) < unusedRES(bestSchedule)$ then
        $bestSchedule \leftarrow currentSchedule$
        $bestProfile \leftarrow unusedRES(bestSchedule)$
    end if
    $i \leftarrow i + 1$
end while
```

4.4. Artificial Forecasts Generation

In real-time coordination, RES forecasts are updated in every rescheduling round. This implies that at the initial timeslot of every rescheduling round, the generation of the forecast matches the RES output, while a divergence occurs in future timeslots.

This feature is modeled by generating artificial forecasts. An artificial forecast is constructed utilizing an RES output as a reference. This way, inspired by the approach from [SGDG$^+$12], the standard deviation is utilized to create a vector $n\,(t)$ in which Gaussian noise is stored: $n\,(t) = \epsilon_t \sim \mathcal{N}\left(0, \sigma_t^2\right)$. This vector is utilized to add cumulative noise to the RES output, and as a result, generating an increasingly divergent forecast in progressive timeslots.

Nevertheless, when adding the cumulative noise, step responses might be ob-

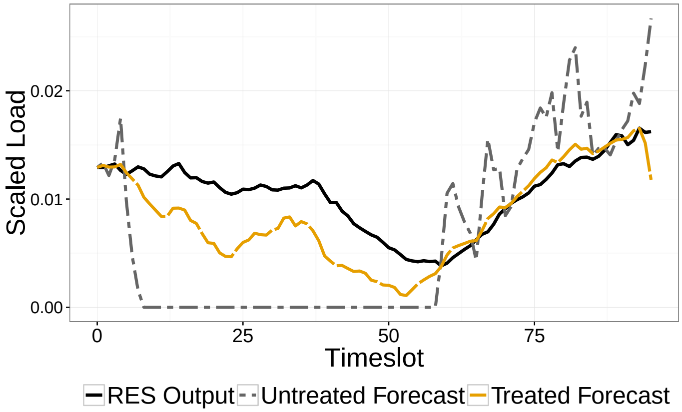


Figure 4.4.: RES output against a treated forecast by a three-five point smoothing and an untreated forecast, obtained through Eq. 4.8.

tained in the artificial forecasts. Hence, to prevent extreme peaks and create reasonable deviations from the RES output, a *three* and *five-point signal smoothing* technique is performed. This way, the forecast vector g^0 is built through:

$$g_t^0\left(t\right) = \begin{cases} g_t^0 = \hat{g}_t & \text{if } t = 0, \\ \frac{g_{t-1}^0 + \hat{g}_t + \hat{g}_{t+1} + \sum\limits_{k=0}^{t} n_k}{3} & \text{if } t = 1 \text{ \& } t = T-1, \\ \frac{g_{t-2}^0 + 2g_{t-1}^0 + 3\hat{g}_t + 2\hat{g}_{t+1} + \hat{g}_{t+2} + \sum\limits_{k=0}^{t} n_k}{9} & \text{if } t \geq 2 \text{ \& } t \leq T-2. \end{cases} \tag{4.8}$$

Where $\hat{\mathbf{g}} = (\hat{g}_0, \ldots, \hat{g}_T)$ corresponds to the real RES output. Additionally, $g_t^0\left(t\right) \geq 0 \ \forall \ t \in T$. An example of an artificial forecast with and without smoothing can be observed in Fig. 4.4. It has to be noted that the total load of the generated forecast and RES output can differ. This issue is later discussed after experimental results are analyzed in Subsection 6.2.2.

At this point it is important to mention that an ideal mechanism for generating artificial forecasts is out of the scope of this thesis. On the other hand, the aim is to generate acceptable forecasts to enable experimentation and evaluate SLC. Finally, as it was mentioned, $\mathbf{g}^i$ is adapted for $i > 0$. Therefore, the forecast gradually resembles the RES output. For the current timeslot full knowledge on generation is assumed, and thus $g_t^i = \hat{g}_t$ for all $t \leq i$.

4.5. Fulfillment of Stigmergy Requirements

In Chapter 3, stigmergic systems were characterized as robust, able to cope with uncertainty and to adapt to changing environments. Moreover, the process of achieving of coherent and cooperative behavior does not disturbs the autonomy of individual nor requires their identities.

These features are certainly desirable for a decentralized load management mechanism. Hence, classifying SLC and SLC-FK as stigmergy implies that, conceptually, the desirable features of stigmergy should be depicted by the approach. To answer if SLC and SLC-FK qualify as stigmergy, the requirements described in Chapter 3 are discussed:

- The element that enables coordination and cooperation in stigmergic systems is the **stigmergic variable**. In the case of stigmergy-based load control, this corresponds to the control signal broadcast to the prosumers by the MGM. Firstly, the signal influences the prosumers, since they do not only begin a rescheduling process once they receive it, but also, utilize the information in the signal to decide upon an updated schedule (Eq. 4.6). Secondly, the information contained in the signal depends on the actions of prosumers. When prosumers modify their load profile, the aggregated micro-grid load profile changes. Since, the control signal considers the current micro-grid load profile for its updating, the values depend on the rescheduling decisions of prosumers (Eq. 4.5 and 4.2). This is a key factor in stigmergy, as explained throughout Section 3.2. Thirdly, the modifications on the value of the signal are **not traceable**. Once the individual load profiles are aggregated, their origin is lost. Therefore, once the signal is constructed and broadcast, it is not possible to unveil the effect of each participant on the signal. In this context, one might argue that the MGM corresponds to a single point of failure and that every participant knows that this entity is modifying the signal. Nevertheless, the role of the MGM is to facilitate the environment to the participants, and it is not part of the production system. Furthermore, the system can continue its operation, with a sub-optimal performance, without any signal being broadcast. Hence, the existence of the MGM does not imply a failure the compliance with the requirements for stigmergic systems. Finally, in stigmergy-based load control, the signal reflects the progress in the level of achievement of the global objective.
- In Subsection 3.2.5, the **environment**, in the domain of stigmergy, was specified as an abstraction within the context of the global objective being faced by the system. Furthermore, its function is to transmit information through signs embedded in it or through its physical alteration. Therefore, the environment in stigmergy corresponds to a tool which enables

coordination and cooperation. In stigmergy-based load control the environment corresponds to the micro-grid load profile, since it is through its actual physical alteration that information is transmitted to the participants. In real-time optimization, this environment is dynamic and in the absence of any prosumer, the profile continues to change as a consequence of the updating RES forecast. Moreover, this definition of environment implies that, within the taxonomy described in Subsection 3.2.3, the signal corresponds to a *sematectonic variable*.

- In stigmergy-based load control, the **population of agents** corresponds to the prosumers. Clearly they are not able to exchange information between each other. Moreover, they do not differentiate if the changes on the signal values are a consequence of the rescheduling process of other participants or their own. The signal only influences the probabilistic rescheduling process (Eq. 4.6), and its weight on the decision making process for rescheduling is decided by the prosumers. Furthermore, the stochastic response of prosumers to the signal implies that stigmergy-based load control is a *qualitative stigmergic system* (Subsection 3.2.3).

- The overall design, observable in Fig. 4.1, considers a feedback loop in which the alterations of the load profile of a prosumer, implies that the micro-grid load profile will change, and, as a consequence, in the next rescheduling round the signal utilized for influencing the behavior of the micro-grid will also be modified. Therefore, it can be said that agents are a source of stimuli of other agents, allowing the **response-stimuli sequence** to occur.

- The **inherent behavior** of the prosumers is to reschedule their devices operation times, and begin their execution according to their schedule. The control signal, stigmergic stimulus, only guides the decision process for rescheduling these devices.

- Prosumers have a limited effect on the modification of the micro-grid load profile. Their ability to alter the global profile is limited to the load profile of the devices under their domain in conjunction with the user-defined flexibility intervals for each device. These elements, define the **local environment** of each prosumer, and their impact on the environment.

- In stigmergy-based load control, prosumers can freely participate in the rescheduling process by ignoring or responding to the control signal. Responsive prosumers will try to absorb load imbalances generated by non-responsive prosumers. This would obviously have an impact on the performance. Nevertheless, the overall functioning of the approach would

> not be disturbed, nor it would be required the restart of the system to include additional participants. Hence, stigmergy-based load control can be considered exhibit **dynamic openness** [She01, WM15].

Since stigmergy-based load control fulfills the requirements of stigmergy, the approach qualifies as an artificial stigmergic system. Therefore, an implementation of the approach should depict the previously specified features of these systems. In addition, stigmergy-based load control has been categorized as a *sematectonic-quantitative* stigmergic system, within the taxonomy provided in Subsection 3.2.3.

An important feature of stigmergy-based load control, is that the system is inherently asynchronous. In order to build the control signal, the MGM requires the profiles, or schedules, of the prosumers. Nevertheless, the sorting in which it receives them or the identity of the sender is irrelevant for the signal construction process. This feature enables anonymity of participants, which is a desired asset for customers in the context of energy system management, as discussed in Section 2.2.

Although it is preferable that all prosumers respond to the signal, the system can survive if some participants are unable to perform the rescheduling process during a given number of timeslots. Furthermore, if the MGM does not broadcast the signal, the prosumers continue with their scheduled execution plan, until they receive the stigmergic stimuli once more. In this sense, it can be said that SLC is tolerant to failure of some of its components. As discussed in Chapter 3, this is a standard feature of stigmergic system and a desired characteristic of power systems.

4.6. Summary

In this chapter a load management mechanism for autonomous flexible loads has been presented, named stigmergy-based load control. This approach is inspired by the fundamental coordination mechanism from nature, namely stigmergy.

Stigmergy-based load control is meant to be utilized for both, real-time coordination of prosumers flexible loads to increase RES utilization, and to centrally generate global schedules for all participants as a meta-heuristic. The formal model for real-time optimization is implemented in Chapter 6 for experimental evaluation of the approach in this context. The formal model for static optimization is implemented in Chapter 5 for the same purposes and the pseudo-code of the algorithm for both scenarios was provided. Moreover, stigmergy-based load control was classified as an artificial stigmergic system, since it fulfilled the requirements for stigmergic systems. Hence, from a conceptual perspective it is expected that stigmergy-based load control depicts the desirable properties of stigmergy when utilized for managing the power grid. These elements are later considered for a conceptual discussion in Chapter 7.

Contributions in this chapter regard the presentation of the formal model for stigmergy-based load control, its generalized form, the pseudo-code for real-time and static optimization, and the assessment of stigmergy-based load control as an artificial stigmergic system. Additional contributions correspond to the presented model for generating artificial forecasts for real-time coordination.

5. Combinatorial Optimization with Stigmergy-Based Scheduling

> *Bad results are bad... But amazing results which you can't explain, those are the worst!*
>
> Sebastian Gottwalt, *Informal discussions*, 2015

Flexible appliances provide a great opportunity to achieve the required permanent balance between power supply and demand in the power grid. These devices may be scheduled to times of the day where RES output is larger. Hence, imbalances generated as a consequence of larger supply than demand would be reduced, while the operation of power system efficiency would be increased. Nevertheless, the selection of their operation times to maximize the RES usage corresponds to a complex combinatorial optimization problem (COP). Rescheduling appliances to increase usage of RES might generate imbalances at other times of the day. Furthermore, scheduling should also comply with user-defined flexibility intervals.

In this chapter, a meta-heuristic based on the concept of stigmergy is evaluated to assess its ability to achieve global schedules which maximize usage of a given RES output. The formal model for this approach was presented in Chapter 4, Section 4.3. Solutions are decentrally constructed and centrally evaluated, in an iterative process which produces good quality global schedules that increase utilization of intermittent generation in a simulated day. This meta-heuristic is referred to as **SLC-FK**, standing for **S**tigmergy-based **L**oad **C**ontrol (SLC) with **F**ull-**K**nowledge of the RES output. The assessment of the performance of this approach will also investigate the possibility of extending its applicability to other COPs.

In Section 5.1, the experimental setup for the evaluation of SLC-FK is presented, including the approach to data analysis. In Section 5.2 the performance and stability of the meta-heuristic is evaluated under different conditions and parameter configurations. In addition, the possibility of implementing a deterministic or adaptive parameter control approach for SLC-FK is discussed. In Section 5.3, SLC-FK is compared to a price-based heuristic in different scenarios. Finally, a discussion and a summary are provided in Section 5.4.

Conceptual implications from the results and conclusions of this chapter, are source of further discussion in Chapter 7. Core sections of this chapter have been submitted for publication. Specifically, the internal analysis of SLC-FK (Section 5.2) is an extension of the working paper [RKS16].

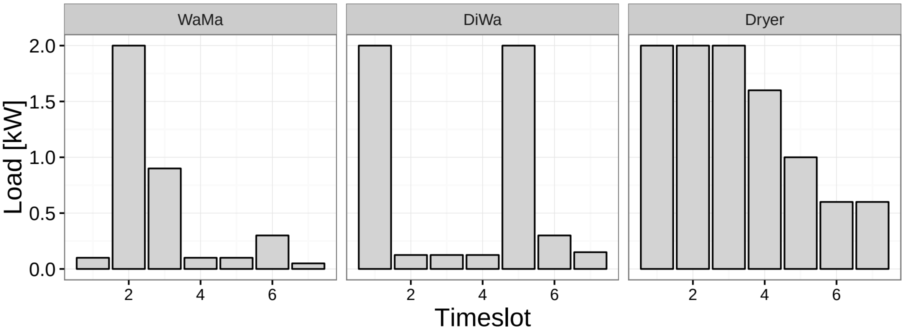
5.1. Experimental Setup

In this section, the factors utilized for experimentation and the empirical evaluation of SLC-FK are described. Moreover, the strategy for the data analysis is presented. The analysis of SLC-FK under these different scenarios will provide a detail of the perspective of the internal process for constructing solutions.

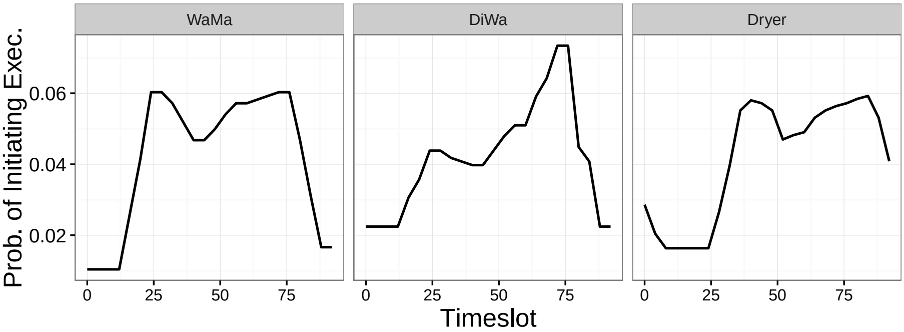
5.1.1. Residential Flexible Loads

In Chapter 4, buildings provided with flexible loads were referred to as prosumers. In an applied scenario, these buildings can correspond to small industries or commercial facilities. In this thesis, residential households are considered as the prosumers populating the idealized isolated micro-grid. Furthermore, flexible loads can correspond to different types of devices, provided with a user-defined flexibility interval and/or the ability to modify their operation according to some incentive. Typical examples are washing machines, dryers, fridges, freezers, micro combined heat and power plants (micro-CHP) or heating, ventilation and air conditioning systems (HVAC), among many others. In this thesis, and in order to assess the validity of SLC-FK, flexible loads are represented by three shiftable appliances which operate once per day: dryer, dishwasher and washing machine. A unique load profile for each type of appliance has been considered, based on [Sta08] (Fig. 5.1a, for details cf. Appendix A: Tables A.1).

At the moment of writing this thesis, no reliable statistic was found regarding user-defined flexibility intervals. Therefore, artificial intervals have been constructed considering the distribution of the starting times of the appliances in [Sta08] (Fig. 5.1b). After the intervals are constructed, the initial time of execution for the appliances is uniformly distributed within the corresponding interval. This strategy is based on the approach from [VST13]. In a real-world application, this information would be programmed by the user and stored in a household management device (HMD - [AS11]). Afterwards, the flexibility



(a) Load profiles of a washing machine (WaMa), dishwasher (DiWa), and dryer (Dryer). Each timeslot corresponds to a single 15-minutes interval.



(b) Distribution of the execution times for a generic washing machine (WaMa), dishwasher (DiWa), and dryer (Dryer) [Sta08].

Figure 5.1.: Load profiles and distribution of the execution times of the appliances.

intervals and the proposed execution times of the appliances would be sent to the MGM by the smart meter [1].

In addition to shiftable appliances, the existence of electric vehicles (EV) in the micro-grid is assumed. Different standards for EV charging may be considered in concordance to the specifications of current available EVs [FIG$^+$13]. The same applies to the utilized charging profiles, which can be negotiated based on standard protocols, such as the ISO/IEC 15118 [USD$^+$13]. In this thesis,

---

[1] It has to be noticed that the requirement of transmitting flexibility information to the MGM only applies to SLC-FK and, as it will be later discussed in this chapter, can be avoided in order to prevent privacy issues. Regarding real-time coordination (Chapter 6) the transmission of flexibility information to the MGM does not occur at all.

Table 5.1.: Flexiblity intervals and daily consumption for appliances.

Device	Daily Consumption	Micro-Grid Penetration	Interval	Share
Washing Machine	0.89 kWh	100%	00:00-06:30	20%
			06:30-12:00	32%
			12:00-20:00	46%
			20:00-00:00	2%
Dryer	2.45 kWh	25%	00:00-08:00	20%
			08:00-13:30	35%
			13:30-20:00	40%
			20:00-00:00	5%
Dish Washer	1.2 kWh	80%	00:00-06:30	20%
			06:30-12:00	30%
			12:00-17:30	40%
			17:30-00:00	10%
Battery Electric Vehicle	4.8 kWh	25%	00:00-13:45	30%
			00:00-07:15	30%
			15:00-00:00	20%
			16:15-00:00	20%

in order to evaluate the ability of the approach to shift highly flexible loads, such as EVs, a simplified scenario is considered. This way, each EV can charge with 3.7 kW and their flexibility intervals have been artificially generated following the previous approach. The EV is only power and energy restricted. Therefore, its load profile can be separated in different timeslots throughout its corresponding user-defined flexibility interval.

Different intelligent devices have different occurrence frequencies within the micro-grid population. Table 5.1 summarizes these frequencies, the share of the corresponding appliances per interval, the user-defined flexibility intervals and the daily consumption of the four flexible devices. These values are based on real information, [Sta08], and artificial data utilized in comparable simulated scenarios [VST13, SGC^{+}13, GSF^{+}13].

5.1.2. Renewable Generation Supply and Coverage

German Transmission System Operators provide data on wind and solar power (PV) generation in their balancing areas in 15-minute time resolution. For wind generation, data is obtained from the balancing zone of 50Hertz[2]. For PV gen-

---

[2] http://www.50hertz.com/de/Kennzahlen

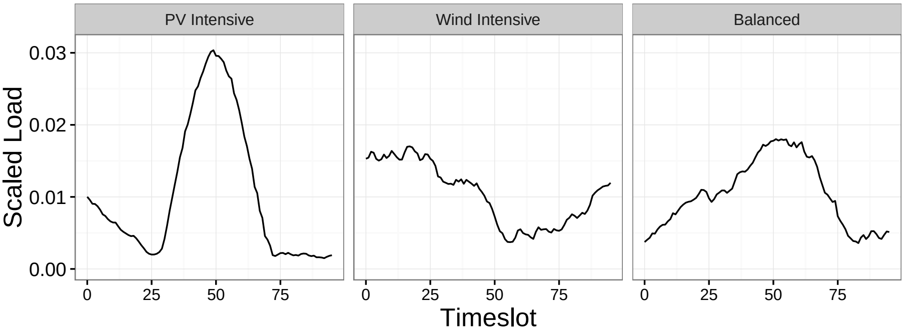


Figure 5.2.: Types of RES output selected for experimentation.

eration, data is obtained from the balancing zone from Transnet BW[3]. These zones have been selected as they have a high share of intermittent generation. Moreover, 360 days of the year 2014 of each transmission company have been selected for experimentation.

Wind and PV generation data is added such that a unique RES output for each day is obtained, with mixed shares of generation. The historical generation time series are scaled to cover 100% of the total energy demand of the households during the single day simulation period.

5.1.3. The RES Output Shape

The shape of the RES output has a relevant impact on the performance of any approach for load scheduling. The micro-grid load and the RES output can match by coincidence. On the other hand, RES generation can concentrate at times where load flexibility is not available. Hence, the performance might be reduced for reasons beyond the abilities of any load management mechanism. This situation generates nuisance and disturbs the analysis of the approach, since the global optima can largely differ from one RES output to another. Therefore, to reach conclusions the analysis should focus on the observed tendencies of the behavior, rather than the absolute performance of the approach under a specific RES output.

To address this issue, twelve RES outputs with different shapes have been selected from the pool. Each output corresponds to a different day in 2014. These outputs are exemplary of three types of days (Fig. 5.2): *(i) PV Intensive*, which corresponds to large PV generation and marginal wind generation. *(ii) Wind*

---

[3] http://www.transnetbw.de/de/kennzahlen

Intensive, days with large wind power generation and marginal PV generation. *(iii) Balanced*, with a similar PV and wind generation. These types of outputs impose specific challenges on the scheduling mechanism.

5.1.4. Summary of Input Parameters and Factors

For assessing the performance of SLC-FK and comparing it with other approaches, three different load compositions for the households are considered: *(i)* Three intelligent devices, washing machine, dishwasher and dryer, each with a unique load profile, and an electric vehicle (EV), which is only power and energy restricted[4]. *(ii)* Three intelligent devices without the EVs in the micro-grid. *(iii)* Washing machines represent the only flexible load in the power grid.

Twelve RES outputs are selected for experimentation, which are categorized according to their load distribution throughout the simulated day into PV intensive, wind intensive and balanced[5]. The population of the micro-grid increases in a logarithmic scale from 40 to $40,000$ households. As explained in Chapter 4, parameter α balances the relation between historic information, given by the previous values of the control signal, and current information, given by the difference between the current micro-grid load profile and the RES forecast, in the signal updating process. Defining $\alpha = 1.0$ means that historic information and current information have the same weight in the signal updating process. Whereas smaller values mean that historic information has larger relative weight in this process. Moreover, this parameter regulates the level of exploration/exploitation in the solution construction process. Hence, different values for the parameter are considered to assess the effect of α. In a real application, parameter α would be the only controllable factor. All other factors are defined by the application context. A summary of the different values of the factors utilized for experimentation is provided in Table 5.2. Additionally, each run of SLC-FK considers $10,000$ rescheduling rounds and ten runs are perform in each evaluation.

Individual observations which provided unexpected results are discussed in Section 6.3.6. In addition, unless explicitly stated otherwise, the performance measure is the percentage of unused RES and every device is considered as part of the micro-grid load composition (first level of the factor *Load Composition*, in Table 5.2). Finally, for the remainder of this thesis, the term *problem instance* is utilized to address specific combinations of the factors. Hence, an exemplary

---

[4] For details of the load profile of each device, cf. Appendix A, Table A.1.

[5] For each individual RES output shape, cf. Appendix A, Fig. A.1.

Table 5.2.: Summary of factors and values utilized for experimentation in the load scheduling problem. Different combinations of the factors correspond to different problem instances.

Factor	**Levels**	**Values**
RES Output	12	RES outputs 1, 5, 7, 11, 12 (Balanced), 4, 6, 8 (PV Intensive), 2, 3, 9, and 10 (Wind intensive)
Population Size	4	40, 400, $4,000$, and $40,000$ households
α	6	1.0, 0.5, 0.1, 0.05, 0.01 and 0.0
Load Composition	3	All appliances, No EV, Only washing machines

problem instance can consider RES output number six, a population size of 400 households, No EV in the simulated micro-grid and and $\alpha = 1.0$.

5.1.5. Approach to Data Analysis

The observations and significance of the results from this chapter are assessed through statistical analyses which are performed for each set of experiments in the corresponding subsections. These analyses follow the same structure in each evaluation.

To test the proposed hypotheses in each presented scenario, the statistical analysis is conducted as follows: The compliance of the data to be normally distributed is assessed through a one-sample Kolmogorov-Smirnov test. Consistently, for every scenario the results from the normality tests rejected the hypothesis that the data is normally distributed. Afterwards, a summary of the main statistics is constructed for the corresponding evaluation. Since the data is not normally distributed, the summaries focus on medians rather than means. Once the summaries are constructed, the different evaluations to be compared are grouped. To assess the significance of the differences between evaluations, a Kruskal-Wallis rank-sum test is selected. Once more, this test is chosen due to the data not being normally distributed. Finally, a post-hoc analysis performed. The selected test corresponds to an unpaired Wilcoxon rank-sum test for pairwise comparisons.

The detailed analysis of each scenario is provided in the appendix. Details of each normality test are available in Appendix B. The detailed Kruskal-Wallis rank-sum tests are presented in Appendix C. The post-hoc analyses are presented in Appendix D. Finally, the summaries of each evaluation are available in Appendix E.

These specific tests are referenced throughout this chapter, in order to support statements regarding the performance under different parameter configurations and in comparison to other load scheduling approaches.

5.2. Analysis of SLC-FK

In the following, SLC-FK is analyzed to obtain profound insights on its functioning. Firstly, the scalability of the approach is assessed. This is an essential issue to understand the potential of SLC-FK as a meta-heuristic. In addition, the effect of modifying parameter α is investigated. Afterwards, the convergence of SLC-FK is analyzed and potential improvements are proposed.

5.2.1. Exemplary Run

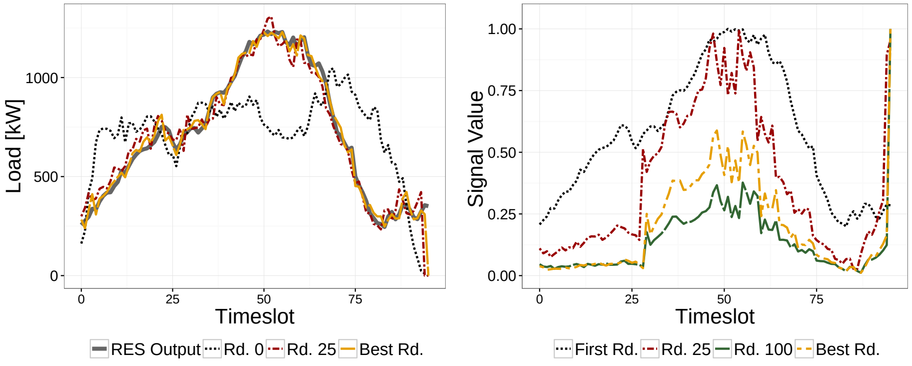
To calculate global schedules with SLC-FK, each household is represented by an agent in charge of a solution component: The *household schedule*. The RES output is assumed to be known from the beginning[6] and its utilization is desired to be maximized.

Fig. 5.3 shows an exemplary run of SLC with $4,000$ households and $\alpha = 0.5$, throughout 100 rescheduling rounds. Each curve represents the aggregated load, or micro-grid load profile, at the end of a single rescheduling round. An increasing resemblance of the micro-grid load profile with the RES output can be observed in progressive rounds. Moreover, no step responses or oscillations are obtained as the algorithm gradually converges, achieving good solutions (Fig. 5.3a).

In Fig. 5.3b, the behavior of the signal in the solution searching process is depicted. Each curve corresponds to the stigmergic stimulus broadcast to every household, which references the requirement to shift load to specific timeslots in the day, from a global perspective. Agents, representing households, are influenced by these values. Moreover, agents also modify the stimuli for future rescheduling rounds by modifying the operation times of their appliances. Then, the shape of the stimuli changes between rounds, as a function of the

---

[6] In a real-world application, this output would correspond to a forecast of the daily generation.



(a) Performance evolution of SLC-FK.

(b) Signal evolution of SLC-FK.

Figure 5.3.: Example run of SLC-FK throughout 100 rescheduling rounds. **Rd.** stands for rescheduling round.

distance between the target behavior and the real behavior. This change increases the desirability to shift load to timeslots where RES output has not been matched, and reduces the desirability on timeslots where overload exists[7].

The signal always has values in $[0, 1]$, with value 1.0 representing the largest load imbalance in a given timeslot for the corresponding rescheduling round. Hence, SLC-FK constantly promotes load shifting with more intensity to positions were imbalances are larger. This process guides the search towards solutions which increase RES usage reducing additional load imbalances. A large steep in the values of the signal can be observed at the end of the plot for every rescheduling round after the first one. This occurs because the largest imbalances consistently concentrate in that part of the day, due load restrictions imposed by the user-defined flexibility intervals.

In the following sections, the scalability of SLC-FK and the effect of modifying parameter α on the performance are evaluated. Later, these results are utilized to propose and implement improvements on the approach and to compare the SLC-FK with a price-based alternative.

5.2.2. Scalability of SLC-FK

To assess the scalability of SLC-FK, the performance of the algorithm is evaluated under different population sizes. For this, the tested hypothesis is formally

---

[7] The signal construction process can be found in Subsection 4.3.1.

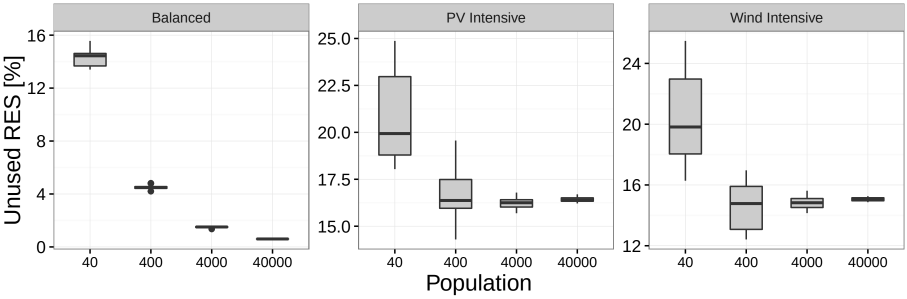


Figure 5.4.: Example performances of SLC-FK with different population sizes and RES output type.

defined as: H_0 : Data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not. Both, x and y, are the performance of SLC-FK, generated with the same RES output and α configuration, but varying the population size. Hence, the rejection of H_0 implies that differences in performance between two samples with different population size, are significant.

Results of the analysis show that there is a clear tendency to improve in performance as a consequence of the increase in the network size. Therefore, evidence exists to reject H_0[8]. This tendency can be observed in Fig. 5.4. Moreover, the performance becomes more robust, which is appreciated through the drastic reduction of outliers when the population size increases. The tendencies described are constant for each type of RES outputs, regardless of the α configuration. Therefore, for the ease of exposition, the following analysis considers RES output 3, 6, and 12, which are wind intensive, PV intensive and balanced, respectively, and $\alpha = 0.05$.

As observed in Fig. 5.4, with a balanced output the performance improves each time the population size increases. Performances with a population of $40,000$ households dominated all of those with smaller network sizes[9]. Nevertheless, the absolute performance improvement is also smaller in each test. Hence, it is reasonable to assume that a performance threshold, related to the size of the network, exists. After this threshold is crossed, the absolute performance improves no more.

The reason for this is that with smaller population sizes, there are fewer alternatives to reschedule the appliances within their flexibility intervals, such

---

[8] For the Kruskal-Wallis rank-sum tests, cf. Appendix C, Table C.13.

[9] For the post-hoc analysis of these cases, cf. *RES Outputs 1*, *5*, *7*, *11*, and *12* at Appendix D, Tables D.20 and D.21.

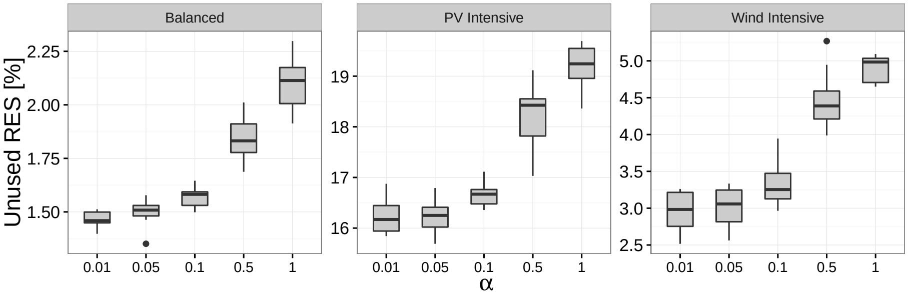
that RES usage is increased. This means, there is less potential for optimization. Additionally, since the RES output is scaled to the total amount of energy available (which depends on the number of devices), when the population is smaller the impact of rescheduling a single device on the micro-grid load profile is more relevant compared with larger populations. On the contrary, above a certain population size, the effect of individual devices is reduced to the point where only aggregated behavior has a relevant impact on the overall performance. This way, when the population size is larger, SLC-FK is able to promote small differences to the current global schedule to increase RES usage. Then, with larger population sizes, opportunities to promote these differences increase. This corresponds to a traditional feature of natural stigmergic systems [TB99].

When the RES output is wind intensive, this tendency is reduced and unexpected behavior can be observed. In this case, the best performance is obtained with a population of 400 households, and it slightly deteriorates with larger population sizes. A similar behavior is observed when the RES output is PV intensive. Although it is possible that the value of the global optima of the two example RES Outputs with a population size 400 is smaller than with $4,000$ or $40,000$, it is highly unlikely. When the relative weight of the load of individual devices with regard to the total micro-grid load is smaller, there are more alternatives to reschedule them to timeslots where RES utilization is increased. Hence, a probable reason for this performance is that, with these type of RES output, SLC-FK tends to get trapped in a local optima when the population size increases.

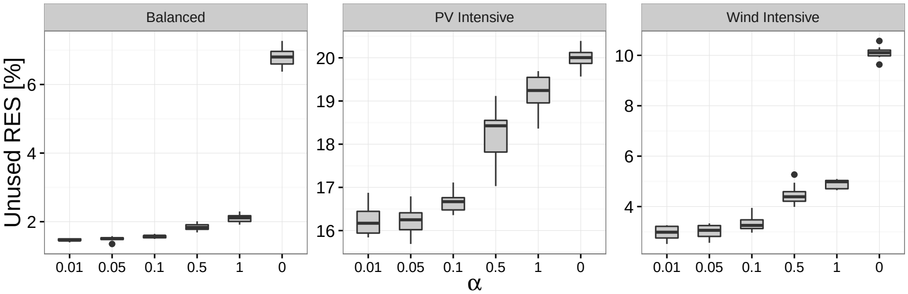
In conclusion, it can be said that when the RES output is balanced, performance improves with larger size of the network. Moreover, a performance threshold related to the population size might exist, which is located above $4,000$ households. When the RES output is wind or PV intensive, unexpected behavior is observed, in which with smaller network sizes SLC-FK produced better performances than with larger.

5.2.3. Configuration of Parameter α

Parameter α regulates the weight of the current micro-grid load profile in the control signal construction process, with $\alpha \in [0, 1]$ (Chapter 4, Section 4.3). On the one hand, $\alpha = 1.0$ means that the current difference between RES output and micro-grid schedule (derived into a load profile), has the same weight as previous historic evaluations of the same difference. On the other hand, $\alpha = 0.0$ means that the current micro-grid load profile is not included at all in the signal construction process. Hence, $\alpha = 0.0$ implies that the same scaled form of the RES output is broadcast to the agents in every rescheduling round.



(a) Performance of SLC-FK under different α configurations.



(b) Performance of SLC-FK under different α configurations including $\alpha = 0.0$.

Figure 5.5.: Performance of SLC-FK with different α values and RES outputs.

To assess the effect of α for the load scheduling problem, the value of the parameter is modified while other factors remain static. Formally, the hypothesis to be tested goes as follows: H_0 : Data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not. Both, x and y, are the performances produced by SLC-FK, with the same RES output and population size, but varying the value of α. Hence, the rejection of H_0 implies that differences in performance between two samples with different α configurations, are significant.

The analysis provides evidence to reject H_0. Therefore, it can be said that significant differences in the performance of SLC-FK, as a consequence of different α configurations[10]. Fig. 5.5a depicts the tendency of the performance when the value of α is reduced, with three RES outputs, PV intensive, wind intensive and balanced, and a population of $4,000$ households[11]. These results are

---

[10] For details of the Kruska-Wallis rank-sum tests, cf. Appendix C, Table C.14.

[11] For the post-hoc analysis of these specific examples, cf. *RES Output 6*, *9*, and *12* at Appendix D, Tables D.22 and D.23.

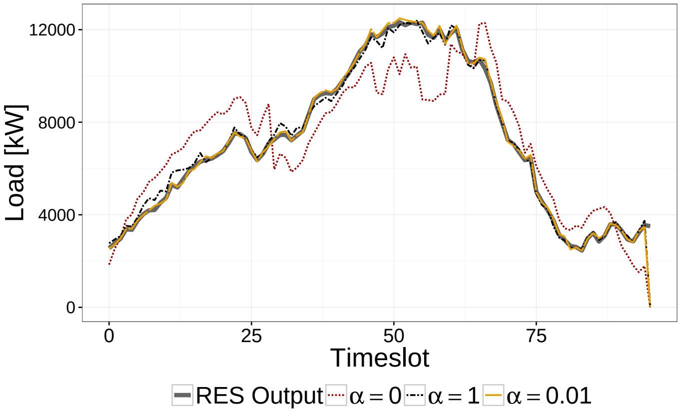


Figure 5.6.: Micro-grid load profiles generated with different α configurations.

consistent for each RES output type. It can be observed that, the performance improves with smaller α values. This tendency is strongest with balanced outputs ($\alpha = 0.01$ outperforms every other configuration). Moreover, it can clearly be observed that when no adaption of the signal is used, $\alpha = 0.0$, performance is by far the worst (Fig. 5.5b). Hence, it is empirically demonstrated that the signal adaptation is required to achieve quality performances, rather than broadcasting the same signal all the time.

An additional aspect to analyze is the absence of step responses and oscillations in the micro-grid load profile. In Fig. 5.6, different micro-grid load profiles generated with different α configurations, a population of $40,000$ households on a balanced RES output (RES output 5), can be observed. Non of these profiles depict imbalances nor step responses. In this case, the profile obtained with $\alpha = 0.0$ shows a vague resemblance with the RES output. Whereas $\alpha = 1.0$ and $\alpha = 0.01$ follow the RES output almost exactly. The best performance is obtained with $\alpha = 0.01$, with a percentage of unused RES bellow 1%. In SLC-FK, the evaluation function selects micro-grid schedules which derive into minimized load imbalances with large RES usage. Hence, global schedules which increase RES utilization on some timeslots but generate additional imbalances are not selected as the current best solution. Furthermore, these results show that the α configuration does not have an impact on the stability of the generated profile.

The best performing α configurations are presented in Table 5.3. It can be observed that $\alpha = 0.01$ produces the best performances in most scenarios. These configurations are later utilized for comparing the performance of the approach

Table 5.3.: Best performing α configurations for each RES output and each population size on the micro-grid.

Population	Problem Instance											
	1	2	3	4	5	6	7	8	9	10	11	12
40	0.01	0.01	0.05	0.01	0.05	0.1	0.1	0.05	0.01	1.0	0.1	0.05
400	0.01	0.05	0.05	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
4,000	0.01	0.01	0.1	0.05	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
40,000	0.01	0.01	0.1	0.05	0.01	0.05	0.01	0.01	0.01	0.01	0.01	0.01

against a price-based heuristic in Section 5.3.

5.2.4. Convergence and Deterministic Parameter Control

In some situations, it is desirable for an algorithm to provide a good solution as soon as possible, rather than a better solution much later. In this case, the speed of convergence towards quality solutions is a factor which determines if an approach is appropriate for a given application. Previous results clearly show that $\alpha = 0.01$ produced better performance in the vast majority of the evaluated problem instances. Nevertheless, a question remains regarding how fast these results are achieved.

Analysis of the Convergence

To assess the convergence speed of SLC-FK, the last rescheduling round in which the algorithm improves the current solution, is utilized. This value can be considered as an indicator of convergence, since it describes how many rounds are performed before the algorithm finds the final solution, regardless of the quality of that solution.

Fig. 5.7 depicts the distribution of this indicator for different α configurations and population sizes. It can be observed that a tendency exists, in which the larger the population size, the fastest the convergence. Moreover, a tendency can also be observed with regard to the RES output type. When the output is PV intensive, convergence seems to occur quite fast, regardless of the α configuration. In the case of balanced and wind intensive outputs, larger α values tend to converge much faster than smaller ones. From an overall perspective, this seems to be the general rule.

On the one hand, with larger α values, the last improvement on the current solution tends to occur early into the run. On the other hand, for smaller values the last improvement on the current solution, tends to occur later into the run.

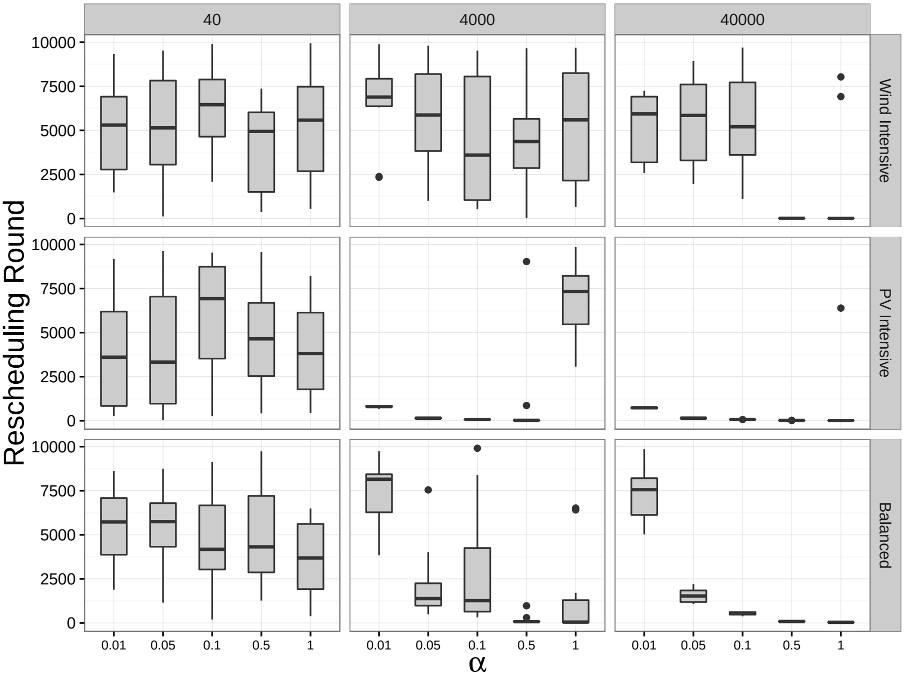


Figure 5.7.: Distribution of the last improve on the *current best solution* for different α values, population sizes and RES outputs. Population size= 400 was deliberately left out since it showed the same tendency as population= 40.

Hence, in general, even when $\alpha = 0.01$ generates the best performances, it also depicts slower convergence. Meanwhile, even when, in general, $\alpha = 1.0$ generates the worst performances, these performances are achieved much faster than with other configuration. These behaviors are representative of what is observed in other RES outputs of the corresponding type.

Additional insights are obtained through the analysis of Fig. 5.8. Here, the evolution of the performance of SLC-FK throughout single runs with different α values on a balanced RES output (RES output 5), can be observed. In the $5,000$ *rounds* scenario, the previously described behavior is confirmed. A fast convergence followed by stagnation of the performance, is observed with $\alpha = 1.0$, whereas for $\alpha = 0.01$ a slow but consistent improve of the performance occurs. The difference between the two configurations, is initially quite large. Nevertheless, the $\alpha = 0.01$ configuration eventually outperforms $\alpha = 1.0$ and all other α value.

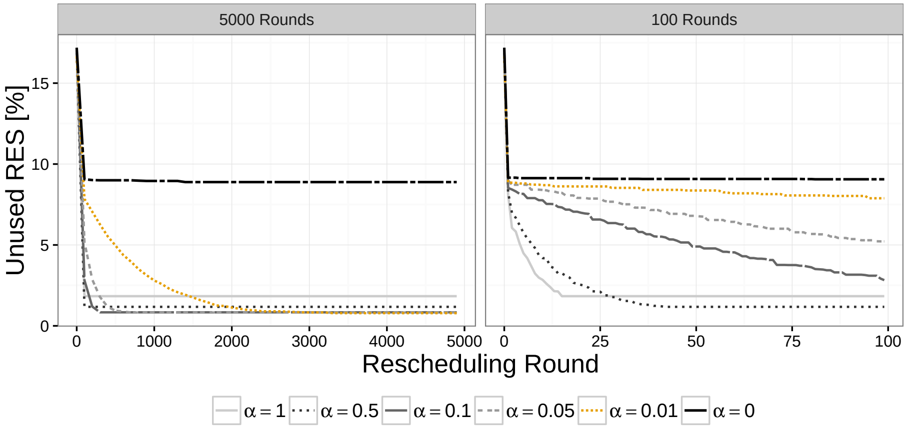


Figure 5.8.: Improvement of the performance throughout rescheduling rounds for different α configurations, throughout $5,000$ and 100 rounds.

When the algorithm is executed for 100 rounds (Fig. 5.8, *100 Rounds*) a clear outperform of larger α values is observed in comparison with smaller values. $\alpha = 1.0$ achieves its best performance within the first 25 rescheduling rounds, while $\alpha = 0.5$ within the first 50 rounds. $\alpha = 0.1$ and $\alpha = 0.05$ show a slow but consistent performance improve. Nevertheless, within 100 rounds their performance is not competitive with $\alpha = 1.0$ and $\alpha = 0.5$ configurations. Moreover, $\alpha = 0.01$ is vastly outperformed, achieving a small improvement in comparison with the performance of SLC-FK without any signal adaptation ($\alpha = 0.0$).

The previous observations are complemented with Fig. 5.9. Here, the performance evolution of the *current best solution* and the *generated solution* in each rescheduling round can be observed throughout 500 rescheduling rounds. For $\alpha = 1.0$, it can be observed that after a steep improvement of the performance (roughly at round 25), the new solutions generated are clearly inferior to the ones obtained at the beginning of the execution of the algorithm. A similar situation can be observed for $\alpha = 0.5$. For $\alpha = 0.1$, after mild improvements throughout the first 200 rounds, SLC-FK performs consistent but small improvements on the current solution. Then, the situation repeats. This behavior was observed for every α configuration: After a consistent improvement of solutions, either fast or slow, new global schedules reduce their performance and new found solutions are clearly inferior in comparison with the current best solution. As a consequence, no more improvements occur and the search stagnates. In the case of $\alpha = 0.05$ and 0.01, this threshold is usually crossed after 500 and $4,000$ rescheduling rounds, respectively. Specific values generally var-

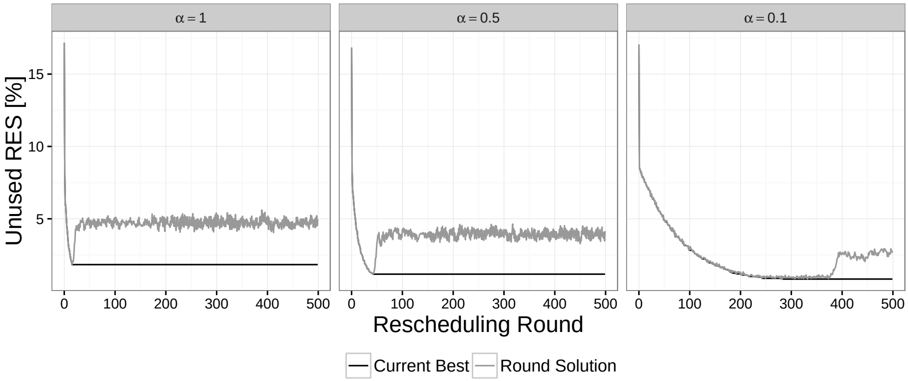


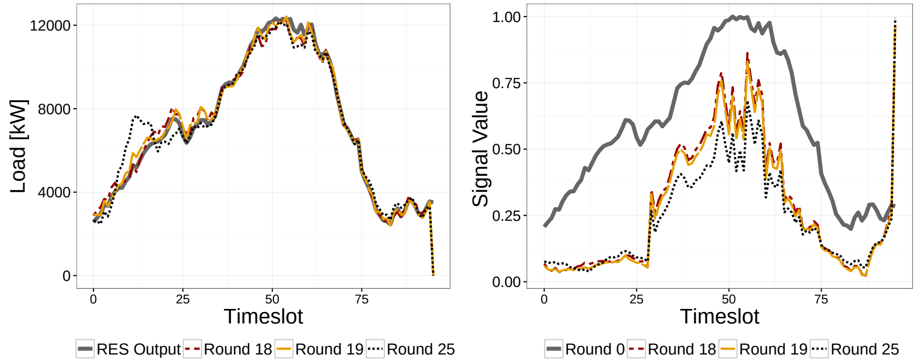
Figure 5.9.: Performance behavior of the *current best solution* and the *generated solution* in each rescheduling round throughout 500 rounds for different α configurations.

ied depending on the type of RES output and the behavior was strongest with larger population sizes.

To further understand this behavior, Fig. 5.10a depicts the performance and the control signal in different rescheduling rounds with the previous RES output. More specifically, in the immediate round before the best solution is found, in the round when the best solution is found, and after the search stagnates. Individual runs are performed with $\alpha = 1.0$, and the best performance is achieved at rescheduling round 19, after which the previous phenomenon is observed. It can be seen, that large differences in performance between round 18 and 19 are not obvious. Only by deriving the percentage of unused RES, the best profile can be identified. At round 25, differences in the quality of the performance begin to be visible. After this round, the behavior described in Fig. 5.9 occurs.

The behavior of the signal in the same rounds can be observed in Fig. 5.10b. The value of the signal during the morning is close to zero. This means that the weight of imbalances in those timeslots in comparison to other imbalances, is minor. At the end of the day, the value is one. This timeslot concentrates the largest imbalances of the day. In the middle of the day, the values reduce in each progressive round, implying that the relative weight of imbalances in those timeslots reduces. From an overall perspective, although the signal is similar in each round is similar, it flattens. Hence, load scheduling eventually will disperse throughout the day. This can be observed in Fig. 5.10a, at *Round 25*, where a bulge starts to be observable at roughly timeslot 15.

Hence, after a certain number of rescheduling rounds, the control signal is not



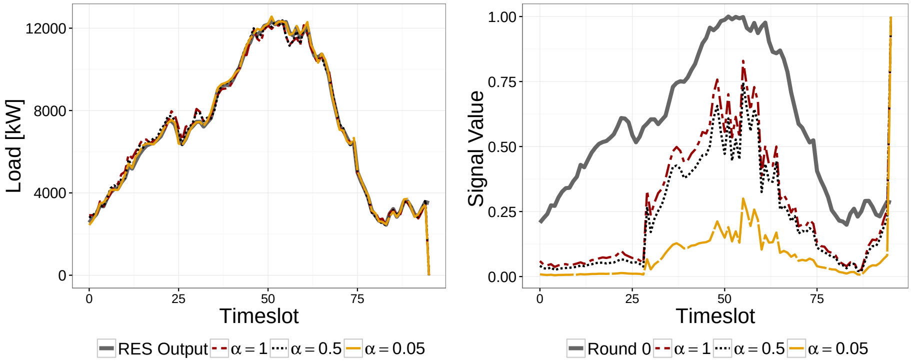
(a) Micro-grid load profile throughout progressive rescheduling rounds.

(b) Control signal throughout progressive rescheduling rounds.

Figure 5.10.: Micro-grid load profile and control signal behavior at different rescheduling rounds 18, 19 and 25. The best solution is obtained at round 19, while the deviation to a sub-optimal behavior occurs at round 25 and thereafter.

able to effectively stimulate load relocation, due to the flattening of the curves shape. As a consequence, the search moves to a region of the fitness landscape in which only lower quality local optima are produced (*Round Solution* curve in Fig. 5.9). This *threshold round* is different for each α configuration and it is reached slower when alterations on the signal are smaller. As a consequence, with $\alpha \leq 0.05$, the search of quality schedules in the close vicinity of the current solution is performed more thoroughly before the signal redirects the search to less optimal regions.

Fig. 5.11 provides additional evidence to support this explanation. In Fig. 5.11a, the best micro-grid load profile obtained with different α configurations can be observed. The shapes are fairly similar to the RES output. The configuration which provided the best performance is $\alpha = 0.05$. Fig. 5.11b depicts the broadcast signals in the rounds when these results were obtained for each run. As it can be observed, they are quite different. This way, with every α configuration a scanning process occurs, in which, after a number rescheduling round, the stimuli is not able to promote effective search. With smaller α values, the shape of the signal is slightly modified from one round to the next one, contrary to what occurs with $\alpha = 1.0$. Hence, the process is more gradual. As a consequence, minor modifications on the global schedule are promoted and a thorough exploration of the fitness landscape is performed in the vicinity of the current best solution. This way, the signal can reach a *flattened shape* and



(a) Best micro-grid load profiles achieved with different α configurations.

(b) Signals at the rescheduling rounds in which the best performances were obtained.

Figure 5.11.: Best micro-grid load profiles for individual runs with different α configurations and the corresponding control signals which produced them. For $\alpha = 1.0$ the profile is obtained at rescheduling round 19.

still produce good quality results. From Fig. 5.11 it can assumed that for each α configuration, a different threshold exists for the shape of the signal, after which the search moves to a sub-optimal region.

To provide conclusive evidence regarding the existence of this threshold, 100 runs have been performed with different α configurations on a balanced RES output (RES output 5) and a population of $40,000$ households. Afterwards, the control signals which produced the best schedules are compared.

From Fig. 5.12 it can be observed that a tendency for a specific shape of the signal exists. This shape is different between the two α configurations. In addition, it can be observed that deviations from the averaged shape of the signal reduces with $\alpha = 0.1$. This supports the proposal that with smaller α values a thorougher exploration is performed, since the number of rounds dedicated to promote small alterations of the global schedule, is larger.

In this context, the *threshold signal* is a sub-product of the individual solution searching process performed in each run. As a consequence, storing a signal which provides great results to directly utilize it in a different run later, would not provide the same quality results. Therefore, it can be said that the shape of the *threshold signal* is specific to each α configuration and, implicitly, each problem instance.

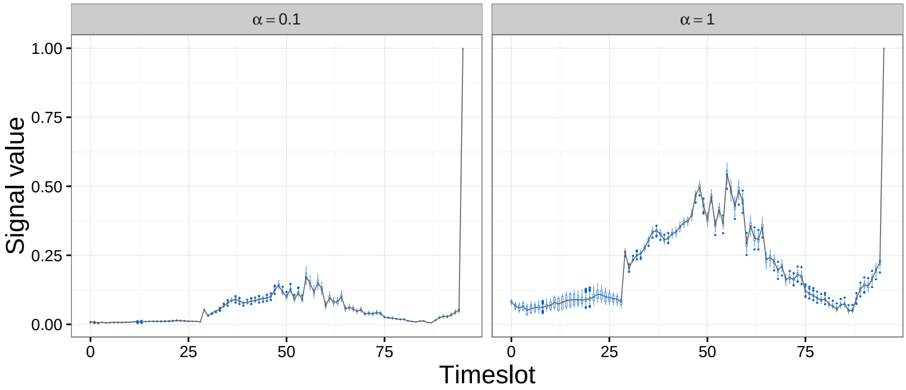


Figure 5.12.: Distributions of the control signal values in each timeslot for two α configurations in 100 independent runs. Mean values are linked to obtain the average shape of the control signal.

From the perspective of the internal functioning of SLC-FK,s results show that the signal shape is related to the searching process, which is regulated by α. Moreover, results imply that α does not regulate exploration and exploitation in the same way as other stigmergy-based optimization algorithms, namely ACO algorithms [SLIP$^+$12]. This can be explained by the internal differences in between both algorithms[12]. From a performance perspective, even when large α values achieve fast convergence, they do not enable the algorithm to perform a continuous and effective search. This is not the case with smaller values of the parameter, where, better results are unveiled continuously and eventually runs with higher α values are outperformed.

In conclusion, it can be said that the best solution obtained with $\alpha = 1.0$ is found rather fast, in comparison with $\alpha = 0.01$. Meanwhile, when the number of rounds is not a restriction the best performance is obtained with $\alpha = 0.01$.

A Parameter Control Approach for SLC-FK

Previous results support that α values for SLC-FK could be modified in runtime to promote fast convergence in the first stages of the search, to later continue with a thorough exploration of the fitness landscape. This way, the utilization of a *parameter control* alternative becomes suitable. Two alternatives found in literature might be appropriate in this case ([EHM99]). On the one hand, a *deterministic parameter control* approach would allow the modification

---

[12] This issue is further discussed in Chapter 7, Subsection 7.1.2.

Algorithm 4 Rule for determining α in SLC-FKd. An integer specifying the rescheduling round ($round$) is received and a real value for α is returned.

```
function DETERMINISTICPARAMETERCONTROL($round$)
    if $round \geq 400$ then
        return $0.01$
    end if
    if $round \geq 200$ then
        return $0.05$
    end if
    if $round \geq 20$ then
        return $0.1$
    end if
    return $1.0$
end function
```

of parameter α according to a fixed function, such that the values of the parameter changes from larger values in the early stages of the search, to smaller values during the run of SLC-FK. On the other hand, an *adaptive parameter control* approach would consider a feedback mechanism which, provides information regarding the current state of the search. With this information, the MGM would have to decide how to modify the value of α, in order to actively redirect the search process. The latter alternative is further discussed in Chapter 7, Section 7.3. The former alternative is considered for experimentation.

To implement a deterministic parameter control approach in SLC-FK, a fixed rule is defined. According to this rule, the value of α is reduced after a specific number of rescheduling rounds to improve convergence speed and efficiency in the search. The objective is to rapidly obtain quality solutions. Once these solutions are obtained, the strategy is gradually adapted to improve the current solution with small adaptations and avoid stagnation in local optima. Hence, the number of rescheduling rounds dedicated to performing a thorough search is increased. This rule is depicted in Algorithm 4. From now on, the adaptation of the original algorithm is referred to as **SLC-FKd**, standing for SLC-FK with deterministic parameter control.

Fig. 5.13 depicts an exemplary run for SLC-FKd versus SLC-FK with different α configurations. From the evolution of the *Current Best* solution scenario, it can be observed that SLC-FKd achieves good results with fast convergence. Moreover, contrary to what occurs with $\alpha = 1.0$, the adapted algorithm does stagnates after the initial rescheduling rounds. It can also be observed that eventually, SLC-FK with $\alpha = 0.1$ reaches competitive solutions against SLC-FKd. This occurs because, after a certain point, it becomes harder to generate

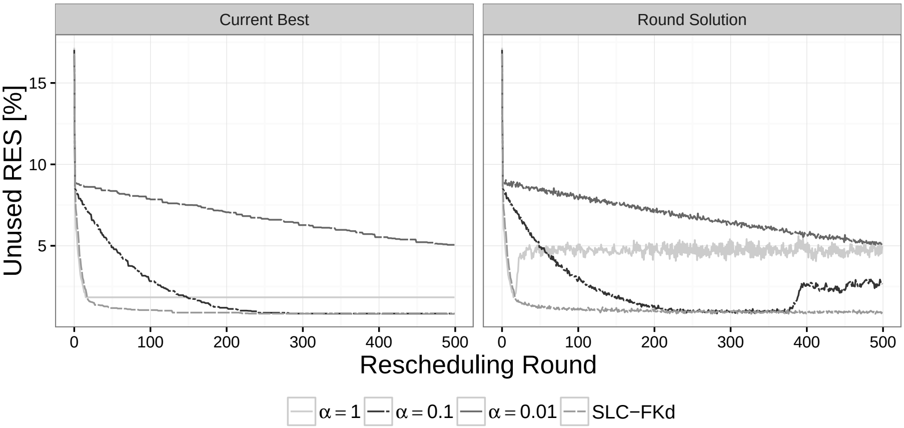


Figure 5.13.: Evolution of the performance for exemplary runs of SLC-FKd and SLC-FK with different α values. *Current Best* depicts the evolution of the best performance throughout the execution. *Round Solution* depicts the solution produced in each rescheduling round.

major improvements over the current solution. Additionally, SLC-FK with $\alpha = 0.01$ is not able to produce competitive solutions within the first 500 rounds.

Details of the search process can be obtained by observing the *Round Solution* scenario. It can be seen that, with $\alpha = 1.0$ and $\alpha = 0.1$ the previously described threshold is crossed, after which the search is performed in a sub-optimal position of the fitness landscape. On the other hand, due to the modification of the α value, SLC-FKd is able to rapidly improve the performance in the beginning of the execution, to continue with a thorough search in the same vicinity of the current best solution. This analysis shows that this version of the original algorithm is able to avoid the described behavior during the search process. Hence, SLC-FKd is able to increase execution time on a thorougher search of quality solutions, by utilizing smaller values for α in more appropriate circumstances. It has to be mentioned, however, that after certain execution time, SLC-FKd will depict the same behavior as SLC-FK, since the redirection of the search is a consequence of the adaption of the control signal, which continues to be performed indefinitely for both approaches.

These results are complemented with Fig. 5.14. In this case, the distribution of the round in which the best solution is found, is compared between SLC-FK with $\alpha = 0.01$ and $\alpha = 1.0$, which produced the best performance and fastest convergence respectively, and SLC-FKd. As mentioned, this measurement can be considered as an indicator of the speed of convergence of the al-

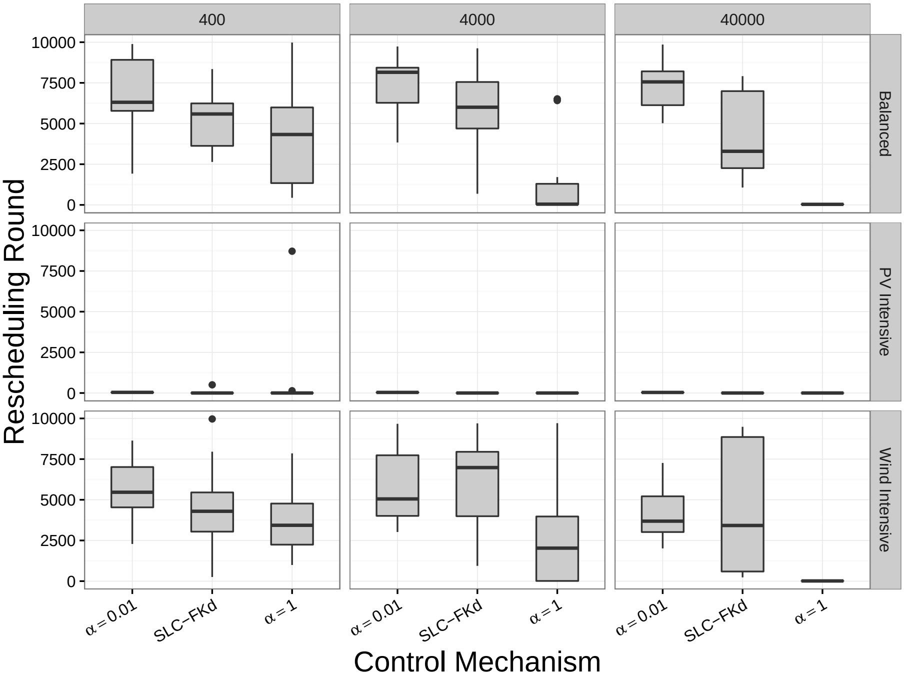


Figure 5.14.: Distribution of the last rescheduling round in which performance is improved for SLC-FK, with $\alpha = 1.0$ and $\alpha = 0.01$, and SLC-FKd for different population sizes and RES outputs.

gorithms. It can be observed that with a PV intensive output, the previously described tendency maintains. This is, all approaches converge rapidly to a solution during the first rescheduling rounds. Regarding balanced and unbalanced outputs, it can be observed that, for SLC-FKd, the distribution of the final improvement of the solution is spread throughout the run. Therefore, although a steep improvement of the performance of SLC-FKd is observed in the beginning of the run, stagnation occurs much later. The contrary, can be observed with $\alpha = 1.0$, where stagnation occurs much earlier. Fig. 5.14, in conjunction with Fig. 5.13, provide evidence to support that, although SLC-FKd can achieve good results very fast, it also continues the search throughout the $10,000$ rescheduling rounds. These tendencies are constant for each corresponding RES output type.

These, results lead to the conclusion that SLC-FKd is able to find quality solutions faster that SLC-FK with a fixed α configuration. Moreover, results also show that the searching process depicts the desired behavior for SLC-FKd:

A permanent search for good solutions while avoiding the redirection of the search to sub-optimal regions of the fitness landscape in early stages. Nevertheless, since the rule described in Algorithm 4 is fixed, the performance might be affected by specific RES outputs. Moreover, the search has a component of randomness due to the probabilistic selection of operation times of the appliances. Therefore, it might occur that the value of α is modified too early, before a thorough search is required, or too late, after a long period of stagnation in sub-optimal locations of the fitness landscape. The design of the rule, however, is very simple and drastically improves the convergence speed of the performance.

Finally, this analysis has concentrated on the convergence of both approached. In the following, the performance is analyzed in detail in comparison with a synchronized price-based approach.

5.3. Comparative Results

In this section, SLC-FK and SLC-FKd are compared with a synchronized closed-loop pricing approach. This approach is referred to as CLP-FK, standing for **C**losed-**L**oop **P**ricing with **F**ull **K**nowledge of the RES output. CLP-FK utilizes a greedy selection process to synchronously select the operation times of the appliances. For the rescheduling of highly flexible loads, such as EVs, CLP-FK has been shown to achieve close-to-optimal solutions ([Got15]). Therefore, it is a reasonable candidate to compare the performance of SLC-FK. The detailed functioning of its behavior and expected performance are described in Subsection 5.3.1.

To compare these load scheduling strategies, the population size and the RES output are varied. Subsequently, the performance of the approaches is compared with a different load composition in the micro-grid and RES outputs, while considering a fixed population size. Afterwards, a discussion is performed regarding the relevance of synchronization for CLP-FK is empirically assessed.

Novel contributions in this section include the comparison of SLC-FKd with CLP-FK and SLC-FK. Additional contributions are the analysis of the performance of each approach in a micro-grid with different load compositions and the assessment of the effect of sorting in the performance. Moreover, the comparisons regarding SLC-FK and CLP-FK, and a specific comparison of the effect of sorting appliances (Subsection 5.3.3) have been submitted for publication [RKS16].

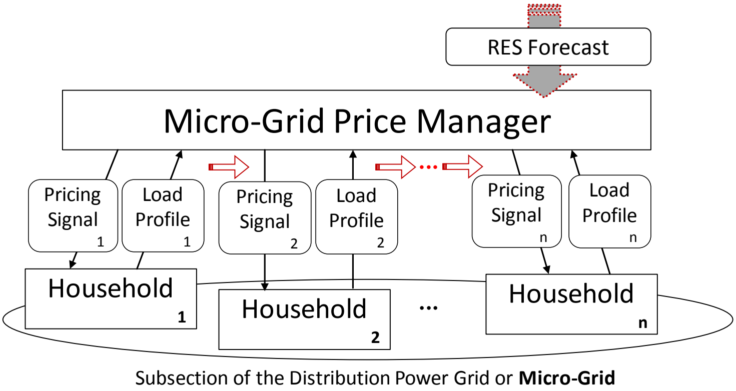


Figure 5.15.: Information flow for CLP and CLP-FK, between the micro-grid price manager (MGPM) and households within an idealized micro-grid.

5.3.1. Closed-Loop Pricing with Full Knowledge

Under a CLP-FK regime, a micro-grid price manager (MGPM) is given an RES output[13]. The MGPM transforms the RES output into a pricing signal. This signal expresses the electricity price for each timeslot in the simulated day, in reference to RES availability according to the output. Hence, higher RES availability implies cheaper prices.

The MGPM proceeds to broadcast the signal to a single household. The household performs a greedy selection based on the signal. This is, it selects the cheapest operation time for its devices. Then, it sends its updated load profile to the MGPM. Once the MGPM has received this first household schedule, it discounts the derived load profile from the RES output. Afterwards, it updates the pricing signal according to the new RES availability. The updated pricing signal is broadcast to the next household and the process is repeated. When all households have rescheduled their appliances, a single rescheduling round is finished. In the next rescheduling round, the price-based signal expresses once again the prices according to the RES output. The process continues until the end of the simulation. The best performing global schedules are selected from each rescheduling round. The information flow in CLP-FK is described in Fig. 5.15.

The process of synchronously selecting the cheapest timeslots and adapting

---

[13] CLP-FK is later utilized in Chapter 6. In that scenario, an RES forecast is utilized and updated in each rescheduling round, instead of the RES output. This difference is depicted in Fig. 5.15 with the red dotted arrow, to show that this step is not performed in CLP-FK.

the price signal according to the new RES availability, allows CLP-FK to obtain high quality solutions. Nevertheless, it has to be noted that this approach only works if there is synchronization among participants. When this requirement is not met, extreme load peaks can be obtained ([GKB$^+$11, GSF$^+$13]).

Disruption in CLP-FK comes from the sorting in which households are selected for receiving the pricing signal. Different sorting will imply that households with different load compositions will have the priority to select the best prices, influencing the final micro-grid load profile. Hence, different high quality solutions might be found. In the present thesis, households provided with devices with the highest flexibility (BEVs) are scheduled at the end of the rescheduling round. This sorting allows CLP to absorb breaches and deviations from RES forecast. Additional discussion regarding conceptual implications of CLP in the context of stigmergy, is presented in and Chapter 7.

5.3.2. Scalability and Overall Performances

To compare the performances of each approach regarding scalability and the effect of different types of RES outputs, both factors are modified simultaneously. The analysis, is performed for each individual problem instance. Therefore, formally the hypothesis to be tested is: H_0 : Data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not. x is performance generated with a load-scheduling algorithm (such as SLC-FK) and y is performance generated with another load-scheduling regime (such as CLP-FK). Both performances are generated with the same RES output and population size. Hence, the rejection of H_0 implies that differences in performance between two samples with different load scheduling strategies, are significant.

Results provide evidence to support the rejection of H_0 for every RES output and every population size[14]. Therefore, it can be said that significant differences exist when the three approaches are compared. In this sense, Fig. 5.16 provides a perspective of the performance of each approach. These specific examples describe the overall behavior for each type of RES output and population size analyzed.

It is observed that, the performance of CLP-FK is superior to SLC-FK and SLC-FKd. Nevertheless, differences between both types of strategy tend to reduce with larger population sizes. This tendency is stronger with balanced outputs, where differences in performance are on the order of 1% of unused RES output. In the case of PV intensive outputs, the opposite tendency is observed: With

---

[14] For a detail analysis of the Kruskal-Wallis rank-sum test, cf. Appendix C, Table C.15.

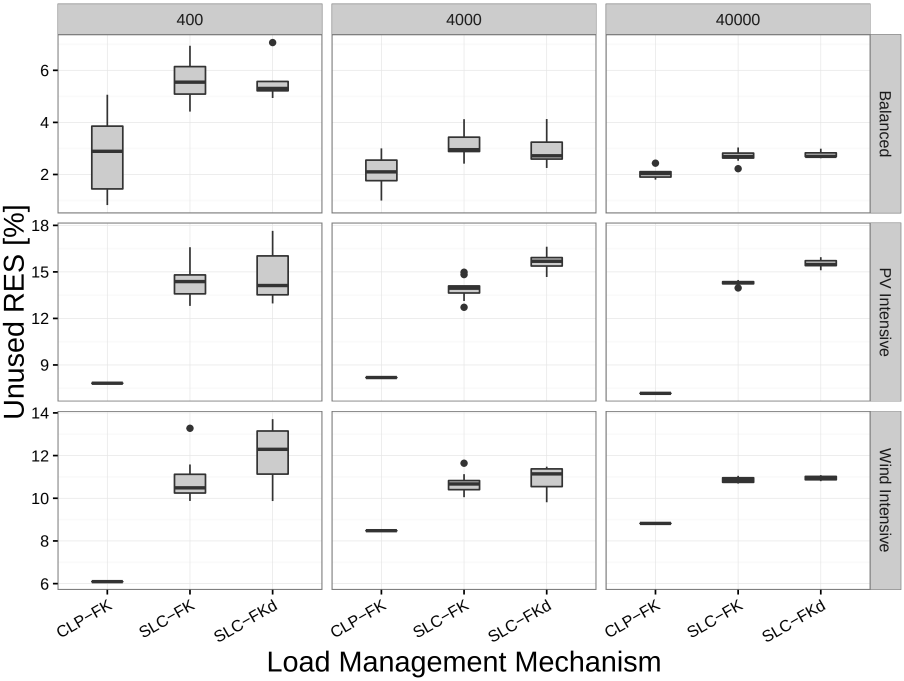


Figure 5.16.: Performance of CLP-FK, SLC-FK and SLC-FKd under different population sizes and RES outputs.

larger population size, the differences in performance between CLP-FK and SLC-FK or SLC-FKd increase.

A reason for this is that the greedy selection of rescheduling hours in CLP-FK is much more effective to exploit large single load peaks, than the probabilistic selection process performed with the stigmergy-based approaches. Therefore, with larger population sizes, these differences are intensified under these type of outputs. This also explains the small dispersion observed for CLP-FK with balanced outputs, and not with PV intensive outputs.

Due to its greedy selection process, intuition dictates that exactly the same schedules would be obtained every time for CLP-FK. Nevertheless, a source of variability is the breaking of ties in which the approach selects randomly the operation times when prices are equal. As a consequence, small differences between global schedules in different runs can be found. The impact of tie breaking is reduced with PV intensive outputs. In those cases, all the load is required to be allocated in a single peak. Hence, tie breaking does not disperse the loads. As a consequence, outliers are almost non-existent with CLP-FK[15].

Regarding the comparative performance of SLC-FK versus SLC-FKd, it can be said that SLC-FKd achieves competitive solutions when compared with SLC-FK. Although with PV intensive outputs SLC-FK tends to outperform SLC-FKd, with balanced and wind intensive outputs, most of the times, no significant differences are found between the performance of both approaches, regardless of the population size[16]. These results show that SLC-FKd not only converges to good results faster than SLC-FK utilizing a fixed α configuration which produces good performances (Subsection 5.2.4), but also, that the final performance of both approaches is similar. Therefore, regarding the solution construction process of SLC-FKd, the search does not get trapped in sub-optimal regions of the fitness landscape, as it occurs with SLC-FK. As a consequence, it can conclusively be stated that SLC-FKds performance describes the desirable behavior for which it was designed. This is, fast convergence followed by a thorough search which leads to quality solutions.

5.3.3. Load Composition and Synchronization

In [Got15], is mentioned that CLP-FK, is able to achieve close-to-optimal results when solving the load scheduling problem with a micro-grid populated exclusively with EVs. These devices are extremely flexible, since they are only power and energy constrained. Therefore, they can separate their consumption to individual timeslots, in concordance with contextual requirements. In the case of appliances such as a washing machine, once the device begins its operation, it cannot stop until the execution finishes. As a consequence, its load cannot be separated to cover specific breaches between the micro-grid load profile and the RES output.

Therefore, for CLP-FK to achieve its best performances, households provided with EVs should receive the signal and perform the rescheduling at the end of the rescheduling round. This way, EVs will be able to cover the breaches generated by less flexible appliances. Moreover, it is reasonable to assume that, in a scenario where the sorting of EVs is not adequate or where the micro-grid is deprived of EVs, CLP might reduce its performance. In this subsection, two scenarios are investigated to assess these inquires. Firstly, the effect of depriving the micro-grid of highly flexible devices (EVs) is assessed. Secondly, the impact of sorting EVs at the beginning of the rescheduling round is assessed.

---

[15] For a summary of the results with each RES output and population size, cf. Appendix E, Tables E.16 and E.17.

[16] For details of the post-hoc analysis with pairwise comparisons between both approaches, cf. Appendix D, Tables D.24 and D.25.

These analyses will also provide a perspective of the limitations of SLC-FK and SLC-FKd as a meta-heuristic for solving the load scheduling problem.

Different Load Composition in the Micro-Grid

Two scenarios are considered for assessing the performance of these approaches when the micro-grid is not provided with highly flexible devices such as EVs. The first scenario considers the previous penetration of intelligent washing machines, dishwashers and dryers in the micro-grid remains the same, without any penetration of EVs. The second scenario considers that households are provided solely with intelligent washing machines.

The effect of different load compositions in the households, is evaluated by comparing the percentage of unused RES in these scenarios with the original load composition utilized throughout this chapter. Therefore, the hypothesis tested is: H_0 : Data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not. x is performance generated with a load-scheduling algorithm (such as SLC-FKd) and y is performance generated with another load-scheduling regime (such as CLP-FK). Both performances are generated with the same RES output and load composition in the micro-grid. Hence, the rejection of H_0 implies that differences in performance between the two samples with different load scheduling strategies, are significant. The population in the micro-grid is fixed, with $4,000$ households.

Example performances with three RES outputs of different type are depicted in Fig. 5.17. It can be observed that differences in performance between strategies reduce when EVs are not considered. Moreover, the performances seem to become similar when only washing machines are considered as flexible loads. This tendency maintains regardless of the type of RES output. An interesting observation, is that, in general, the absolute performance of every approach seems to improve when the RES output is PV intensive, and high flexibility devices are not considered (Fig. 5.17, *No EVs.* and *Only Washing Machine* scenarios).

These observations are confirmed by a more profound analysis. The results show that when washing machines are considered in the micro-grid as the only flexible load, in almost every case, differences in performance between the approaches are not significant[17]. In addition, for every scenario, the differences in performance between SLC-FK and SLC-FKd rarely are significant[18], implying that in these scenarios, the deterministic parameter control technique utilized does not affect performance negatively.

---

[17] For details of Kruskal-Wallis analysis for each case, cf. Appendix C, Table C.16.

[18] For details of the post-hoc analysis, cf. Appendix D, Table D.26.

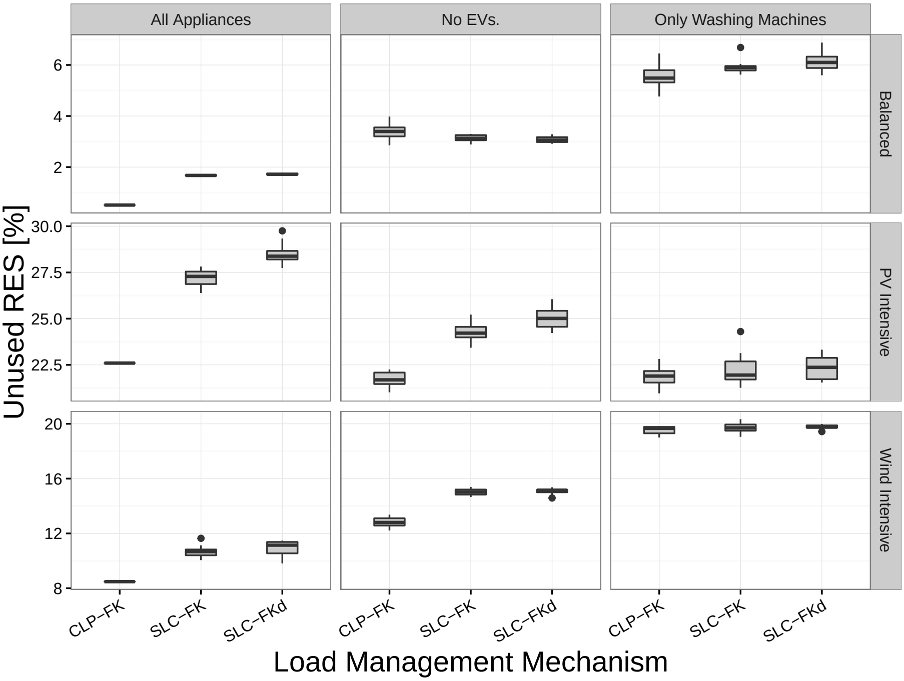


Figure 5.17.: Performances generated CLP-FK, SLC-FK and SLC-FKd for different RES outputs in a micro-grid with all four appliances described in Table 5.1, without EVs and only with intelligent washing machines, respectively.

Reasons for these behaviors have been previously presented. Since EVs are removed from the micro-grid, small gaps between micro-grid load profile and RES output cannot be precisely filled with CLP-FK. This effect is further intensified when only a single *load shape* is available for rescheduling (*Only Washing Machine* scenario). In this context, restrictions imposed by the problem instance limit the abilities of the greedy synchronized selection process of CLP-FK, reducing its relative performance with respect to scenarios with higher load diversification, particularly with balanced and wind intensive RES outputs. Hence, without highly flexible devices and with limited diversification of the load composition, stigmergy-based approaches increase competitiveness and in some isolated cases, are superior to CLP-FK (Fig. 5.17, *No EVs.*, *Balanced Output*).

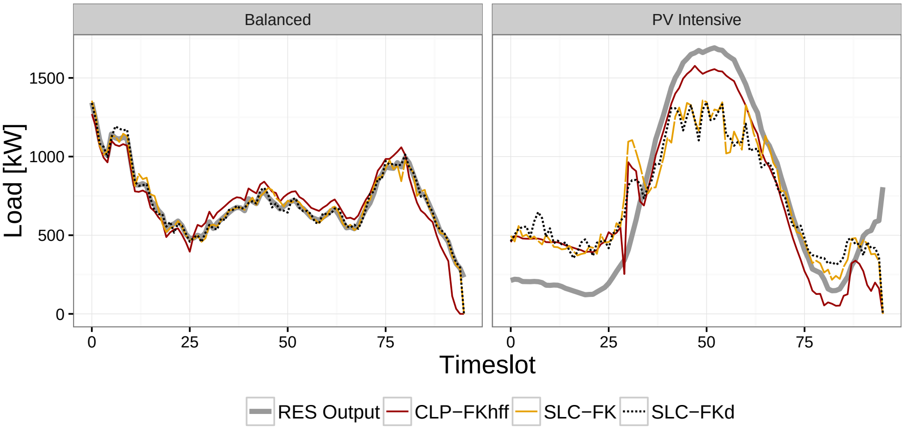


Figure 5.18.: Example micro-grid load profiles generated by CLP-FKhff, SLC-FK and SLC-FKd for different RES outputs.

The Impact of Sorting

One of the strengths of both stigmergy-based approaches, is that they do not require synchronization of the participants to search and construct solutions. To obtain a more precise perspective of the importance of this feature, in this subsection, SLC-FK and SLC-FKd are compared with a variation of CLP-FK which sends its pricing signal first to households provided with highly flexible appliances (EVs). This variation is referred to as CLP-FKhff, standing for CLP-FK with *highly flexible devices first*.

In Fig. 5.18, differences in the micro-grid load profile generated by each approach, can be observed. Regarding the balanced output, it is observed that, the shape of micro-grid load profile generated with CLP-FKhff emulates that of the corresponding RES output. Nevertheless, although the result has high performance, a breach exists between the two curves. It seems, that CLP-FKhff is not able to exploit alternatives which imply deviations from the RES output shape [RKS16].

This occurs precisely because households with EVs are scheduled at the beginning of the round. At the end of the round, the micro-grid has no flexible loads which can be scheduled on single timeslots to absorb small imbalances. As a consequence, the CLP-FKhff profile shape is almost identical to the RES output, but with a gap which separates them. A similar situation is observed PV intensive outputs. In this case, however, the performance of CLP-FKhff is clearly

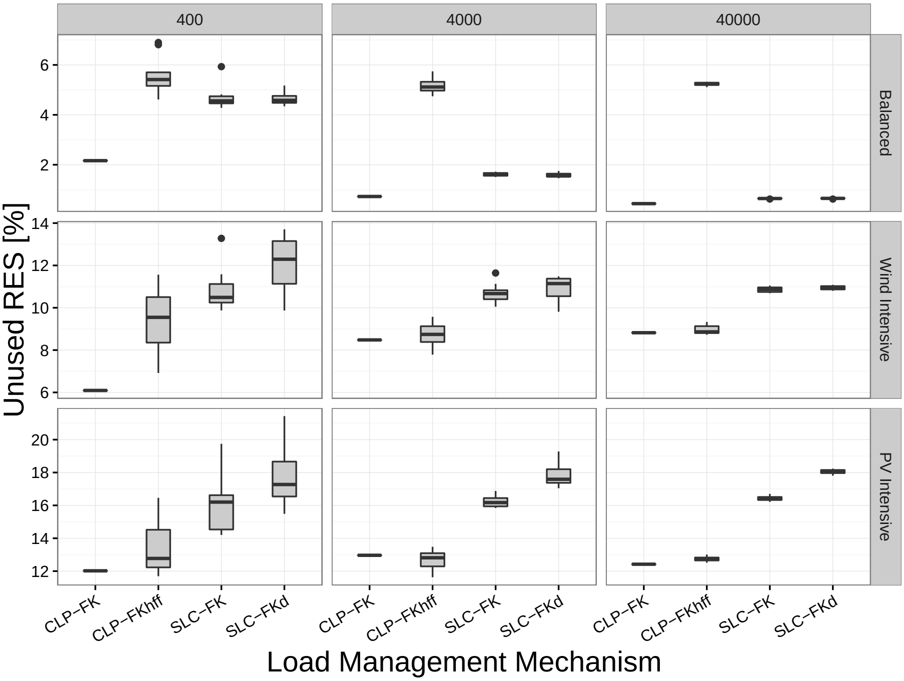


Figure 5.19.: Performances generated CLP-FK, CLP-FKhff, SLC-FK and SLC-FKd for different RES outputs and population sizes.

superior to those of the stigmergy-based approaches. Therefore, the *breach* is not visible.

A clearer perspective of the reduction in performance, as a consequence of an inadequate sorting in the price-based alternatives, can be obtained from Fig. 5.19. Here, CLP-FK, in which households with EVs receive the pricing signal at the end of the round, is also displayed. In this case, when the EVs are scheduled at the end, the performance clearly improves. Moreover, this tendency is intensified with larger population sizes and balanced outputs. In this case, CLP-FK, SLC-FK and SLC-FKd achieve similar performances, while CLP-FKhff depicts the worst performances. Nevertheless, an interesting behavior is observed in Fig. 5.19, *PV Intensive*, population size *4,000*. In these cases, CLP-FKhff outperforms all other approaches. In regard to the stigmergy-based approaches, reasons have been previously explained. In regards to CLP-FK, a likely reason is that the approach gets trapped in a local optima. This issue is further discussed in Chapter 6, Subsection 6.3.6.

These results help to quantify the differences between the best performance with an adequate and inadequate sorting for CLP-FK. Moreover, the results show that to obtain its best possible performances, specially with balanced RES outputs, CLP-FK requires that households are sorted according to their flexibility. This implies that, to obtain the best performances with CLP-FK, the internal load composition of households has to be known, in order to sort them properly. As a consequence, the privacy of customers is reduced, since individual information is utilized by an external entity.

In addition, the implementation of a sorting mechanism increases the complexity of the approach. This is certainly a strength of SLC-FK and SLC-FKd, since in both approaches, communication is asynchronous. Moreover, agents that simulate households can be considered as *black boxes*, from which a load profile is obtained. Therefore, when the stigmergy-based approaches converge to a good solution, the MGM can reference the desired load profile from each agent, without knowledge of its internal composition nor their specific schedule [RKS16]. In has to be noted, however, that in a realistic scenario, CLP-FK would randomly broadcast the pricing signal, reducing privacy concerns. This scenario was not evaluated. However, a slight reduction of the performance would be expected.

This analysis reveals strengths and weaknesses of price-based and stigmergy-based approaches. Both, SLC-FK and SLC-FKd, are able to extend the search to different locations in the fitness landscape, and diverge from the shape of the RES output to construct schedules which outperform CLP-FKhff. This is possible, because their rescheduling is based on a probabilistic decision process, rather than a greedy selection, which might direct the search always trough the same regions in the fitness landscape. Nevertheless, the very decision process which enables SLC-FK and SLC-FKd to perform well with balanced RES outputs, prevents them from exploiting large single load peaks (PV intensive outputs). With all in consideration, the advantage of SLC-FK and SLC-FKd is that it does not require synchronization, nor sorting of customers for broadcasting the control signal. Moreover, since the stigmergy-based approaches do not require private information of customers regarding appliances flexibility, the risk of violating the privacy of customers is reduced [RKS16].

5.4. Discussion and Summary

In this chapter, the experimental analysis of the stigmergy-based load control (SLC-FK) meta-heuristic is discussed. SLC-FK is designed to distributively generate global schedules in an iterative manner, which can maximize usage of a given RES output. The formal model to this approach was presented in Chapter

4. The evaluation of the performance provides insights regarding the possibility to extend the approach for solving other COPs.

Results from the analysis of the internal behavior of SLC-FK show that with larger population sizes, the absolute performance of the approach improves. Moreover, results show that a performance threshold related to the population size might exist. This threshold should be located above a $4,000$ households population. After this networks size is reached, the absolute performance of the approach does not improve further. In this sense, unexpected behavior was observed with PV intensive and wind intensive RES outputs. In these scenarios, occasionally the performance of SLC-FK with smaller network sizes was better than with larger populations. A proposed reason for this behavior, is that the performance might get trapped in a local optima when the population size increases. In this case, however, these issues are related to specific RES outputs.

Regarding the configuration of the internal parameter α, it was found that smaller values produce better performances. Nevertheless, smaller values for α also imply slower convergence speed. Therefore, after a comprehensive analysis of the convergence of the performance, a deterministic parameter control for SLC-FK was proposed, which considers a fixed rule to modify the value of parameter α during execution. Through the implementation of this rule, an adaptation to the original approach was developed, SLC-FKd, which increases the convergence speed.

Both approaches were compared to a synchronized closed-loop pricing scheme (CLP-FK). It was observed that when RES outputs are balanced, differences in the performance of all approaches are minor, in the order of 3% of unused RES. For PV intensive outputs, these differences increase. Afterwards, the effect of reducing highly flexible appliances (EVs) in the micro-grid and altering the sorting of households for CLP-FK was assessed. It was found that when EVs are removed from the micro-grid, the competitiveness of the stigmergy-based approaches increases largely. Moreover, with balanced RES outputs, when the price signal is sent first to households with EVs, SLC-FK and SLC-FKd outperform CLP-FK. This implies that to achieve its best possible performance, CLP-FK requires knowledge of the level of flexibility of households. These results are in line with [FG16], and show that more complex power systems require more complex management mechanisms to further maximize RES usage. However, the more complex the management mechanism, the more fragile can it be, and larger customer concessions it might require.

This analysis shows strengths and weaknesses of stigmergy-based approaches. On the one hand, SLC-FK and SLC-FKd are asynchronous. From an application perspective, this implies more robustness and simplicity. On the other hand, even when CLP-FK achieved better performances, the requirement of synchronization implies that the approach is more complex in its implementation, operation and management.

For complementing stigmergy-based approaches and reduce privacy concerns, agents can be considered as *black boxes*, from which only the load profile is obtained. The individual load profiles which produced the best global performance can be referenced, and agents which own those profiles will execute the concordant schedule. Therefore, anonymity of participants is preserved. Moreover, in this scenario SLC-FK and SLC-FKd can be complemented with approaches to conceal details of the shape of households profiles ([FB14]), further enhancing privacy. An additional implementation strategy for SLC-FK considers performing the scheduling process directly with the households, instead of an agent representation of them. In this case, privacy issues would be drastically reduced, since households would be anonymous from the perspective of the network structure[19]. Nevertheless, communication overheads should be considered due to the requirement of many rescheduling rounds to achieve quality results. In this sense, SLC-FKd would be preferable due to its fastest convergence.

Regarding the performance of SLC-FK in comparison with SLC-FKd, results obtained with SLC-FKd are easy to generalize. Although SLC-FK outperformed SLC-FKd in some isolated cases, the fast achievement of quality results with the latter might privilege the selection of SLC-FKd. This leads to the question: Do the benefits of the stigmergy-based approaches compensate for the gap in performance with CLP-FK? This conclusion is finally related to the application scenario. In cases where a small reduction in the performance is acceptable, and privacy, scalability and simplicity are relevant issues, stigmergy-based approaches conform a better alternative. Within these scenarios, if fast convergence to good results is relevant, SLC-FKd should be selected over SLC-FK.

Finally, these results support the enhancing and adaptation of SLC-FK to be applied to other COPs. In this sense, the presented scenario can be considered as the first example of the applicability of the meta-heuristic. Future steps in this direction consider adapting the approach to solve other scheduling problems, cutting stock problems, and two-dimensional bin packing problems, among others.

---

[19] This configuration is later considered in Chapter 6, for real-time coordination.

6. Real-Time Load Balancing with Stigmergy-Based Load Control

> *Extraordinary claims require extraordinary evidence.*
>
> Carl Sagan, *Cosmos, Encyclopedia Galactica*, 1980

Real-time optimization presents many challenges for decentralized management and load scheduling of autonomous devices. To increase RES utilization in the power grid, a specific global behavior has to be promoted, without generating load imbalances. This implies that each participant should coherently and cooperatively schedule its appliances, such that the aggregated behavior of individuals coincides with the desired global behavior. If deviations occur during the execution, the power grid should be able to reduce these deviations and guide the performance of the system within acceptable boundaries. As a consequence, when participants select inadequate operation times for their devices, which increase imbalances, other participants should reschedule in order to absorb these imbalances.

In addition, the load management mechanism needs to be able to react to a changing environment. The utilization of RES forecasts allows the rescheduling of loads in consideration of possible RES availability in the future. Nevertheless, differences (either large or small) between a forecast and an RES output imply dynamism in the load scheduling problem. Hence, a real-time load scheduling mechanism needs to be able to adapt the scheduling process during run time, such that new and more accurate information can be included. In this context, the larger the differences between forecasts and RES output, the more dynamic the environment will be, as a consequence of the alterations in the problem definition. In this context, intuition dictates that, on the one hand, when a load management mechanism utilizes better quality forecasts its performance should improve. On the other hand, when the forecast quality becomes worse, flexible loads might be shifted to sub-optimal timeslots with regard to RES output, generating load imbalances in the micro-grid. Therefore, if dynamism in the problem is large, the importance of new information should increase, as it helps to correct inaccurate RES forecasts.

In this chapter, the ability of stigmergy-based load control to reschedule autonomous flexible loads in real-time, is assessed. In this context, the approach is referred to as **SLC**. Three aspects of SLC are investigated in detail: Firstly, the potential of SLC to increase RES utilization by guiding the scheduling of operation times of households appliances. This means, promoting a specific global behavior of autonomous entities. The second aspect investigated, regards the correlation of the performance of SLC with increasing forecast quality. The third aspect, assesses the relevance of past versus current information, balanced by an internal parameter, with regard to the level of dynamism in the problem definition. After a detailed analysis of SLC is performed, the approach is compared against a synchronized price-signal alternative. This reference approach is an adaptation of the close-loop pricing scheduling mechanism described in Chapter 5. In consideration of the performance and abilities of each approach to guide global autonomous behavior, weaknesses and strengths of SLC against the alternative are discussed.

6.1. Experimental Setup and Data Preparation

In the context of load balancing, the availability of flexible loads reduces during the scheduling process, since some devices will have initiated their execution. Hence, one can only optimize for the future, while past and present cannot be modified. If autonomous participants are considered, the obtained power grid load profile might be of lower quality than previously generated profiles. Moreover, potentially optimal solutions cannot be saved and utilized in the future unless specific schedules are imposed on customers, therefore reducing their autonomy.

For implementing SLC in a real-time scenario, as mentioned in Chapter 4, a receding horizon is utilized [SGC$^+$13], which enables the modeling of the previous scenario. An idealized isolated subsection of the power grid (micro-grid) and a day discretized in timeslots of 15-minutes resolution are considered within a simulation environment. In each timeslot a rescheduling round is performed. When moving from one round to the following, the loads scheduled to begin operation in the current timeslot become unavailable for rescheduling. A specific challenge of this approach is that the optimization horizon is continuously reducing, as the simulation gets closer to the end of the day.

This section presents the factors for performing the evaluation of the SLC coordination approach in the micro-grid scenario described in Chapter 4. Some of these factors are not parameters controllable by the approach. Nevertheless, it is relevant to evaluate their effect on the performance to assess relevant issues such as scalability, adaptability to dynamism, and robustness of SLC. In this sense, the simulation scenario from Chapter 5 is considered for experimentation, with minor adjustments to address the real-time optimization context. Furthermore, additional features relevant to the evaluation of the approach are specified when it corresponds.

6.1.1. Household Consumption

Flexible load is represented by three shiftable appliances and electric vehicles (EV), as in Chapter 5. The penetrations, user-defined flexibility intervals, share of each corresponding device per interval and the daily consumption of each device is specified in Table 5.1.

The Federal Association of Energy and Water Industries of Germany (BDEW) provides the so called H_0 *standard load profile* for the electricity consumption of a standardized German household in a 15-minutes resolution[1]. This profile varies between working day, Saturday and Sunday, and between winter, summer, and transition time. For experimentation, only working days of a transition time are considered.

Each household has a fixed base load represented by the H_0 profile. Two scenarios are studied: *(i)* All load is flexible, and the base load is not considered. *(ii)* Flexible loads represent between 10% and 40% of the micro-grid load composition. Even though scenario *(i)* is unrealistic for the current context of the power grid, it allows to study the maximum potential to exploit load rescheduling. On the other hand, scenario *(ii)* is consistent with estimations regarding current load flexibility within the power grid [Hil14, QH99]. Hence, to some extent, scenario *(ii)* allows the study of the current potential for intelligent rescheduling to increase RES utilization in the power grid.

These scenarios are depicted in Fig. 6.1. Cases *10% Flexibility* and *40% Flexibility*, depict the scaling of the micro-grid base load and the total micro-grid load for different shares of load flexibility. When load flexibility is less, the shape of the H_0 profile, which is not flexible, becomes clearer. On the other hand, the shape of the micro-grid profile changes as a consequence of the increase in load flexibility. The increasing load peak in the beginning of the the day is explained by the EVs parked and charging. Fig. 6.1, *100% Flexibility*, depicts the total load of the micro-grid when all the load is flexible. It can be observed that the effect of the base load is nullified and the shape of the profile depends exclusively on the distribution of the appliances according to Table 5.1.

---

[1] http://www.kommenergie.de/netz/standardlastprofil/standardlastprofile-slp/

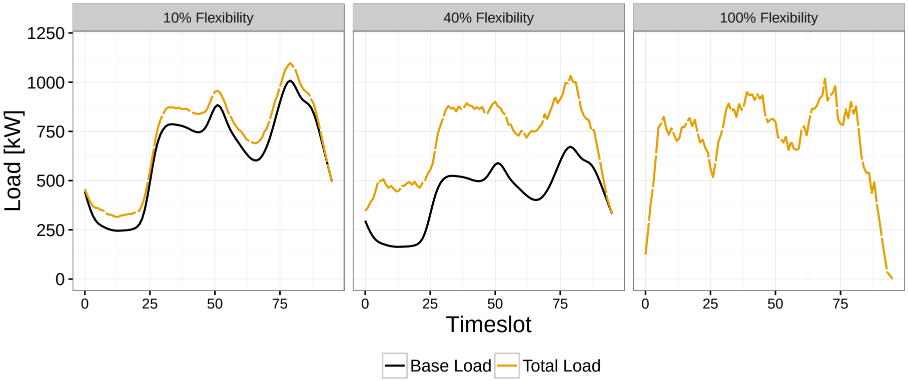


Figure 6.1.: Base load and micro-grid total load under different shares of load flexibility in the micro-grid. Flexible loads are distributed uniformly within their user-defined flexibility intervals (Table 5.1).

6.1.2. Renewable Generation Supply and Coverage

The selected RES outputs in Chapter 6 are also utilized for experimentation in this chapter. In addition to these outputs, the German Transmission System Operators also provide data on wind and PV forecasts for the corresponding outputs with the same 15-minutes resolution.

For analyzing the internal behavior of SLC, a base scenario is considered with a share of 100% load coverage. This means that the total electricity demand equals the total generation from RES. For comparing SLC with other strategies, different shares of load coverage are also considered, namely 25%, 50%, and 75% of the micro-grid load requirements are supplied by RES. In these cases, the difference between the coverage capacity and the micro-grid load requirements are assumed to be supplied by conventional generation.

6.1.3. Artificial Forecasts Classification

Artificial forecasts for the RES outputs are generated through the process described in Subsection 4.4. For each day, the forecast and RES output are scaled to the total output load of the day. Therefore, final values for the RES output will vary in $[0, 1]$, representing the share of the total load of the day in each time series. However, since the scaling is done according to the total output of the day, values larger than one are possible for the forecast.

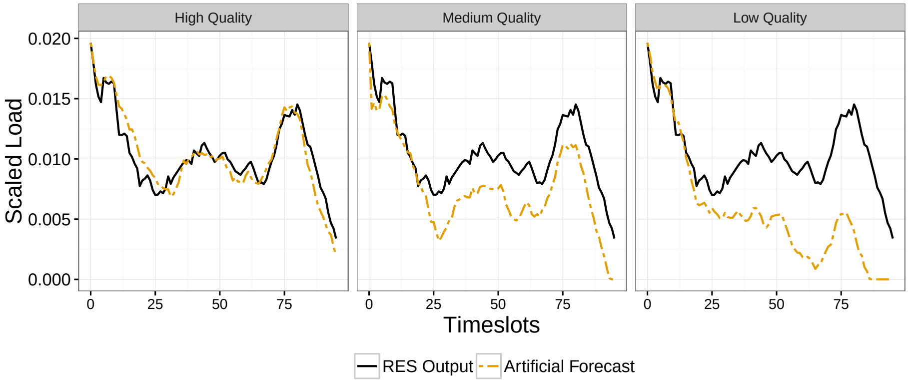


Figure 6.2.: Exemplary RES output with three artificially generated forecasts. The forecasts are classified according to the RMSE.

For each RES output, 50 artificial forecasts are generated, resulting in a pool of $18,000$ output-forecast combinations available for experimentation. These forecasts were classified into three categories: *high quality*, *medium quality*, and *low quality* forecasts. The category of each forecast is determined according to the Root Mean Squared Error (RMSE) between the forecasts and their corresponding RES output. A forecast g^0 is of high quality if $RMSE\left(g^0\right) < 0.002$, medium quality if $0.002 \leq RMSE\left(g^0\right) < 0.004$, and low quality if $0.004 \leq RMSE\left(g^0\right)$. An example of a RES output with a forecast of each category can be observed in Fig. 6.2.

6.1.4. Summary of the Experimental Design

Three experimental designs for evaluating SLC are considered. A summary of the different values of the factors utilized for experimentation is provided in Table 6.1. In all experiments, ten runs are considered for each problem instance, e. g. combination of the factors.

The first experimental design is utilized for evaluating the internal behavior of SLC. Factors to be modified are the RES output, forecast quality, population size and the configurations of α. As mentioned, twelve RES outputs have been selected for experimentation[2]. Since RES forecasts are relative to each RES output and can differ between each other, to avoid nuisance generated by specific forecasts, ten samples of each category have been selected. The population size

---

[2] For each individual RES output shape, cf. Appendix A, Fig. A.1.

Table 6.1.: Summary of factors and values utilized for experimentation in real-time coordination. Different combinations of the factors correspond to different problem instances.

Factor	**Levels**	**Values**
RES Output	12	RES outputs 1, 5, 7, 11, 12 (Balanced), 4, 6, 8 (PV Intensive), 2, 3, 9, and 10 (Wind Intensive)
Forecast Category	3	Low, Medium, and High quality with ten samples of each
Population Size	4	40, 400, $4,000$, and $40,000$ households
Micro-Grid Load Flexibility	4	25%, 50%, 75%, and 100%
Load Coverage	5	10%, 20%, 30%, 40% and 100%
α	5	1.0, 0.5, 0.1, 0.05, and 0.01

increases in a logarithmic scale from 40 to $40,000$ households. Finally, for parameter α different values have been considered, expressing different weights of current and historic information in the control signal construction process. Hence, for analyzing the internal behavior of SLC (Section 6.2), RES output has twelve levels, forecasts have three levels, population size has four levels and α has five levels. In a real application, only α would be a controllable factor. All other factors are defined by the application context.

The second experimental design is utilized for the first set of comparisons between SLC and other load scheduling strategies (Subsections 6.3.2, 6.3.3 and 6.3.4). In this case, α values are fixed to the best performing configurations. These configurations are obtained from the analysis of SLC. Therefore, factors to be modified are the RES output, population size and forecast category. All factors are varied considering the previously described levels.

The third experimental design is utilized for analyzing and comparing the performance of SLC in a more realistic scenario (Subsection 6.3.5). This scenario considers different shares of load flexibility and RES coverage over the micro-grid load requirements. A mixed-level factorial design is utilized. RES output and forecast are once more considered factors in the experiment. Moreover, the share of flexibility in the power grid, with four levels, and the RES coverage, with three levels, are included as additional factors. These factors are defined by the context application, and are not controllable by the load management approaches. Moreover, in this specific experimental design, the population size is fixed, with $4,000$ households.

Finally, the performance measure of every following experiment is the percentage of unused RES at the end of each simulated day. Moreover, the optimization objective is to minimize the amount of unused RES, this is, the area under the curve of the corresponding RES output.

6.1.5. Approach to Data Analysis

To support observations and assess the significance of the obtained results in this chapter, an statistical analysis is performed for each set of experiments in the corresponding subsections.

The approach is similar as the one described in Chapter 5. As a remainder, the statistical analysis is conducted as follows: The normality of the data is assessed through a one-sample Kolmogorov-Smirnov test. Once more, evidence supported the rejection of data being normally distributed. Afterwards, a summary of the main statistics is constructed for the corresponding evaluation, focused on medians. To assess the significance of the differences between evaluations, a Kruskal-Wallis rank-sum test is utilized. Finally, a post-hoc analysis is applied, which corresponds to an unpaired Wilcoxon rank-sum test for pairwise comparisons.

The detailed analysis of each scenario is provided in the appendix. Details of each normality test are available at Appendix B. The detailed Kruskal-Wallis rank-sum tests are presented in Appendix C. The post-hoc analyses are presented in Appendix D. Finally, the summaries of each evaluation are available at Appendix E.

Specific tests are referenced throughout this chapter, to support statements regarding the performance under different parameter configurations and in comparison to other scheduling approaches.

6.2. SLC Analysis

In this section, the behavior of SLC is assessed. The algorithm is analyzed under different population sizes, in order to evaluate scalablity on the performance. Afterwards, SLC is evaluated under the previously defined forecast categories (Subsec 6.1.3) to asses if better forecasts translate into better performances. In conjunction with the forecast quality evaluation, different values for the α parameter, from Eq. 4.1, are considered. Parameter α balances the weight of new information in the control signal construction process. Hence, the objective is to discover if different α configurations can improve the performance of SLC under different levels of dynamism on the problem definition. For this, selected values for the parameter range from $\alpha = 1.0$, same weight

Table 6.2.: Extract of the summary of the performances of the analysis of the scalability of SLC, with different RES output types.

Statistic	**Balanced**				**PV Intensive**				**Wind Intensive**			
	Population				**Population**				**Population**			
	40	400	$4,000$	$40,000$	40	400	$4,000$	$40,000$	40	400	$4,000$	$40,000$
Min.	18.1%	7.5%	6.6%	6.9%	20.4%	15.5%	17.9%	18.6%	18.9%	8.6%	8.0%	8.0%
1st Qu.	21.1%	10.2%	8.1%	7.8%	26.5%	20.0%	19.7%	19.7%	21.6%	11.4%	10.2%	10.1%
Median	22.2%	10.8%	8.7%	8.4%	28.6%	20.9%	20.2%	20.2%	22.8%	12.1%	10.6%	10.4%
3rd Qu.	23.6%	11.4%	9.2%	8.9%	31.0%	22.0%	20.8%	20.6%	24.3%	12.8%	11.0%	10.7%
Max.	27.5%	13.5%	11.1%	10.9%	40.1%	24.8%	22.6%	21.8%	28.3%	14.4%	12.7%	12.3%

of historic information with current information, to $\alpha = 0.01$. As mentioned in Subsection 6.1.1, the initial schedules are obtained by uniformly distributing the execution times of the devices within their corresponding flexibility interval (Table 5.1). Moreover, a 100% flexibility and a 100% micro-grid load coverage are considered.

6.2.1. Effects of Different Population Sizes

To evaluate the scalability of SLC, a population size of 40 households is considered, and a logarithmic scale is utilized for selecting additional population sizes for evaluation. Hence, the idealized micro-grid is populated by 40, 400, $4,000$, and $40,000$ households for each set of experiments. The two former correspond to a low-voltage grid scenario, whereas the two later imply managing a subsection of a distribution power grid. In this set of experiments, factors modified are the RES output, population size and α. Hence, 300 runs are considered in each evaluation. An extract of the summary of the performances, comprising three exemplary RES outputs of each type, are depicted in Table 6.2[3].

Results show that, regardless of the α configurations and the RES output, performance seems to improve as the population size increases. Similarly as with static optimization (Chapter 5), a performance threshold seems to exist, which is related to the population size. After this threshold is surpassed performance does not seem to improve. This threshold seems to be located between a population of 400 and $4,000$ households. This behavior was observed in every problem instance when modifying the population size while keeping the other factors unchanged. An exemplary case can be observed in Fig. 6.3 which described the behavior for a balanced RES output and $\alpha = 0.5$ (for the detailed data, cf. Table 6.2).

---

[3] For the full summary of the performances of this experiment, the interested reader is referred to Appendix E, Tables E.1 and E.1.

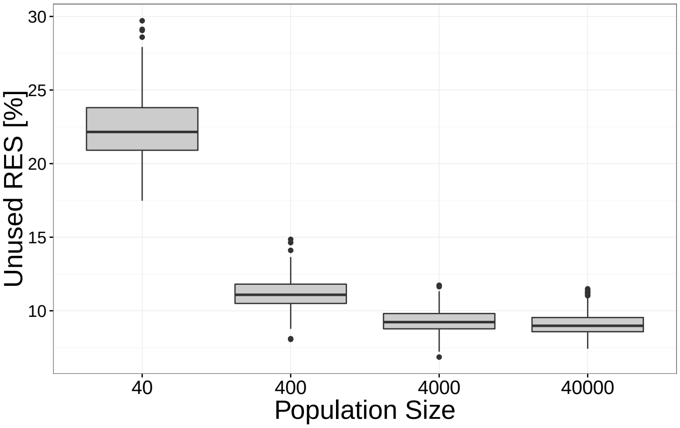


Figure 6.3.: Exemplary evaluation for assessing the effect of the population size on the performance of SLC.

Results of the post-hoc analysis confirmed previous observations in every case. Not only the absolute performance improves with increasing population sizes, but above a certain population size is reached (at least $4,000$ households), differences in performance are not significant[4]. Hence, one is led to the conclusion that a performance threshold exists, in regard to the size of the network. In addition, outliers are drastically reduced in conjunction with this tendency. Therefore, the performance does not only improves, but becomes more robust.

Reason for this have been previously explained. With smaller population sizes, there are fewer alternatives to reschedule the appliances within their flexibility intervals such that RES usage is increased. This means, there is less potential for optimization.

6.2.2. Forecasts Accuracy and Problem Dynamism

Intuition dictates that when dynamism in the problem is large, the importance of new information should increase, as it helps to correct inaccurate RES forecasts. Higher dynamism is related to lower forecast quality, since the difference between the real RES output and the predicted output is larger.

In Section 4.3.1, it is discussed that parameter α regulates the weight of new information in the signal construction process. Therefore, it is proposed that

---

[4] For a detailed view of the post-hoc analysis, the interested reader is referred to Appendix D, Tables D.1 and D.2.

when the problem is less dynamic, the weight of new information should be reduced (smaller values for α), in order to have a more directed search. On the other hand, when the problem is more dynamic (low quality forecasts), the weight of new information should be increased (larger values for α) to cope with variability and promote rapid adaptation to a new scenario. To assess the performance of SLC in dynamic scenarios, the evaluation is divided in three subsections and is conducted as follows:

- Firstly, the three forecast categories are evaluated for different α configuration. This evaluation assesses if SLC improves its performance in concordance with the forecast qualities.
- Secondly, all α configurations are compared within each forecast category. Results provide information about the absolute performance of each α configuration. Moreover, a conclusion is drawn regarding the role of new information on the performance of SLC in a receding horizon scenario.
- Finally, the effect of modeling the problem as a receding horizon and convergence of SLC throughout rescheduling rounds is assessed.

Identifying the Effect of Forecast Quality

The proposed hypothesis states that with better forecast qualities, the performance of SLC should improve. Formally: H_0 : Data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not, where x and y are the performance of SLC, generated with different forecast quality but the same RES output, population size and α configuration. In addition, each evaluation of the problem instances considers 100 runs. If H_0 is rejected, it can be stated that differences exist in the performance of SLC as a consequence of the quality of the forecast.

The analysis reveals that for the smallest population size (40 households), different forecasts do not seem to have a clear impact on improving or reducing performance[5]. These results complement the observations from Subsection 6.2.1. Since the performance becomes more robust with larger population sizes ($400 - 40,000$ households), the effect of different forecast qualities becomes clearer. Hence, a more detailed analysis of the performance is possible. Therefore, the following analysis describes the behavior observed for population sizes 400, $4,000$, and $40,000$.

Results show that the hypothesis is falsified with larger values for the α parameter, e. g., $\alpha = 1.0$ and $\alpha = 0.5$, this is, there was not enough evidence

---

[5] The interested reader is referred to Appendix C, Tables C.2 for the Kruskal-Wallis analysis with a 40 households population.

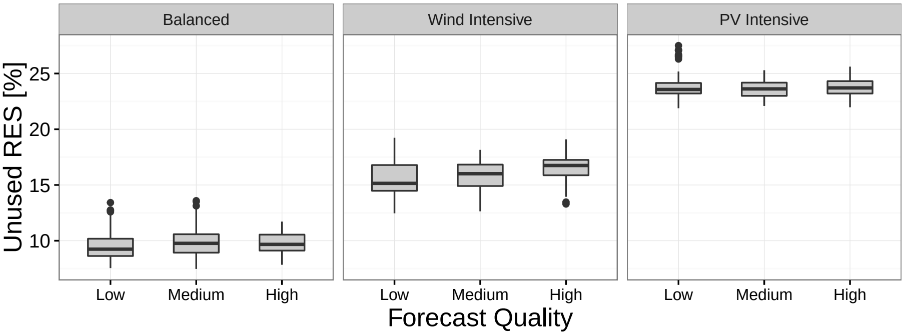


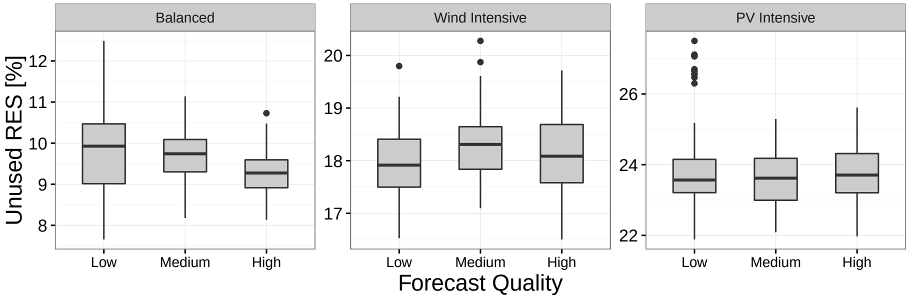
Figure 6.4.: Example performance of SLC with regard to different forecast qualities. The three RES output types are considered with $\alpha = 1.0$ and $4,000$ households.

reject H_0 in these scenarios. In general, for these parameter configurations the performance is not greatly affected by different forecast qualities. The analysis reveals that often no specific forecast quality produced a performance that outperformed with confidence the others[6]. Fig. 6.4 depicts an example case of this behavior for the three types of output: balanced, wind and PV intensive. Hence, it can be said that, in a receding horizon context, with larger values for α ($\{0.5, 1.0\}$) different forecast qualities do not have a clear effect on the performance of SLC.

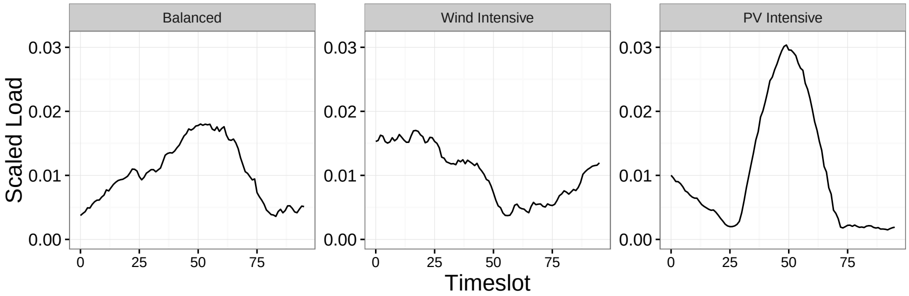
For smaller α values ($\{0.01, 0.05, 0.1\}$), evidence supported the rejection of H_0, implying that differences exist in the performance as a consequence of forecat quality for these parameter configurations. However, different tendencies on the performance are observed, which do not always concord with the prediction of the hypothesis. In scenarios with balanced RES outputs, the hypothesis was confirmed (Fig. 6.5, *Balanced*). In this case, an improvement in performance can be observed as the forecast quality increases. In scenarios with wind intensive RES outputs, the performance behaved unexpectedly: It remained roughly constant or deteriorated as the forecast quality improved (Fig. 6.5, *Wind Intensive*). Hence, the hypothesis is falsified. These outputs are characterized by having more generation by timeslot in the morning and/or afternoon than in the middle of the day. Whenever the RES output is PV intensive, the performance tends to either oscillate or remain constant (Fig. 6.5, *PV Intensive*). In these cases, the impact of using more accurate information in the rescheduling process was not clear.

---

[6] For specific examples, the interested reader is referred to Appendix D, Tables D.8 and D.9 which includes the post-hoc analysis of the scenarios presented in Fig. 6.4.



(a) Performances with different forecast qualities and different RES outputs. The population size is $4,000$ households and $\alpha = 0.1$.



(b) Load profiles of different RES output types.

Figure 6.5.: Example performance of SLC under a balanced, wind and PV intensive outputs.

These results show the relevance of the RES output in the process of shifting loads intelligently[7]. When the RES output does not match the micro-grid load composition in conjunction with the user-defined flexibility intervals (PV and wind intensive RES outputs), imbalances will be obtained regardless of the load management mechanism. In those cases, lower quality forecasts may unveil better solutions by redirecting the search and allowing SLC to escape local optima (Fig. 6.5a, *PV* and *Wind Intensive*). Similar strategies have been proposed in combinatorial optimization problems (COPs) for allowing meta-heuristics to escape local optima by increasing exploration to other zones of the search space [SLIP$^+$12, vLM13, ES03]. In SLC, as a consequence of variability introduced by a low quality forecast, the algorithm is able to extend the exploration and escape local optima. Additionally, in PV intensive scenarios, SLC is not able to

---

[7] The interested reader is referred to Appendix E, Table E.9 and E.10 for a full summary of all results with a population of $4,000$. Furthermore, for details of the post-hoc analysis, cf. Appendix D, Tables D.8, D.9, D.10 andD.11.

exploit large unique load peaks, due to its probabilistic decision making process. Hence, in those cases, the effects of the forecasts quality are blurred by the obstacles imposed by these specific RES outputs on SLC. This issue is further discussed in Subsection 6.3.6.

This unexpected behavior is problem-related, rather than an issue of SLC. Therefore, it can be stated that when the RES output and the micro-grid load composition in conjunction with the flexibility intervals of the shiftable loads, match, the effect of forecast quality followes the hypothesized behavior. On the other hand, when much of the RES output is not accessible due to user-defined restriction on the flexibility of appliances, the effect of different forecast qualities is hindered. Additionally, the effect of different forecast qualities is clearly smaller with larger values for parameter α.

Weight of New Information in the Control Signal Construction

The second hypothesis states that, as the scenario becomes more dynamic (low quality forecasts) larger values for α should be selected, and vice-versa. The first implication of this hypothesis is that with higher α values SLC should be less vulnerable to changes in the forecast quality and no large reduction in performance should be obtained. The second implication is that lower α values should be more vulnerable to low quality forecasts, whereas the performance should clearly increase with high quality forecasts.

This expected behavior is based on the idea that when the dynamism of the problem is smaller a more directed search is required (promoted by smaller α values), rather than an exploratory one (promoted by higher α values). In those scenarios, if α values are high the algorithm will not be able to direct the search to globally good schedules and might get trapped in a randomly oscillating search process. On the other hand, with higher α values the relevance of newer information in the signal construction process increases. Hence, the ability of SLC to cope with a dynamic environment should increase.

This way, the hypothesis if formulated as follows: H_0 : The data in x and y is sampled from continuous distributions with equal medians, against the alternative that they are not sampled from those distributions. x and y are are the performance of SLC, generated with different α configurations, but with the same RES output, population size and forecast quality. Hence, the rejection of H_0 implies that significant differences in the performance exist between different α values with the same forecast quality.

Similarly to the last analysis, when the population size is small ($\{40, 400\}$ households), differences in the performances with different α configurations were

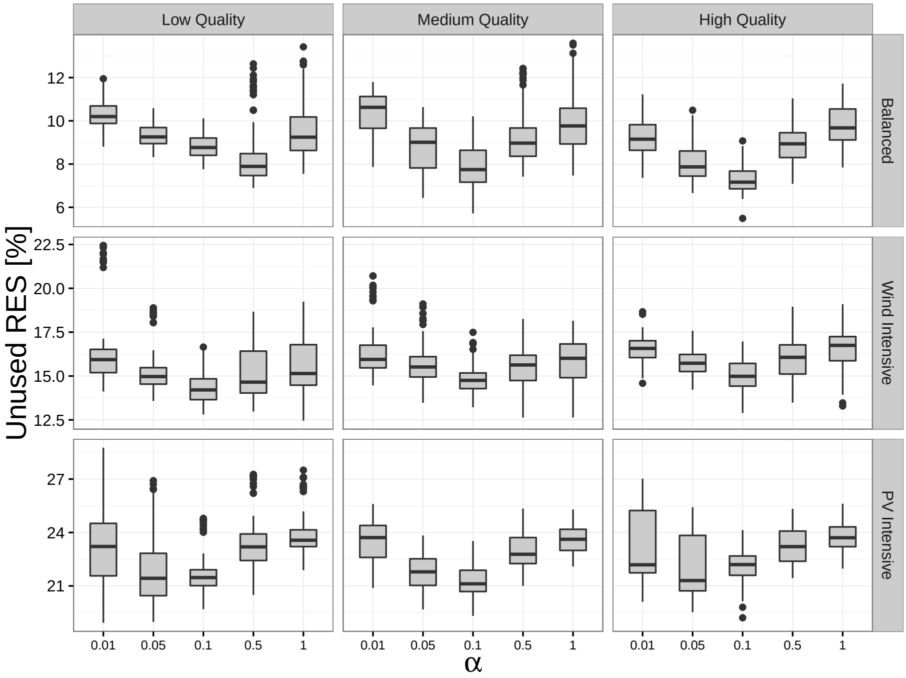


Figure 6.6.: Example performance of SLC with different α configurations and different forecast quality, for balanced, PV and wind intensive RES outputs.

consistently less significant[8]. Hence, with smaller population sizes, the impact of α is hindered. On the contrary, differences in performance with larger populations are quite clear, implying the rejection of H_0. For the ease of exposition, in the following the depicted analysis considers a micro-grid population of $4,000$ households.

The first observation is that the performance depicts a U-shape, were best performing configurations tend to be around $\alpha = 0.1$ and the extremes are clearly outperformed (Fig. 6.6). Therefore, it cannot be said that with high quality forecasts, the best performances are achieved with smaller α values, neither that for low quality forecasts large α values are required. The statistical analysis further supports these observations. Significant differences in performance exist which often favor intermediate α values ($\{0.1, 0.05\}$) regardless of the forecast

---

[8] The interested reader can find the post-hoc analysis for 40 and 400 population at Appendix D, Tables D.12 and D.13, respectively.

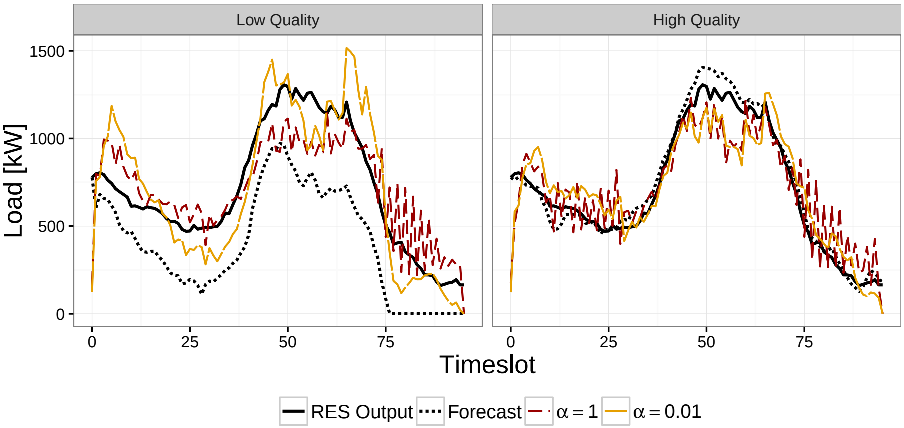


Figure 6.7.: Micro-grid load profiles for two single runs with $\alpha = 1.0$ and $\alpha = 0.01$, on low and high quality forecasts for a balanced RES output.

category[9]. Hence, in a receding horizon context, the hypothesis is falsified and it cannot be stated that with more dynamism in the problem, larger α values should be utilized[10].

Reasons for this behavior and more detailed information can be obtained by analyzing Fig. 6.7. For a low quality forecasts (Fig. 6.7, *Low Quality*) and $\alpha = 1.0$, load shifting in the initial timeslots of the simulated day, generates a micro-grid load profile reasonably similar to the RES output. Nevertheless, at the end of the simulated day, the performance depicts an oscillating behavior. Fig. 6.7, *High Quality* shows this oscillating behavior both in the afternoon and the morning (timelots $[10 - 30]$).

For both figures, with $\alpha = 1.0$, the oscillation in the afternoon can be explained by the reduction in the size of the optimization horizon. This reduction forces the signal construction process (Fig. 6.8), exacerbating minor differences between old and new information during the signal construction process. Correspondingly, the micro-grid tries to absorb these exaggerated imbalances expressed through the control signal. As a consequence, it generates additional load peaks. In the following rescheduling round, the signal construction process addresses these new load peaks by promoting load shifting to cover the new imbalances. This way, a step response is obtained, as a consequence of

---

[9] For the post-hoc analysis of the data depicted in Fig. 6.6, the interested reader is referred to Appendix D, Table D.14.

[10] A summary of the results is available in Appendix E, Table E.9 and E.10.

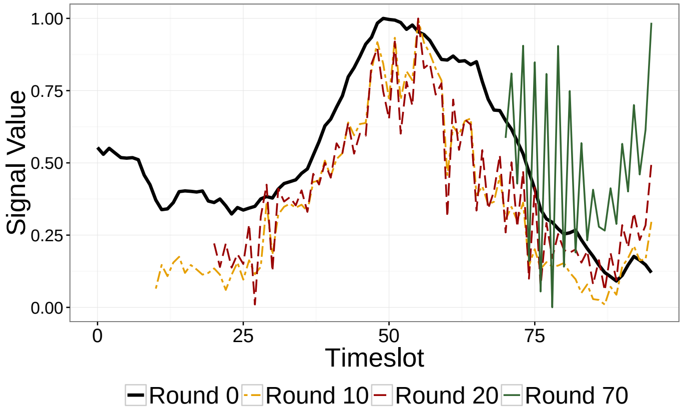


Figure 6.8.: Signal evolution corresponding to the *High Quality* forecast scenarios from Fig. 6.7 with $\alpha = 1.0$.

the optimization horizon size reduction. The oscillating behavior observed in the morning occurs when the RES forecast is constant, without peaks or valleys (Fig. 6.7, *High Quality*). As a consequence, small differences are again exaggerated. Nevertheless, in this case the reason is exclusively the high weight of new information in the signal construction process. Once the load hill begins (around timeslot 30), the households are not required to choose between equally desirable alternatives, which would trigger step responses. Hence, this oscillating behavior is not found when a load peak on the RES output appears. This shows that in a real-time optimization context, the effect of the RES output shape for larger α values is relevant.

In the case of small values for α and with a low quality forecast, adaptation of the control signal is not enough to produce good quality performances while the optimization horizon is reduced. Therefore, although no oscillations are generated, the micro-grid tends to adapt its load to an outdated forecast (Fig. 6.7, *Low Quality Forecast*). With high quality forecasts, the obtained micro-grid load profile is of better performance (Fig. 6.7, *High Quality*). Since the forecast resembles the RES output, SLC is able to exploit current solutions to improve the overall performance in future rescheduling rounds, without generating large imbalances. Nevertheless, $\alpha = 0.01$ continues to be outperformed by $\alpha = 0.1$ (Fig. 6.6).

Hence, in a receding horizon optimization context, too much or too less weight of new information in the signal updating process has a negative impact on the performance. Therefore, a precise balance between new and old information is

Table 6.3.: Detailed performance of single runs of SLC with different α values and forecast quality. *Final Performance* refers to the performance at the end of the run. *Best Performance* refers to the best performance throughout the run. Values correspond to percentage of unused RES.

	Low Quality Forecast			**High Quality Forecast**		
α	**Final Performance**	**Best Performance**	**Best Round**	**Final Performance**	**Best Performance**	**Best Round**
0.01	11.001	10.875	71	8.374	7.795	52
0.1	7.515	7.042	43	5.578	5.332	62
1.0	10.177	7.060	5	8.877	5.047	8

required for SLC to achieve its best performances. Moreover, this balance does not depend on the forecast quality.

Convergence and Internal Behavior of SLC

In general, $\alpha = 0.1$ provided the best performances for most scenarios. This regards the micro-grid load obtained once the simulation has terminated. Nevertheless, during the course of the simulation, as previously explained, better performances might be achieved. As the micro-grid moves from one rescheduling round to the next, good solutions might be lost as a consequence of the autonomous rescheduling of appliances. Table 6.3 depicts that with a low quality forecast, the best performance for $\alpha = 1.0$ is competitive against the best performance for $\alpha = 0.1$. Whereas with a high quality forecast, the best performance for $\alpha = 1.0$ is superior to all other alternatives. Moreover, the performance largely deteriorates between the best and final performances with $\alpha = 1.0$ in both scenarios. This provides evidence that during run-time, better performances are obtained, than the one produced at the end of the simulation.

Fig. 6.9 clearly explains the situation. With $\alpha = 1.0$ the performance converges rapidly to good solutions, but as the rescheduling rounds are performed and the optimization horizon gets reduced, performance deteriorates. Moreover, not only the absolute performance is better for $\alpha = 1.0$ during the first rounds, but step responses are not present in the micro-grid load profile. This can be observed in Fig. 6.10, were the best performing micro-grid load and final micro-grid load for this example run are compared. On the contrary, with $\alpha = 0.1$ and $\alpha = 0.01$ the performance exhibits a slower but consistent improvement towards good quality solutions.

These individual observations complement previous results, regarding different α configurations. During the first rounds, high values for the parameter promote fast convergence to good results (Table 6.3, column *Best Round* and

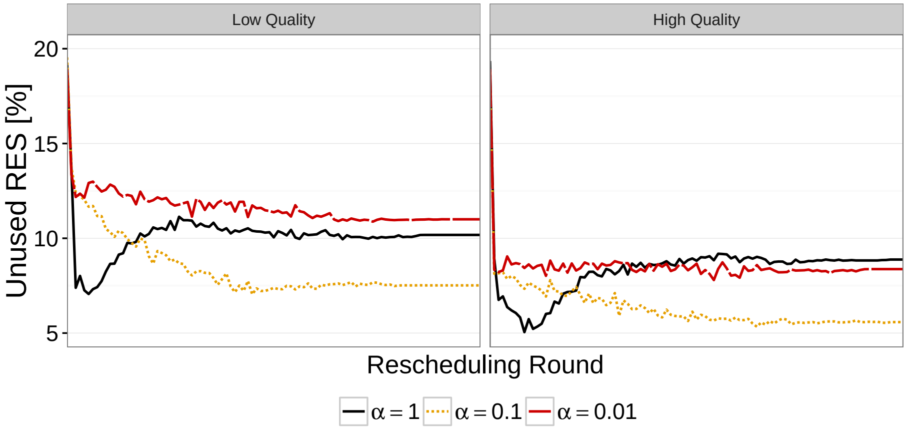


Figure 6.9.: Performance evolution throughout rescheduling rounds for the single runs described in Table 6.3.

Fig. 6.9). Nevertheless, after some rescheduling rounds the performance reduces as a consequence of the receding horizon. Moreover, the high sensibility of SLC to specific RES output features when $\alpha = 1.0$, generates step responses in the final micro-grid load profile. In this case, it can be said that after achieving good quality solutions, SLC jumps from one local optima to another, unable to promote small differences in the micro-grid load profile such that other areas of the search space are explored.

Therefore, results support that higher values for α should be utilized in the beginning of the simulation, while they are gradually reduced in the following rescheduling rounds. In that scenario, a fast convergence to good results without large imbalances would be obtained. Then, after a few round and according to some criteria, smaller α values would promote small differences in the current micro-grid load profile, such that the search space is effectively explored as the optimization horizon deteriorates. Therefore, a deterministic or adaptive parameter control alternative for SLC could be implemented to improve convergence and further increase RES utilization ([EHM99]).

6.2.3. Internal Functioning of SLC and Best Performances

The previous analysis assessed two hypotheses regarding the performance of SLC. Firstly, that with better forecast qualities the performance of SLC should improve. Secondly, that with low quality forecasts, higher values for α should

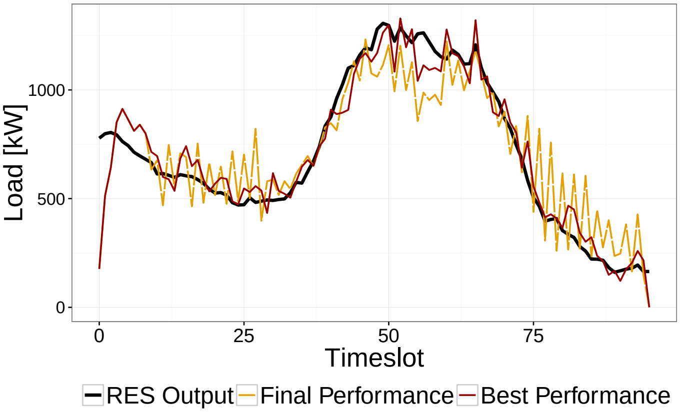


Figure 6.10.: Micro-grid load profile of the final and best performances obtained throughout a single SLC run for the *High Quality Forecast* scenario described in Table 6.3 with $\alpha = 1.0$.

be utilized, and with better quality forecasts, smaller values should be utilized. Furthermore, the effect of different populations sizes on the performance has been also evaluated.

Results show that larger population sizes improved the performance and robustness of SLC. Above a certain threshold, only aggregated behavior can modify the global tendencies in the performance of the approach. The effect of the population size was also observed in every following experiment, where the impact of different forecasts qualities and α configurations was hindered when the micro-grid was composed by smaller populations.

The effect of different forecast qualities is subjected to the micro-grid load composition, in conjunction with the user-defined degrees of freedom, in comparison with the RES output. When the micro-grid load composition and the RES output match, the performance improves with more accurate forecasts. On the other hand, when this condition is not met, a detriment of performance as the forecast quality increases may be obtained. Therefore, validated the first hypothesis only when micro-grid load composition and the RES output match.

The analysis of different α configurations revealed that best performances concentrated on $\alpha = 0.1$. These results lead to the conclusion that a precise balance between old and new information in the control signal updating process, which is regulated by α, is required in order to obtain good performances. Therefore, the second hypothesis was falsified.

This last analysis revealed the effect of the receding horizon in the rescheduling process. In a receding horizon context, the schedule of devices is updated in each rescheduling round. This process takes place in every rescheduling round, but only loads on the future timeslots are considered available for rescheduling. Appliances scheduled for the previous or current timeslot are not available for rescheduling. Hence, the optimization horizon is continuously reduced. Moreover, SLC needs to optimize considering the previous state of the micro-grid. Since the process of rescheduling is distributed and households perform autonomous decisions, the performance might decreases from one rescheduling round to the next one. This is a fundamental difference compared with other approaches, specially centralized ones. SLC is not able to keep a current optimal solution, since households respond autonomously to the control signal in each rescheduling timeslot. Hence, the global behavior needs to constantly and consistently be guided such that RES utilization increases. If the performance decreases as a consequence of the autonomous decisions, SLC must be able to be able to guide the global behavior in real-time, correcting the current performance such that it remains within acceptable boundaries and, potentially, improve.

In addition, results show that larger α values ($\alpha = 1.0$) make the approach susceptible to the reduction of the optimization horizon. As a consequence, the correction of sub-optimal behavior SLC tends to generate step responses and performance deteriorates. With smaller values ($\alpha = 0.01$), step responses were not observed, but the global behavior could not be guided as effectively. Hence, a precise balance between old and new information for the control signal construction process is required, in order to increase RES usage.

This analysis provides strong evidence supporting that SLC is able to coherently guide the global behavior of autonomous entities such that RES utilization is increased. Moreover, this behavior is achieved without direct communication between individuals in a decentralized manner. Additionally, results show that SLC is able to adapt to a changing environment, represented by the changing RES forecast. From a conceptual perspective, the design of the different system components, such as MGM, micro-grid, and households, and the processes within the system, such as signal construction process and its interpretation, enable the micro-grid to depict the stigmergic coordination process (Section 3.2.5). This implies that SLC is able to depict desirable features of stigmergic systems (Section 3.2.2). In the following section, SLC is compared to two approaches in order to assess its competitiveness.

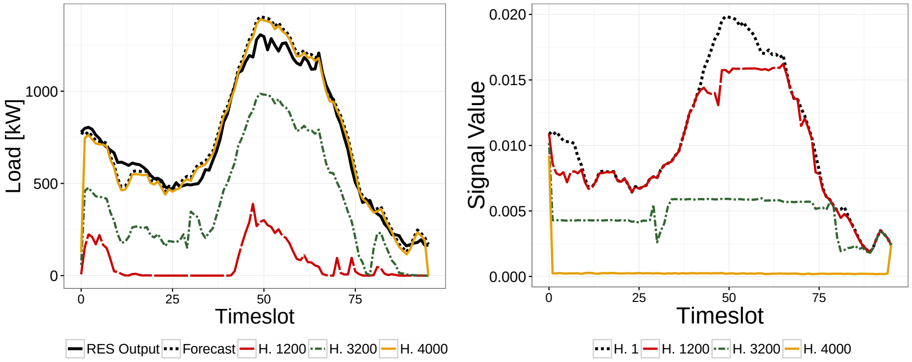
6.3. Comparative Results

In this section, SLC is compared with two alternatives for loads management. The first is **N**on-**L**oad **C**ontrol (NLC). In this approach the consumption of residential households cannot be influenced. Moreover, residential load is distributed and executed according to Table 5.1. This provides a perspective of the ability of each approach to reschedule load in comparison to the initial load distribution in the micro-grid.

The second approach corresponds to an adapted version of the synchronized closed-loop pricing approach presented in Chapter 5 (CLP-FK). As a reminder, under a CLP-FK regime a centralized entity broadcasts a pricing signal to each participant in a synchronous manner, one after the other. This signal expresses the electricity price for each timeslot in the simulated day, in reference to a given RES output. Each individual household selects the cheapest operation time for its devices. Then, it sends its updated load profile to the central controller, which discounts the profile from the RES output. Afterwards, the controller updates the pricing signal according to the new RES availability and broadcasts the price signal to the next agent and the process is repeated. When all households have rescheduled their appliances, a single rescheduling round is finished. In this chapter, however, full knowledge is not considered, but an RES forecast. Hence, the forecast is updated in every rescheduling round. Moreover, the optimization horizon also reduces. Therefore, similarly to SLC, in the context of real-time optimization is referred to as **CLP**.

The evolution of the micro-grid load profile and the price signal broadcast to different households within a single rescheduling round in CLP can be observed in Fig. 6.11. In Fig. 6.11a, it is observed that the load increasingly resembles the RES forecast, as households receive a new pricing signal in a synchronous manner and reschedule their appliances selecting the cheapest operation times. Fig. 6.11b depicts how the pricing signal shape is modified and adapted to match the new RES availability, after a given number of households have rescheduled their appliances. Each signal is valid for only one household. The whole process occurs within a single CLP rescheduling round. Additional discussion regarding conceptual implications of CLP in the context of stigmergy, is presented in and Chapter 7.

The experimental setup considers varying the RES output, forecast quality, population size, load flexibility and load coverage (Table 6.1). α configurations for SLC in each scenario, correspond to those which produced the best performances in the internal analysis of SLC (Table 6.4). In the first set of experiments, all approaches are evaluated considering all the load in the micro-grid to be flexible and that the RES output covers the total load of the micro-grid.



(a) Micro-grid load profile evolution after the rescheduling of single households. *H.* $1,200$ corresponds to household number $1,200$ in the micro-grid.

(b) Pricing signals broadcasts to different households. The higher the value of the signal, the cheaper the electricity price at that specific timeslot.

Figure 6.11.: Micro-grid load profile and price-based signal evolution for CLP.

This means, full-flexibility and full load coverage. In the second set of experiments, different shares of load flexibility are considered in conjunction with different levels of RES coverage over the micro-grid load requirements, while a fixed population size. Through these analyses a perspective is obtained regarding the ability of all approaches to exploit the maximum potential of load rescheduling (100% flexibility) for increasing RES usage, and their performance in more realistic scenarios (reduced load flexibility and different load coverage). Additionally, an analysis of the convergence of the performance of SLC and CLP is performed. Through this analysis, the ability of each approach to direct the search, while the definition of the problem changes, is assessed.

Contributions in this section regard the discussion and conclusions from the comparative analysis between SLC and the other approaches in a receding horizon scenario. Additional contributions are the comparative analysis of SLC in scenarios with low flexibility and different RES coverage.

6.3.1. Explanatory Example

In Fig. 6.12, an exemplary run can be observed for each load scheduling approach. Runs were performed on a $4,000$ households micro-grid, with a high quality forecast. The performance of each load scheduling mechanism can be visualized through the resemblance between the achieved micro-grid load profile and the RES output.

Table 6.4.: Best performing α configurations for each problem instance.

(a) Population of 40 households.

Forecast Quality	**RES Output**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Low	1.0	0.5	0.1	0.05	1.0	0.1	0.1	0.01	0.1	1.0	1.0	0.1
Medium	0.5	0.5	0.05	0.05	0.1	0.1	1.0	0.05	0.5	0.5	1.0	0.1
High	1.0	1.0	0.1	0.1	1.0	0.1	0.5	0.1	0.1	1.0	1.0	0.1

(b) Population of 400 households.

Forecast Quality	**RES Output**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Low	0.5	0.1	0.1	0.1	0.5	0.1	0.1	0.05	0.1	0.1	0.1	0.1
Medium	0.5	0.1	0.1	0.1	0.1	0.05	0.1	0.05	0.1	0.1	0.1	0.1
High	0.1	0.1	0.1	0.05	0.1	0.1	0.1	0.05	0.1	0.1	0.1	0.1

(c) Population of 4, 000 households.

Forecast Quality	**RES Output**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Low	0.5	0.1	0.1	0.05	0.5	0.5	0.1	0.05	0.1	0.1	0.1	0.1
Medium	0.5	0.1	0.05	0.1	0.1	0.05	0.1	0.05	0.1	0.1	0.1	0.1
High	0.1	0.1	0.1	0.05	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

(d) Population of 40, 000 households.

Forecast Quality	**RES Output**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Low	0.5	0.1	0.1	0.05	0.5	0.5	0.1	0.05	0.1	0.1	0.1	0.1
Medium	0.5	0.1	0.05	0.1	0.1	0.05	0.1	0.05	0.1	0.1	0.1	0.1
High	0.1	0.1	0.1	0.05	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

In NLC, the load of the participants cannot be influenced and renewable generation can be used only when load and generation are matched by coincidence. Hence, different RES peaks and valleys cannot be exploited. Therefore, much of the RES generation is lost, since the load flexibility of customers is not used. As mentioned, the residential load is distributed according to Table 5.1. This can be considered a base scenario, since it resembles what occurs in households without any demand side management mechanism. In the case of CLP, the synchronized deterministic decision process allows to schedule load one at-a-time, clearly increasing RES utilization and making efficient use of the flexibility of customers. Nevertheless, small deviations can be observed, as a consequence of the forecasts. In this case, load which has already begun execution in a suboptimal position, is not available to be rescheduled once the forecast accuracy increases.

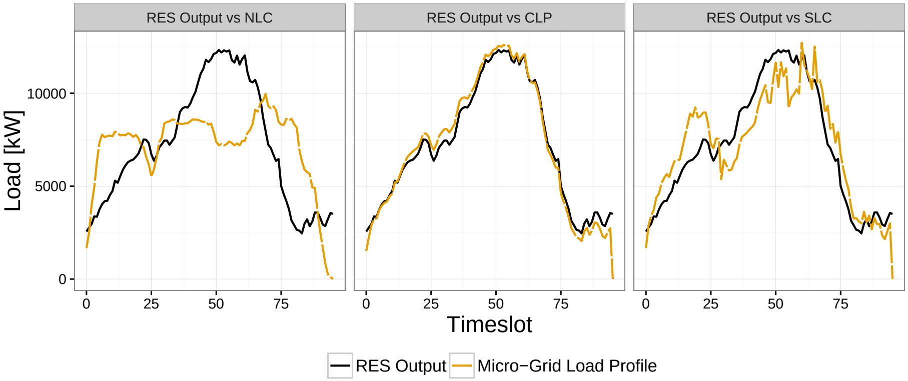


Figure 6.12.: Exemplary runs of NLC, CLP and SLC with a high quality forecast in a $4,000$ households micro-grid.

In the following, the performance of all approaches is compared. Firstly, scalability is assessed by analyzing the approaches performance under different population sizes. Then, the effect of different forecast qualities on of each approach, is evaluated. This analysis will allow to conclude which approach is more robust to dynamic environments. Finally, all approaches are evaluated with different levels of RES coverage and load flexibility, in order to assess a more realistic scenario.

6.3.2. Different Population Sizes

To assess the scalability of each load scheduling alternative, the population size of the micro-grid is increased from 40 to $40,000$ in a logarithmic scale. Different RES output types are considered, while forecast categories are considered as part of the same sample. Moreover, each evaluation considers 300 runs. Formally, the hypothesis to be tested is: H_0 : The data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not, where x is the performance of one load scheduling strategy (such as SLC), and y the performance of another (such as CLP), generated with the same RES output and population. Hence, if H_0 is rejected, it can be stated that significant differences exist between the performance of the two strategies being compared under a specific population size.

Results of the analysis show that CLP outperforms with significance[11] the other

---

[11] For the post-hoc analysis of the evaluation of scalability, cf. Appendix D, Tables D.16 and D.17.

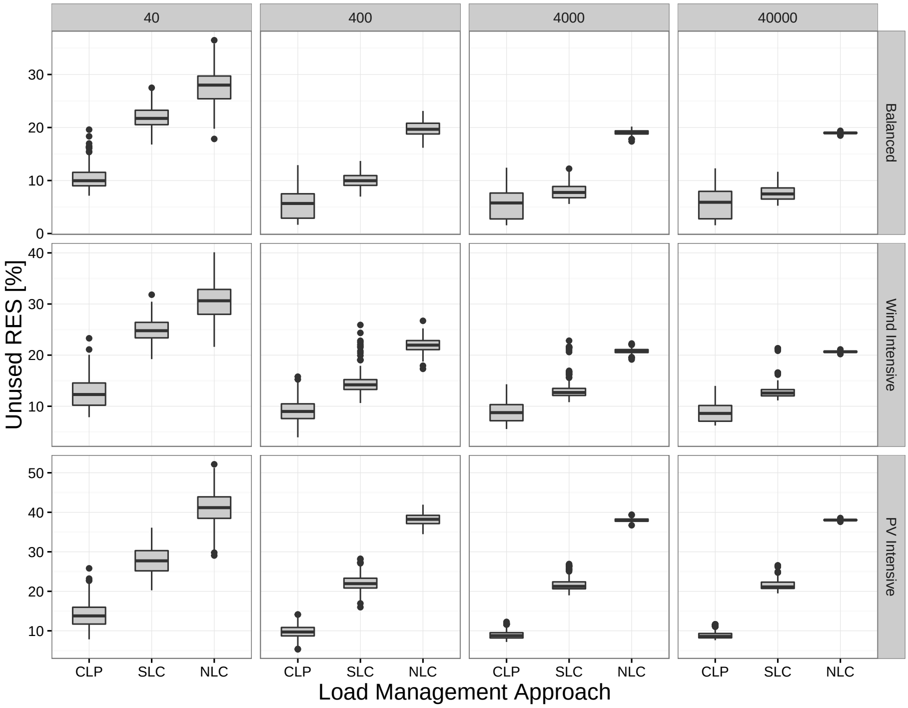


Figure 6.13.: Example performance of SLC, NLC, and CLP with different population sizes and RES outputs.

approaches for every population size within the power grid, in every problem instance evaluated[12]. This is expected due to the rescheduling process utilized by CLP. In addition, results reveal that as the population size increases all approaches improve their performances (Fig. 6.13). Nevertheless, the improvement in performance is larger with SLC. Hence, the delta in performance between SLC and CLP becomes smaller when the population size increases. This tendency is stronger in with balanced RES outputs. When the RES output is PV or wind intensive, SLC rarely catches up with CLP. This can be observed in Fig. 6.13 for the corresponding scenarios.

Reasons for these performances are that the sequential load allocation process of CLP enables a precise scheduling of the operation times. In the case of SLC, the calculation of the new times is asynchronous and probabilistic. Therefore, with smaller population sizes individual behavior can misguide the group, since small differences have a larger relative significance. Above a certain pop-

---

[12] A summary of all the performances is available at Appendix E, Table E.11.

ulation size the global performance can only be guided and significantly altered by aggregated behavior. This was previously discussed in Subsection 6.2.1. Hence, it can be said that when this population size threshold is surpassed, SLC increases its competitiveness against CLP.

6.3.3. Adaptability to Dynamic Scenarios

To compare the ability of each strategy to adapt to dynamic scenarios, represented by the updating forecasts, the performance is compared under the three different forecast categories. As a remainder, lower quality forecast scenarios imply larger dynamism in the problem, whereas high quality forecast scenarios imply smaller dynamism. The evaluation is performed on every type of RES output. Moreover, the analysis concentrates on the behavior of each approach considering a $4,000$ households population.

Formally, the hypothesis to be tested is: H_0 : The data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not, where x is the performance of one load scheduling strategy (such as SLC), and y the performance of another (such as CLP), generated with the same RES output and forecast quality. Hence, if H_0 is rejected, it can be stated that significant differences exist between the performance of the two strategies being compared under a specific forecast quality. Furthermore, it can be stated that the two strategies react differently to different levels of dynamism.

Results show that the best performances are produced by CLP[13]. The differences in performance are significant and provide evidence to reject H_0[14]. Nevertheless, in cases where the RES output is balanced, the performance of SLC becomes more competitive when the problem dynamism increases, this is, with low quality forecasts. In addition, robustness of the performance does not seem to be greatly affected in SLC. This can be observed in Fig. 6.14, *Balanced*, where the 1^{st} and 3^{rd} quartiles are roughly at the same distance regardless of the forecast category for SLC. This does not occur with CLP, where performance dramatically improves its robustness with higher forecast qualities.

When the RES output is wind intensive no conclusive tendency is observed. In this case, Fig. 6.14 shows oscillating behavior from both, CLP and SLC, when the forecast quality changes. Moreover, robustness of the performance with CLP was not consistent nor related to specific wind intensive outputs. On the contrary, differences in the robustness of the performance of SLC are usually

---

[13] A summary of the results is available at Appendix E, Tables E.12 and E.13.

[14] For the post-hoc analysis, cf. Appendix D, Tables D.18 and D.19.

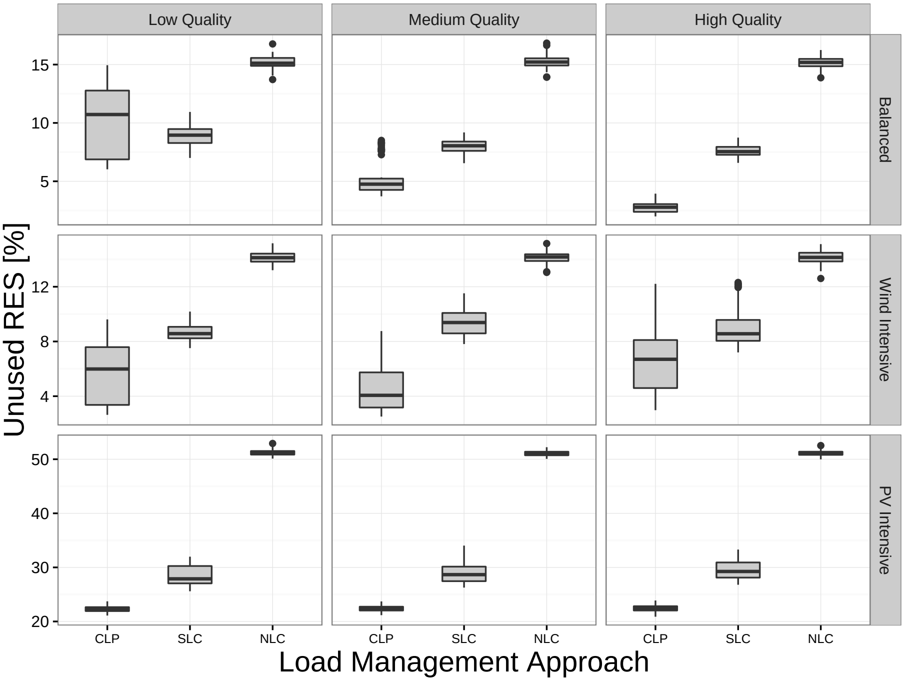


Figure 6.14.: Example performances of SLC, NLC, and CLP, under different forecast categories and RES outputs.

minor and do not depend on the RES output[15]. In cases where the RES output is PV intensive, CLP clearly outperforms SLC. Moreover, in these scenarios, CLP performance is remarkably robust depicting minor outliers (6.14, *PV Intensive*). Hence, CLP is highly effective in exploiting large unique load peaks. Moreover, with these type of RES outputs the effect of the forecast quality is marginal in the performance of the price-based approach.

The reason for these performances is that CLP performs a greedy selection process of the operation times. Specially with balanced RES outputs and higher forecast qualities, CLP is able to effectively schedule the appliances to close-to-optimal operation times. Since the forecasts closely resemble the RES output, the profile does not require major modifications throughout the execution. As a consequence, the performance tightly surrounds the median (Fig. 6.14, *High Quality, Balanced*). On the other hand, when the forecast has low quality, deviations imply more or less generation on any given timeslot with respect to the

---

[15] The interested reader is referred to Appendix E, Tables E.12 and E.13, specifically to the unbalanced RES outputs 2, 3, 9 and 10.

RES output. In those cases, CLP effectively reschedules the appliances according to the given forecast. Nevertheless, since the deviations between forecasts and RES output are larger, many loads are executed in sub-optimal timeslots. Moreover, these sub-optimal timeslots are specific to each forecast. This increases the dispersion of the performances obtained by CLP with low quality forecasts.

Therefore, results suggest that the performance of SLC is more robust than CLP. Moreover, that SLC is less vulnerable to dynamic environments, since its performance is more competitive with lower quality forecasts, particularly in balanced RES output scenarios.

6.3.4. Convergence of the Approaches

Previous results have shown the effect of different qualities of forecast on the performance of SLC and CLP. This performance expresses the quality of the final micro-grid profile obtained by each strategy. Nevertheless, the effect of different forecasts *during* the simulation is also relevant, since it provides details of the ability and behavior of the approaches when facing dynamism. To understand how each strategy performance is affected by dynamism in the problem during the execution, single runs of SLC and CLP are analyzed (Fig. 6.15) under different forecast qualities with a micro-grid population of $4,000$ households. This way, the performance obtained in reach rescheduling round provides information regarding the adaptability of each approach.

When the forecast closely resembles the RES output (Fig. 6.15, *High Quality*) a fast convergence in the first rescheduling round can be observed for CLP. This is followed by a rather constant but small improve throughout the following rounds. A similar behavior can be observed for SLC. Nevertheless, convergence is more gradual and a clear breach between performances exist, which is favorable to CLP.

In the case of a *Medium Quality* forecast, CLP again shows a fast convergence. However, its performance does not improve in the following rounds, but it aggravates. Reasons for this behavior have been previously discussed. CLP effectively schedules loads according to the forecasts. When the forecast is updated, some flexible loads are not available anymore for rescheduling. Therefore, the ability of CLP to absorb unpredictable imbalances is reduced. Regarding SLC, the performance maintains its tendency. This is, it exhibits a permanent improvement throughout the rescheduling rounds. As a consequence, in this specific run (Fig. 6.15, *Medium Quality*) SLC is competitive against CLP.

The performance of CLP is clearly affected when the forecast has low quality. Again CLP quickly converges in the first round. However, directly after

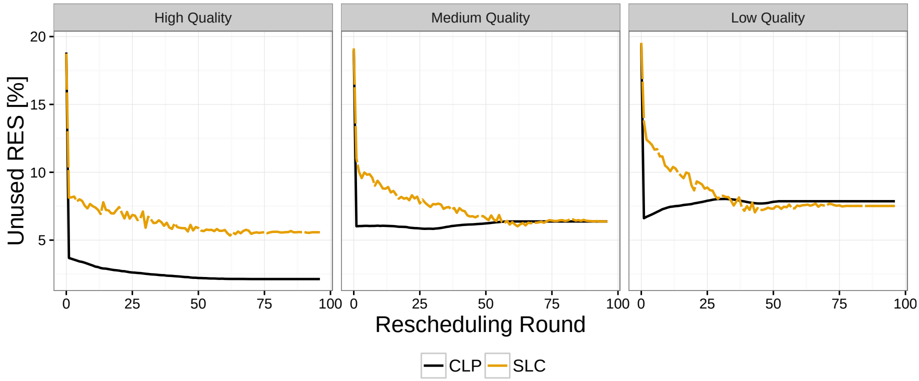


Figure 6.15.: Convergence of single runs of SLC and CLP with different forecast qualities and a balanced RES output.

performance consistently aggravates. This tendency continues roughly until the middle of the simulated day (rescheduling round 50), after which performance becomes stable. Since the differences between forecast and RES output are large, the effect of scheduling flexible devices in sub-optimal timeslots is increased. On the other hand, the overall tendency of the behavior of SLC does not seem to be greatly affected. Again, a consistent improvement of the performance is depicted throughout the rescheduling rounds until final stages of the simulation. As a consequence, SLC catches up CLP, and eventually outperforms it in this specific RES output.

These results complement those of Subsection 6.3.3 and provide evidence that SLC is more robust than CLP regarding the level of dynamism of the environment, since the impact of low quality forecasts over SLC is less than over CLP. Nevertheless, it has to be noted that, although the described tendency continues, when the RES output and the micro-grid load composition do not match, SLC is not able outperform nor catch up CLP. In these cases, the gap of performance between both approached does not reduce even in low quality forecast scenarios. This can be observed in Table 6.6, *RES outputs 4*, which corresponds to PV intensive RES output. On the contrary, in Table 6.6, *RES outputs 5* (balanced output) a clear improve on the performance can be observed for CLP with less dynamism (*High Quality*). Whereas performance maintains roughly constant, describing a minor improvement with better forecasts.

Table 6.6.: Extract of the summary of the performance regarding tolerance to dynamism between SLC and CLP. For the full summary, cf. Appendix E, Tables E.12 and E.13.

RES Output	**Statistic**	**SLC**			**CLP**		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**
4	**Min.**	19.0%	19.3%	19.5%	7.3%	7.4%	7.2%
	1st Qu.	20.5%	20.7%	20.7%	8.0%	8.3%	8.2%
	Median	21.4%	21.1%	21.3%	8.5%	8.8%	9.0%
	3rd Qu.	22.8%	21.9%	23.8%	10.4%	9.3%	9.7%
	Max.	26.9%	23.5%	25.4%	12.3%	12.2%	11.7%
5	**Min.**	6.9%	5.7%	5.5%	5.5%	3.5%	1.5%
	1st Qu.	7.5%	7.2%	6.9%	6.5%	4.6%	1.7%
	Median	7.9%	7.7%	7.2%	7.8%	5.6%	2.3%
	3rd Qu.	8.5%	8.6%	7.7%	8.6%	7.2%	2.9%
	Max.	12.6%	10.2%	9.1%	11.0%	8.4%	3.5%

6.3.5. Different Coverage and Load Flexibility

Acknowledging the potential of SLC, an analysis on a more general model setting is utilized to provide insights of the possibilities of the approach on real-world power systems. Therefore, different shares of flexible loads are investigated. More specifically, the share of flexible load in the micro-grid load composition has been scaled to 10%, 20%, 30% and 40%. The rest of the micro-grid load requirement are assumed to be supplied by conventional generation. These shares coincide with estimations regarding current load flexibility within the power grid ([Hil14, QH99]). Moreover, different shares of coverage of the RES output over the micro-grid load requirements have been considered. More specifically, 25%, 50% and 75% shares of RES generation on the total load are analyzed. This way, tendencies are unveiled regarding the ability of the approaches to reschedule load when the RES output and the total micro-grid load do not match.

RES Output Coverage

To assess the impact of different load coverage on the performance of each strategy, different levels of this factor are considered: 25%, 50% and 75% shares of RES generation on the total load, respectively. The evaluation is performed for each RES output with a $4,000$ households population, while the share of load flexibility in the power grid is considered at 40%. Additionally, all forecast categories are grouped in the same sample and each evaluation considers 300 runs. Therefore, the hypothesis tested is: H_0 : The data in x and y are samples from continuous distributions with equal medians, against the alternative that they are not, where x is the performance of one load scheduling strategy (such as SLC), and y the performance of another (such as CLP), generated with the same RES output, load coverage and flexibility. Hence, if H_0 is rejected, it can be stated that significant differences exist between the performance of the two strategies being compared under a specific RES load coverage share.

The analysis revealed that increasing the RES output coverage, leads to an increase of unused RES. When the RES output covered 25% of the micro-grid load requirements the unused RES was never above 1% and rarely above 0%. In this case, there was not enough evidence to reject H_0[16]. Therefore, it is concluded that the performance of all strategies in the same in this scenario. The reason for this performance is that unless the RES output depicts large load peaks, this output is easily absorbed without any load shifting (Fig. 6.16, *25% Coverage*).

Differences start to become visible when the RES output covers 50% of the total micro-grid load. NLC stays behind against the other approaches in most problem instances. Contrary to the previous situation, the share of RES is large enough to surpass the micro-grid load profile. Therefore, some form of load rescheduling is required in order to maximize RES utilization. In this situation, SLC continues to be competitive in comparison to CPL in most problem instances, since usually performances of SLC are not dominated by CLP. Additionally, forecasts begin to have an effect on the performance, which is illustrated by the increase in the dispersion of data (Fig. 6.16, *50% Coverage*).

When the output covers 75% of the micro-grid, imbalances due to unused RES generation begin to appear throughout the day in every problem instance. In this case, there is evidence to reject H_0 in every evaluation. NLC is clearly outperformed by the other approaches, since it cannot reschedule load to absorb the imbalances. Moreover, CLP outperforms SLC in a similar fashion as described in previous subsections. Nevertheless, SLC manages to remain competitive in some problem. Additionally, forecasts have a clear effect on the performance, expressed through on the increase in data dispersion (Fig. 6.16, *75% Coverage*). Moreover, these tendencies are consistent throughout each type of RES output[17].

With a 75% coverage level of the micro-grid load requirements by the RES output, intuition dictates that the share of flexibility on the micro-grid should have

---

[16] For the Kruskal-Wallis rank-sum tests, cf. Appendix C, Table C.12.

[17] For a summary of the results, cf. Appendix E, Table E.14. For the post-hoc analysis, cf. Appendix D, Table D.3.

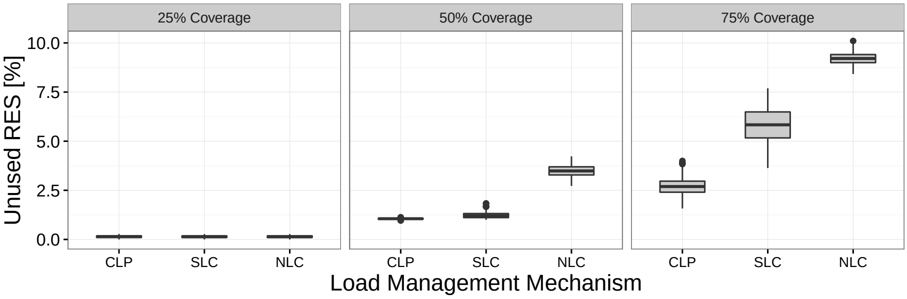


Figure 6.16.: Example performance of SLC, CLP and NLC with different shares of RES output coverage on a balanced RES output. Load flexibility represents 40% of the total load and different forecast categories are part of the same sample.

a clear effect on increasing or reducing the performance. More flexibility translates into increased RES utilization. With smaller coverage, the differences between RES output and micro-grid load profile are small enough to be absorbed by rescheduling a reduced number of appliances. On the contrary, when RES coverage is larger, the imbalances between RES output and micro-grid load profile increase. Therefore, the requirement for flexibility to absorb these imbalances should increase. To address this issue, in the following, the effect and comparative behavior of different shares of flexibility in the micro-grid load is further analyzed.

Micro-Grid Load Flexibility

Previous results led to the conclusion that with 25% and 50% of micro-grid load coverage by the RES output, the effect of different shares of flexibility was hindered. Therefore, to understand the effect of different flexibility levels, the following analysis considers 75% of micro-grid load coverage. The analysis is performed for each RES output separately and all forecast categories are grouped in the same sample. Moreover, each evaluation considers 300 runs.

In line with the results from previous experiments, a tendency can be observed when load flexibility is increased in the micro-grid. An example case for a balanced RES output is observed in Fig. 6.17. As flexibility increases, NLC becomes less competitive in comparison to the other approaches. This occurs because imbalances generated by the RES output are not absorbed by NLC, since this approach does not provide any load shifting feature. Circumstantial increases in RES utilization are explained by the shape the micro-grid load

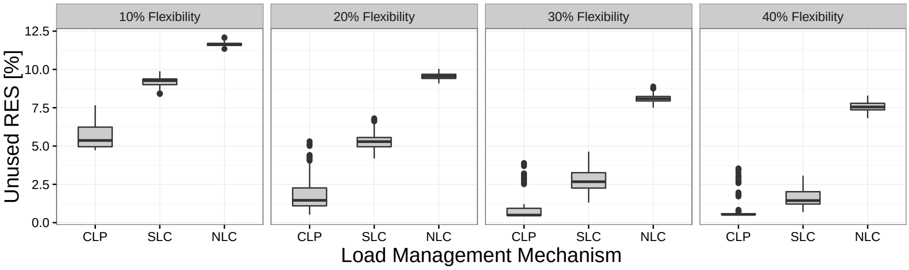


Figure 6.17.: Example performance of SLC, CLP and NLC with different shares of flexible load on the micro-grid on a balanced RES output.

profile adopts when load flexibility shares are larger, which depend on the initial execution times of the devices, cf. Fig. 6.1 and Table 5.1. Regarding CLP and SLC, robustness of the performance also decreases when the flexibility increases. The reason for this behavior is that with larger shares of flexible load, the effect of different forecasts on the rescheduling process also increases. Hence, the relative impact of scheduling devices in optimal, or sub-optimal timeslots depending on the RES forecast, is magnified.

Both, CLP and SLC, show a clear tendency to improve performance when load flexibility increases. Nevertheless, a performance delta exists, which is favorable to CLP. In some cases, however, SLC is competitive against CLP. Reasons for this have been previously described, e. g., influence of different quality forecasts. Hence, the effect of earlier discussed factors is submitted to the share of load flexibility in the micro-grid. Moreover, the increasing delta between NLC and the load management approaches suggest that as more RES generation is available, the flexibility on the demand side increases its relevance. The utilization of the RES output capacity is larger (Fig. 6.17, *40% Flexibility*) when the micro-grid is able to adapt its consumption (SLC and CLP) to fit the available RES generation. Hence, with increasing penetration of RES, larger flexibility is required in order to absorb imbalances generated by intermittent generation. Therefore, it is reasonable to conclude that with higher demand side flexibility, the unused RES generation can be reduced.

This is relevant, since it points out that to increase the share of intermittent generation fed to the system, the share of load flexibility in the power grid has to be considered. In addition, this observations are consistent throughout each type of RES output[18].

---

[18] For summary of the results of these experiments, cf. Appendix E, Table E.15.

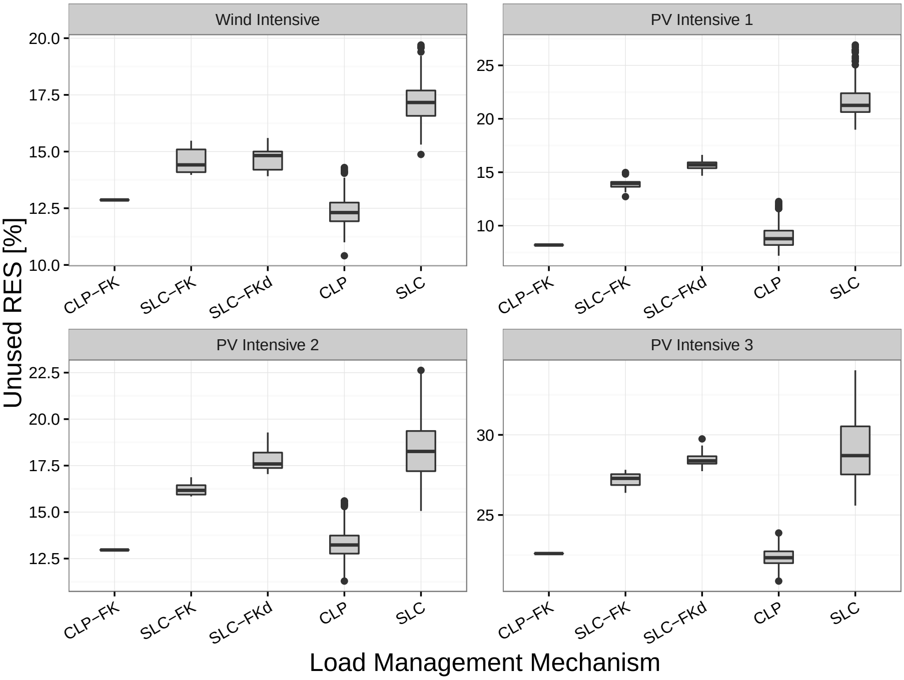


Figure 6.18.: Controversial results between a real-time and static optimization. $4,000$ households are considered.

6.3.6. Controversial Results

During the course of the analysis in static and real-time optimization, individual observations provided findings which might look contradictory to the conclusions of the analysis. Intuition dictates that, since CLP-FK, SLC-FK and SLC-FKd have full knowledge regarding the RES output and do not operate within a receding horizon context, they should consistently achieve better performances than under a real-time optimization context. Fig. 6.18 compares the performance of CLP and SLC with CLP-FK, SLC-FK and SLC-FKd from Chapter 5, which correspond to a static optimization context, in cases which provided contradictory results.

Contrary to what is expected, in these problem instances CLP outperforms the full-knowledge alternatives. A likely reason for this behavior, is the shape of the fitness landscape. As a consequence of the utilization of RES forecasts, real-time coordination alternatives are forced to generate imbalances with respect to the final RES output. Hence, their search is redirected to a different zone from the fitness landscape where they are able to search for solutions which outperform the full-knowledge scenario.

A conclusion which can be drawn, is that the fitness landscape in these type of load scheduling problems depicts steep hills separated by deep valleys. Therefore, once an approach begins the hill-climb to a local optima, it is highly unlikely that it can travel down to a new deep valley and find a better hill. This way, the forecasts force the travel through these valleys and enable the finding of these better solutions.

This behavior is observed with wind and PV intensive RES outputs, and tends to be stronger when the population size is smaller. In addition, these results reveal other complexities of the problem and the importance of variability in the solution construction process.

6.4. Discussion and Summary

In this chapter, the ability of stigmergy-based load control (SLC) to balance load in the power grid in real-time is assessed. For this purpose the internal behavior of the approach is analyzed in depth through a series of experiments and then compared with other approaches.

Firstly, results have empirically shown that SLC, is able to coherently guide the global behavior of a simulated micro-grid and increase RES usage in a real-time scenario. This performance is achieved without participants engaging in direct communication and in compliance with the requirements defined for artificial stgimergic systems (Chapter 3). As a consequence, it is expected that SLC depicts properties of these systems, such as robustness, adaptability, anonymity and autonomy of its participants, among others. These features are desirable for the power grid and particularly for decentralized management of flexible autonomous devices. Regarding scalability, results show that a population threshold exists, above which, only aggregated behavior can change global tendencies in performance. This feature is usually found in natural stigmergic systems and provides tolerance to disturbances to the global behavior.

Secondly, the performance of SLC is assessed under different forecast qualities. Better forecasts imply less dynamism in the problem definition, since differences between the initial forecast and RES output are small. Hence, updating the forecasts imply minor changes to problem definition, in comparison to lower forecast qualities. As a consequence, a load management mechanism requires only small corrections on its generated micro-grid load profile throughout execution. It has been shown, that the performance of SLC tends to improve with better forecast qualities. Nevertheless, these results also depend on the RES output. If the RES output does not match the micro-grid load composition and user-defined restrictions, oscillating behavior can be obtained. Hence, the RES output is identified as the main factor in limiting the ability of SLC to increase RES usage.

Thirdly, it is shown that a precise balance between historic and current information in the signal construction process is required, to achieve the best performances. This balance is regulated by parameter α. Results show that when the weight of new information on the signal construction process is too large ($\alpha = 1.0$) or too small ($\alpha = 0.01$), performance deteriorates.

A relevant aspect to notice is the effect of modeling the problem as a receding horizon. It is observed that, under this modeling approach, SLC depicts step responses at the end of the simulated day, especially when the weight of new information is larger. This occurs because the approach has to comply with the restriction of scheduling every appliance within the simulated day, while the optimization horizon reduces. Alternatives to face this issue in future research consider modeling the problem with a rolling window approach, or modeling three days with a rolling horizon. In the latter, only the middle day would be evaluated and nuisance as a consequence of the reduction of the optimization horizon, would be minimized.

Two scenarios are considered to compare SLC with other alternatives. In the first one, the totality of the load within the power grid is considered to be flexible. This allows to analyze the full potential for optimization of each approach. The second one considers more realistic scenarios, with different shares of load flexibility and RES coverage capacity over the simulated micro-grid load requirements. It is observed that even when a price-based alternative (CLP) clearly outperforms SLC, the latter achieves reasonable performances and can be competitive against the price-based approach. This is mainly observed in scenarios with larger populations and high dynamism in the problem definition (low quality forecasts). Moreover, in these scenarios the performance throughout the simulation is shown to be more robust for SLC, depicting a continuous improvement.

These results are quite promising. CLP performs a deterministic selection process, based on a greedy approach (selection of the cheapest electricity price) which requires synchronization. If the requirement of synchronization is not met, the approach generates large imbalances, as all customers select the same operation times. On the other hand, SLC is fully asynchronous. This conforms a strength of the approach, since synchronization in a real-time optimization scenario, with thousand of autonomous customers increases complexity and implementation costs. In this sense, SLC is more simple, affordable and robust than CLP. Under these considerations, the investment in a decentralized load management mechanism could lead to the selection of SLC, especially in the presented scenarios.

Contributions in this chapter regard the empirical analysis of the internal functioning of SLC and the assessment of its ability to shift flexible loads and increase RES utilization, in a receding horizon context (Section 6.2). Additional contributions regard the comparison of SLC with other approaches, in different scenarios (Section 6.3). Moreover, results and conclusions from this chapter are later addressed in Chapter 7, to discuss conceptual implications of artificial stigmergic systems in real-time optimization scenarios.

7. Extended Discussion

> *Discussion is impossible with someone who claims not to seek the truth, but already to possess it.*
>
> Romain Rolland, *Above the Battle*, 1916

In this chapter, different aspects of stigmergy-based load scheduling are discussed. Firstly, implications of the results obtained from the experimental evaluations of the approach in real-time coordination (Chapter 6) and as a distributed load scheduler (Chapter 5), are analyzed. Additionally, a conceptual comparison is made with ant colony optimization (ACO), regarding the functioning of both approaches. Then, in consideration of the obtained results, the concept of stigmergy is once more visited. Afterwards, limitations of the approach and future possibilities of stigmergy-based load scheduling are discussed. Finally, a short summary is presented.

Sections of this chapter have been submitted for publication. Specifically, the comparison between stigmergy-based load scheduling (Subsection 7.1.2) is an extension of concepts described in [RKS16].

7.1. Stigmergy-Based Load Control Evaluation

In this section, the applied and conceptual implications of the evaluation of stigmergy-based load scheduling are discussed. SLC-FK/d is utilized to reference SLC-FK and SLC-FKd in conjunction.

7.1.1. Summary of the Experimental Results and Discussion

The performance of stigmergy-based load control was assessed in two scenarios. Firstly, the approach was implemented to distributively calculate global schedules (SLC-FK/d - Chapter 5). Afterwards, the approach was implemented for the real-time coordination of the load consumption of autonomous households in a rolling horizon context (SLC - Chapter 6). In both cases, the objective is to maximize RES usage.

Load Balancing in a Static Scenario

In the case of SLC-FK, the objective is to distributively generate the best schedule for each appliance within a simulated micro-grid, such that the usage of RES is maximized. The schedules generated are evaluated centrally to select the best performing alternative.

The internal analysis of SLC-FK showed that, a specific parameter configuration provided the best performances. This configuration promotes a gradual updating of the control signal utilized to guide the solution construction process. Nevertheless, this same parameter configuration reduces the convergence speed of the algorithm. As a consequence, a deterministic parameter control approach was developed, namely SLC-FKd. This approach increases the convergence speed of the original algorithm, while enabling a thorough search to unveil close-to-optimal solutions.

Both approaches were compared with an adaptation of CLP for this scenario, named CLP-FK. Results provided evidence to support that SLC-FK/d are competitive with CLP-FK, specially in balanced RES output scenarios. Moreover, when highly flexible devices (EVs) are removed from the micro-grid or a single type of flexible load is considered (such as an intelligent washing machine), differences between CLP-FK and stigmergy-based approaches are often not significant, and occasionally SLC-FK/d outperforms CLP-FK. Additionally, for CLP-FK it was empirically shown that, if households receive the pricing signal in the wrong order, performance deteriorates. As a consequence, in this scenario SLC-FK/d is able to outperform CLP-FK. This reveals an important strength of SLC-FK/d: It does not require knowledge of the flexibility of customers to achieve good performances.

These results reveal important aspects of SLC-FK/d. From a conceptual perspective, they show that the approach provides quality solutions for COPs, such as load scheduling. Hence, evidence supports additional research for assessing the performance of these approaches with other COPs. Additionally, the adaptation to SLC-FKd improves convergence speed of the approach, increasing its competitiveness in scenarios where the execution time is a limitation.

From a case application perspective, it can be concluded that privacy preservation, scalability and simplicity of implementation are strengths of SL-FK/d. Although in some cases CLP-FK outperformed SLC-FK/d, differences are not large, especially with balanced and wind intensive RES outputs. In this sense, privacy issues related to centralized load management approaches could be reduced with SLC-FK/d, due to its asynchronous solution construction process. Individual agents, representing households, can be considered as *black boxes*, from which only their load profile is utilized to evaluate the current solution. Then, the MGM would reference the load profiles, which generated the best solutions, without knowledge of the internal load composition of participants (Subsection 5.3.3). An additional implementation scenario considers performing the scheduling directly with the households, instead of an agent representation of them. This would clearly increase privacy, as communication would be completely anonymous. Nevertheless, potential communication overheads should be considered.

Real-Time Load Balancing

In the context of real-time load balancing with uncertain RES forecasts, the main hypothesis evaluated was whether SLC is able to guide the global behavior of autonomous consumers in an asynchronous manner, following the requisites of stigmergic systems (Chapter 3), such that unused RES is minimized. Experimental results provided conclusive evidence to support the truthfulness of this hypothesis.

Additionally, SLC was compared with a synchronous close-loop pricing approach (CLP), which generates close-to-optimal performances [Got15]. The evaluation considered different levels of dynamism (given by quality of the RES forecasts), different shares of load coverage of the micro-grid load requirements, and different shares of load flexibility of the micro-grid's load. Results are clear: CLP outperformed SLC in most evaluated instances. Nevertheless, the absolute difference between the performance of each approach is often not large, especially with balanced and wind intensive RES outputs.

Results also suggest that the performance of SLC is more robust. The impact of lower quality forecasts on the quality of solutions and on the solution construction process itself is minor, in comparison with CLP (Subsection 6.3.5). In addition, when the RES output covers up to 50% of the micro-grid load requirements, differences in the performance between SLC and CLP are often not significant. Whereas with a micro-grid load flexibility of 40%, absolute differences between both load shifting strategies are not large.

From an overall perspective, the implications of these results for SLC are clear. Firstly, it was shown that SLC can guide the global behavior of an autonomous system to a desired target zone. Regarding the comparison of the approach with CLP, it has to be noticed that better performances of the price-based approach are possible due to its synchronized allocation of resources. If this requirement is not met, CLP results in extreme load peaks and imbalances. The requirement of real-time synchronization for CLP also implies a privacy vulnerability and increases complexity in the implementation of this approach. On the contrary, SLC is fully asynchronous. Furthermore, due to its indirect communication process, participants are anonymous and their autonomy is respected. As a consequence, robustness in the operation of the micro-grid and the privacy of customers is enhanced. In this sense, the main advantages of SLC are: Robustness of its operation, improved privacy due its participants anonymity, tolerance to failure and adaptability due to its asynchronous indirect communication, simplicity of the required network for the interactions between participants, and cooperation and coordination in the achievement of high level objectives.

Regarding both scenarios, SLC and SLC-FK/d, results show the importance of increasing load flexibility as the input of intermittent hard-to-predict generation to the power grid increases. In this context, approaches like the one presented in this thesis can help utility companies to increase efficiency in energy usage. Hence, incentives for customers to participate and provide larger flexibility intervals for their appliances, should be encouraged by these utilities. Alternatives can be to provide discount rates to customers according to their reported flexibility. Nevertheless, this specific issue escapes the domain of stigmergy-based load scheduling.

7.1.2. Stigmergy-Based Load Control and Ant Systems

In Chapter 3, Subsection 3.2.4, ant colony optimization (ACO - [BL08]) was presented as the most well-known artificial stigmergic system. In this sense, although stigmergy-based load scheduling and ACO are inspired by the same coordination mechanism, fundamental differences exist between both approaches.

Firstly, differences exist in the solution construction process by the swarm of agents. In the case of a Traveling Salesperson Problem (TSP) application of ACO, a colony of agents (ants) is selected to progressively create solutions. These solutions correspond to routes in a graph representation of the problem. In each iteration, each agent constructs a solution, guided by a heuristic value and an artificial pheromone. Hence, at the end of the iteration the colony has a set solutions. From this set, the best solution is selected and compared with the current best solution found so far. If the best solution of a given iteration performs better than the current best, the former replaces the latter as the current best solution. Before moving to the next iteration, the components of the current best solution are enforced with additional artificial pheromones to guide the search in the vicinity of that solution. In the next iteration, the process is repeated. Hence, the decision process of the ants is guided by this new pheromone concentration. Since in each iteration, there is only one currently best solution, low quality solutions are discarded [DBT00].

On the contrary, in SLC and SLC-FK/d each agent, which corresponds to a household, is in charge of a single component of the solution, this is, the schedule of the household or load profile depending on the application. Every component is required to create a solution, therefore, results obtained from individual agents cannot be voluntarily neglected. Additionally, in each rescheduling round, a single solution is generated, rather than a set of solutions. Moreover, the concept of population also differs. A micro-grid with $40,000$ households requires that $40,000$ agents represent them in the simulation. Hence, it is the problem instance that determines the size of the swarm to be utilized. In ACO, the size of the swarm is a modifiable parameter in the algorithm.

A relevant difference is the stimuli definition. In ant systems, the auto-catalytic effect, which enables the incremental construction of solutions, is traditionally triggered by artificial pheromones. These pheromones reference individual solution components (arcs in a TSP context) and are modified by any agent, which utilizes these components in their solution. In SLC and SLC-FK/d, the control signal broadcast to every agent corresponds to the stimuli. Agents react to this signal and reschedule their appliances, modify its definition for future rescheduling rounds. The signal received is the same for the whole population. However, each agent is able to modify only specific portions of it, due to the user-defined flexibility intervals. From a conceptual perspective, stimuli in SLC and SLC-FK/d represent the distance between the desired state and the current state of the system (Chapter 4, Section 4.3). In the case of ACO, pheromones express the quality of individual components by means of how much they have been previously utilized ([RKS16]). They are not considered as an indicator of the distance to the desired objective.

Additionally, an explicit parameter is utilized in ACO to regulate exploration and exploitation. An increase in the value of this parameter implies more exploration and less exploitation[1]. On the contrary, stigmergy-based load scheduling does not utilize an explicit mechanism to regulate these aspects of the search. Exploration and exploitation are managed by the same parameter, namely α (Chapter 4). On the one hand, with larger values for α faster convergence is achieved, but the algorithm is not able to perform a continuous and effective search, nor the escaping from stagnation. This sounds contradictory, since this behavior is usually related to exploitation. Nevertheless, as discussed in Chapter 6 and 5, larger α values promote much rescheduling in the population of appliances, which can be considered *exploration* in the context COPs. On the

---

[1] It has to be noticed that initial versions of Ant Systems did not use this mechanism [DBT00].

other hand, smaller values for α unveil good solutions continuously and enable the algorithm to escape from stagnation, however, with much slower convergence speed (Subsections 6.2.2, 6.3.4 and 5.6). This features are usually related to *exploration*. Nevertheless, this parameter configuration promotes only gradual and located rescheduling of appliances within the micro-grid, which can be consider as *exploitation*.

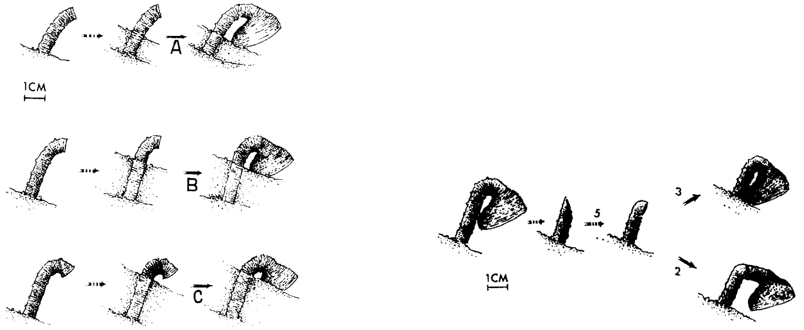
In this context, two approaches considered the utilization of an ACO-based algorithm for demand side management and load balancing ([DPR14, SMCO15]). In both cases, a graph structure, representing the possible combination of the tasks to be scheduled is required. The edges in this graph, represent the operational costs of scheduling a specific task to a specific timeslot. This graph is utilized to solve a shortest route problem, in which all tasks are connected, with a colony of artificial ants. The issues with this approaches are evident from two perspectives, in the context of future power systems. Firstly, larger networks will dramatically increase execution time, since not only the problem of the shortest route has to be solved, but the graph has to be constructed. Secondly, privacy of customers is affected, since precise knowledge of the load composition of each participant is required. In this case, it can be observed that ACO might not be adequate for load balancing in the power grid, due to the requirement of graph representations of the problem. This occurs, because ACO is based on the foraging behavior of ants, rather than their cooperation and coordination mechanism [MMS02, FH13, ABPV08].

On the contrary, the described features of stigmergy-based load scheduling allow the modeling and facing of combinatorial optimization problems, such as load scheduling, in a direct manner [RKS16]. In the case of load balancing, these features enable scalability, simplicity of the implementation, and preservation of the privacy of customers.

7.2. Stigmergy Revisited

The keen reader might have noticed that CLP and CLP-FK share some conceptual similarities with stigmergy-based load scheduling (Subsection 5.3.1). Then, a reasonable question is: Does CLP also qualifies as form of stigmergy?

To answer this question, the fulfillment of requirements for artificial stigmergic systems can be considered (Chapter 3, Subsection 3.2.5): Firstly, the pricing-signal stimulates behavior from agents and is also modified after each household reschedules its appliances. Therefore, it can qualify as a *stigmergic variable*. The *environment* is the same as in SLC, which was also shown to comply with the requirements of stigmergy. Households have an *inherent behavior*, and



(a) Experiment 4: Altering the funnel stem length during stage II.

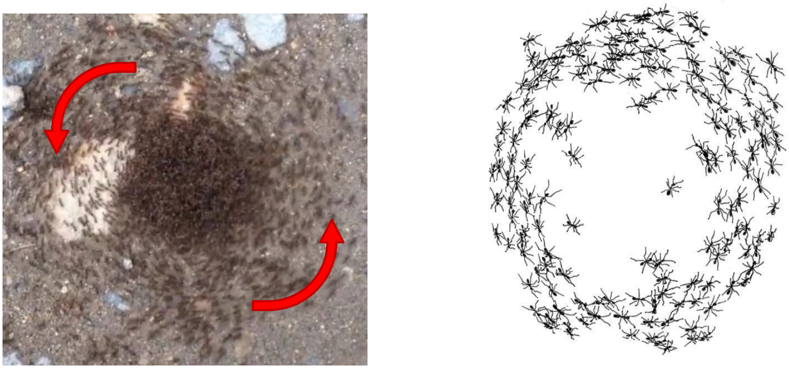
(b) *Experiment 7*: Effect of presenting conflicting stimuli during stage II.

Figure 7.1.: Effect of misguidance, through the alteration of the stigmergic stimuli, in the *Paralastor sp.* funnel construction process [Smi78].

perform their rescheduling *autonomously*. Since the signal triggers behavior of agents, and their actions modify the value of the signal, it can be said that the *response-stimuli sequence* takes place in CLP. Finally, households are not required to interact directly and they do not reveal their identity to one another. Hence, it seems that CLP does qualifies as stigmergy.

Nevertheless, from a conceptual perspective, an important difference between CLP and SLC remains. This is, that CLP requires synchronization to achieve quality performances, otherwise, chaotic behavior is obtained. Therefore, the following question is stated: Can a system which requires synchronization to be stable, also be stigmergic? To answer this question, an example from nature is revisited.

In Chapter 3, Subsection 3.2.1, the experiments performed by Dr. Andrew P. Smith were discussed as a form of guiding behavior in stigmergic systems [Smi78], specifically, the construction of a wasp funnel. In this example, the stigmergic stimuli triggered well defined sequential responses from participants. The described experiment refers to Dr. Smith making holes above a finished funnel, which triggers the construction of an additional funnel on top of the first one. Nevertheless, this was only one of a set of experiments performed by Dr. Smith. Additional experiments considered the effect of presenting conflicting stimuli or misguidance during the funnel construction process. This can be observed in Figs. 7.1a and 7.1b. Here, it can be observed that, although a stigmergic process occurs, since the communication and coordination process fulfills all requirements of stigmergic systems, the end result is undesired from a global perspective. This occurs because, at key stages, the process



(a) Ant vortex phenomena.

(b) Laboratory simulation of the ant vortex or ant mill phenomena [CF02].

Figure 7.2.: Chaotic behavior in army ants due to pheromonal communication perturbations.

was guided in the wrong direction. More specifically, the correct completion of each stage was not respected, hence, abnormal funnels are constructed. These examples reveal that to finish the project properly, each stage has to be correctly terminated, before the next stage occurs. In other words, some level of synchronization, determined by the level of fulfillment of the stages, is required to obtain a stable result from the stigmergic system.

This example clearly shows that specific instances of stigmergic systems can require synchronization to prevent chaotic behavior. However, this is not an inherent requirement of the mechanism itself. Therefore, given the previous examples, the requirement of synchronization in CLP to achieve high quality results, is not a impediment to classify it as an artificial stigmergic system. Hence, in can be categorized as one. In this sense, qualitative stigmergic systems, such as this one, might be rather vulnerable to chaotic behavior, if the stimuli are not embedded appropriately in the environment. Nevertheless, they also enable the cooperative achievement of specific, well defined tasks, such as the construction of a precise type of funnel.

This type of chaotic behavior is not exclusive of qualitative stigmergic systems, though. Army ants are characterized by being nomadic and blind, among others. Hence, they fully depend on pheromones, which corresponds to a marker-based stimuli in quantitative stigmergy context, to find their path. It has been observed that sometimes, when the colony is moving to a new nest, isolated groups of foragers are separated from the main column, due to perturbations in their pheromone field, which affects their communication [Del03, CF02]. As a consequence, the isolated ants begin to follow their own pheromone trail, stimulating themselves, in a *deadlock-kind* of behavior (Fig. 7.2). Eventually, the ants form a densely packed circle until, increasing its pheromone deposition and getting trapped in a *vortex of ants*. The ants are not able to escape this vortex, since being blind they can only decide their future position based on the pheromones, and, as a consequence, they eventually die of exhaustion. In this case, ants follow the pheromones according to the rules defined by the paradigm. Nevertheless, misplaced stimuli triggers chaotic behavior and threatens the final objective of the system.

These examples reveal a fragile aspect of the mechanism. This is, corrupt stimuli can guide the system to a spiral of coordinated behavior which can lead to its destruction. In this case, participants cannot prevent this final results, since they function and perform within the rules defined by the mechanism. Moreover, the final result might not even be relevant to them. Hence, the corruption of the stimuli can be considered a major threat for the correct functioning of these systems. Therefore, in the context of artificial stigmergy, the utilization of an entity to guide the global behavior to a target zone, such as the MGM in stigmergy-based load scheduling, becomes justified.

7.3. Future Opportunities and Limitations

In this section, limitations of the approach, both for the real-time coordination and the load scheduling problem scenario, are discussed. Afterwards, possible approaches to face these limitations including future possibilities and perspectives of the approach are debated.

7.3.1. Limitations and Weaknesses

Although the results obtained throughout this thesis show the strengths of stigmergy-based load scheduling, some limitations have been identified.

In real-time coordination, it was shown that SLC was usually not able to outperform CLP. Moreover, it was observed that under certain internal parameter configurations, SLC tended to generate step responses in the final micro-grid load profile. In this sense, it was observed that the utilization of a receding-horizon to model the effect of real-time was a relevant driver in the increase of step-responses from the SLC. Reasons for this are that the approach has to comply with the restriction of scheduling all appliances within the simulated day, while the optimization horizon is reduced. From a simulation scenario perspective, only a single day has been simulated. Hence, additional information regarding the ability of the approach to operate through an extended period of time, e. g., a week or a month, is not currently available.

Regarding the load scheduling problem, it was observed that SLC-FK/d is competitive and in some isolated scenarios outperforms CLP-FK. Considering the specific application, this is certainly positive. Nevertheless, from a metaheuristic perspective one might be drawn to select CLP-FK, since its performance was consistently better than the other approaches.

Additionally, in each optimization scenario, when the RES output was PV intensive the stigmergy-based load scheduling approach achieved clearly inferior performances than the synchronized closed-loop pricing. This is a consequence of the rescheduling process, which is based on autonomous probabilistic decisions of agents. In this case, rescheduled appliances concentrate on a unique position only up to a certain amount. Moreover, since schedules cannot be imposed on participants, some load is left unused. As a consequence, with large unique load peaks, both, SLC-FK and SLC-FK/d, are not able to relocate load to maximize utilization with these outputs.

7.3.2. Future Opportunities

There are ample opportunities to extend stigmergy-based load scheduling, in both scenarios. From a simulation scenario perspective, to prevent step responses as a consequence of the receding horizon, the problem can be modeled with a rolling window approach [CMB10]. Another alternative is to simulate three days with the current model and evaluate only the middle one. In both cases, strange behavior, as a consequence of the reduction of the optimization horizon and the obligation to reschedule all flexible loads within a specific simulated day in real-time coordination, would be reduced.

From the demand side perspective, RES usage with PV intensive scenarios might be increased by processing the signal by the households (Chapter 4, Subsection 4.3.2), such that the desirability to increase load remains high until the RES is utilized. Nevertheless, this alternative has to be carefully studied, since modifying the interpretation mechanism might trigger chaotic behavior [RKS16].

Additional enhancements on the demand side are the inclusion of residential generation through micro-PV. This type of generation shares similar features as large scale PV generation, it is intermittent, hard to predict, and not dispatchable. In addition, generation is local and unique to the building, which generates it. From a customer perspective, the utilization of this locally generated RES should be a priority. This scenario could be addressed in SLC and SLC-FK/d through the inclusion of an additional term in the decision making process of households (Chapter 4, Eq. 4.6). The value of this term would be different for each household since it would depend on its physical location and the amount of micro-PV generation on any given moment.

In this context, the control signal could also account for residential generation. In the current interpretation scheme, the signal only references timeslots where it would be desirable to increase load consumption. Nevertheless, additional interpretations could give information regarding the timeslots for which it is required to have power input from households, in vehicle-to-grid or residential generation scenarios [MAS12]. This way, households would not only be able to reschedule their devices and increase utilization of an RES output, but also, they would be able to reduce load peaks in the micro-grid by supplying their own residential generation, if appliances cannot be rescheduled.

Even though SLC and SLC-FK/d are oriented to fulfill load objectives, pricing signals or additional objectives, can be included. An alternative to address this scenario is for the MGM to deliver two signals. Each signal would correspond to a different stigmergic stimulus, the load objective and the pricing objective. To react to this additional stimulus, households would need to include it in its decision process through an additional term with a specification of the relative weight of each signal (Chapter 4, Eq. 4.6).

Many of these enhancements consider increasing the complexity of the signal, to cope with more advanced scenarios. In this context, other definitions for the control signal might be evaluated, such as a percentage of utilization of the current available load, instead of the difference between used and unused RES. Regarding real-time coordination, the MGM could be improved such that it can include features to analyze and evaluate the current behavior of the system, predict future consumption and calculate the accuracy of the utilized forecasts. Then, the MGM would operate the control signal to guide the behavior more accurately and prevent potential step responses, while allowing the micro-grid to self-organize and increase RES usage autonomously, as it has been shown. This would imply the usage of an advanced *adaptive parameter control* technique, through the utilization of feedback and inferences for updating of control signal [EHM99]. An adequate architecture to this purpose might be the Observer/-Controller architecture, which provides these type of features and is oriented to guide the behavior of autonomous self-organized systems in dynamic environments [SPB$^+$11]. In the case of SLC-FK, the effectiveness of a deterministic parameter control technique has already been demonstrated. Hence, evidence supports the implementation of an adaptive parameter control for this scenario. This implementation, however, should not increase the complexity in the operation of the algorithm.

From the perspective of stigmergy-based load scheduling as a meta-heuristic, the next step is to adapt the algorithm such that the range of applicable problems can be extended. For this, the generalization of the stimuli definition and probabilistic decision making process of the agents, described in Chapter 4, Subsection 4.3.4 will be of great use. In this sense, natural candidates for applying the problem are other forms of the load scheduling problem, such as resource constrained project scheduling problem, job-shop scheduling problem, followed by two-dimensional bin packing problems and cutting stock problems. This will allow to clearly compare the possibilities and performance of the approach against standard well-known meta-heuristics.

In addition to the benefits that anonymity brings to the approach, SLC can be complemented by other security mechanisms, e.g. SMART-ER protocol in [FB14]. Through this means, the MGM would have access to the aggregated micro-grid load profile, while the profiles of customers would be untraceable for the receiver.

7.4. Summary

In connection with Chapter 2, techniques to balance load which can reliably reduce imbalances through the increase in RES usage improve the power grid stability and promote the development of new market and business models. Under this new structure of distributed generation and high customer flexibility, managing entities, in charge of procuring load balance between supply and demand, can cooperate with residential and commercial customer to guarantee local stability of the power grid. Nevertheless, this cooperation should recognize the requirements of customers, such as privacy and autonomy preservation.

In this chapter, stigmergy-based load scheduling has been discussed in consideration of the results obtained throughout this thesis. Implications of the approach, as a real-time coordination mechanism and as a distributed load scheduler (Chapter 6 and 5 respectively), are discussed. Moreover, conceptual, design and operational differences between the approach and ACO, the most well-known artificial stigmergic-system, are presented. The concept of stigmergy is revisited once more to discuss the role of synchronization and the circumstances, which trigger chaotic behavior in this paradigm. Finally, limitations and future possibilities of stigmergy-based load control are discussed, both from a real-time coordination mechanism for load balancing perspective, and as a meta-heuristic for solving COPs.

Emphasis of stigmergy-based load control are customer privacy, both in SLC as in SLC-FK/d, customer autonomy, simplicity, robustness of the global behavior, flexibility and openness to include different types of flexible devices or customers, and coordinated behavior for increasing RES usage. In this context, and as it has been discussed throughout this work, the conceptual framework provided by stigmergy and self-organization allows the approach to achieve these objectives to great extent.

Novel contributions of this chapter are the discussion of the role of synchronization in stigmergy and specific segments of the discussion regarding the evaluation of stigmergy-based load scheduling.

8. Conclusion and Outlook

> *Some people say, How can you live without knowing? I do not know what they mean. I always live without knowing. That is easy. How you get to know is what I want to know.*
>
> Richard Feynman, *The Meaning of It All*, 1999

The main motivation of this thesis has been the exploration and understanding of the relation between three research fields, namely self-organization, nature-inspired algorithms and energy informatics. To comprehend this relation, firstly, the conceptual and practical implications of guiding the global behavior of stigmergic systems, which are a type of self-organizing systems, are addressed (Chapter 3). With the results of this investigation, an architecture and a formal model for an stigmergy-based meta-heuristic and multi-agent coordination mechanism are proposed (Chapter 4). These two developments are implemented as DR mechanisms to increase the utilization of RES generation. Details of the experimental results for both implementation scenarios are presented in Chapter 5 and 6. A detailed discussion regarding the conceptual and practical implications of these results is provided in Chapter 7. Furthermore, limitations and future work of the approach from the perspective of a meta-heuristic and as multi-agent coordination mechanism for load balancing, are presented in the same chapter.

8.1. Objectives and Achievements

To assess the connection between the previously mentioned research fields, this thesis proposes the utilization of a fundamental coordination mechanism from nature, namely stigmergy, for achieving load balance within a balancing group (BG). For this, a comprehensive and detailed analysis of the mechanism is performed. Based on this analysis, a formal model for a new meta-heuristic is proposed. In this context, the scientific and experimental results, allowed the assessment of the research questions stated in Chapter 1.

> **Research Question 1:** *How can the global behavior of a stigmergic system be guided?*

The literature review on self-organizing systems provided evidence to support that the global behavior of these systems, both in natural and artificial scenarios, can be guided, to achieve specific global behavior. Moreover, different types of guidance were discussed, regarding the level of control performed over individual participants.

In the case of stigmergy, it was concluded that the global behavior of these system can also be guided. The element that gives raise and regulates cooperation and coordination is the stigmergic variable. Participants communicate indirectly through untraceable alterations of these variables. This gives cohesion, flexibility and robustness to the global behavior. Moreover, this form of communication allows for participants to drastically limit the amount of information they exchange, enhancing privacy and autonomy. Through the alteration of these stimuli, stigmergic systems can be guided to perform in specific manners.

Nevertheless, it was also observed that, although stimuli enable cooperation and coordination to raise, corrupted stimuli can misguide the system towards undesired global behavior. Furthermore, it was observed that in natural systems, misplaced stimuli could lead to a spiral of chaotic behavior, which could result in the destruction of the system. Although the probability of this to occur is quite low, the observation of this phenomenon justifies the existence of an entity, which monitors the global behavior and continuously guides it into a desired target space in artificial systems.

> **Research Question 2:** *How can an artificial stigmergic system be utilized to distributively generate schedules which can maximize a given RES output utilization?*

Different types of stigmergic stimuli and types of response from agents were identified during the analysis of the mechanism. In sematectonic stigmergy, the physical description of the environment is utilized to trigger behavior from participants. An advantage of this type of stimuli is that the distance between the current state of the system and the desired state to be achieved, can be easily represented. This facilitates the assessment of a problem such as load scheduling. In addition, quantitative responses to stimuli from participants or agents, implies a probability-based response[1]. Hence, asynchronous behavior becomes possible in the system, reducing the risk of large imbalances and avalanche effects, while all participants perform in a similar manner at the same time.

---

[1] As a reference, ant colony optimization (ACO) utilizes a sign-based stimulus, artificial pheromones, with a quantitative response from participants (Chapter 3).

A stigmergy-based load control approach to distributively calculate global schedules for a population of simulated prosumers with flexible appliances, was presented (SLC-FK). The objective is to maximize the usage of a given RES output. In SLC-FK an iterative scanning process is performed, in which gradually good quality schedules are revealed. The role of the stimuli is played by a control signal, which is modified in each rescheduling round. This signal is considered in the rescheduling process of appliances.

Results show that SLC-FK is able to create schedules that increase RES usage, achieving a micro-grid load profile that closely resembles that of the corresponding RES output. Furthermore, it was found that the convergence speed of the algorithm can be improved through the implementation of a deterministic parameter control strategy.

From an application perspective, two implementation scenarios are considered. The first one regards the utilization of the meta-heuristic on an agent representation of a population of prosumers. Then, the optimal schedule is distributively calculated for each participant, and later they are implemented such as in direct load control. The second scenario considers implementing the approach directly over a population of prosumers, in a distributed computation-like manner. In this sense, privacy of customers would be largely improved.

From an conceptual perspective, results show the value of SLC-FK as a meta-heuristic for solving COPs. Hence, empirical evidence exists to support the enhancing of the algorithm for solving other COPs. As a first step to this end, a generalized form of the meta-heuristic to address other optimization problems is presented. In this sense, adequate candidates in this direction are resource constrained project scheduling problems, two dimensional bin-packing problems and cutting stock problems.

> **Research Question 3:** *How can artificial stigmergic systems be utilized to guide the global consumption behavior of autonomous customers in real-time and in a dynamic environment, such that RES usage is increased?*

As outlined throughout this thesis, the power grid, as most self-organizing systems, functions within a dynamic environment. In its case, the system has to be able to cope with uncertainty, both from the supply and the demand side, in order to permanently maintain load balance. In this context, the proposed meta-heuristic was adapted to be utilized as a real-time optimization mechanism (SLC), to guide the consumption behavior of a group of consumers. Dynamism is represented by the utilization of an RES forecast which is in continuous update. Real-time execution is modeled as a receding horizon, in which the approach moves from one 15-minutes time interval to the next one, until a simulated day has passed by. Each time the approach moves to the following time interval, the RES forecast is updated with more accurate information regarding RES availability.

Results show that SLC is able to guide the global consumption behavior of customers in real-time, and increase RES usage. Moreover, the approach is able to guide the system and adapt the micro-grid load profile as the RES forecast changes during execution time.

From the perspective of customers, SLC depicts many desirable features. Since participants do not interact directly, possible security risks and attacks are reduced. In the same sense, the privacy and autonomy of the end-customer is preserved.

From a utility perspective, the performance of SLC was robust against different levels of dynamism, which is given by the deviation between the RES output and the RES forecast. Moreover, the approach is flexible and adaptable due to its asynchronous interaction process. As a consequence, the operation of SLC was found to be rather simple, in comparison to other approaches. In the same sense, the lack of direct interaction between participants implies that no complex techniques from multi-agent systems, such as negotiation or argumentation, are required to achieve good solutions or stability of the system.

These features show the value of the approach as a coordination mechanism to increase RES usage and achieve load balance within BGs. In this sense, the results of this thesis and the presented architecture show that SLC might also be applied for the load management of power networks which include commercial buildings or small industries.

8.2. Outlook

In most industrialized countries, the power grid has been experiencing drastic changes during the last decades. These changes are only expected to increase in the future. On the one hand, the requirement of increasing the presence of RES in the power system arises many challenges for the power grid operation and stability. These energy sources are characterized by being hard-to-predict, intermittent, and not-dispatchable. As a consequence, the operational requirement of maintaining a permanent balance between supply and demand in the power grid, might be compromised. On the other hand, customers are increasingly changing their consumption profile, through the inclusion of new technologies, such as flexible appliances, which can autonomously select their operation times, or electric vehicles (EV). These devices will modify the load profile of end-customers while making them less predictable. As a consequence, maintaining load balance within BGs will become an increasingly complex problem.

This thesis addresses the issue of complementing both sides of the power grid operation, in order to bring stability by load matching consumption and supply. In this sense, it is proposed that flexible appliances and EVs can schedule their operation times such that load peaks generated by RES generation can be absorbed. In the context of the energy market, this concept is referred to as demand side management. Furthermore, techniques which imply advanced interactions between utilities and customers to actively change the global consumption behavior, are referred to as demand response (DR) programs.

Results from the present work show that, in order to make DR programs effective in the efficient utilization of intermittent generation, increasing shares of RES generation should be accompanied with increasing flexibility of customers. In this context, managing distributed generation and flexible consumption, to provide a meaningful support to the power grid, will be an essential issue in a diversified power system. This should be achieved minimizing overloads or flow inversion. In this future scenario, ICT should play a main role achieving efficient resource management, specially since DR programs will heavily rely on advanced technologies.

The physical layer of the power grid should also be a source of consideration. The current equipment might not be prepared to handle the operation of the hypothesized future power system. Consequently, new infrastructure might be required to protect a highly distributed network. From a utility-customer interaction perspective, relevant bottlenecks which prevent the implementation of communication channels to implement such DRs programs are observed. If these challenges can be overcome, new structures, such as virtual power plants or community heating approaches, will further increase distribution of generation and security of energy supply. Furthermore, such approaches will promote the development of new markets which will certainly make use of innovative DR programs. Issues traditionally related to online network security, such as privacy, security and autonomy of participants will be essential in this new context.

8.3. Final Remarks

The approach for load balancing presented in this thesis is only one of many. In this case, the emphasis of the presented work has two perspectives. From an individual perspective, the main focus is the respect of participants' autonomy and privacy. From a global perspective, the main objectives are to achieve the emergence of robustness, flexibility, coordination and cooperation in the system. These systems' features are found in nature, and so, this work is heavily inspired by natural systems. Our role as scientists is to observe these systems, be inspired by them and implement their conceptual tools in the best possible way, to improve our lives.

Bibliography

[ABPV08] Davide Anghinolfi, Antonio Boccalatte, Massimo Paolucci, and Christian Vecchiola. Performance evaluation of an adaptive ant colony optimization applied to single machine scheduling. *Simulated Evolution and Learning*, 5361:411–420, 2008.

[All14] Florian Allerding. *Organic Smart Home - Energiemanagement für Intelligente Gebäude*. 2014.

[AMS14] F Allerding, I Mauser, and H Schmeck. Customizable Energy Management in Smart Buildings using Evolutionary Algorithms. *16th European Conference on the Applications of Evolutionary and Bio-inspired Computation (in press)*, 2014.

[APSS12] Florian Allerding, Marc Premm, Pradyumn Kumar Shukla, and Hartmut Schmeck. Electrical load management in smart homes using evolutionary algorithms. *Proceedings of the main European Events on Evolutionary Computation*, pages 99–110, 2012.

[AS11] Florian Allerding and Hartmut Schmeck. Organic Smart Home - Architecture for Energy Management in Intelligent Buildings. In *8th International Conference on Autonomic Computing, ICAC 2011 and Co-located Workshops - 2011 Workshop on Organic Computing, OC'11*, pages 67–76, New York, New York, USA, 2011. ACM Press.

[BAR$^+$10] Birger Becker, Florian Allerding, Ulrich Reiner, Mattias Kahl, Urban Richter, Daniel Pathmaperuma, Hartmut Schmeck, and Thomas Leibfried. Decentralized energy-management to control smart-home architectures. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 5974 LNCS, pages 150–161, 2010.

[BF12] Seth Blumsack and Alisha Fernandez. Ready or not, here comes the smart grid! *Energy*, 37(1):61–68, 2012.

[BHJY07] Sven A Brueckner, Salima Hassas, Márk Jelasity, and Daniel Yamins. *Engineering Self-Organising Systems*, volume 4335. Springer-Verlag, 2007.

[BL08] Christian Blum and Xiaodong Li. *Swarm Intelligence.* 2008.

[Blu05] Christian Blum. Ant colony optimization: Introduction and recent trends, December 2005.

[Blu07] Steven W Blume. *Electric Power System Basics.* John Wiley & Sons, Inc., New Jersey, 2007.

[BMM14] Fayal Bouhafs, Michael Mackay, and Madjid Merabti. *Communication Challenges and Solutions in the Smart Grid.* Springer Berlin Heidelberg, Liverpool, 2014.

[BMMS⁺06] Jürgen Branke, Moez Mnif, Christian Müller-Schloer, Holger Prothmann, Urban Richter, Fabian Rochner, and Hartmut Schmeck. Organic Computing Addressing Complexity by Controlled Self-Organization. *Second International Symposium on Leveraging Applications of Formal Methods, Verification and Validation (isola 2006)*, pages 185–191, November 2006.

[BMW12] BMWi. Germanys new energy policy. Technical report, Federal Ministry of Economics and Technology (BMWi), Munich, 2012.

[BS14] Bernd M Buchholz and Zbigniew Styczynski. *Smart grids - Fundamentals and technologies in electricity networks.* Springer Vieweg, 2014.

[Bun] Statistisches Bundesamt. Gross electricity production in Germany from 2013 to 2015.

[CF02] I. D. Couzin and N. R. Franks. Self-organized lane formation and optimized traffic flow in army ants. *Proceedings of the Royal Society London B*, 270(September 2002):139–146, 2002.

[CF09] Jens Czogalla and Andreas Fink. Fitness landscape analysis for the resource constrained project scheduling problem. In *Learning and Intelligent Optimization*, volume 5851, pages 104–118. Springer Berlin Heidelberg, 2009.

[CMB10] a J Conejo, J M Morales, and L Baringo. Real-Time Demand Response Model. *Smart Grid, IEEE Transactions on*, 1(3):236–242, 2010.

[CMMS⁺07] Emre Cakar, Moez Mnif, Christian Muller-Schloer, Urban Richter, and Hartmut Schmeck. Towards a quantitative notion of self-organisation. *2007 IEEE Congress on Evolutionary Computation*, pages 4222–4229, September 2007.

[CX14] Tinggui Chen and Renbin Xiao. Enhancing artificial bee colony algorithm with self-adaptive searching strategy and artificial immune network operators for global optimization. *TheScientificWorldJournal*, 2014:438260, January 2014.

[CYKD13] Albert Chen, Jun Yao, Todd Kuiken, and Julius P a Dewald. Cortical motor activity and reorganization following upper-limb amputation and subsequent targeted reinnervation. *NeuroImage: Clinical*, 3:498–506, 2013.

[DBT00] Marco Dorigo, Eric Bonabeau, and Guy Theraulaz. Ant algorithms and stigmergy. *Future Generation Computer Systems*, 16(8):851–871, 2000.

[DD99] Marco Dorigo and Gianni Di Caro. The ant colony optimization meta-heuristic. *New Ideas in Optimization*, page 450, 1999.

[DE13] Arne Dammasch and Bernd Engel. Reducing the use of compensation energy in a balancing group using a virtual power plant. *Internationaler ETG-Kongress*, 9:1–5, 2013.

[Del03] Frédéric Delsuc. Army ants trapped by their evolutionary history, 2003.

[DGF$^+$91] J.L. Deneubourg, S. Goss, N Franks, A. Sendova-Franks, C. Detrain, and L. Chrétien. The Dynamics of Collective Sorting Robot . Like Ants and Ant . Like Robots. *Proceedings of the first international conference on simulation of adaptive behavior on From animals to animats*, pages 356–363, 1991.

[DMC91] M Dorigo, V Maniezzo, and A Colorni. The ant system: An autocatalytic optimizing process. Technical report, Politecnico di Milano, 1991.

[Dob14] Ian Dobson. Cascading Network Failure in Power Grid Blackouts. *Encyclopedia of Systems and Control*, pages 1–9, 2014.

[DPR14] Tim Dethlefs, Thomas Preisler, and Wolfgang Renz. Multi-Agent-based Distributed Optimization for Demand-Side-Management Applications. *Proceedings of the 2014 Federated Conference on Computer Science and Information Systems*, 2:1517 – 1524, 2014.

[DRWA11] Christian Dänekas, Sebastian Rohjans, Carsten Wissing, and H Appelrath. Future Energy Grid Migration Paths into the Internet of Energy. *Proc. 2011 eChallenges Conference*, pages 1–8, 2011.

[EdM08] Wilfried Elmenreich and Hermann de Meer. Self-Organizing Networked Systems for Technical Applications: A Discussion on Open Issues. In *Proceedings of the Third International Workshop on Self-Organizing Systems*, pages 1–9, 2008.

[EHM99] A.E. Eiben, R. Hinterding, and Z. Michalewicz. Parameter control in evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 3(2):124–141, July 1999.

[ES03] Agoston Endre Eiben and Jim E. Smith. What is an Evolutionary Algorithm? *Introduction to Evolutionary Computing*, pages 15–35, 2003.

[FB14] Soren Finster and Ingmar Baumgart. SMART-ER: Peer-based privacy for smart metering. *Proceedings - IEEE INFOCOM*, pages 652–657, 2014.

[FD11] Regina Frei and Giovanna Di Marzo Serugendo. Advances in complexity engineering. *International Journal of Bio-Inspired Computation*, 3(4):199, 2011.

[FG16] Christoph M. Flath and Sebastian Gottwalt. Price-based Load Coordination Revisited : Augmenting Open-Loop Coordination Approaches. *Business Research*, 2016.

[FH13] Andreas Fink and Jörg Homberger. An ant-based coordination mechanism for resource-constrained project scheduling with multiple agents and cash flow objectives. *Flexible Services and Manufacturing Journal*, 25(1-2):94–121, 2013.

[FIG$^+$13] Christoph M Flath, Jens P Ilg, Sebastian Gottwalt, Hartmut Schmeck, and Christof Weinhardt. Improving Electric Vehicle Charging Coordination Through Area Pricing. (January 2014):0–16, 2013.

[Fro05] Jochen Fromm. Ten Questions about Emergence. Technical report, 2005.

[Gel85] C W Gellings. The concept of demand-side management for electric utilities. *Proceedings of the IEEE*, 73(10):1468–1470, 1985.

[Ger05] Carlos Gershenson. A General Methodology for Designing Self-Organizing Systems. *Design*, M(33):1–28, 2005.

[Ger07] Carlos Gershenson. *Design and Control of Self-organizing Systems (PhD Thesis)*. PhD thesis, Vrije Universiteit Brussel, 2007.

[GH03] C Gershenson and F Heylighen. When can we call a system self-organzing? *submitted to ECAL 2003*, 2003.

[GHPS08] T. a. Guldemond, J. L. Hurink, J. J. Paulus, and J. M J Schutten. Time-constrained project scheduling. *Journal of Scheduling*, 11(2):137–148, 2008.

[GKB$^+$11] Sebastian Gottwalt, Wolfgang Ketter, Carsten Block, John Collins, and Christof Weinhardt. Demand side managementA simulation of household behavior under variable prices. *Energy Policy*, 39(12):8163–8174, December 2011.

[Gla09] Hans Glavitsch. Large-Scale Electricity Transmission Grids: Lessons Learned from the European Electricity Blackouts. In *Wiley Handbook of Science and Technology for Homeland Security*. 2009.

[GlBK11] Sebastian Gräß le, Birger Becker, and Thomas Knapp. Intelligent Control System for CHP-Equipment in Smart-Homes. In *MICRoGEN'II 2nd International Conference on Microgeneration an Related Technologies*, 2011.

[Got15] Sebastian Gottwalt. *Managing Flexible Loads in Residential Areas*. PhD thesis, Karlsruher Institut für Technologie, 2015.

[Gov14] Government of Germany. The German Government s Climate Action Programme 2020. Technical Report December, Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMUB), Paderborn, 2014.

[GSF$^+$13] Sebastian Gottwalt, Alexander Schuller, Christoph Flath, Hartmut Schmeck, and Christof Weinhardt. Assessing load flexibility in smart grids: Electric vehicles for renewable energy integration. *IEEE Power and Energy Society General Meeting*, pages 1–5, 2013.

[GWT$^+$13] Lingwen Gan, Adam Wierman, Ufuk Topcu, Niangjun Chen, and Steven H. Low. Real-time deferrable load control: handling the uncertainties of renewable generation. *Proceedings of the Fourth International Conference on Future Energy Systems (e-Energy '13)*, pages 113–124, 2013.

[GZA10] Matthias D. Galus, Marek Zima, and Göran Andersson. On integration of plug-in hybrid electric vehicles into existing power system structures. *Energy Policy*, 38(11):6736–6745, 2010.

[Hey11] Francis Heylighen. Stigmergy as a generic mechanism for coordination : definition , varieties and aspects. *Cognition*, pages 1–23, 2011.

[Hey15] Francis Heylighen. Stigmergy as a Universal Coordination Mechanism : components , varieties and applications. *Human Stigmergy: Theoretical Developments and New Applications*, pages 1–43, 2015.

[HG03] Francis Heylighen and Carlos Gershenson. The Meaning of Self-organization in Computing, 2003.

[Hil14] Lutz Hillemacher. *Lastmanagement mittels dynamischer Strompreissignale bei Haushaltskunden*. PhD thesis, Karlsruher Institut fur Technologie (KIT), 2014.

[HRJ08] Hongbing Huang, Chuanjun Ren, and Shiyao Jin. "Signs" is the sign: Towards a unified view of stigmergy. In *Proceedings of the 2008 IEEE International Conference on Information and Automation, ICIA 2008*, pages 535–540. IEEE, June 2008.

[HVS11] Christian Hinrichs, Ute Vogel, and Michael Sonnenschein. Approaching Decentralized Demand Side Management via Self-Organizing Agents. *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems*, 2011.

[IA09] Ali Ipakchi and Farrokh Albuyeh. Grid of the future. *IEEE Power and Energy Magazine*, 7(2):52–62, March 2009.

[IEA09] IEA. Key World Energy Statistics 2009. Technical report, International Energy Agency, 2009.

[Jin11] Cheng Jin. Smart Home Networking: Lessons from Combining Wireless and Powerline Networking. *Smart Grid and Renewable Energy*, 02(02):136–151, 2011.

[Joh00] Barbro B. Johansson. Brain Plasticity and Stroke Rehabilitation: The Willis Lecture. *Stroke*, 31(1):223–230, 2000.

[KBD09] Holger Kasinger, Bernhard Bauer, and Jörg Denzinger. Design pattern for self-organizing emergent systems based on digital infochemicals. *Proceedings - 6th IEEE International Conference and Workshop on the Engineering of Autonomic and Autonomous Systems, EASe 2009*, pages 45–55, 2009.

[KML$^+$15] Christian Klabunde, Natalia Moskalenko, Pio Lombardi, Przemyslaw Komarnicki, and Zbigniew Styczynski. Optimal Onshore Wind Power Integration Supported by Local Energy Storages. *Power & Energy Society General Meeting, 2015 IEEE*, pages 1–5, 2015.

[KP11] Johann J. Kranz and Arnold Picot. Toward an End-to-End Smart Grid : Overcoming Bottlenecks to Facilitate Competition and Innovation in Smart Grids. Technical Report June, National Regulatory Research Institute, Munich, 2011.

[LMM02] Andrea Lodi, Silvano Martello, and Michele Monaci. Two-dimensional packing problems: A survey. *European Journal of Operational Research*, 141(2):241–252, 2002.

[MAS12] Marc Multin, Florian Allerding, and Hartmut Schmeck. Integration of electric vehicles in smart homes - an ICT-based solution for V2G scenarios. In *2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*, pages 1–8. IEEE, January 2012.

[MBB$^+$10] Albert Molderink, Vincent Bakker, Maurice G C Bosman, Johann L. Hurink, and Gerard J M Smit. Management and control of domestic smart grid technology. *IEEE Transactions on Smart Grid*, 1(2):109–119, 2010.

[MCA02] Marc Martin, Bastien Chopard, and Paul Albuquerque. Formation of an ant cemetery: Swarm intelligence or statistical accident? *Future Generation Computer Systems*, 18(7):951–959, 2002.

[MCS11] Moez Mnif and ChristianMüller-Schloer. Quantitative Emergence. In Christian Müller-Schloer, Hartmut Schmeck, and Theo Ungerer, editors, *Organic Computing - A Paradigm Shift for Complex Systems*, number July 2006, pages 179–192. Springer Basel, Basel, 2011.

[MFBB12] Francesco Marra, Y. Tarek Fawzy, Thorsten Bulo, and Boštjan Blažič. Energy storage options for voltage support in low-voltage grids with high penetration of photovoltaic. *IEEE PES Innovative Smart Grid Technologies Conference Europe*, pages 1–7, October 2012.

[MMS02] D. Merkle, M. Middendorf, and H. Schmeck. Ant colony optimization for resource-constrained project scheduling. *IEEE Transactions on Evolutionary Computation*, 6(4):333–346, 2002.

[MO08] Leslie Marsh and Christian Onof. Stigmergic epistemology, stigmergic cognition. *Cognitive Systems Research*, 9(1-2):136–149, March 2008.

[MOP14] Felix Müsgens, Axel Ockenfels, and Markus Peek. Economics and design of balancing power markets in Germany. *International Journal of Electrical Power and Energy Systems*, 55:392–401, 2014.

[MRWJ+10] Amir Hamed Mohsenian-Rad, Vincent W S Wong, Juri Jatskevich, Robert Schober, and Alberto Leon-Garcia. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. *IEEE Transactions on Smart Grid*, 1(3):320–331, 2010.

[MSS10] Christian Müller-Schloer and Hartmut Schmeck. Organic Computing: A Grand Challenge for Mastering Complex Systems. *it - Information Technology*, 52(03):135–141, May 2010.

[PB11] H. Parunak and Sven Brueckner. Software Engineering for Self-Organizing Systems. *International Workshop on AgentOriented Software Engineering (AOSE 2011)*, 2011.

[PD11] Peter Palensky and Dietmar Dietrich. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Transactions on Industrial Informatics*, 7(3):381–388, August 2011.

[Pil04] ML Pilat. Wasp-inspired construction algorithms. *Masters coursework (CSPC 607) at the University of Calgary*, pages 1–14, 2004.

[PR09] T Phan and RA Russell. Quantitative information in sematectonic stigmergy for swarm robots. *Australasian Conference on Robotics and Automation*, 2009.

[PR10] Tuan A. Phan and R. Andrew Russell. An effective collaboration algorithm for swarm robots communicating by sematectonic stigmergy. In *2010 11th International Conference on Control Automation Robotics & Vision*, number December, pages 390–397. IEEE, December 2010.

[QH99] V. Quaschning and R. Hanitsch. Lastmanagement einer zukünftigen Energieversorgung. *Bwk*, 1999.

[Ric09] Urban Richter. *Controlled Self-Organisation - Using Learning Classifier Systems*. PhD thesis, Karlsruhe Institut für Technologie, Karlsruhe, 2009.

[RKS16] Fredy H. Rios S., Lukas König, and Hartmut Schmeck. Stigmergy-Based Scheduling of Flexible Loads. In *Proceedings of the 2016 EvoStar Conference*, pages 475–490, Porto, 2016. Springer.

[ROV+07] Alessandro Ricci, Andrea Omicini, Mirko Viroli, Luca Gardelli, and Enrico Oliva. Cognitive Stigmergy: Towards a Framework Based on Agents and Artifacts. *Environments for MultiAgent Systems III*, 4389:124–140, 2007.

[RS07] George Rzevski and Petr Skobelev. Emergent Intelligence in Large Scale Multi-Agent Systems. *International Journal of Education and Information Technologies*, 1(4):64–71, 2007.

[RS15] Fredy Rios and Hartmut Schmeck. An Architecture for a Self-Organized Load Control Mechanism. In *EES 2015 - Multidisciplinary Symposium on Energy, Efficiency and Sustainability*, Berlin, 2015. Kassel University Press.

[RVRJ11] Sarvapali Ramchurn, Perukrishnen Vytelingum, Alex Rogers, and Nick Jennings. Agent-Based Control for Decentralised Demand Side Management in the Smart Grid. *10th Int. Conference on Autonomous Agents and Multiagent Systems, Taipei, Taiwan*, pages 5–12, 2011.

[Sch05] Hartmut Schmeck. Organic computing - A new vision for distributed embedded systems. In *Proceedings - Eighth IEEE International Symposium on Object-Oriented Real-Time Distributed Computing, ISORC 2005*, volume 2005, pages 201–203. IEEE, 2005.

[SD97] F. a. Sharpe and L. M. Dill. The behavior of Pacific herring schools in response to artificial humpback whale bubbles. *Canadian Journal of Zoology*, 75(1982):725–730, 1997.

[SGC+13] Anand Subramanian, Manuel J. Garcia, Duncan S. Callaway, Kameshwar Poolla, and Pravin Varaiya. Real-time scheduling of distributed resources. *IEEE Transactions on Smart Grid*, 4(4):2122–2130, 2013.

[SGDG+12] A Subramanian, M. Garcia, A. Dominguez-Garcia, D. Callaway, K. Poolla, and P. Varaiya. Real-time scheduling of deferrable electric loads. *American Control Conference (ACC)*, pages 3643–3650, 2012.

[She01] Onn Shehory. Software architecture attributes of multi-agent systems. *Agent-Oriented Software Engineering*, pages 77–90, 2001.

[Sim97] Tiu Similä. Sonar observations of killer whales (Orcinus orca) feeding on herring schools. *Aquatic Mammals*, 23(3):119–126, 1997.

[SLIP+12] Thomas Stutzle, Manuel Lopez-Ibanez, Paola Pellegrini, Michael Maur, Marco Montes de Oca, Mauro Birattari, and Marco Dorigo. Parameter Adaptation in Ant Colony Optimization. *Autonomous Search*, pages 191–215, 2012.

[SMCO15] Andre Silva, Joao Marinheiro, Henrique Lopes Cardoso, and Eugenio Oliveira. Demand-Side Management in Power Grids: An Ant Colony Optimization Approach. In *2015 IEEE 18th International Conference on Computational Science and Engineering*, pages 300–306, 2015.

[Smi78] Andrew P. Smith. An investigation of the mechanisms underlying nest construction in the mud wasp Paralastor sp. (Hymenoptera: Eumenidae). *Animal Behaviour*, 26:232–240, 1978.

[SMSc$^+$10] Hartmut Schmeck, Christian Müller-Schloer, Emre Çakar, Moez Mnif, and Urban Richter. Adaptivity and self-organization in organic computing systems. *ACM Transactions on Autonomous and Adaptive Systems*, 5(3):1–32, September 2010.

[SMSc$^+$11] Hartmut Schmeck, Christian Müller-Schloer, Emre Çakar, Moez Mnif, and Urban Richter. Adaptivity and Self-organisation in Organic Computing Systems. *Organic Computing - A Paradigm Shift for Complex Systems*, 5:179–192, 2011.

[SPB$^+$11] Sven Tomforde, Holger Prothmann, Jürgen Branke, Jörg Hähner, Moez Mnif, Christian Müller-Schloer, Urban Richter, and Hartmut Schmeck. Observation and Control of Organic Systems. In Christian Müller-Schloer, Hartmut Schmeck, and Theo Ungerer, editors, *Organic Computing A Paradigm Shift for Complex Systems*, pages 179–192. Springer Basel, Basel, 2011.

[ST07] Fitzgerald Steele and Geb Thomas. Directed stigmergy-based control for multi-robot systems. In *Proceeding of the ACM/IEEE international conference on Human-robot interaction - HRI '07*, page 223. ACM Press, 2007.

[Sta08] Rainer Stamminger. Synergy Potential of Smart Appliances D2.3. Technical Report 3, University of Bonn, Bonn, 2008.

[Str08] Goran Strbac. Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426, December 2008.

[SYH12] Merwais Shinwari, Amr Youssef, and Walaa Hamouda. A water-filling based scheduling algorithm for the smart grid. *IEEE Transactions on Smart Grid*, 3(2):710–719, 2012.

[TAMU14] Mosaddek Hossain Kamal Tushar, Chadi Assi, Martin Maier, and Mohammad Faisal Uddin. Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances. *IEEE Transactions on Smart Grid*, 5(1):239–250, 2014.

[TB99] Guy Theraulaz and Eric Bonabeau. A brief history of stigmergy. *Artificial life*, 5(2):97–116, April 1999.

[TBN+02] Guy Theraulaz, Eric Bonabeau, Stamatios C Nicolis, Ricard V Solé, Vincent Fourcassié, Stéphane Blanco, Richard Fournier, Jean-Louis Joly, Pau Fernández, Anne Grimal, Patrice Dalle, and Jean-Louis Deneubourg. Spatial patterns in ant colonies. *Proceedings of the National Academy of Sciences of the United States of America*, 99(15):9645–9649, 2002.

[TCR+05] Luca Tummolini, Cristiano Castelfranchi, Alessandro Ricci, Mirko Viroli, and Andrea Omicini. Exhibitionists and Voyeurs do it better: A Shared Environment Approach for Flexible Coordination with Tacit Messages. *Environments for Multi-Agent Systems. First International Workshop, E4MAS 2004, New York, NY, July 19, 2004, Revised Selected Papers*, 3374:215–231, 2005.

[THLW13] Shaojie Tang, Qiuyuan Huang, Xiang Yang Li, and Dapeng Wu. Smoothing the energy consumption: Peak demand reduction in smart grid. *Proceedings - IEEE INFOCOM*, pages 1133–1141, 2013.

[USD+13] Mathias Uslar, Michael Specht, Christian Dänekas, Jörn Trefke, Sebastian Rohjans, José M. González, Christine Rosinger, and Robert Bleiker. *Standardization in Smart Grids: Introduction to IT-Related Methodologies, Architectures and Standards*, volume 71. Springer-Verlag Berlin Heidelberg, Oldenburg, 2013.

[Van06] H. Van Dyke Parunak. A Survey of Environments and Mechanisms for Human-Human Stigmergy. In *Proc. of the 2nd Int'l Conf. on Environments for Multi-Agent Systems II (E4MAS '05)*, volume 3830, pages 163–186, 2006.

[VB11] S Vandael and Nelis Boucké. Decentralized coordination of plug-in hybrid vehicles for imbalance reduction in a Smart Grid. *10th Int. Conf. on Autonomous Agents and Multiagent Systems Innovative Applications Track*, (section 3):803–810, 2011.

[VGVV07] Paul Valckenaers, Bart Saint Germain, Paul Verstraete, and Hendrik Van Brussel. MAS coordination and control based on stigmergy. *Computers in Industry*, 58(7):621–629, September 2007.

[VKV04] Paul Valckenaers, Martin Kollingbaum, and Hendrik Van Brussel. Multi-agent coordination and control using stigmergy. *Computers in Industry*, 53(1):75–96, January 2004.

[vLM13] Matej Črepinšek, Shih-Hsi Liu, and Marjan Mernik. Exploration and Exploitation in Evolutionary Algorithms. *ACM Computing Surveys*, 45(3):1–33, 2013.

[VST13] Menkes Van Den Briel, Paul Scott, and Sylvie Thiébaux. Randomized load control: A simple distributed approach for scheduling smart appliances. *IJCAI International Joint Conference on Artificial Intelligence*, pages 2915–2922, 2013.

[WM07] H. Van Dyke Weyns, DannyParunak and Fabien Michel. *Environments for Multi-Agent Systems III*, volume 4389. Springer-Verlag Berlin Heidelberg, 2007.

[WM15] Danny Weyns and Fabien Michel. *Agent Environments for Multi-Agent Systems IV*, volume 9068. Springer International Publishing, 2015.

[WN06] Justin Werfel and Radhika Nagpal. Extended stigmergy in collective construction, 2006.

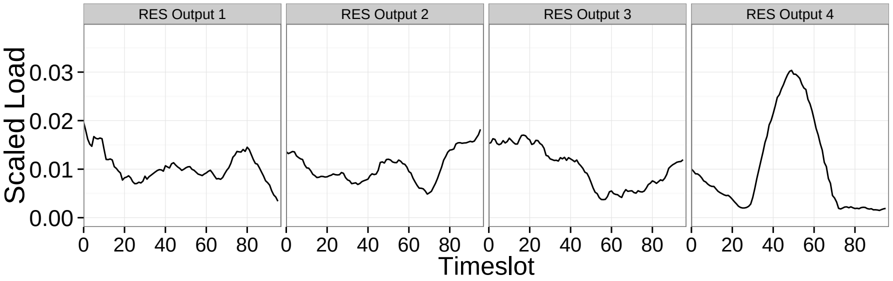
[Wol83] Stephen Wolfram. Statistical mechanics of cellular automata. *Reviews of Modern Physics*, 55(3):601–644, 1983.

[XCL$^+$10] Jin Xiao, Jae Yoon Chung, Jian Li, Raouf Boutaba, and James Won Ki Hong. Near optimal demand-side energy management under real-time demand-response pricing. *Proceedings of the 2010 International Conference on Network and Service Management, CNSM 2010*, pages 527–532, 2010.

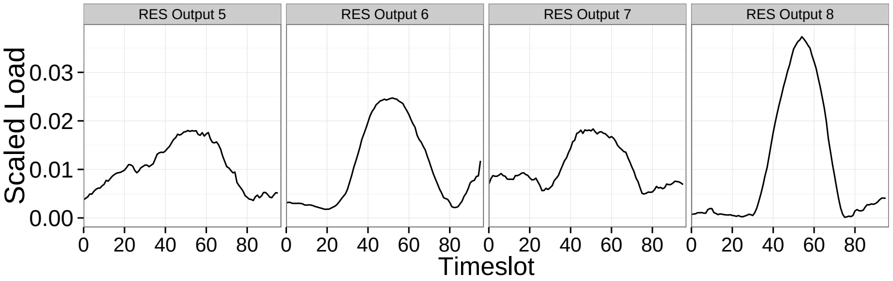
A. Load Profiles and RES Outputs

Table A.1.: Load profiles of a washing machine (WaMa), dryer, dishwasher (DiWa - [Sta08]) and electric vehicle (EV). EVs are only only power constraint, therefore, their profile can be separated into different timeslots.

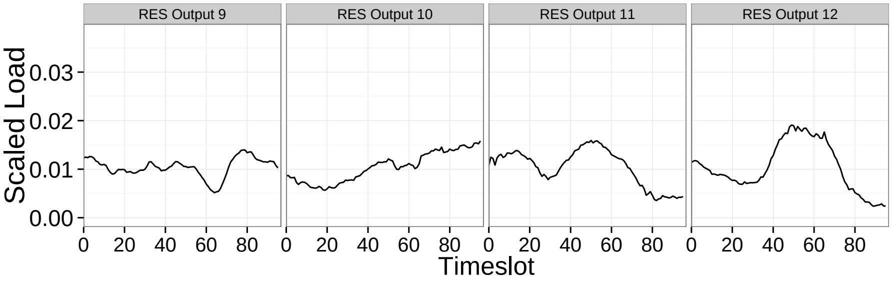
Device	**Load [kW]**						
DiWa	2.0	0.125	0.125	0.125	2.0	0.3	0.15
WaMa	0.1	2.0	0.9	0.1	0.1	0.3	0.05
Dryer	2.0	2.0	2.0	1.6	1.0	0.6	0.6
EV	3.7	3.7	3.7	3.7	3.7	0.67	



(a) RES outputs 1 to 4.



(b) RES outputs 5 to 8.



(c) RES outputs 9 to 12.

Figure A.1.: RES outputs utilized for experimentation.

B. Assessment of Normality

B.1. Normality Test for Real-Time Optimization

Table B.1.: One-sample Kolmogorov-Smirnov normality test for the performance data with different population sizes and different α values for each RES output. Forecast categories are grouped in the samples.

RES Output	**Test Results**	40 **Households** α **Value**					400 **Households** α **Value**					$4,000$ **Households** α **Value**					$40,000$ **Households** α **Value**				
		1.0	**0.5**	**0.1**	**0.05**	**0.01**	**1.0**	**0.5**	**0.1**	**0.05**	**0.01**	**1.0**	**0.5**	**0.1**	**0.05**	**0.01**	**1.0**	**0.5**	**0.1**	**0.05**	**0.01**
1	Statistic	0.5694	0.5718	0.5705	0.5714	0.5735	0.5321	0.5301	0.5317	0.5330	0.5378	0.5273	0.5265	0.5254	0.5286	0.5324	0.5296	0.5276	0.5252	0.5289	0.5334
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
2	Statistic	0.5789	0.5761	0.5754	0.5728	0.5769	0.5479	0.5470	0.5423	0.5469	0.5504	0.5477	0.5439	0.5430	0.5472	0.5511	0.5492	0.5459	0.5444	0.5475	0.5524
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
3	Statistic	0.5819	0.5802	0.5819	0.5836	0.5817	0.5575	0.5574	0.5547	0.5590	0.5580	0.5655	0.5625	0.5591	0.5588	0.5587	0.5658	0.5656	0.5627	0.5598	0.5603
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5815	0.5846	0.5784	0.5769	0.5803	0.5796	0.5736	0.5701	0.5639	0.5689	0.5866	0.5812	0.5762	0.5753	0.5751	0.5887	0.5845	0.5773	0.5772	0.5778
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
5	Statistic	0.5708	0.5665	0.5628	0.5710	0.5658	0.5323	0.5319	0.5275	0.5290	0.5328	0.5298	0.5275	0.5219	0.5256	0.5294	0.5303	0.5282	0.5238	0.5253	0.5306
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
6	Statistic	0.5863	0.5816	0.5764	0.5724	0.5807	0.5725	0.5641	0.5596	0.5576	0.5619	0.5751	0.5711	0.5616	0.5599	0.5656	0.5770	0.5736	0.5633	0.5629	0.5675
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5652	0.5685	0.5674	0.5683	0.5678	0.5366	0.5323	0.5294	0.5304	0.5329	0.5304	0.5267	0.5216	0.5245	0.5289	0.5312	0.5274	0.5214	0.5246	0.5291
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
8	Statistic	0.6082	0.5997	0.5930	0.5947	0.5901	0.6103	0.6022	0.5926	0.5920	0.5939	0.6177	0.6143	0.6055	0.6010	0.6021	0.6207	0.6172	0.6062	0.6032	0.6044
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	0.5743	0.5749	0.5653	0.5715	0.5717	0.5393	0.5356	0.5329	0.5379	0.5396	0.5376	0.5320	0.5287	0.5324	0.5381	0.5372	0.5319	0.5294	0.5335	0.5389
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5751	0.5760	0.5731	0.5760	0.5802	0.5480	0.5510	0.5486	0.5504	0.5554	0.5496	0.5503	0.5510	0.5536	0.5561	0.5527	0.5520	0.5512	0.5543	0.5580
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
11	Statistic	0.5689	0.5666	0.5651	0.5679	0.5681	0.5336	0.5319	0.5308	0.5307	0.5322	0.5284	0.5274	0.5261	0.5259	0.5282	0.5300	0.5297	0.5272	0.5271	0.5312
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
12	Statistic	0.5695	0.5664	0.5667	0.5682	0.5667	0.5350	0.5354	0.5278	0.5284	0.5322	0.5305	0.5298	0.5222	0.5245	0.5273	0.5313	0.5310	0.5209	0.5237	0.5299
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.2.: One-sample Kolmogorov-Smirnov normality test for the performance data with different forecast qualities and α values in each RES output. The simulated micro-grid has a population of 40 households.

RES Output	**Test Results**	**0.01 Forecast Quality**			**0.05 Forecast Quality**			**0.1 Forecast Quality**			**0.5 Forecast Quality**			**1.0 Forecast Quality**		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
1	Statistic	0.5737	0.5740	0.5735	0.5730	0.5731	0.5714	0.5722	0.5722	0.5705	0.5723	0.5747	0.5718	0.5710	0.5744	0.5694
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
2	Statistic	0.5816	0.5819	0.5769	0.5728	0.5750	0.5762	0.5754	0.5792	0.5798	0.5762	0.5783	0.5761	0.5828	0.5789	0.5795
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
3	Statistic	0.5837	0.5882	0.5817	0.5836	0.5848	0.5891	0.5819	0.5819	0.5832	0.5838	0.5810	0.5802	0.5895	0.5880	0.5819
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
4	Statistic	0.5829	0.5803	0.5843	0.5803	0.5839	0.5714	0.5825	0.5784	0.5838	0.5866	0.5846	0.5856	0.5815	0.5843	0.5925
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
5	Statistic	0.5658	0.5734	0.5638	0.5715	0.5711	0.5710	0.5661	0.5687	0.5618	0.5718	0.5665	0.5671	0.5717	0.5708	0.5712
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
6	Statistic	0.5840	0.5757	0.5870	0.5799	0.5728	0.5757	0.5867	0.5803	0.5712	0.5865	0.5907	0.5808	0.5924	0.5941	0.5863
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
7	Statistic	0.5741	0.5728	0.5678	0.5722	0.5712	0.5683	0.5702	0.5682	0.5674	0.5685	0.5763	0.5705	0.5605	0.5685	0.5698
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
8	Statistic	0.5847	0.5954	0.5934	0.5947	0.5981	0.5997	0.5981	0.5963	0.6005	0.5997	0.6060	0.6026	0.6257	0.6015	0.6178
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
9	Statistic	0.5742	0.5791	0.5717	0.5715	0.5749	0.5742	0.5708	0.5617	0.5713	0.5750	0.5771	0.5749	0.5745	0.5780	0.5743
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
10	Statistic	0.5802	0.5844	0.5823	0.5760	0.5777	0.5760	0.5731	0.5831	0.5771	0.5773	0.5760	0.5796	0.5785	0.5751	0.5758
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
11	Statistic	0.5705	0.5748	0.5681	0.5739	0.5688	0.5679	0.5771	0.5651	0.5710	0.5666	0.5687	0.5691	0.5691	0.5693	0.5689
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
12	Statistic	0.5667	0.5718	0.5674	0.5759	0.5749	0.5682	0.5723	0.5667	0.5689	0.5762	0.5673	0.5664	0.5695	0.5720	0.5739
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$

Table B.3.: One-sample Kolmogorov-Smirnov normality test for the performance data with different forecast qualities and α values in each RES output. The simulated micro-grid has a population of 400 households.

RES Output	**Test Results**	**0.01**			**0.05**			**0.1**			**0.5**			**1.0**		
			Forecast Quality			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**	
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
1	Statistic	0.5378	0.5409	0.5388	0.5345	0.5330	0.5360	0.5331	0.5317	0.5335	0.5312	0.5301	0.5342	0.5366	0.5321	0.5323
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
2	Statistic	0.5529	0.5504	0.5568	0.5495	0.5469	0.5469	0.5428	0.5444	0.5423	0.5470	0.5493	0.5497	0.5489	0.5515	0.5479
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
3	Statistic	0.5580	0.5657	0.5581	0.5590	0.5610	0.5596	0.5573	0.5602	0.5547	0.5639	0.5574	0.5603	0.5575	0.5607	0.5621
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
4	Statistic	0.5650	0.5764	0.5722	0.5731	0.5733	0.5635	0.5736	0.5701	0.5754	0.5787	0.5735	0.5770	0.5806	0.5800	0.5796
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
5	Statistic	0.5352	0.5328	0.5347	0.5334	0.5290	0.5313	0.5335	0.5275	0.5304	0.5319	0.5340	0.5329	0.5361	0.5323	0.5338
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
6	Statistic	0.5744	0.5597	0.5653	0.5702	0.5599	0.5576	0.5654	0.5596	0.5636	0.5617	0.5690	0.5674	0.5731	0.5732	0.5725
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
7	Statistic	0.5347	0.5329	0.5366	0.5323	0.5332	0.5304	0.5294	0.5301	0.5306	0.5323	0.5355	0.5343	0.5366	0.5381	0.5376
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
8	Statistic	0.5970	0.5939	0.5963	0.5990	0.5895	0.5987	0.5993	0.5979	0.5923	0.6082	0.6055	0.6023	0.6103	0.6148	0.6114
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
9	Statistic	0.5388	0.5429	0.5431	0.5379	0.5414	0.5379	0.5329	0.5357	0.5347	0.5344	0.5411	0.5395	0.5393	0.5410	0.5406
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
10	Statistic	0.5555	0.5554	0.5594	0.5504	0.5538	0.5536	0.5496	0.5486	0.5547	0.5510	0.5524	0.5535	0.5488	0.5496	0.5480
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
11	Statistic	0.5376	0.5322	0.5327	0.5356	0.5307	0.5312	0.5337	0.5319	0.5308	0.5322	0.5324	0.5319	0.5353	0.5336	0.5346
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
12	Statistic	0.5322	0.5371	0.5324	0.5329	0.5316	0.5284	0.5342	0.5299	0.5278	0.5354	0.5357	0.5361	0.5367	0.5364	0.5350
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$

Table B.4.: One-sample Kolmogorov-Smirnov normality test for the performance data with different forecast qualities and α values in each RES output. The simulated micro-grid has a population of $4,000$ households.

RES Output	**Test Results**		**0.01**			**0.05**			**0.1**			**0.5**			**1.0**	
			Forecast Quality			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**	
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
1	Statistic	0.5349	0.5324	0.5343	0.5314	0.5286	0.5300	0.5288	0.5254	0.5278	0.5290	0.5265	0.5283	0.5288	0.5273	0.5307
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
2	Statistic	0.5570	0.5511	0.5546	0.5484	0.5472	0.5475	0.5439	0.5431	0.5430	0.5439	0.5499	0.5487	0.5477	0.5517	0.5495
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
3	Statistic	0.5619	0.5639	0.5587	0.5595	0.5608	0.5588	0.5591	0.5612	0.5618	0.5625	0.5644	0.5628	0.5656	0.5679	0.5655
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
4	Statistic	0.5751	0.5827	0.5797	0.5753	0.5780	0.5774	0.5781	0.5766	0.5762	0.5812	0.5832	0.5849	0.5866	0.5874	0.5870
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
5	Statistic	0.5351	0.5314	0.5294	0.5332	0.5256	0.5265	0.5309	0.5228	0.5219	0.5275	0.5296	0.5283	0.5301	0.5298	0.5313
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
6	Statistic	0.5775	0.5656	0.5755	0.5673	0.5599	0.5646	0.5685	0.5616	0.5639	0.5711	0.5727	0.5761	0.5751	0.5787	0.5781
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
7	Statistic	0.5289	0.5299	0.5304	0.5245	0.5265	0.5245	0.5216	0.5235	0.5235	0.5270	0.5267	0.5290	0.5309	0.5304	0.5330
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
8	Statistic	0.6021	0.6072	0.6085	0.6010	0.6036	0.6037	0.6061	0.6055	0.6056	0.6149	0.6143	0.6150	0.6180	0.6177	0.6177
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
9	Statistic	0.5393	0.5397	0.5381	0.5324	0.5347	0.5327	0.5300	0.5311	0.5287	0.5320	0.5377	0.5361	0.5381	0.5397	0.5376
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
10	Statistic	0.5561	0.5575	0.5580	0.5540	0.5536	0.5566	0.5510	0.5526	0.5513	0.5516	0.5503	0.5536	0.5496	0.5503	0.5529
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
11	Statistic	0.5336	0.5282	0.5300	0.5307	0.5259	0.5260	0.5279	0.5261	0.5262	0.5300	0.5274	0.5293	0.5305	0.5284	0.5298
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
12	Statistic	0.5311	0.5320	0.5273	0.5264	0.5257	0.5245	0.5300	0.5240	0.5222	0.5298	0.5310	0.5310	0.5305	0.5326	0.5324
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$

Table B.5.: One-sample Kolmogorov-Smirnov normality test for the performance data with different forecast qualities and α values in each RES output. The simulated micro-grid has a population of $40,000$ households.

RES Output	**Test Results**	**0.01**			**0.05**			**0.1**			**0.5**			**1.0**		
		Forecast Quality			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**			**Forecast Quality**		
		Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**		**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
1	Statistic	0.5352	0.5334	0.5349	0.5315	0.5289	0.5316	0.5280	0.5252	0.5276	0.5284	0.5276	0.5285	0.5296	0.5314	0.5301
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
2	Statistic	0.5568	0.5524	0.5559	0.5496	0.5482	0.5475	0.5456	0.5445	0.5444	0.5459	0.5495	0.5511	0.5492	0.5533	0.5504
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
3	Statistic	0.5614	0.5682	0.5603	0.5598	0.5637	0.5599	0.5631	0.5627	0.5633	0.5656	0.5660	0.5660	0.5658	0.5687	0.5678
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
4	Statistic	0.5778	0.5850	0.5818	0.5772	0.5800	0.5795	0.5798	0.5773	0.5792	0.5845	0.5858	0.5853	0.5894	0.5887	0.5890
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
5	Statistic	0.5368	0.5345	0.5306	0.5341	0.5253	0.5259	0.5310	0.5238	0.5241	0.5282	0.5295	0.5302	0.5310	0.5303	0.5327
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
6	Statistic	0.5789	0.5675	0.5766	0.5691	0.5629	0.5674	0.5715	0.5633	0.5658	0.5736	0.5761	0.5769	0.5770	0.5791	0.5787
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
7	Statistic	0.5291	0.5314	0.5305	0.5246	0.5275	0.5265	0.5214	0.5247	0.5230	0.5274	0.5295	0.5302	0.5315	0.5312	0.5322
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
8	Statistic	0.6044	0.6082	0.6098	0.6032	0.6054	0.6052	0.6062	0.6068	0.6082	0.6172	0.6172	0.6173	0.6207	0.6216	0.6207
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
9	Statistic	0.5399	0.5399	0.5389	0.5344	0.5367	0.5335	0.5306	0.5306	0.5294	0.5319	0.5385	0.5370	0.5372	0.5392	0.5381
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
10	Statistic	0.5580	0.5598	0.5615	0.5543	0.5554	0.5582	0.5512	0.5542	0.5535	0.5526	0.5520	0.5541	0.5527	0.5529	0.5553
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
11	Statistic	0.5344	0.5314	0.5312	0.5321	0.5271	0.5275	0.5292	0.5274	0.5272	0.5307	0.5297	0.5297	0.5308	0.5300	0.5301
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
12	Statistic	0.5313	0.5334	0.5299	0.5283	0.5271	0.5237	0.5302	0.5247	0.5209	0.5312	0.5310	0.5311	0.5313	0.5340	0.5319
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$

Table B.6.: One-sample Kolmogorov-Smirnov normality test for the performance data of NLC and CLP with different population sizes for each RES output. Forecast categories are grouped in the samples.

NLC

RES Output	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**	**RES Output**	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**	**RES Output**	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**
1	Statistic	0.5700	0.5464	0.5507	0.5540	2	Statistic	0.5856	0.5687	0.5759	0.5801	3	Statistic	0.5916	0.5797	0.5883	0.5923
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.6166	0.6348	0.6432	0.6465	5	Statistic	0.5672	0.5539	0.5626	0.5660	6	Statistic	0.6144	0.6220	0.6324	0.6344
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5799	0.5625	0.5711	0.5746	8	Statistic	0.6668	0.6809	0.6914	0.6940	9	Statistic	0.5779	0.5513	0.5502	0.5537
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5737	0.5605	0.5621	0.5645	11	Statistic	0.5730	0.5501	0.5546	0.5575	12	Statistic	0.5750	0.5643	0.5690	0.5733
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$

CLP

RES Output	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**	**RES Output**	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**	**RES Output**	**Test Results**	40 **Households**	400 **Households**	$4,000$ **Households**	$40,000$ **Households**
1	Statistic	0.5291	0.5095	0.5091	0.5095	2	Statistic	0.5313	0.5157	0.5221	0.5248	3	Statistic	0.5324	0.5274	0.5414	0.5466
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5320	0.5212	0.5286	0.5304	5	Statistic	0.5259	0.5062	0.5060	0.5062	6	Statistic	0.5340	0.5366	0.5449	0.5490
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5279	0.5070	0.5066	0.5068	8	Statistic	0.5591	0.5723	0.5827	0.5862	9	Statistic	0.5271	0.5102	0.5100	0.5103
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5332	0.5220	0.5330	0.5358	11	Statistic	0.5291	0.5080	0.5080	0.5083	12	Statistic	0.5284	0.5066	0.5062	0.5062
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.7.: One-sample Kolmogorov-Smirnov normality test for the performance data of NLC and CLP under different forecast categories. The micro-grid population size is 40.

NLC

RES Output	Test Results	Low	Medium	High	RES Output	Test Results	Low	Medium	High	RES Output	Test Results	Low	Medium	High
1	Statistic	0.5732	0.5700	0.5767	2	Statistic	0.5865	0.5915	0.5856	3	Statistic	0.5949	0.5850	0.5978
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.6143	0.6266	0.6198	5	Statistic	0.5705	0.5714	0.5713	6	Statistic	0.6177	0.6200	0.6111
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5859	0.5833	0.5791	8	Statistic	0.6729	0.6601	0.6704	9	Statistic	0.5779	0.5838	0.5789
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5795	0.5770	0.5783	11	Statistic	0.5774	0.5763	0.5726	12	Statistic	0.5825	0.5708	0.5888
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

CLP

RES Output	Test Results	Low	Medium	High	RES Output	Test Results	Low	Medium	High	RES Output	Test Results	Low	Medium	High
1	Statistic	0.5291	0.5294	0.5291	2	Statistic	0.5330	0.5313	0.5327	3	Statistic	0.5324	0.5336	0.5372
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5353	0.5359	0.5313	5	Statistic	0.5313	0.5301	0.5259	6	Statistic	0.5346	0.5367	0.5340
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5297	0.5279	0.5290	8	Statistic	0.5591	0.5594	0.5592	9	Statistic	0.5289	0.5285	0.5271
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5370	0.5332	0.5347	11	Statistic	0.5339	0.5303	0.5291	12	Statistic	0.5303	0.5284	0.5295
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.8.: One-sample Kolmogorov-Smirnov normality test for the performance data of NLC and CLP under different forecast categories. The micro-grid population size is 400.

NLC

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5502	0.5472	0.5464	2	Statistic	0.5687	0.5711	0.5755	3	Statistic	0.5826	0.5797	0.5861
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.6362	0.6348	0.6366	5	Statistic	0.5572	0.5512	0.5602	6	Statistic	0.6247	0.6220	0.6233
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5625	0.5653	0.5636	8	Statistic	0.6809	0.6818	0.6845	9	Statistic	0.5517	0.5513	0.5541
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5622	0.5627	0.5605	11	Statistic	0.5542	0.5501	0.5527	12	Statistic	0.5667	0.5643	0.5654
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

CLP

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5096	0.5097	0.5095	2	Statistic	0.5191	0.5157	0.5177	3	Statistic	0.5237	0.5364	0.5307
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5212	0.5216	0.5220	5	Statistic	0.5185	0.5139	0.5062	6	Statistic	0.5434	0.5404	0.5366
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5075	0.5076	0.5070	8	Statistic	0.5761	0.5723	0.5725	9	Statistic	0.5121	0.5108	0.5102
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5220	0.5256	0.5220	11	Statistic	0.5230	0.5156	0.5080	12	Statistic	0.5237	0.5121	0.5066
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.9.: One-sample Kolmogorov-Smirnov normality test for the performance data of NLC and CLP under different forecast categories. The micro-grid population size is $4,000$.

NLC

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5508	0.5509	0.5507	2	Statistic	0.5770	0.5759	0.5775	3	Statistic	0.5903	0.5883	0.5906
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.6432	0.6449	0.6439	5	Statistic	0.5642	0.5626	0.5646	6	Statistic	0.6326	0.6329	0.6324
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5712	0.5713	0.5711	8	Statistic	0.6919	0.6917	0.6914	9	Statistic	0.5525	0.5519	0.5502
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5626	0.5621	0.5625	11	Statistic	0.5546	0.5553	0.5552	12	Statistic	0.5705	0.5690	0.5711
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

CLP

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5091	0.5094	0.5111	2	Statistic	0.5247	0.5243	0.5221	3	Statistic	0.5438	0.5414	0.5444
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5289	0.5297	0.5286	5	Statistic	0.5220	0.5139	0.5060	6	Statistic	0.5471	0.5477	0.5449
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5066	0.5070	0.5069	8	Statistic	0.5835	0.5838	0.5827	9	Statistic	0.5105	0.5100	0.5119
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5332	0.5330	0.5344	11	Statistic	0.5240	0.5148	0.5080	12	Statistic	0.5273	0.5113	0.5062
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.10.: One-sample Kolmogorov-Smirnov normality test for the performance data of NLC and CLP under different forecast categories. The micro-grid population size is $40,000$.

NLC

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5545	0.5543	0.5540	2	Statistic	0.5804	0.5804	0.5801	3	Statistic	0.5924	0.5928	0.5923
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.6465	0.6469	0.6471	5	Statistic	0.5661	0.5663	0.5660	6	Statistic	0.6344	0.6352	0.6354
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5746	0.5749	0.5749	8	Statistic	0.6943	0.6940	0.6943	9	Statistic	0.5537	0.5539	0.5541
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5652	0.5650	0.5645	11	Statistic	0.5583	0.5575	0.5588	12	Statistic	0.5733	0.5736	0.5739
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

CLP

RES Output	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**	**RES Output**	**Test Results**	**Low**	**Medium**	**High**
1	Statistic	0.5095	0.5100	0.5118	2	Statistic	0.5252	0.5253	0.5248	3	Statistic	0.5470	0.5466	0.5472
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	0.5304	0.5314	0.5307	5	Statistic	0.5231	0.5143	0.5062	6	Statistic	0.5503	0.5501	0.5490
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5068	0.5076	0.5068	8	Statistic	0.5865	0.5862	0.5864	9	Statistic	0.5120	0.5103	0.5125
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	0.5360	0.5358	0.5370	11	Statistic	0.5248	0.5154	0.5083	12	Statistic	0.5283	0.5118	0.5062
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table B.11.: One-sample Kolmogorov-Smirnov normality test for performance of SLC, NLC and CLP under different load coverage and load flexibility. Population size is $4,000$ and forecasts are grouped in the samples.

SLC

RES Output	**Test Results**	**50% Coverage**				**75% Coverage**				**RES Output**	**Test Results**	**50% Coverage**				**75% Coverage**			
		10% Flex.	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**			**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**
1	Statistic	0.5207	0.5058	0.5041	0.5040	0.5527	0.5384	0.5259	0.5155	2	Statistic	0.5071	0.5039	0.5049	0.5057	0.5430	0.5317	0.5220	0.5171
	p-value	$1.9e-13$	$1.1e-12$	$1.4e-12$	$1.4e-12$	$3.4e-15$	$2.2e-14$	$1.0e-13$	$3.6e-13$		p-value	$9.7e-13$	$1.4e-12$	$8.5e-12$	$7.9e-12$	$1.2e-14$	$5.1e-14$	$1.7e-13$	$3.0e-13$
3	Statistic	0.5504	0.5314	0.5166	0.5065	0.5895	0.5772	0.5670	0.5565	4	Statistic	0.5099	0.5017	0.5000	0.5001	0.5847	0.5717	0.5615	0.5506
	p-value	$4.7e-15$	$5.2e-14$	$3.2e-13$	$1.0e-12$	$2.2e-16$	$2.2e-16$	$5.6e-16$	$2.1e-15$		p-value	$7.0e-13$	$1.8e-12$	$2.2e-12$	$2.2e-12$	$2.2e-16$	$2.2e-16$	$1.1e-15$	$4.6e-15$
5	Statistic	0.5000	0.5000	0.5000	0.5000	0.5209	0.5074	0.5003	0.5000	6	Statistic	0.5000	0.5004	0.5010	0.5017	0.5646	0.5542	0.5432	0.5321
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.9e-13$	$9.4e-13$	$2.1e-12$	$1.4e-11$		p-value	$1.4e-11$	$1.3e-11$	$1.3e-11$	$1.2e-11$	$6.7e-16$	$2.9e-15$	$1.2e-14$	$4.8e-14$
7	Statistic	0.5000	0.5000	0.5000	0.5000	0.5215	0.5069	0.5012	0.5010	8	Statistic	0.5562	0.5380	0.5221	0.5108	0.6364	0.6216	0.6057	0.5911
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.8e-13$	$9.9e-13$	$1.9e-12$	$2.0e-12$		p-value	$2.2e-15$	$2.3e-14$	$1.6e-13$	$6.3e-13$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	0.5025	0.5003	0.5011	0.5021	0.5350	0.5239	0.5131	0.5090	10	Statistic	0.5012	0.5020	0.5026	0.5033	0.5081	0.5076	0.5079	0.5081
	p-value	$1.6e-12$	$2.1e-12$	$1.2e-11$	$1.7e-12$	$3.3e-14$	$1.3e-13$	$4.8e-13$	$7.8e-13$		p-value	$1.2e-11$	$1.1e-11$	$1.1e-11$	$1.0e-11$	$8.6e-13$	$9.1e-13$	$8.8e-13$	$8.6e-13$
11	Statistic	0.5183	0.5037	0.5002	0.5004	0.5521	0.5400	0.5288	0.5180	12	Statistic	0.5000	0.5001	0.5003	0.5005	0.5350	0.5167	0.5052	0.5028
	p-value	$2.6e-13$	$1.4e-12$	$2.1e-12$	$2.1e-12$	$3.8e-15$	$1.8e-14$	$7.2e-14$	$2.7e-13$		p-value	$1.4e-11$	$2.2e-12$	$1.3e-11$	$1.3e-11$	$3.3e-14$	$3.1e-13$	$1.2e-12$	$1.6e-12$

CLP

RES Output	**Test Results**	**50% Coverage**				**75% Coverage**				**RES Output**	**Test Results**	**50% Coverage**				**75% Coverage**			
		10% Flex.	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**			**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**
1	Statistic	0.5141	0.5033	0.5037	0.5039	0.5499	0.5344	0.5196	0.5063	2	Statistic	0.5027	0.5038	0.5048	0.5057	0.5350	0.5188	0.5082	0.5081
	p-value	$4.3e-13$	$1.5e-12$	$9.6e-12$	$9.4e-12$	$5.0e-15$	$3.6e-14$	$2.2e-13$	$1.1e-12$		p-value	$1.6e-12$	$9.5e-12$	$1.3e-12$	$7.8e-12$	$3.3e-14$	$2.4e-13$	$8.5e-13$	$6.2e-12$
3	Statistic	0.5442	0.5212	0.5035	0.5040	0.5847	0.5704	0.5568	0.5454	4	Statistic	0.5000	0.5000	0.5000	0.5001	0.5742	0.5544	0.5369	0.5198
	p-value	$1.0e-14$	$1.8e-13$	$1.5e-12$	$1.4e-12$	$2.2e-16$	$3.3e-16$	$2.0e-15$	$8.9e-15$		p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$2.2e-16$	$2.8e-15$	$2.6e-14$	$2.1e-13$
5	Statistic	0.5000	0.5000	0.5000	0.5000	0.5091	0.5004	0.5001	0.5000	6	Statistic	0.5000	0.5004	0.5010	0.5017	0.5529	0.5326	0.5186	0.5089
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$7.7e-13$	$2.1e-12$	$2.2e-12$	$1.4e-11$		p-value	$1.4e-11$	$1.3e-11$	$1.3e-11$	$1.2e-11$	$3.3e-15$	$4.5e-14$	$2.5e-13$	$7.9e-13$
7	Statistic	0.5000	0.5000	0.5000	0.5000	0.5088	0.5000	0.5003	0.5008	8	Statistic	0.5346	0.5006	0.5000	0.5000	0.6282	0.6060	0.5857	0.5677
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$7.9e-13$	$1.4e-11$	$1.3e-11$	$1.3e-11$		p-value	$3.5e-14$	$2.0e-12$	$1.4e-11$	$1.4e-11$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$4.4e-16$
9	Statistic	0.5000	0.5004	0.5012	0.5021	0.5302	0.5153	0.5041	0.5044	10	Statistic	0.5012	0.5020	0.5026	0.5033	0.5046	0.5040	0.5045	0.5051
	p-value	$2.2e-12$	$1.3e-11$	$1.2e-11$	$1.7e-12$	$6.1e-14$	$3.7e-13$	$1.4e-12$	$8.9e-12$		p-value	$1.2e-11$	$1.1e-11$	$1.1e-11$	$1.0e-11$	$1.3e-12$	$1.4e-12$	$8.8e-12$	$1.2e-12$
11	Statistic	0.5113	0.5000	0.5000	0.5003	0.5480	0.5330	0.5185	0.5065	12	Statistic	0.5000	0.5000	0.5003	0.5006	0.5235	0.5054	0.5020	0.5020
	p-value	$5.9e-13$	$1.4e-11$	$1.4e-11$	$1.3e-11$	$6.4e-15$	$4.3e-14$	$2.5e-13$	$1.0e-12$		p-value	$1.4e-11$	$1.4e-11$	$1.3e-11$	$2.0e-12$	$1.4e-13$	$1.2e-12$	$1.7e-12$	$1.7e-12$

NLC

RES Output	**Test Results**	**50% Coverage**				**75% Coverage**				**RES Output**	**Test Results**	**50% Coverage**				**75% Coverage**			
		10% Flex.	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**			**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**
1	Statistic	0.5294	0.5205	0.5155	0.5115	0.5573	0.5476	0.5404	0.5335	2	Statistic	0.5125	0.5105	0.5136	0.5166	0.5485	0.5431	0.5394	0.5395
	p-value	$6.7e-14$	$2.0e-13$	$3.6e-13$	$5.8e-13$	$1.9e-15$	$6.8e-15$	$1.7e-14$	$4.0e-14$		p-value	$5.1e-13$	$6.5e-13$	$4.5e-13$	$3.2e-13$	$6.0e-15$	$1.2e-14$	$1.9e-14$	$1.9e-14$
3	Statistic	0.5537	0.5391	0.5270	0.5174	0.5931	0.5852	0.5782	0.5730	4	Statistic	0.5235	0.5240	0.5246	0.5245	0.5997	0.5984	0.5978	0.5975
	p-value	$3.0e-15$	$2.0e-14$	$9.0e-14$	$2.9e-13$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$		p-value	$1.4e-13$	$1.3e-13$	$1.2e-13$	$1.2e-13$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
5	Statistic	0.5000	0.5000	0.5000	0.5000	0.5294	0.5219	0.5178	0.5154	6	Statistic	0.5017	0.5024	0.5031	0.5043	0.5746	0.5752	0.5763	0.5753
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$6.7e-14$	$1.7e-13$	$2.7e-13$	$3.6e-13$		p-value	$1.8e-12$	$1.7e-12$	$1.5e-12$	$1.3e-12$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	0.5000	0.5000	0.5000	0.5000	0.5315	0.5227	0.5175	0.5183	8	Statistic	0.5758	0.5757	0.5748	0.5735	0.6511	0.6500	0.6494	0.6482
	p-value	$1.4e-11$	$1.4e-11$	$1.4e-11$	$1.4e-11$	$5.2e-14$	$1.5e-13$	$2.8e-13$	$2.6e-13$		p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	0.5063	0.5023	0.5026	0.5051	0.5385	0.5312	0.5240	0.5216	10	Statistic	0.5017	0.5042	0.5070	0.5103	0.5131	0.5148	0.5183	0.5221
	p-value	$1.1e-12$	$1.7e-12$	$1.6e-12$	$1.2e-12$	$2.1e-14$	$5.4e-14$	$1.3e-13$	$1.7e-13$		p-value	$1.2e-11$	$9.1e-12$	$9.8e-13$	$6.7e-13$	$4.8e-13$	$3.9e-13$	$2.6e-13$	$1.6e-13$
11	Statistic	0.5225	0.5076	0.5014	0.5015	0.5545	0.5441	0.5344	0.5264	12	Statistic	0.5012	0.5005	0.5009	0.5013	0.5453	0.5364	0.5300	0.5272
	p-value	$1.6e-13$	$9.1e-13$	$1.9e-12$	$1.8e-12$	$2.8e-15$	$1.1e-14$	$3.6e-14$	$9.6e-14$		p-value	$1.9e-12$	$2.1e-12$	$2.0e-12$	$1.9e-12$	$9.0e-15$	$2.8e-14$	$6.3e-14$	$8.8e-14$

B.2. Normality Test for Static Optimization

Table B.12.: One-sample Kolmogorov-Smirnov normality test for the performance data of SLC-FK with different population sizes and different α values for each RES output.

RES Output	**Test Results**	**40**						**400**						**4.000**						**40.000**					
		α						α						α						α					
		1.0	0.5	0.1	0.05	0.01	0.0	1.0	0.5	0.1	0.05	0.01	0.0	1.0	0.5	0.1	0.05	0.01	0.0	1.0	0.5	0.1	0.05	0.01	0.0
1	Statistic	0.5574	0.5580	0.5541	0.5524	0.5545	0.5602	0.5212	0.5188	0.5178	0.5179	0.5171	0.5334	0.5102	0.5084	0.5066	0.5065	0.5060	0.5334	0.5100	0.5045	0.5029	0.5027	0.5025	0.5363
	p-value	0.0009	0.0009	0.0010	0.0011	0.0010	0.0009	0.0024	0.0025	0.0026	0.0026	0.0026	0.0017	0.0031	0.0032	0.0033	0.0033	0.0034	0.0017	0.0031	0.0035	0.0036	0.0037	0.0037	0.0016
2	Statistic	0.5702	0.5689	0.5619	0.5605	0.5581	0.5614	0.5382	0.5339	0.5327	0.5306	0.5242	0.5494	0.5354	0.5325	0.5286	0.5294	0.5277	0.5537	0.5346	0.5324	0.5308	0.5298	0.5299	0.5559
	p-value	0.0007	0.0007	0.0008	0.0009	0.0009	0.0008	0.0015	0.0017	0.0018	0.0019	0.0022	0.0012	0.0017	0.0018	0.0020	0.0019	0.0020	0.0010	0.0017	0.0018	0.0019	0.0019	0.0019	0.0010
3	Statistic	0.5800	0.5704	0.5761	0.5646	0.5661	0.5720	0.5552	0.5561	0.5573	0.5494	0.5533	0.5655	0.5602	0.5587	0.5556	0.5562	0.5573	0.5738	0.5644	0.5609	0.5596	0.5591	0.5593	0.5778
	p-value	0.0005	0.0007	0.0006	0.0008	0.0007	0.0006	0.0010	0.0010	0.0009	0.0012	0.0010	0.0008	0.0009	0.0009	0.0010	0.0010	0.0009	0.0006	0.0008	0.0009	0.0009	0.0009	0.0009	0.0005
4	Statistic	0.5801	0.5726	0.5532	0.5742	0.5591	0.5689	0.5621	0.5553	0.5473	0.5510	0.5491	0.5654	0.5600	0.5593	0.5530	0.5506	0.5535	0.5808	0.5622	0.5590	0.5568	0.5555	0.5564	0.5833
	p-value	0.0005	0.0006	0.0010	0.0006	0.0009	0.0007	0.0008	0.0010	0.0012	0.0011	0.0012	0.0008	0.0009	0.0009	0.0011	0.0011	0.0010	0.0005	0.0008	0.0009	0.0010	0.0010	0.0010	0.0005
5	Statistic	0.5609	0.5598	0.5551	0.5545	0.5561	0.5592	0.5242	0.5212	0.5191	0.5183	0.5173	0.5278	0.5094	0.5081	0.5070	0.5065	0.5066	0.5313	0.5058	0.5044	0.5033	0.5031	0.5029	0.5350
	p-value	0.0009	0.0009	0.0010	0.0010	0.0010	0.0009	0.0022	0.0024	0.0025	0.0025	0.0026	0.0020	0.0031	0.0032	0.0033	0.0033	0.0033	0.0018	0.0034	0.0035	0.0036	0.0036	0.0036	0.0017
6	Statistic	0.5738	0.5711	0.5590	0.5716	0.5648	0.5653	0.5697	0.5580	0.5564	0.5568	0.5565	0.5645	0.5728	0.5676	0.5650	0.5623	0.5629	0.5776	0.5734	0.5706	0.5645	0.5644	0.5644	0.5806
	p-value	0.0006	0.0006	0.0009	0.0006	0.0008	0.0008	0.0007	0.0009	0.0010	0.0010	0.0010	0.0008	0.0006	0.0007	0.0008	0.0008	0.0008	0.0005	0.0006	0.0007	0.0008	0.0008	0.0008	0.0005
7	Statistic	0.5617	0.5568	0.5536	0.5557	0.5550	0.5565	0.5225	0.5199	0.5196	0.5192	0.5191	0.5292	0.5120	0.5095	0.5082	0.5079	0.5071	0.5278	0.5083	0.5070	0.5049	0.5042	0.5036	0.5320
	p-value	0.0008	0.0010	0.0010	0.0010	0.0010	0.0010	0.0023	0.0024	0.0024	0.0025	0.0025	0.0019	0.0029	0.0031	0.0032	0.0032	0.0033	0.0020	0.0032	0.0033	0.0035	0.0035	0.0036	0.0018
8	Statistic	0.6082	0.6126	0.5681	0.5866	0.5985	0.5799	0.6070	0.6064	0.5991	0.5948	0.6002	0.5942	0.6092	0.6106	0.6057	0.6065	0.6040	0.6073	0.6132	0.6105	0.6087	0.6080	0.6070	0.6096
	p-value	0.0002	0.0002	0.0007	0.0004	0.0003	0.0005	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002	0.0002	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
9	Statistic	0.5583	0.5580	0.5540	0.5544	0.5534	0.5669	0.5251	0.5257	0.5213	0.5205	0.5176	0.5387	0.5185	0.5159	0.5118	0.5102	0.5100	0.5384	0.5147	0.5128	0.5093	0.5098	0.5090	0.5409
	p-value	0.0009	0.0009	0.0010	0.0010	0.0010	0.0007	0.0021	0.0021	0.0023	0.0024	0.0026	0.0015	0.0025	0.0027	0.0029	0.0031	0.0031	0.0015	0.0028	0.0029	0.0031	0.0031	0.0032	0.0014
10	Statistic	0.5636	0.5685	0.5587	0.5624	0.5572	0.5654	0.5472	0.5505	0.5424	0.5336	0.5393	0.5510	0.5506	0.5478	0.5395	0.5424	0.5400	0.5569	0.5514	0.5501	0.5469	0.5454	0.5426	0.5592
	p-value	0.0008	0.0007	0.0009	0.0008	0.0009	0.0008	0.0012	0.0011	0.0014	0.0017	0.0015	0.0011	0.0011	0.0012	0.0015	0.0014	0.0015	0.0010	0.0011	0.0011	0.0012	0.0013	0.0014	0.0009
11	Statistic	0.5576	0.5536	0.5550	0.5534	0.5530	0.5590	0.5238	0.5216	0.5199	0.5195	0.5176	0.5255	0.5176	0.5171	0.5111	0.5115	0.5096	0.5290	0.5192	0.5175	0.5133	0.5123	0.5089	0.5321
	p-value	0.0009	0.0010	0.0010	0.0010	0.0011	0.0009	0.0022	0.0023	0.0024	0.0025	0.0026	0.0021	0.0026	0.0026	0.0030	0.0030	0.0031	0.0019	0.0025	0.0026	0.0029	0.0029	0.0032	0.0018
12	Statistic	0.5607	0.5569	0.5537	0.5533	0.5535	0.5583	0.5203	0.5183	0.5171	0.5168	0.5165	0.5259	0.5076	0.5067	0.5060	0.5054	0.5056	0.5254	0.5031	0.5025	0.5023	0.5023	0.5021	0.5292
	p-value	0.0009	0.0010	0.0010	0.0010	0.0010	0.0009	0.0024	0.0025	0.0026	0.0026	0.0026	0.0021	0.0033	0.0033	0.0034	0.0034	0.0034	0.0021	0.0036	0.0037	0.0037	0.0037	0.0037	0.0019

Table B.13.: One-sample Kolmogorov-Smirnov normality test for the performance of SLC-FKd and CLP-FK data with different population sizes and each RES output.

RES Output	**Test Results**	**SLC-FKd**				**CLP-FK**			
		40	**400**	**4,000**	**40,000**	**40**	**400**	**4,000**	**40,000**
1	Statistic	$5.5e-01$	$5.2e-01$	$5.1e-01$	$5.0e-01$	$5.4e-01$	$5.1e-01$	$5.0e-01$	$5.0e-01$
	p-value	$1.1e-03$	$2.6e-03$	$3.4e-03$	$3.7e-03$	$3.0e-03$	$5.7e-03$	$6.4e-03$	$6.5e-03$
2	Statistic	$5.6e-01$	$5.3e-01$	$5.3e-01$	$5.3e-01$	$5.3e-01$	$5.2e-01$	$5.2e-01$	$5.2e-01$
	p-value	$9.7e-04$	$1.9e-03$	$1.9e-03$	$1.9e-03$	$3.6e-03$	$4.8e-03$	$4.4e-03$	$4.3e-03$
3	Statistic	$5.6e-01$	$5.5e-01$	$5.6e-01$	$5.6e-01$	$5.8e-01$	$5.6e-01$	$5.5e-01$	$5.5e-01$
	p-value	$7.8e-04$	$1.1e-03$	$9.9e-04$	$9.0e-04$	$1.2e-03$	$1.8e-03$	$2.3e-03$	$2.4e-03$
4	Statistic	$5.6e-01$	$5.5e-01$	$5.6e-01$	$5.6e-01$	$5.6e-01$	$5.3e-01$	$5.3e-01$	$5.3e-01$
	p-value	$8.2e-04$	$1.1e-03$	$9.2e-04$	$8.7e-04$	$1.7e-03$	$3.5e-03$	$3.4e-03$	$3.7e-03$
5	Statistic	$5.5e-01$	$5.2e-01$	$5.1e-01$	$5.0e-01$	$5.3e-01$	$5.0e-01$	$5.0e-01$	$5.0e-01$
	p-value	$1.0e-03$	$2.6e-03$	$3.3e-03$	$3.6e-03$	$3.3e-03$	$6.2e-03$	$6.5e-03$	$6.5e-03$
6	Statistic	$5.6e-01$	$5.6e-01$	$5.7e-01$	$5.7e-01$	$5.5e-01$	$5.5e-01$	$5.5e-01$	$5.5e-01$
	p-value	$8.6e-04$	$8.4e-04$	$7.1e-04$	$6.6e-04$	$2.4e-03$	$2.5e-03$	$2.3e-03$	$2.4e-03$
7	Statistic	$5.5e-01$	$5.2e-01$	$5.1e-01$	$5.0e-01$	$5.3e-01$	$5.0e-01$	$5.0e-01$	$5.0e-01$
	p-value	$1.0e-03$	$2.6e-03$	$3.3e-03$	$3.6e-03$	$3.5e-03$	$6.3e-03$	$6.4e-03$	$6.4e-03$
8	Statistic	$5.9e-01$	$6.0e-01$	$6.1e-01$	$6.1e-01$	$5.9e-01$	$5.9e-01$	$5.9e-01$	$5.9e-01$
	p-value	$3.5e-04$	$2.5e-04$	$2.2e-04$	$2.1e-04$	$9.2e-04$	$1.1e-03$	$9.6e-04$	$1.0e-03$
9	Statistic	$5.6e-01$	$5.2e-01$	$5.1e-01$	$5.1e-01$	$5.3e-01$	$5.0e-01$	$5.0e-01$	$5.1e-01$
	p-value	$9.9e-04$	$2.4e-03$	$3.2e-03$	$3.1e-03$	$3.7e-03$	$6.2e-03$	$6.2e-03$	$6.0e-03$
10	Statistic	$5.6e-01$	$5.4e-01$	$5.4e-01$	$5.4e-01$	$5.3e-01$	$5.2e-01$	$5.3e-01$	$5.4e-01$
	p-value	$9.5e-04$	$1.5e-03$	$1.5e-03$	$1.4e-03$	$3.8e-03$	$4.1e-03$	$3.4e-03$	$3.3e-03$
11	Statistic	$5.5e-01$	$5.2e-01$	$5.1e-01$	$5.1e-01$	$5.3e-01$	$5.0e-01$	$5.0e-01$	$5.1e-01$
	p-value	$1.0e-03$	$2.4e-03$	$3.2e-03$	$3.0e-03$	$2.0e-03$	$3.6e-03$	$3.5e-03$	$3.3e-03$
12	Statistic	$5.5e-01$	$5.2e-01$	$5.1e-01$	$5.0e-01$	$5.2e-01$	$5.0e-01$	$5.0e-01$	$5.0e-01$
	p-value	$1.1e-03$	$2.6e-03$	$3.4e-03$	$3.7e-03$	$2.2e-03$	$3.7e-03$	$3.8e-03$	$6.6e-03$

C. Differences Within Groups

C.1. Kruskal-Wallis Analysis for Real-Time Optimization

Table C.1.: Kruskal-Wallis rank sum test for assessing if samples in Table B.1, grouped by the same α while varying the population size, come from identical populations.

RES Output		**α Configuration**				
		1.0	**0.5**	**0.1**	**0.05**	**0.01**
1	Statistic	935.1894	955.3973	925.2571	897.6334	851.8727
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
2	Statistic	790.7671	810.3262	769.6548	751.9770	754.2401
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
3	Statistic	740.6308	781.4195	763.3839	723.7414	683.3480
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	559.6602	553.9343	563.2296	512.4050	418.8540
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
5	Statistic	814.8346	852.1352	899.6874	859.5869	817.3561
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
6	Statistic	691.6809	709.7994	689.9401	643.3267	629.2582
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	893.5490	915.1562	920.4020	860.0012	791.8198
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
8	Statistic	546.4297	524.5367	380.4086	384.7694	265.1728
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	898.6162	899.2813	930.3618	917.3063	874.9671
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	685.9563	709.0608	770.3421	761.4560	752.5864
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
11	Statistic	895.3614	948.4177	947.6549	914.8305	839.8583
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
12	Statistic	899.1447	923.5793	864.1878	874.3262	837.2353
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table C.2.: Kruskal-Wallis rank sum test for assessing if samples in Table B.2, grouped by the same RES output and α configuration while varying the forecast quality for a population of 40 households, come from identical populations.

RES Output		α **Configuration**				
		0.01	**0.05**	**0.1**	**0.5**	**1.0**
1	Statistic	1.885087	1.566235	7.630190	4.131168	0.781589
	p-value	0.389636	0.456979	0.022036	0.126744	0.676519
2	Statistic	1.042655	2.685643	1.770581	0.471806	1.091777
	p-value	0.593732	0.261108	0.412594	0.789857	0.579327
3	Statistic	0.410185	5.164585	3.377321	1.651849	1.694674
	p-value	0.814572	0.075601	0.184767	0.437830	0.428555
4	Statistic	0.002889	5.479689	1.710748	6.805358	1.266793
	p-value	0.998557	0.064580	0.425124	0.033284	0.530786
5	Statistic	1.127864	1.724268	6.064021	6.723072	5.167912
	p-value	0.568967	0.422260	0.048219	0.034682	0.075475
6	Statistic	13.293148	11.820409	10.183274	0.664348	0.404308
	p-value	0.001298	0.002712	0.006148	0.717362	0.816969
7	Statistic	1.745581	7.508032	3.102530	2.616672	1.042336
	p-value	0.417784	0.023423	0.211980	0.270269	0.593826
8	Statistic	6.020667	2.991085714	1.361860465	3.284845183	7.76535814
	p-value	0.049275	0.224127	0.506146	0.193511	0.020596
9	Statistic	0.654827907	3.140356146	5.821238538	0.32127309	3.024927575
	p-value	0.720785	0.208008	0.054442	0.851602	0.220366
10	Statistic	0.784233887	1.352986047	2.155776744	0.13067907	6.67704186
	p-value	0.675625	0.508397	0.340313	0.936749	0.035489
11	Statistic	0.407250498	3.079314286	7.692233887	2.051596013	0.289626578
	p-value	0.815768	0.214455	0.021363	0.358510	0.865184
12	Statistic	6.436967442	4.61494485	5.379795349	11.80435083	8.164369435
	p-value	0.040016	0.099512	0.067888	0.002733	0.016871

Table C.3.: Kruskal-Wallis rank sum test for assessing if samples in Table B.3, grouped by the same RES output and α configuration while varying the forecast quality for a population of 400 households, come from identical populations.

RES Output		**α Configuration**				
		0.01	**0.05**	**0.1**	**0.5**	**1.0**
1	Statistic	1.386666	1.837629	2.488242	3.394559	2.762921
	p-value	0.499907	0.398992	0.288194	0.183181	0.251211
2	Statistic	10.167293	3.857831	0.713023	4.208510	3.317414
	p-value	0.006197	0.145306	0.700114	0.121936	0.190385
3	Statistic	15.468872	15.778533	15.756441	11.662902	9.480343
	p-value	0.000437	0.000375	0.000379	0.002934	0.008737
4	Statistic	4.717850	0.011421	18.625191	0.510381	0.459437
	p-value	0.094522	0.994306	0.000090	0.774769	0.794757
5	Statistic	27.755437	48.051288	51.453140	6.993531	0.855423
	p-value	$9.40e-07$	$3.68e-11$	$6.72e-12$	0.030295	0.651999
6	Statistic	52.881903	90.775912	56.086296	2.115750	3.400165
	p-value	$3.29e-12$	$< 2e-16$	$6.62e-13$	0.347193	0.182668
7	Statistic	10.110692	8.289850	7.505959	2.037060	3.075926
	p-value	0.006375	0.015845	0.023448	0.361125	0.214818
8	Statistic	6.237132	5.930092	4.280061	2.880800	2.592330
	p-value	0.044221	0.051558	0.117651	0.236833	0.273579
9	Statistic	20.753337	23.412975	15.656821	1.470509	9.206610
	p-value	0.000031	0.000008	0.000398	0.479383	0.010019
10	Statistic	0.289013	18.092627	20.313507	13.732728	5.693504
	p-value	0.865449	0.000118	0.000039	0.001042	0.058032
11	Statistic	37.111131	53.042793	41.911232	24.917175	39.658039
	p-value	$8.74e-09$	$3.03e-12$	$7.93e-10$	0.000004	$2.45e-09$
12	Statistic	95.472003	80.288946	122.424454	24.645021	16.958586
	p-value	$< 2e-16$	$< 2e-16$	$< 2e-16$	0.000004	0.000208

Table C.4.: Kruskal-Wallis rank sum test for assessing if samples in Table B.4, grouped by the same RES output and α configuration while varying the forecast quality for a population of $4,000$ households, come from identical populations.

RES Output		**α Configuration**				
		0.01	**0.05**	**0.1**	**0.5**	**1.0**
1	Statistic	0.9728	2.0564	15.0134	1.041	1.8604
	p-value	0.6148	0.3577	0.0005494	0.5942	0.3945
2	Statistic	0.7871	3.4324	1.4177	17.0506	49.695
	p-value	0.6746	0.1797	0.4922	0.0001984	$1.618e-11$
3	Statistic	31.0601	21.7374	33.1259	17.8849	13.2108
	p-value	$1.8e-07$	$1.905e-05$	$6.409e-08$	0.0001307	0.001353
4	Statistic	5.9893	1.7211	39.3153	4.2508	2.0302
	p-value	0.05005	0.4229	$2.903e-09$	0.1194	0.3624
5	Statistic	75.7728	78.484	124.3926	45.2619	6.2125
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$1.484e-10$	0.04477
6	Statistic	105.7729	136.8052	144.5957	19.8117	15.0638
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$4.988e-05$	0.0005357
7	Statistic	17.1013	17.3218	22.9691	4.4025	2.135
	p-value	0.0001934	0.0001732	$1.029e-05$	0.1107	0.3439
8	Statistic	12.4125	8.2879	4.08	5.8071	8.762
	p-value	0.002017	0.01586	0.13	0.05483	0.01251
9	Statistic	31.5509	31.207	29.6326	8.9117	12.3577
	p-value	$1.409e-07$	$1.673e-07$	$3.676e-07$	0.01161	0.002073
10	Statistic	21.3784	32.0625	33.5574	19.4081	22.072
	p-value	$2.279e-05$	$1.091e-07$	$5.165e-08$	$6.104e-05$	$1.611e-05$
11	Statistic	73.2987	95.8921	127.3367	65.5977	72.242
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$5.697e-15$	$< 2.2e-16$
12	Statistic	146.1938	132.9511	205.7396	35.0108	35.5964
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$	$2.497e-08$	$1.864e-08$

Table C.5.: Kruskal-Wallis rank sum test for assessing if samples in Table B.5, grouped by the same RES output and α configuration while varying the forecast quality for a population of $40,000$ households, come from identical populations.

RES Output		**α Configuration**				
		0.01	**0.05**	**0.1**	**0.5**	**1.0**
1	Statistic	1.005483	5.120391	18.382328	4.066262	5.047665
	p-value	0.604870	0.077290	0.000102	0.130925	0.080152
2	Statistic	0.183950	4.914849	1.030177	19.796447	37.575200
	p-value	0.912128	0.085655	0.597448	0.000050	$6.93e-09$
3	Statistic	32.453265	23.493643	44.540056	40.889337	42.545560
	p-value	$8.97e-08$	0.000008	$2.13e-10$	$1.32e-09$	$5.77e-10$
4	Statistic	5.815274	1.267320	42.861786	2.553324	4.444516
	p-value	0.054605	0.530646	$4.93e-10$	0.278967	0.108364
5	Statistic	82.802435	85.494549	126.772165	60.675710	7.187211
	p-value	$< 2e-16$	$< 2e-16$	$< 2e-16$	$6.67e-14$	0.027499
6	Statistic	128.575312	140.487758	161.302400	40.766307	27.756393
	p-value	$< 2e-16$	$< 2e-16$	$< 2e-16$	$1.41e-09$	0.000001
7	Statistic	14.293611	24.298214	23.354682	4.284872	0.393507
	p-value	0.000787	0.000005	0.000008	0.117369	0.821393
8	Statistic	13.601592	8.442780	9.923378	17.541706	19.555745
	p-value	0.001113	0.014678	0.007001	0.000155	0.000057
9	Statistic	46.086517	42.923979	26.649217	10.679609	20.605845
	p-value	$9.83e-11$	$4.78e-10$	0.000002	0.004797	0.000034
10	Statistic	38.299952	46.339902	36.984417	21.610440	23.302496
	p-value	$4.82e-09$	$8.66e-11$	$9.31e-09$	0.000020	0.000009
11	Statistic	92.492726	133.500457	146.264316	89.062836	71.692659
	p-value	$< 2e-16$	$< 2e-16$	$< 2e-16$	$< 2e-16$	$< 2e-16$
12	Statistic	155.637935	147.775965	221.118753	31.946809	37.297467
	p-value	$< 2e-16$	$< 2e-16$	$9.65e-49$	$1.16e-07$	$7.96e-09$

Table C.6.: Kruskal-Wallis rank sum test for assessing if samples in Table B.2, grouped by α configurations and RES output for different forecast qualities, come from identical populations. Micro-grid population size: 40 households.

RES Output		**Forecast Quality** **Low**	 **Medium**	 **High**
1	Statistic	28.04951952	28.40675353	27.99582946
	p-value	$1.22e-05$	$1.03e-05$	$1.25e-05$
2	Statistic	31.66044263	21.0744412	34.98752862
	p-value	$2.24e-06$	0.0003061	$4.67e-07$
3	Statistic	37.93020838	18.7981279	17.79447952
	p-value	$1.16e-07$	0.0008611	0.0013536
4	Statistic	25.69254707	30.38378443	37.03769006
	p-value	$3.65e-05$	$4.09e-06$	$1.77e-07$
5	Statistic	6.583187545	17.00833246	22.07931018
	p-value	0.1596238	0.0019258	0.0001933
6	Statistic	10.64787641	36.90940838	59.80865341
	p-value	0.0308199	$1.88e-07$	$3.18e-12$
7	Statistic	28.12919856	15.39207377	13.48365892
	p-value	$1.17e-05$	0.0039534	0.0091391
8	Statistic	93.40832575	40.81583521	42.04625341
	p-value	$2.48e-19$	$2.93e-08$	$1.63e-08$
9	Statistic	26.10165365	30.46001437	41.2776709
	p-value	$3.02e-05$	$3.94e-06$	$2.35e-08$
10	Statistic	35.19092503	12.24314347	24.42725844
	p-value	$4.24e-07$	0.0156319	$6.56e-05$
11	Statistic	17.08352862	18.01195305	12.18474826
	p-value	0.0018620	0.0012275	0.0160290
12	Statistic	10.35679042	12.24825677	8.417883593
	p-value	0.0348279	0.0155976	0.0774157

Table C.7.: Kruskal-Wallis rank sum test for assessing if samples in Table B.3, grouped by α configurations and RES output for different forecast qualities, come from identical populations. Micro-grid population size: 400 households.

RES Output		**Forecast Quality** **Low**	 **Medium**	 **High**
1	Statistic	109.092858	132.025485	89.051755
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
2	Statistic	183.301577	92.247336	143.518300
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
3	Statistic	69.669246	92.832261	85.974163
	p-value	$2.67e - 14$	$< 2.2e - 16$	$< 2.2e - 16$
4	Statistic	48.473534	136.698949	54.735797
	p-value	$7.52e - 10$	$< 2.2e - 16$	$3.69e - 11$
5	Statistic	66.980549	92.436812	139.415196
	p-value	$9.84e - 14$	$< 2.2e - 16$	$< 2.2e - 16$
6	Statistic	80.531887	177.513842	191.706393
	p-value	$1.34e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
7	Statistic	86.855577	77.972632	134.467438
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
8	Statistic	149.920043	92.102773	60.787279
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$1.98e - 12$
9	Statistic	126.681806	124.490970	118.064735
	p-value	$< 2.2e - 16$	$< 2.2e - 16$	$< 2.2e - 16$
10	Statistic	62.043665	52.051042	20.512554
	p-value	$1.08e - 12$	$1.35e - 10$	$3.96e - 04$
11	Statistic	63.765166	77.403824	63.761771
	p-value	$4.68e - 13$	$< 2.2e - 16$	$4.69e - 13$
12	Statistic	47.350738	123.092493	204.833192
	p-value	$1.29e - 09$	$< 2.2e - 16$	$< 2.2e - 16$

Table C.8.: Kruskal-Wallis rank sum test for assessing if samples in Table B.4, grouped by α configurations and RES output for different forecast qualities, come from identical populations. Micro-grid population size: $4,000$ households.

RES Output		**Forecast Quality** **Low**	**Medium**	**High**
1	Statistic	210.6034	190.9293	153.8189
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
2	Statistic	265.6218	176.2064	164.4733
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
3	Statistic	168.8529	225.3962	$133.$
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
4	Statistic	134.2839	254.375	113.4353
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
5	Statistic	200.4815	187.3983	272.3094
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
6	Statistic	169.7178	295.2094	360.3229
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
7	Statistic	139.7026	113.889	241.2115
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
8	Statistic	217.4953	170.7335	117.3857
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
9	Statistic	292.807	233.3089	184.9128
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
10	Statistic	99.6933	80.9729	116.3309
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
11	Statistic	107.9386	175.6177	203.1686
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
12	Statistic	68.1969	266.5106	360.7499
	p-value	$5.451e-14$	$< 2.2e-16$	$< 2.2e-16$

Table C.9.: Kruskal-Wallis rank sum test for assessing if samples in Table B.5, grouped by α configurations and RES output for different forecast qualities, come from identical populations. Micro-grid population size: $40,000$ households.

RES Output		**Forecast Quality** **Low**	 **Medium**	 **High**
1	Statistic	217.966878	216.269430	156.573070
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
2	Statistic	287.407746	192.100155	178.052136
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
3	Statistic	168.711277	299.585798	134.122640
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
4	Statistic	131.598347	294.595334	119.836995
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
5	Statistic	217.510262	199.777634	283.071082
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
6	Statistic	200.328398	308.455687	375.452224
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
7	Statistic	151.798022	111.029423	242.949032
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
8	Statistic	233.111137	195.606604	129.633576
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
9	Statistic	312.023154	260.752396	207.411406
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
10	Statistic	99.633844	105.054253	136.036343
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
11	Statistic	130.408263	230.607395	283.352811
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$
12	Statistic	75.123364	319.284734	381.590803
	p-value	$< 2.2e-16$	$< 2.2e-16$	$< 2.2e-16$

Table C.10.: Kruskal-Wallis rank sum test for assessing if the data of the performances from SLC, CLP and NLC, grouped by population size, come from identical populations.

RES Output	**Test Results**	40	400	4.000	40.000
1	Statistic	673.5509721	767.8294199	708.8902677	699.8090585
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
2	Statistic	739.8598477	759.6944948	714.8964636	707.5766912
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
3	Statistic	671.5869071	789.1052016	799.1120977	799.1120977
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	792.0087738	799.1120977	799.1120977	799.1120977
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
5	Statistic	727.6129765	764.9939689	662.2981052	651.0159619
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
6	Statistic	767.8424589	794.3111048	798.9700586	799.1120977
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	755.9084115	747.8621385	669.4700278	664.115489
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
8	Statistic	752.773432	796.8102207	799.1120977	799.1120977
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	694.886044	769.0947205	730.595494	723.3780423
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	592.2065351	579.4483028	637.9655353	665.0343536
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
11	Statistic	698.1512797	681.5959307	638.974013	638.4014233
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$
12	Statistic	746.3189567	725.3800504	648.0169487	636.8825829
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table C.11.: Kruskal-Wallis rank sum test for assessing if the data of the performances from SLC, CLP and NLC, grouped by forecast category with population size of $4,000$, come from identical populations.

RES Output	Test Results	Low	Medium	High
1	Statistic	221.3804651	229.3947349	261.3906286
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
2	Statistic	264.9329542	240.6870645	220.4864877
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
3	Statistic	265.7807309	265.7807309	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
4	Statistic	265.7807309	265.7807309	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
5	Statistic	200.5501023	233.7042286	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
6	Statistic	265.7807309	265.7807309	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
7	Statistic	236.9305542	212.0361355	224.4177648
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
8	Statistic	265.7807309	265.7807309	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
9	Statistic	241.4151256	263.0453581	225.9762286
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
10	Statistic	176.4936797	247.8954764	227.165297
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
11	Statistic	204.5353116	244.4721355	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$
12	Statistic	201.9299508	263.2276651	265.7807309
	p-value	$2.2e-16$	$2.2e-16$	$2.2e-16$

Table C.12.: Kruskal-Wallis rank sum test for assessing if the data of the performances from SLC, CLP and NLC, grouped by different levels of micro-grid load coverage and load flexibility with population size of $4,000$, come from identical populations.

RES	**Test**		**25% Coverage**				**50% Coverage**				**75% Coverage**		
Output	**Results**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**	**10% Flex.**	**20% Flex.**	**30% Flex.**	**40% Flex.**
1	Statistic	–	–	0.416	0.216	399.113	398.900	394.105	366.099	399.078	399.113	399.113	398.4932052
	p-value	–	–	$8e-01$	$9e-01$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
2	Statistic	–	–	–	209.020	375.890	342.401	301.481	299.983	397.242	391.222	390.430	397.0242566
	p-value	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
3	Statistic	–	–	–	–	394.745	397.611	395.545	397.432	399.113	399.113	399.113	399.1131083
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
4	Statistic	–	–	–	–	401.454	407.642	400.122	353.169	399.113	399.113	399.113	399.113082
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
5	Statistic	–	–	–	–	374.414	–	–	–	399.113	399.301	341.638	333.2009044
	p-value	–	–	–	–	$2e-16$	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
6	Statistic	–	–	–	–	383.713	425.369	425.369	425.369	399.113	399.113	399.113	399.113082
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
7	Statistic	–	–	–	–	10.666	6.027	–	–	399.113	398.523	391.958	348.4190441
	p-value	–	–	–	–	$5e-03$	$5e-02$	–	–	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
8	Statistic	–	–	–	–	399.113	399.113	406.632	413.835	399.113	399.113	399.113	399.113082
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
9	Statistic	–	–	–	–	378.707	317.545	299.652	299.346	398.670	399.024	399.024	398.7056481
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
10	Statistic	–	–	–	–	425.370	425.369	425.369	402.743	383.836	399.113	394.451	377.9043441
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
11	Statistic	–	–	–	–	383.608	372.670	296.134	302.605	384.917	386.767	381.711	376.8318636
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$
12	Statistic	–	–	–	–	299.063	300.673	299.657	299.413	399.113	393.449	365.947	356.7917363
	p-value	–	–	–	–	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2e-16$	$2.2e-16$

C.2. Kruskal-Wallis Analysis for Static Optimization

Table C.13.: Kruskal-Wallis rank sum test for assessing if samples in Table B.13, grouped by the same α while varying the population size, come from identical populations.

RES Output	Test Results	1.0	0.5	0.1	0.05	0.01	0.0
1	Statistic	33.0732	36.5854	36.5854	36.5854	36.5854	28.3010
	p-value	$3.1e-07$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$3.1e-06$
2	Statistic	32.6649	30.0746	32.4922	29.5566	28.4620	26.3766
	p-value	$3.8e-07$	$1.3e-06$	$4.1e-07$	$1.7e-06$	$2.9e-06$	$8.0e-06$
3	Statistic	26.9868	21.8751	24.9907	22.2366	23.5376	17.1498
	p-value	$5.9e-06$	$6.9e-05$	$1.6e-05$	$5.8e-05$	$3.1e-05$	$6.6e-04$
4	Statistic	26.7468	26.6107	14.5200	23.8888	21.0220	12.2093
	p-value	$6.7e-06$	$7.1e-06$	$2.3e-03$	$2.6e-05$	$1.0e-04$	$6.7e-03$
5	Statistic	36.5854	36.5854	36.5854	36.5854	36.5854	29.3502
	p-value	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$1.9e-06$
6	Statistic	16.6815	16.3712	6.5078	20.6473	14.0678	15.7595
	p-value	$8.2e-04$	$9.5e-04$	$8.9e-02$	$1.2e-04$	$2.8e-03$	$1.3e-03$
7	Statistic	36.5854	36.5854	36.5854	36.5854	36.5854	24.4200
	p-value	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$2.0e-05$
8	Statistic	15.5810	15.8693	9.9000	0.6498	6.2883	7.8307
	p-value	$1.4e-03$	$1.2e-03$	$1.9e-02$	$8.8e-01$	$9.8e-02$	$5.0e-02$
9	Statistic	36.5854	36.5854	36.5854	35.6327	34.9302	30.5254
	p-value	$5.6e-08$	$5.6e-08$	$5.6e-08$	$9.0e-08$	$1.3e-07$	$1.1e-06$
10	Statistic	22.4063	26.5010	23.9020	23.4541	23.4541	23.6473
	p-value	$5.4e-05$	$7.5e-06$	$2.6e-05$	$3.2e-05$	$3.2e-05$	$3.0e-05$
11	Statistic	33.1376	33.0190	32.9283	34.3332	34.5205	22.7956
	p-value	$3.0e-07$	$3.2e-07$	$3.3e-07$	$1.7e-07$	$1.5e-07$	$4.5e-05$
12	Statistic	36.5854	36.5854	36.5854	36.5854	36.5854	31.2688
	p-value	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$5.6e-08$	$7.5e-07$

Table C.14.: Kruskal-Wallis rank sum test for assessing if samples in Table B.13, grouped by the population size and RES output while varying α, come from identical populations.

RES Output	**Test Results**	40	400	$4,000$	$40,000$
1	Statistic	29.388	46.951	53.558	57.249
	p-value	$1.9e-05$	$5.8e-09$	$2.6e-10$	$4.5e-11$
2	Statistic	27.252	42.567	48.853	52.600
	p-value	$5.1e-05$	$4.5e-08$	$2.4e-09$	$4.1e-10$
3	Statistic	4.926	28.376	42.241	50.915
	p-value	$4.2e-01$	$3.1e-05$	$5.3e-08$	$9.0e-10$
4	Statistic	16.463	37.426	48.036	51.368
	p-value	$5.6e-03$	$4.9e-07$	$3.5e-09$	$7.3e-10$
5	Statistic	33.190	49.490	55.105	56.663
	p-value	$3.5e-06$	$1.8e-09$	$1.2e-10$	$5.9e-11$
6	Statistic	14.073	25.024	52.157	51.324
	p-value	$1.5e-02$	$1.4e-04$	$5.0e-10$	$7.4e-10$
7	Statistic	24.043	48.842	52.428	55.064
	p-value	$2.1e-04$	$2.4e-09$	$4.4e-10$	$1.3e-10$
8	Statistic	17.129	24.355	33.755	50.376
	p-value	$4.3e-03$	$1.9e-04$	$2.7e-06$	$1.2e-09$
9	Statistic	29.877	50.197	51.498	51.426
	p-value	$1.6e-05$	$1.3e-09$	$6.8e-10$	$7.1e-10$
10	Statistic	9.039	27.943	50.722	57.121
	p-value	$1.1e-01$	$3.7e-05$	$9.9e-10$	$4.8e-11$
11	Statistic	6.887	26.789	49.960	56.840
	p-value	$2.3e-01$	$6.3e-05$	$1.4e-09$	$5.5e-11$
12	Statistic	34.760	52.239	54.369	55.770
	p-value	$1.7e-06$	$4.8e-10$	$1.8e-10$	$9.1e-11$

Table C.15.: Kruskal-Wallis rank sum test for assessing if samples in Table B.13, grouped by the population size and RES output, come from identical populations.

RES Output	**Test Results**	40	400	$4,000$	$40,000$
1	Statistic	33.5396	33.4683	33.6244	33.6244
	p-value	$2.5e-07$	$2.6e-07$	$2.4e-07$	$2.4e-07$
2	Statistic	33.4504	33.4579	33.5173	33.9261
	p-value	$2.6e-07$	$2.6e-07$	$2.5e-07$	$2.1e-07$
3	Statistic	22.2978	24.4145	33.4683	33.4445
	p-value	$5.7e-05$	$2.0e-05$	$2.6e-07$	$2.6e-07$
4	Statistic	28.0503	33.4504	36.8692	37.1606
	p-value	$3.5e-06$	$2.6e-07$	$4.9e-08$	$4.3e-08$
5	Statistic	33.5396	34.6946	35.2654	33.4504
	p-value	$2.5e-07$	$1.4e-07$	$1.1e-07$	$2.6e-07$
6	Statistic	34.0391	34.6099	37.1606	37.1606
	p-value	$1.9e-07$	$1.5e-07$	$4.3e-08$	$4.3e-08$
7	Statistic	33.6585	33.8741	33.4817	33.5396
	p-value	$2.3e-07$	$2.1e-07$	$2.5e-07$	$2.5e-07$
8	Statistic	29.8607	34.2308	37.0134	37.1606
	p-value	$1.5e-06$	$1.8e-07$	$4.6e-08$	$4.3e-08$
9	Statistic	33.5396	34.3007	33.7358	33.4980
	p-value	$2.5e-07$	$1.7e-07$	$2.3e-07$	$2.5e-07$
10	Statistic	33.2171	34.3735	33.7789	34.0391
	p-value	$2.9e-07$	$1.7e-07$	$2.2e-07$	$1.9e-07$
11	Statistic	32.9985	31.4620	29.0517	32.7907
	p-value	$3.2e-07$	$6.8e-07$	$2.2e-06$	$3.6e-07$
12	Statistic	32.9985	33.1039	32.9634	33.6585
	p-value	$3.2e-07$	$3.1e-07$	$3.3e-07$	$2.3e-07$

Table C.16.: Kruskal-Wallis rank sum test for assessing if samples generated by different load scheduling strategies with the same type of load composition and RES output, come from identical populations.

RES Output	**Test Results**	**Only Washing Machines**	**No EVs.**	**All Appliances**
1	Statistic	0.021	22.165	20.417
	p-value	0.98971	$1.5e-05$	$3.7e-05$
2	Statistic	3.785	19.791	20.224
	p-value	0.15072	$5.0e-05$	$4.1e-05$
3	Statistic	3.223	20.101	20.135
	p-value	0.19957	$4.3e-05$	$4.2e-05$
4	Statistic	8.230	23.081	26.265
	p-value	0.01633	$9.7e-06$	$2.0e-06$
5	Statistic	9.262	7.628	23.374
	p-value	0.00975	0.02206	$8.4e-06$
6	Statistic	3.332	25.055	26.790
	p-value	0.18904	$3.6e-06$	$1.5e-06$
7	Statistic	0.588	7.280	20.159
	p-value	0.74513	0.02625	$4.2e-05$
8	Statistic	2.341	22.516	26.525
	p-value	0.31027	$1.3e-05$	$1.7e-06$
9	Statistic	2.140	20.015	20.617
	p-value	0.34301	$4.5e-05$	$3.3e-05$
10	Statistic	2.883	19.520	20.695
	p-value	0.23662	$5.8e-05$	$3.2e-05$
11	Statistic	1.350	19.357	12.521
	p-value	0.50924	$6.3e-05$	0.00191
12	Statistic	13.288	13.675	19.419
	p-value	0.00130	0.00107	$6.1e-05$

D. Post-Hoc Analysis

Table D.1.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.1 for each RES output. Continues in Table D.2.

RES Output 1

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–
40.000	2.2e − 16	2.2e − 16	2.1e − 03	40.000	2.2e − 16	2.2e − 16	7.7e − 04	40.000	2.2e − 16	2.2e − 16	1.0e − 02	40.000	2.2e − 16	2.2e − 16	5.5e − 02	40.000	2.2e − 16	2.2e − 16	1.1e − 01

RES Output 2

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	1.9e − 14	–	4.000	2.2e − 16	5.0e − 11	–	4.000	2.2e − 16	3.9e − 13	–
40.000	2.2e − 16	2.2e − 16	9.7e − 01	40.000	2.2e − 16	2.2e − 16	3.9e − 01	40.000	2.2e − 16	2.2e − 16	6.6e − 01	40.000	2.2e − 16	2.2e − 16	5.2e − 01	40.000	2.2e − 16	2.2e − 16	1.0

RES Output 3

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	1.4e − 01	–	4.000	2.2e − 16	1.0e − 13	–	4.000	2.2e − 16	3.7e − 08	–	4.000	2.2e − 16	8.5e − 14	–	4.000	2.2e − 16	7.85045e − 06	–
40.000	2.2e − 16	3.1e − 09	1.1e − 03	40.000	2.2e − 16	2.2e − 16	8.6e − 02	40.000	2.2e − 16	8.3e − 16	1.8e − 02	40.000	2.2e − 16	2.2e − 16	1.0	40.000	2.2e − 16	2.4e − 07	1.0

RES Output 4

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	9.7e − 03	–	4.000	2.2e − 16	3.8e − 02	–	4.000	2.2e − 16	3.9e − 03	–	4.000	2.2e − 16	2.5e − 03	–	4.000	2.2e − 16	8.0e − 01	–
40.000	2.2e − 16	1.7e − 03	1.0	40.000	2.2e − 16	3.8e − 02	1.0	40.000	2.2e − 16	1.9e − 03	1.0	40.000	2.2e − 16	1.2e − 03	1.0	40.000	2.2e − 16	4.6e − 01	1.0

RES Output 5

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–	4.000	2.2e − 16	2.2e − 16	–
40.000	2.2e − 16	2.2e − 16	2.9e − 01	40.000	2.2e − 16	2.2e − 16	7.9e − 01	40.000	2.2e − 16	2.2e − 16	5.2e − 01	40.000	2.2e − 16	2.2e − 16	4.6e − 01	40.000	2.2e − 16	2.2e − 16	9.8e − 01

RES Output 6

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–	400	2.2e − 16	–	–
4.000	2.2e − 16	1.7e − 06	–	4.000	2.2e − 16	5.3e − 11	–	4.000	2.2e − 16	6.8e − 11	–	4.000	2.2e − 16	3.8e − 06	–	4.000	2.2e − 16	7.3e − 06	–
40.000	2.2e − 16	1.1e − 08	9.2e − 01	40.000	2.2e − 16	1.5e − 15	5.2e − 01	40.000	2.2e − 16	6.2e − 13	1.0	40.000	2.2e − 16	5.4e − 07	1.0	40.000	2.2e − 16	1.1e − 06	1.0

Table D.2.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.1 for each RES output. Continuation from Table D.1.

RES Output 7

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–
40.000	$2.2e-16$	$2.2e-16$	$4.1e-01$	40.000	$2.2e-16$	$2.2e-16$	$1.6e-01$	40.000	$2.2e-16$	$2.2e-16$	$4.1e-02$	40.000	$2.2e-16$	$2.2e-16$	$1.3e-01$	40.000	$2.2e-16$	$2.2e-16$	$4.3e-01$

RES Output 8

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$5.1e-06$	–	4.000	$2.2e-16$	$3.3e-08$	–	4.000	$2.2e-16$	$1.4e-03$	–	4.000	$2.2e-16$	$3.1e-02$	–	4.000	$2.2e-16$	$5.6e-01$	–
40.000	$2.2e-16$	$9.8e-08$	$8.2e-01$	40.000	$2.2e-16$	$4.5e-10$	$8.4e-01$	40.000	$2.2e-16$	$5.1e-04$	1.0	40.000	$2.2e-16$	$1.0e-02$	1.0	40.000	$2.2e-16$	$4.8e-01$	1.0

RES Output 9

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–
40.000	$2.2e-16$	$2.2e-16$	$2.7e-02$	40.000	$2.2e-16$	$2.2e-16$	$1.7e-04$	40.000	$2.2e-16$	$2.2e-16$	$9.3e-04$	40.000	$2.2e-16$	$2.2e-16$	$1.7e-02$	40.000	$2.2e-16$	$2.2e-16$	$8.8e-03$

RES Output 10

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$2.7e-04$	–	4.000	$2.2e-16$	$7.9e-10$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–
40.000	$2.2e-16$	$6.5e-04$	1.0	40.000	$2.2e-16$	$3.6e-12$	1.0	40.000	$2.2e-16$	$2.2e-16$	1.0	40.000	$2.2e-16$	$2.2e-16$	$2.0e-01$	40.000	$2.2e-16$	$2.2e-16$	$5.5e-01$

RES Output 11

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–
40.000	$2.2e-16$	$2.2e-16$	$7.0e-03$	40.000	$2.2e-16$	$2.2e-16$	$5.6e-04$	40.000	$2.2e-16$	$2.2e-16$	$6.7e-05$	40.000	$2.2e-16$	$2.2e-16$	$1.4e-02$	40.000	$2.2e-16$	$2.2e-16$	$3.7e-01$

RES Output 12

	$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$		
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–	400	$2.2e-16$	–	–
4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–	4.000	$2.2e-16$	$2.2e-16$	–
40.000	$2.2e-16$	$2.2e-16$	1.0	40.000	$2.2e-16$	$2.2e-16$	$1.3e-02$	40.000	$2.2e-16$	$2.2e-16$	$1.4e-01$	40.000	$2.2e-16$	$2.2e-16$	$9.4e-02$	40.000	$2.2e-16$	$2.2e-16$	$3.8e-01$

Table D.3.: Pairwise comparison with unpaired Wilcoxon rank-sum test with Bonferroni. Post-hoc analysis for assessing significant differences in performance of SLC, CLP and NLC, as a consequence of different shares of load coverage within groups specified in Table C.12 for each RES output. 40% of load flexibility for the micro-grid is considered.

RES Output 1. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 1. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 2. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$7e-01$	$2e-16$

RES Output 2. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 3. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 3. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 4. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 4. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 5. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$4e-16$	$2e-16$

RES Output 6. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	1	$2e-16$

RES Output 6. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 7. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 8. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 8. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 9. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	1	$2e-16$

RES Output 9. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 10. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	1	$2e-16$

RES Output 10. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 11. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$1e-03$	$2e-16$

RES Output 11. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

RES Output 12. 50% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	1	$2e-16$

RES Output 12. 75% Coverage

	CLP	**NLC**
NLC	$2e-16$	–
SLC	$2e-16$	$2e-16$

Table D.4.: Pairwise comparison with unpaired Wilcoxon rank-sum test with Bonferroni. Post-hoc analysis for assessing significant differences in performance of SLC, CLP and NLC as a consequence of different shares of load flexibility within groups specified in Table C.12 for each RES output. 75% of load coverage by the RES output is considered. Continues in Table D.5.

RES Output 1. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 1. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 1. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 1. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$3.7e-16$	$2.2e-16$

RES Output 6. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 7. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

Table D.5.: Pairwise comparison with unpaired Wilcoxon rank-sum test with Bonferroni. Post-hoc analysis for assessing significant differences in performance of SLC, CLP and NLC as a consequence of different shares of load flexibility within groups specified in Table C.12 for each RES output. 75% of load coverage by the RES output is considered. Continuation from Table D.4.

RES Output 7. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 7. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 7. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 10. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 10. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 10. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 10. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 11. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 11. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 11. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 11. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. 10% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. 20% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. 30% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. 40% Flex.

	CLP	**NLC**
NLC	$2.2e-16$	–
SLC	$2.2e-16$	$2.2e-16$

Table D.6.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, with fixed RES outputs, α configurations and a population of 40. Evaluations correspond to those in Table C.2 where differences between samples within groups where found were significant.

RES Output 1. $\alpha = 0.1$

	High	**Low**
Low	$3.72e-02$	–
Medium	1.00	$7.73e-02$

RES Output 4. $\alpha = 0.5$

	High	**Low**
Low	$1.11e-01$	–
Medium	$5.14e-02$	1.00

RES Output 5. $\alpha = 0.5$

	High	**Low**
Low	$9.09e-02$	–
Medium	1.00	$6.22e-02$

RES Output 5. $\alpha = 0.1$

	High	**Low**
Low	$6.77e-02$	–
Medium	1.00	$1.51e-01$

RES Output 6. $\alpha = 0.1$

	High	**Low**
Low	$1.05e-02$	–
Medium	1.00	$2.85e-02$

RES Output 6. $\alpha = 0.05$

	High	**Low**
Low	$1.90e-03$	–
Medium	$2.82e-01$	$2.20e-01$

RES Output 6. $\alpha = 0.01$

	High	**Low**
Low	$4.79e-01$	–
Medium	$8.76e-02$	$8.59e-04$

RES Output 7. $\alpha = 0.05$

	High	**Low**
Low	1.00	–
Medium	$7.35e-02$	$3.93e-02$

RES Output 8. $\alpha = 1.0$

	High	**Low**
Low	$1.67e-02$	–
Medium	1.00	$2.25e-01$

RES Output 8. $\alpha = 0.01$

	High	**Low**
Low	$5.64e-02$	–
Medium	1.00	$2.26e-01$

RES Output 10. $\alpha = 1.0$

	High	**Low**
Low	$5.72e-01$	–
Medium	$5.82e-01$	$3.08e-02$

RES Output 12. $\alpha = 1.0$

	High	**Low**
Low	$2.91e-02$	–
Medium	1.00	$6.55e-02$

RES Output 12. $\alpha = 0.5$

	High	**Low**
Low	$4.65e-02$	–
Medium	1.00	$2.80e-03$

RES Output 12. $\alpha = 0.01$

	High	**Low**
Low	$3.52e-02$	–
Medium	1.00	$3.61e-01$

Table D.7.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, with fixed RES outputs, α configurations and a population of 400. Evaluations correspond to those in Table C.3 where differences between samples within groups where found were significant.

RES Output 2. $\alpha = 0.01$

	High	**Low**
Low	$3.88e-01$	–
Medium	$1.18e-02$	$8.44e-02$

RES Output 3. $\alpha = 1.0$

	High	**Low**
Low	$1.11e-01$	–
Medium	$9.73e-01$	$8.72e-03$

RES Output 3. $\alpha = 0.5$

	High	**Low**
Low	$1.48e-02$	–
Medium	1.00	$6.69e-03$

RES Output 3. $\alpha = 0.1$

	High	**Low**
Low	$2.76e-04$	–
Medium	$5.01e-02$	$3.29e-01$

RES Output 3. $\alpha = 0.05$

	High	**Low**
Low	$2.90e-04$	–
Medium	$3.62e-02$	$4.39e-01$

RES Output 3. $\alpha = 0.01$

	High	**Low**
Low	$8.20e-04$	–
Medium	$1.39e-02$	$4.68e-01$

RES Output 4. $\alpha = 0.1$

	High	**Low**
Low	1.00	–
Medium	$3.28e-04$	$1.05e-03$

RES Output 5. $\alpha = 0.5$

	High	**Low**
Low	$2.58e-02$	–
Medium	$4.70e-01$	$6.39e-01$

RES Output 5. $\alpha = 0.1$

	High	**Low**
Low	$1.13e-11$	–
Medium	$5.26e-01$	$6.11e-07$

RES Output 5. $\alpha = 0.05$

	High	**Low**
Low	$5.25e-11$	–
Medium	$1.23e-05$	$5.75e-02$

RES Output 5. $\alpha = 0.01$

	High	**Low**
Low	$1.16e-06$	–
Medium	$2.55e-04$	1.00

RES Output 6. $\alpha = 0.1$

	High	**Low**
Low	$2.18e-11$	–
Medium	1.00	$3.28e-09$

RES Output 6. $\alpha = 0.05$

	High	**Low**
Low	$6.08e-14$	–
Medium	$2.83e-02$	$2.20e-16$

RES Output 6. $\alpha = 0.01$

	High	**Low**
Low	$9.91e-06$	–
Medium	$8.12e-03$	$9.04e-12$

RES Output 7. $\alpha = 0.1$

	High	**Low**
Low	$9.48e-01$	–
Medium	$1.66e-02$	$3.34e-01$

RES Output 7. $\alpha = 0.05$

	High	**Low**
Low	$3.41e-01$	–
Medium	$1.76e-02$	$3.76e-01$

RES Output 7. $\alpha = 0.01$

	High	**Low**
Low	1.00	–
Medium	$9.67e-03$	$3.42e-02$

RES Output 8. $\alpha = 0.01$

	High	**Low**
Low	$3.98e-02$	–
Medium	$7.66e-01$	$5.03e-01$

RES Output 9. $\alpha = 1.0$

	High	**Low**
Low	$5.72e-02$	–
Medium	1.00	$1.41e-02$

RES Output 9. $\alpha = 0.1$

	High	**Low**
Low	$1.41e-01$	–
Medium	$2.01e-01$	$1.76e-04$

RES Output 9. $\alpha = 0.05$

	High	**Low**
Low	$3.15e-01$	–
Medium	$2.33e-02$	$1.31e-06$

RES Output 9. $\alpha = 0.01$

	High	**Low**
Low	$3.62e-04$	–
Medium	1.00	$1.64e-04$

RES Output 10. $\alpha = 0.5$

	High	**Low**
Low	$1.75e-03$	–
Medium	1.00	$1.53e-02$

RES Output 10. $\alpha = 0.1$

	High	**Low**
Low	$1.41e-05$	–
Medium	$3.69e-02$	$2.20e-01$

RES Output 10. $\alpha = 0.05$

	High	**Low**
Low	$3.25e-03$	–
Medium	1.00	$2.25e-04$

RES Output 11. $\alpha = 1.0$

	High	**Low**
Low	$1.89e-09$	–
Medium	$1.77e-01$	$8.31e-05$

RES Output 11. $\alpha = 0.5$

	High	**Low**
Low	$1.08e-05$	–
Medium	1.00	$2.18e-04$

RES Output 11. $\alpha = 0.1$

	High	**Low**
Low	$1.16e-09$	–
Medium	$1.39e-02$	$2.30e-04$

RES Output 11. $\alpha = 0.05$

	High	**Low**
Low	$2.64e-12$	–
Medium	$5.01e-02$	$6.07e-06$

RES Output 11. $\alpha = 0.01$

	High	**Low**
Low	$4.45e-09$	–
Medium	$6.03e-04$	$6.90e-02$

RES Output 12. $\alpha = 1.0$

	High	**Low**
Low	$1.64e-04$	–
Medium	$6.94e-02$	$1.41e-01$

RES Output 12. $\alpha = 0.5$

	High	**Low**
Low	$6.68e-06$	–
Medium	$1.03e-01$	$4.38e-03$

RES Output 12. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$1.09e-10$	$3.04e-09$

RES Output 12. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$1.07e-06$	$2.29e-06$

RES Output 12. $\alpha = 0.01$

	High	**Low**
Low	$2.20e-16$	–
Medium	$1.68e-08$	$5.62e-08$

Table D.8.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, with fixed RES outputs, α configurations and a population of $4,000$. Evaluations correspond to those in Table C.4 where differences between samples within groups where found were significant. Continues in Table D.9.

RES Output 1. $\alpha = 0.1$

	High	**Low**
Low	$5.53e-04$	–
Medium	$4.86e-01$	$3.17e-02$

RES Output 2. $\alpha = 1.0$

	High	**Low**
Low	$6.99e-09$	–
Medium	1.00	$1.57e-09$

RES Output 2. $\alpha = 0.5$

	High	**Low**
Low	$1.78e-04$	–
Medium	$1.55e-02$	$6.31e-01$

RES Output 3. $\alpha = 1.0$

	High	**Low**
Low	$4.94e-01$	–
Medium	$1.20e-01$	$6.64e-04$

RES Output 3. $\alpha = 0.5$

	High	**Low**
Low	$1.47e-02$	–
Medium	$4.56e-01$	$1.25e-04$

RES Output 3. $\alpha = 0.1$

	High	**Low**
Low	$6.19e-07$	–
Medium	$1.07e-01$	$4.61e-05$

RES Output 3. $\alpha = 0.05$

	High	**Low**
Low	$2.00e-05$	–
Medium	$4.09e-03$	$4.75e-01$

RES Output 3. $\alpha = 0.01$

	High	**Low**
Low	$3.32e-07$	–
Medium	$9.86e-05$	$9.02e-01$

RES Output 4. $\alpha = 0.1$

	High	**Low**
Low	$7.62e-05$	–
Medium	$6.99e-09$	$5.53e-02$

RES Output 5. $\alpha = 1.0$

	High	**Low**
Low	$4.59e-02$	–
Medium	1.00	$2.18e-01$

RES Output 5. $\alpha = 0.5$

	High	**Low**
Low	$1.93e-07$	–
Medium	$6.95e-01$	$3.23e-09$

RES Output 5. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$9.25e-05$	$1.83e-11$

RES Output 5. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$3.04e-05$	$5.58e-03$

RES Output 5. $\alpha = 0.01$

	High	**Low**
Low	$1.36e-14$	–
Medium	$3.10e-12$	$2.02e-01$

RES Output 6. $\alpha = 1.0$

	High	**Low**
Low	$3.85e-01$	–
Medium	$8.52e-03$	$1.87e-03$

RES Output 6. $\alpha = 0.5$

	High	**Low**
Low	$7.37e-03$	–
Medium	$7.73e-02$	$1.87e-04$

RES Output 6. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$1.07e-01$	$2.20e-16$

RES Output 6. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$8.70e-06$	$2.20e-16$

RES Output 6. $\alpha = 0.01$

	High	**Low**
Low	$1.72e-12$	–
Medium	$3.13e-06$	$2.20e-16$

RES Output 7. $\alpha = 0.1$

	High	**Low**
Low	$1.25e-03$	–
Medium	$1.64e-05$	$7.88e-01$

RES Output 7. $\alpha = 0.05$

	High	**Low**
Low	$7.54e-02$	–
Medium	$5.74e-05$	$3.04e-01$

RES Output 7. $\alpha = 0.01$

	High	**Low**
Low	$4.66e-01$	–
Medium	$2.50e-04$	$1.31e-02$

RES Output 8. $\alpha = 1.0$

	High	**Low**
Low	$1.31e-02$	–
Medium	$1.70e-01$	$7.24e-01$

RES Output 8. $\alpha = 0.05$

	High	**Low**
Low	$1.39e-02$	–
Medium	$8.99e-01$	$2.07e-01$

RES Output 8. $\alpha = 0.01$

	High	**Low**
Low	$1.26e-03$	–
Medium	$8.03e-01$	$7.98e-02$

Table D.9.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, in different problem instances (Continuation from Table D.8). Evaluated α values corresponds to those in Table C.4 where differences were significant.

RES Output 9. $\alpha = 1.0$

	High	**Low**
Low	$6.21e-01$	–
Medium	$2.53e-01$	$5.16e-04$

RES Output 9. $\alpha = 0.5$

	High	**Low**
Low	1.00	–
Medium	$2.69e-02$	$3.23e-02$

RES Output 9. $\alpha = 0.1$

	High	**Low**
Low	1.00	–
Medium	$1.30e-03$	$3.51e-08$

RES Output 9. $\alpha = 0.05$

	High	**Low**
Low	$8.95e-01$	–
Medium	$1.41e-03$	$1.70e-08$

RES Output 9. $\alpha = 0.01$

	High	**Low**
Low	$1.08e-03$	–
Medium	1.00	$1.51e-08$

RES Output 10. $\alpha = 1.0$

	High	**Low**
Low	$7.06e-05$	–
Medium	$8.59e-04$	$3.96e-01$

RES Output 10. $\alpha = 0.5$

	High	**Low**
Low	$1.44e-04$	–
Medium	$1.26e-02$	$9.43e-02$

RES Output 10. $\alpha = 0.1$

	High	**Low**
Low	$2.40e-07$	–
Medium	$1.17e-01$	$9.05e-05$

RES Output 10. $\alpha = 0.05$

	High	**Low**
Low	$8.56e-08$	–
Medium	$4.43e-01$	$3.05e-04$

RES Output 10. $\alpha = 0.01$

	High	**Low**
Low	$1.27e-05$	–
Medium	$5.22e-03$	$8.89e-01$

RES Output 11. $\alpha = 1.0$

	High	**Low**
Low	$5.84e-15$	–
Medium	1.00	$4.37e-11$

RES Output 11. $\alpha = 0.5$

	High	**Low**
Low	$3.47e-13$	–
Medium	$7.39e-01$	$3.06e-10$

RES Output 11. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$4.76e-07$	$5.12e-14$

RES Output 11. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$7.12e-02$	$4.57e-13$

RES Output 11. $\alpha = 0.01$

	High	**Low**
Low	$9.54e-15$	–
Medium	$4.57e-10$	$2.40e-02$

RES Output 12. $\alpha = 1.0$

	High	**Low**
Low	$4.82e-06$	–
Medium	$1.30e-07$	$6.87e-01$

RES Output 12. $\alpha = 0.5$

	High	**Low**
Low	$1.03e-07$	–
Medium	$6.72e-01$	$1.80e-05$

RES Output 12. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$2.20e-16$	$2.20e-16$

RES Output 12. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$4.18e-12$	$1.17e-11$

RES Output 12. $\alpha = 0.01$

	High	**Low**
Low	$2.20e-16$	–
Medium	$4.34e-15$	$7.21e-14$

Table D.10.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, with fixed RES outputs, α configurations and a population of $40,000$. Evaluations correspond to those in Table C.5 where differences between samples within groups where found were significant. Continues in Table D.11.

RES Output 1. $\alpha = 0.1$

	High	**Low**
Low	$3.34e-04$	–
Medium	1.00	$1.77e-03$

RES Output 2. $\alpha = 1.0$

	High	**Low**
Low	$1.25e-06$	–
Medium	1.00	$1.01e-07$

RES Output 2. $\alpha = 0.5$

	High	**Low**
Low	$4.61e-05$	–
Medium	$2.83e-03$	1.00

RES Output 3. $\alpha = 1.0$

	High	**Low**
Low	$2.29e-03$	–
Medium	$1.01e-02$	$1.09e-10$

RES Output 3. $\alpha = 0.5$

	High	**Low**
Low	$1.18e-04$	–
Medium	$2.44e-01$	$3.77e-10$

RES Output 3. $\alpha = 0.1$

	High	**Low**
Low	$1.68e-08$	–
Medium	$5.86e-03$	$1.92e-06$

RES Output 3. $\alpha = 0.05$

	High	**Low**
Low	$5.12e-06$	–
Medium	$2.46e-03$	$8.75e-01$

RES Output 3. $\alpha = 0.01$

	High	**Low**
Low	$1.08e-06$	–
Medium	$5.99e-06$	1.00

RES Output 4. $\alpha = 0.1$

	High	**Low**
Low	$9.35e-05$	–
Medium	$7.26e-10$	$2.77e-02$

RES Output 5. $\alpha = 1.0$

	High	**Low**
Low	$7.08e-03$	–
Medium	1.00	$9.13e-01$

RES Output 5. $\alpha = 0.5$

	High	**Low**
Low	$2.69e-10$	–
Medium	1.00	$1.15e-11$

RES Output 5. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$6.52e-06$	$4.51e-11$

RES Output 5. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$3.08e-05$	$3.31e-03$

RES Output 5. $\alpha = 0.01$

	High	**Low**
Low	$3.22e-16$	–
Medium	$1.34e-12$	$1.87e-02$

RES Output 6. $\alpha = 1.0$

	High	**Low**
Low	$3.60e-03$	–
Medium	$1.26e-03$	$1.97e-05$

RES Output 6. $\alpha = 0.5$

	High	**Low**
Low	$2.04e-05$	–
Medium	$9.45e-06$	$1.85e-06$

RES Output 6. $\alpha = 0.1$

	High	**Low**
Low	$2.20e-16$	–
Medium	$1.84e-01$	$2.20e-16$

RES Output 6. $\alpha = 0.05$

	High	**Low**
Low	$2.20e-16$	–
Medium	$3.25e-06$	$2.20e-16$

RES Output 6. $\alpha = 0.01$

	High	**Low**
Low	$6.85e-16$	–
Medium	$9.40e-07$	$2.20e-16$

RES Output 7. $\alpha = 0.1$

	High	**Low**
Low	$2.23e-03$	–
Medium	$9.34e-06$	$5.29e-01$

RES Output 7. $\alpha = 0.05$

	High	**Low**
Low	$2.36e-02$	–
Medium	$5.50e-07$	$3.56e-01$

RES Output 7. $\alpha = 0.01$

	High	**Low**
Low	$4.56e-01$	–
Medium	$3.62e-04$	$9.73e-02$

RES Output 8. $\alpha = 1.0$

	High	**Low**
Low	$7.86e-03$	–
Medium	$1.91e-05$	1.00

RES Output 8. $\alpha = 0.5$

	High	**Low**
Low	$3.99e-03$	–
Medium	$1.76e-04$	1.00

RES Output 8. $\alpha = 0.1$

	High	**Low**
Low	$2.46e-03$	–
Medium	1.00	$1.45e-01$

Table D.11.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to forecasts variations, in different problem instances (Continuation from Table D.10). Evaluated α values corresponds to those in Table C.5 where differences were significant.

RES Output 8. $\alpha = 0.05$

	High	**Low**
Low	1.23e − 02	−
Medium	1.00	1.60e − 01

RES Output 8. $\alpha = 0.01$

	High	**Low**
Low	4.37e − 04	−
Medium	1.00	3.28e − 02

RES Output 9. $\alpha = 1.0$

	High	**Low**
Low	1.03e − 01	−
Medium	2.37e − 01	3.55e − 06

RES Output 9. $\alpha = 0.5$

	High	**Low**
Low	1.00	−
Medium	9.15e − 03	2.42e − 02

RES Output 9. $\alpha = 0.1$

	High	**Low**
Low	1.00	−
Medium	1.23e − 03	4.11e − 07

RES Output 9. $\alpha = 0.05$

	High	**Low**
Low	3.26e − 01	−
Medium	2.18e − 04	2.81e − 11

RES Output 9. $\alpha = 0.01$

	High	**Low**
Low	1.70e − 05	−
Medium	1.00	7.08e − 12

RES Output 10. $\alpha = 1.0$

	High	**Low**
Low	5.87e − 05	−
Medium	4.59e − 04	2.88e − 01

RES Output 10. $\alpha = 0.5$

	High	**Low**
Low	3.77e − 05	−
Medium	1.38e − 02	5.87e − 02

RES Output 10. $\alpha = 0.1$

	High	**Low**
Low	4.41e − 08	−
Medium	1.45e − 01	2.94e − 05

RES Output 10. $\alpha = 0.05$

	High	**Low**
Low	1.23e − 10	−
Medium	9.08e − 03	1.07e − 04

RES Output 10. $\alpha = 0.01$

	High	**Low**
Low	2.65e − 09	−
Medium	2.21e − 04	1.33e − 01

RES Output 11. $\alpha = 1.0$

	High	**Low**
Low	4.26e − 15	−
Medium	8.49e − 02	1.38e − 09

RES Output 11. $\alpha = 0.5$

	High	**Low**
Low	2.20e − 16	−
Medium	1.00	3.77e − 14

RES Output 11. $\alpha = 0.1$

	High	**Low**
Low	2.20e − 16	−
Medium	1.40e − 06	2.20e − 16

RES Output 11. $\alpha = 0.05$

	High	**Low**
Low	2.20e − 16	−
Medium	1.30e − 04	1.07e − 14

RES Output 11. $\alpha = 0.01$

	High	**Low**
Low	2.20e − 16	−
Medium	5.85e − 14	1.44e − 02

RES Output 12. $\alpha = 1.0$

	High	**Low**
Low	2.40e − 04	−
Medium	2.91e − 10	1.00

RES Output 12. $\alpha = 0.5$

	High	**Low**
Low	3.80e − 07	−
Medium	3.98e − 02	5.32e − 04

RES Output 12. $\alpha = 0.1$

	High	**Low**
Low	2.20e − 16	−
Medium	2.20e − 16	2.20e − 16

RES Output 12. $\alpha = 0.05$

	High	**Low**
Low	2.20e − 16	−
Medium	5.61e − 15	1.66e − 12

RES Output 12. $\alpha = 0.01$

	High	**Low**
Low	2.20e − 16	−
Medium	2.20e − 16	2.52e − 14

Table D.12.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to different α configurations, with different RES outputs. Evaluations corresponds to those in Table C.6 where differences were significant. Micro-grid population is 40.

RES Output 1. Low Quality

	0.01	0.05	0.1	0.5
0.05	8.26e − 01	–	–	–
0.1	1.00	1.00	–	–
0.5	1.93e − 04	7.65e − 02	3.10e − 02	–
1.0	8.84e − 04	8.84e − 02	2.68e − 02	1.00

RES Output 1. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.77e − 01	1.00	–	–
0.5	6.07e − 05	3.62e − 03	1.26e − 01	–
1.0	2.63e − 03	7.49e − 02	1.00	1.00

RES Output 1. High Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	4.74e − 03	2.98e − 02	–	–
0.5	2.66e − 03	1.77e − 02	1.00	–
1.0	1.32e − 03	1.24e − 02	1.00	1.00

RES Output 2. Low Quality

	0.01	0.05	0.1	0.5
0.05	4.01e − 03	–	–	–
0.1	6.28e − 05	1.00	–	–
0.5	6.97e − 05	1.00	1.00	–
1.0	1.97e − 05	1.00	1.00	1.00

RES Output 2. Medium Quality

	0.01	0.05	0.1	0.5
0.05	2.28e − 01	–	–	–
0.1	2.03e − 03	1.00	–	–
0.5	5.07e − 04	1.00	1.00	–
1.0	2.32e − 03	1.00	1.00	1.00

RES Output 2. High Quality

	0.01	0.05	0.1	0.5
0.05	6.14e − 02	–	–	–
0.1	9.49e − 04	1.00	–	–
0.5	8.77e − 06	2.37e − 01	1.00	–
1.0	2.51e − 06	1.71e − 01	1.00	1.00

RES Output 3. Low Quality

	0.01	0.05	0.1	0.5
0.05	4.76e − 05	–	–	–
0.1	7.38e − 07	1.00	–	–
0.5	1.30e − 01	6.01e − 01	3.95e − 02	–
1.0	3.11e − 01	7.06e − 02	2.68e − 03	1.00

RES Output 3. Medium Quality

	0.01	0.05	0.1	0.5
0.05	4.82e − 03	–	–	–
0.1	3.24e − 03	1.00	–	–
0.5	2.94e − 01	1.00	1.00	–
1.0	1.00	2.37e − 01	1.77e − 01	1.00

RES Output 3. High Quality

	0.01	0.05	0.1	0.5
0.05	2.96e − 01	–	–	–
0.1	1.86e − 03	6.60e − 01	–	–
0.5	6.98e − 03	1.00	1.00	–
1.0	1.94e − 01	1.00	1.00	1.00

RES Output 4. Low Quality

	0.01	0.05	0.1	0.5
0.05	2.10e − 01	–	–	–
0.1	1.00	1.00	–	–
0.5	1.00	3.24e − 03	1.37e − 01	–
1.0	3.28e − 01	1.91e − 04	6.80e − 03	1.00

RES Output 4. Medium Quality

	0.01	0.05	0.1	0.5
0.05	8.34e − 01	–	–	–
0.1	3.07e − 01	1.00	–	–
0.5	1.00	1.28e − 01	2.79e − 02	–
1.0	4.97e − 02	1.83e − 04	2.83e − 05	4.79e − 01

RES Output 4. High Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.00	1.00	–	–
0.5	3.43e − 02	5.28e − 03	2.54e − 04	–
1.0	4.91e − 03	8.57e − 04	1.11e − 05	1.00

RES Output 5. Medium Quality

	0.01	0.05	0.1	0.5
0.05	8.47e − 01	–	–	–
0.1	9.34e − 03	7.39e − 01	–	–
0.5	3.52e − 03	4.45e − 01	1.00	–
1.0	1.83e − 01	1.00	1.00	1.00

RES Output 5. High Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	7.43e − 03	4.63e − 01	–	–
0.5	3.57e − 02	9.25e − 01	1.00	–
1.0	5.23e − 04	4.75e − 02	1.00	1.00

RES Output 6. Low Quality

	0.01	0.05	0.1	0.5
0.05	8.83e − 01	–	–	–
0.1	6.47e − 02	1.00	–	–
0.5	8.52e − 01	1.00	1.00	–
1.0	1.00	1.00	1.37e − 01	1.00

RES Output 6. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	3.36e − 01	4.99e − 01	–	–
0.5	2.51e − 01	2.69e − 01	2.60e − 04	–
1.0	2.84e − 03	3.76e − 03	1.12e − 06	1.00

RES Output 6. High Quality

	0.01	0.05	0.1	0.5
0.05	1.06e − 03	–	–	–
0.1	6.81e − 05	1.00	–	–
0.5	1.00	8.86e − 05	4.98e − 06	–
1.0	1.00	8.92e − 07	2.40e − 08	1.00

RES Output 7. Low Quality

	0.01	0.05	0.1	0.5
0.05	2.49e − 04	–	–	–
0.1	1.71e − 04	1.00	–	–
0.5	1.09e − 04	1.00	1.00	–
1.0	8.26e − 03	1.00	1.00	1.00

RES Output 7. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	4.63e − 01	1.00	–	–
0.5	4.97e − 02	1.00	1.00	–
1.0	1.92e − 03	1.78e − 01	1.00	1.00

RES Output 7. High Quality

	0.01	0.05	0.1	0.5
0.05	1.13e − 01	–	–	–
0.1	2.71e − 02	1.00	–	–
0.5	3.33e − 02	1.00	1.00	–
1.0	3.98e − 02	1.00	1.00	1.00

RES Output 8. Low Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.00	1.00	–	–
0.5	1.59e − 04	1.24e − 03	2.03e − 03	–
1.0	6.17e − 14	1.07e − 12	6.05e − 12	3.29e − 04

RES Output 8. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.00	1.00	–	–
0.5	1.66e − 01	1.22e − 02	2.01e − 01	–
1.0	4.76e − 05	8.12e − 07	2.31e − 05	8.72e − 02

RES Output 8. High Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	8.13e − 01	1.00	–	–
0.5	1.55e − 02	2.17e − 03	1.03e − 06	–
1.0	2.09e − 02	4.65e − 03	3.61e − 06	1.00

RES Output 9. Low Quality

	0.01	0.05	0.1	0.5
0.05	6.35e − 01	–	–	–
0.1	3.72e − 05	4.61e − 02	–	–
0.5	3.66e − 03	1.00	1.00	–
1.0	1.31e − 01	1.00	6.47e − 02	1.00

RES Output 9. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	8.94e − 03	1.32e − 01	–	–
0.5	1.06e − 04	2.05e − 03	1.00	–
1.0	1.77e − 03	3.54e − 02	1.00	1.00

RES Output 9. High Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	4.85e − 06	1.35e − 03	–	–
0.5	5.04e − 05	8.12e − 03	1.00	–
1.0	1.87e − 04	1.74e − 02	1.00	1.00

RES Output 10. Low Quality

	0.01	0.05	0.1	0.5
0.05	7.67e − 01	–	–	–
0.1	4.33e − 04	1.34e − 01	–	–
0.5	6.24e − 04	1.26e − 01	1.00	–
1.0	4.79e − 06	5.48e − 03	1.00	1.00

RES Output 10. Medium Quality

	0.01	0.05	0.1	0.5
0.05	2.90e − 01	–	–	–
0.1	5.83e − 02	1.00	–	–
0.5	1.32e − 02	1.00	1.00	–
1.0	3.01e − 01	1.00	1.00	1.00

RES Output 10. High Quality

	0.01	0.05	0.1	0.5
0.05	3.73e − 01	–	–	–
0.1	3.89e − 02	1.00	–	–
0.5	3.43e − 04	2.45e − 01	1.00	–
1.0	3.02e − 04	2.59e − 01	1.00	1.00

RES Output 11. Low Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.00	1.00	–	–
0.5	8.41e − 02	1.00	9.98e − 01	–
1.0	2.09e − 03	1.01e − 01	8.53e − 02	1.00

RES Output 11. Medium Quality

	0.01	0.05	0.1	0.5
0.05	9.93e − 01	–	–	–
0.1	3.66e − 02	1.00	–	–
0.5	8.56e − 03	7.39e − 01	1.00	–
1.0	4.32e − 03	3.42e − 01	1.00	1.00

RES Output 11. High Quality

	0.01	0.05	0.1	0.5
0.05	4.14e − 01	–	–	–
0.1	1.33e − 01	1.00	–	–
0.5	1.92e − 01	1.00	1.00	–
1.0	7.24e − 03	1.00	1.00	1.00

RES Output 12. Low Quality

	0.01	0.05	0.1	0.5
0.05	1.49e − 01	–	–	–
0.1	4.44e − 02	1.00	–	–
0.5	1.00	1.00	6.49e − 01	–
1.0	1.00	1.00	1.00	1.00

RES Output 12. Medium Quality

	0.01	0.05	0.1	0.5
0.05	1.00	–	–	–
0.1	1.12e − 01	3.40e − 01	–	–
0.5	8.97e − 02	3.07e − 01	1.00	–
1.0	4.17e − 01	1.00	1.00	1.00

Table D.13.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to different α configurations, with different RES outputs. Evaluations corresponds to those in Table C.7 where differences were significant. Micro-grid population is 400.

RES Output 1. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.0325	–	–	–
0.1	$3.90e-14$	$3.60e-06$	–	–
0.5	$< 2e-16$	$4.30e-08$	1	–
1.0	$7.50e-09$	0.0275	0.0561	0.0027

RES Output 1. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00025	–	–	–
0.1	$< 2e-16$	$8.10e-07$	–	–
0.5	$< 2e-16$	$8.30e-08$	1	–
1.0	$7.10e-14$	0.00123	0.41206	0.13364

RES Output 1. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00048	–	–	–
0.1	$7.10e-15$	$1.80e-05$	–	–
0.5	$4.70e-12$	0.00674	0.51052	–
1.0	$7.00e-08$	0.9735	0.00841	0.82559

RES Output 2. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.50e-13$	–	–	–
0.1	$< 2e-16$	$3.20e-08$	–	–
0.5	$< 2e-16$	0.33	$9.80e-06$	–
1.0	$< 2e-16$	0.62	$1.20e-06$	1

RES Output2. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00016	–	–	–
0.1	$5.90e-14$	$6.20e-06$	–	–
0.5	$1.60e-10$	0.20607	0.00213	–
1.0	$5.70e-10$	0.69269	0.00018	1

RES Output 2. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.20e-14$	–	–	–
0.1	$< 2e-16$	0.00039	–	–
0.5	$< 2e-16$	1	$4.40e-05$	–
1.0	$< 2e-16$	1	0.00101	1

RES Output 3. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.20e-08$	–	–	–
0.1	$3.40e-11$	1	–	–
0.5	$5.10e-06$	0.56197	0.00487	–
1.0	0.00011	0.06277	0.00014	1

RES Output 3. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.50e-12$	–	–	–
0.1	$4.40e-16$	1	–	–
0.5	$6.70e-06$	0.0145	$7.50e-05$	–
1.0	0.0014	0.0035	$5.40e-06$	1

RES Output 3. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.40e-10$	–	–	–
0.1	$2.80e-14$	0.53	–	–
0.5	$1.40e-11$	1	0.59	–
1.0	$1.50e-10$	1	0.21	1

RES Output 4. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.01698	–	–	–
0.1	0.00465	1	–	–
0.5	1	0.00424	0.00044	–
1.0	1	$1.70e-06$	$6.00e-09$	0.66327

RES Output 4. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.50e-09$	–	–	–
0.1	$4.60e-16$	0.0025	–	–
0.5	1	$9.90e-06$	$2.80e-12$	–
1.0	1	$1.50e-11$	$< 2e-16$	0.1832

RES Output 4. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.20474	–	–	–
0.1	0.14999	1	–	–
0.5	0.96858	0.00066	$2.00e-05$	–
1.0	0.01656	$6.40e-07$	$9.30e-10$	0.5942

RES Output 5. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00117	–	–	–
0.1	$4.90e-09$	0.24349	–	–
0.5	$2.90e-11$	0.00128	0.27788	–
1.0	0.00067	1	0.09979	0.00017

RES Output 5. Meidum Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.60e-06$	–	–	–
0.1	$1.50e-15$	$7.00e-05$	–	–
0.5	$8.80e-07$	1	0.00015	–
1.0	0.3466	0.03434	$8.50e-11$	0.00894

RES Output 5. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.00e-09$	–	–	–
0.1	$8.70e-14$	0.5909	–	–
0.5	1	$3.50e-08$	$2.40e-13$	–
1.0	0.3977	$3.30e-13$	$< 2e-16$	0.0043

RES Output 6. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.00e-07$	–	–	–
0.1	$2.10e-13$	0.033	–	–
0.5	$2.20e-12$	$3.32e-01$	$1.00E+00$	–
1.0	$1.00e-06$	$1.00E+00$	0.013	0.16

RES Output 6. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.00e-10$	–	–	–
0.1	$5.10e-10$	$1.00E+00$	–	–
0.5	$1.00E+00$	$5.00e-16$	$1.90e-15$	–
1.0	0.00069	$< 2e-16$	$< 2e-16$	$9.76e-03$

RES Output 6. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.30e-15$	–	–	–
0.1	$< 2e-16$	0.0817	–	–
0.5	$5.60e-03$	$3.20e-10$	$5.50e-16$	–
1.0	1	$< 2e-16$	$< 2e-16$	0.0063

RES Output 7. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$9.50e-05$	–	–	–
0.1	$5.60e-11$	0.00339	–	–
0.5	0.00306	1	$1.30e-05$	–
1.0	1	$1.10e-05$	$1.10e-13$	0.00036

RES Output 7. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.90e-05$	–	–	–
0.1	$3.50e-12$	0.02105	–	–
0.5	$2.60e-06$	$1.00E+00$	$1.90e-04$	–
1.0	0.00219	$1.12e-01$	$3.30e-09$	0.03685

RES Output 7. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.30e-08$	–	–	–
0.1	$< 2e-16$	0.00018	–	–
0.5	$1.67e-03$	0.03488	$7.50e-12$	–
1.0	$9.16e-01$	$8.80e-08$	$< 2e-16$	0.04204

RES Output 8. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.19	–	–	–
0.1	1	1	–	–
0.5	$2.50e-06$	$1.30e-15$	$5.50e-13$	–
1.0	$3.40e-10$	$< 2e-16$	$< 2e-16$	0.11

RES Output 8. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.3424	–	–	–
0.1	1	1	–	–
0.5	0.0082	$9.20e-07$	$2.70e-07$	–
1.0	$3.30e-07$	$3.50e-12$	$4.70e-14$	0.0686

RES Output 8. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.0817	–	–	–
0.1	$5.05e-01$	1	–	–
0.5	1.00	$6.30e-06$	0.0011	–
1.0	0.0087	$7.30e-11$	$7.80e-08$	0.0717

RES Output 9. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.4e-09$	–	–	–
0.1	$< 2e-16$	$8.3e-08$	–	–
0.5	$1.2e-06$	1	$3.5e-09$	–
1.0	$2.6e-07$	1.00	$4.9e-11$	1.00

RES Output 9. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.60e-07$	–	–	–
0.1	$< 2e-16$	$4.70e-09$	–	–
0.5	$2.70e-13$	0.028	0.001	–
1.0	$2.40e-10$	1	$1.10e-06$	0.86

RES Output 9. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$8.10e-10$	–	–	–
0.1	$< 2e-16$	0.00018	–	–
0.5	$1.50e-11$	1	$1.80e-05$	–
1.0	$7.90e-10$	1	$4.90e-08$	1

RES Output 10. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.50e-05$	–	–	–
0.1	$1.60e-12$	0.0618	–	–
0.5	$8.90e-08$	1	0.8518	–
1.0	0.0014	1	0.0032	0.4905

RES Output 10. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	1	–	–	–
0.1	$3.40e-08$	$1.90e-05$	–	–
0.5	0.0007	0.0841	0.0853	–
1.0	$1.20e-05$	0.0025	1	1

RES Output 10. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.11482	–	–	–
0.1	0.00031	0.89248	–	–
0.5	0.00543	1	1	–
1.0	0.02398	1	1	1

RES Output 11. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.20e-03$	–	–	–
0.1	$1.60e-11$	$9.90e-04$	–	–
0.5	$1.50e-07$	0.57148	0.19056	–
1.0	$7.05e-03$	1	$7.00e-05$	0.12913

RES Output 11. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$5.80e-08$	–	–	–
0.1	$4.60e-14$	0.0984	–	–
0.5	$4.10e-09$	1.00	0.0557	–
1.0	$3.40e-05$	1.00	0.0002	$9.54e-01$

RES Output 11. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.00e-05$	–	–	–
0.1	$1.80e-10$	0.055	–	–
0.5	$1.10e-02$	0.141	$1.90e-06$	–
1.0	0.062	0.091	$1.60e-06$	1

RES Output 12. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-05$	–	–	–
0.1	$7.30e-09$	1.00	–	–
0.5	$3.10e-05$	1	0.39	–
1.0	$4.60e-05$	1	0.07	1

RES Output 12. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.70e-10$	–	–	–
0.1	$1.40e-15$	0.432	–	–
0.5	0.031	$3.70e-05$	$7.30e-10$	–
1.0	1	$4.00e-10$	$3.00e-15$	0.098

RES Output 12. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.90e-07$	–	–	–
0.1	$< 2e-16$	$5.80e-05$	–	–
0.5	$3.20e-01$	$2.60e-15$	$< 2e-16$	–
1.0	0.0047	$< 2e-16$	$< 2e-16$	0.3242

Table D.14.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to different α configurations, with different RES outputs. Evaluations corresponds to those in Table C.8 where differences were significant. Micro-grid population is $4,000$.

RES Output 1. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.35e-08$	–	–	–
0.1	$2.20e-16$	$6.95e-08$	–	–
0.5	$2.20e-16$	$2.20e-16$	$5.12e-04$	–
1.0	$2.20e-16$	$8.45e-06$	1.00	$6.62e-07$

RES Output 1. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.16e-08$	–	–	–
0.1	$2.20e-16$	$1.50e-09$	–	–
0.5	$2.20e-16$	$2.03e-14$	$5.05e-01$	–
1.0	$2.20e-16$	$2.37e-05$	$2.46e-02$	$9.42e-07$

RES Output 1. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$5.35e-08$	–	–	–
0.1	$2.20e-16$	$2.20e-09$	–	–
0.5	$2.20e-16$	$5.25e-07$	1.00	–
1.0	$1.21e-11$	$7.39e-01$	$4.49e-06$	$8.04e-06$

RES Output 2. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$2.06e-15$	–	–
0.5	$2.20e-16$	$4.90e-02$	$4.73e-11$	–
1.0	$2.20e-16$	$4.37e-02$	$2.18e-13$	1.00

RES Output 2. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$6.98e-12$	–	–	–
0.1	$2.20e-16$	$4.62e-12$	–	–
0.5	$6.27e-16$	$4.99e-01$	$8.61e-11$	–
1.0	$1.20e-12$	$8.61e-01$	$2.21e-16$	$7.55e-05$

RES Output 2. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.21e-13$	–	–	–
0.1	$2.20e-16$	$1.65e-05$	–	–
0.5	$2.20e-16$	$3.95e-01$	$2.66e-09$	–
1.0	$2.20e-16$	$4.86e-02$	$3.70e-10$	1.00

RES Output 3. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.91e-15$	–	–	–
0.1	$2.20e-16$	$7.33e-02$	–	–
0.5	$3.34e-11$	$5.37e-02$	$3.14e-10$	–
1.0	$7.16e-08$	$2.66e-10$	$2.20e-16$	$1.59e-05$

RES Output 3. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	1.00	–	–
0.5	$2.20e-16$	$3.23e-05$	$5.96e-10$	–
1.0	$5.15e-11$	$4.91e-13$	$2.20e-16$	$9.81e-05$

RES Output 3. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$8.59e-13$	–	–	–
0.1	$2.20e-16$	$8.05e-03$	–	–
0.5	$2.20e-16$	$2.31e-01$	$9.91e-02$	–
1.0	$5.67e-15$	1.00	$9.29e-07$	$6.92e-03$

RES Output 4. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.57e-05$	–	–	–
0.1	$6.99e-07$	1.00	–	–
0.5	1.00	$1.02e-09$	$5.09e-16$	–
1.0	1.00	$3.64e-15$	$2.20e-16$	$1.20e-02$

RES Output 4. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$1.72e-03$	–	–
0.5	$2.15e-03$	$2.78e-12$	$2.20e-16$	–
1.0	1.00	$2.20e-16$	$2.20e-16$	$2.97e-05$

RES Output 4. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.11e-05$	–	–	–
0.1	$2.48e-01$	$3.70e-01$	–	–
0.5	$3.28e-01$	$1.73e-08$	$3.29e-11$	–
1.0	$1.58e-03$	$6.90e-11$	$2.20e-16$	$1.17e-02$

RES Output 5. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$1.67e-08$	–	–
0.5	$2.20e-16$	$1.02e-13$	$8.18e-09$	–
1.0	$1.55e-08$	1.00	$3.58e-04$	$8.13e-13$

RES Output 5. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$3.62e-07$	–	–
0.5	$1.46e-10$	1.00	$4.22e-12$	–
1.0	$3.25e-04$	$1.93e-06$	$2.20e-16$	$5.63e-03$

RES Output 5. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.55e-16$	–	–	–
0.1	$2.20e-16$	$5.50e-10$	–	–
0.5	$8.53e-02$	$1.52e-09$	$2.20e-16$	–
1.0	$1.50e-03$	$2.20e-16$	$2.20e-16$	$3.70e-09$

RES Output 6. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.49e-10$	–	–	–
0.1	$2.20e-16$	$6.02e-06$	–	–
0.5	$2.20e-16$	$5.87e-04$	1.00	–
1.0	$4.56e-13$	1.00	$6.55e-11$	$7.37e-08$

RES Output 6. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$5.18e-14$	–	–	–
0.1	$3.29e-16$	1.00	–	–
0.5	$4.54e-02$	$2.20e-16$	$2.20e-16$	–
1.0	$1.11e-06$	$2.20e-16$	$2.20e-16$	$8.59e-13$

RES Output 6. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$2.81e-07$	–	–
0.5	$5.07e-04$	$2.20e-16$	$2.20e-16$	–
1.0	1.00	$2.20e-16$	$2.20e-16$	$1.32e-15$

RES Output 7. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.90e-07$	–	–	–
0.1	$2.20e-16$	$4.52e-04$	–	–
0.5	$1.42e-08$	1.00	$1.01e-05$	–
1.0	1.00	$1.93e-06$	$2.20e-16$	$2.06e-09$

RES Output 7. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.45e-07$	–	–	–
0.1	$1.14e-15$	$1.04e-04$	–	–
0.5	$4.83e-09$	1.00	$1.55e-05$	–
1.0	$3.83e-02$	$2.92e-04$	$7.93e-14$	$7.55e-05$

RES Output 7. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.63e-12$	–	–	–
0.1	$2.20e-16$	$1.27e-08$	–	–
0.5	$4.76e-04$	$1.70e-04$	$2.20e-16$	–
1.0	1.00	$2.20e-16$	$2.20e-16$	$3.53e-09$

RES Output 8. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.48e-03$	–	–	–
0.1	1.00	$1.34e-01$	–	–
0.5	$4.93e-05$	$2.20e-16$	$2.20e-16$	–
1.0	$4.41e-11$	$2.20e-16$	$2.20e-16$	$4.00e-12$

RES Output 8. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.97e-04$	–	–	–
0.1	$2.38e-02$	1.00	–	–
0.5	$2.29e-06$	$4.62e-12$	$6.53e-15$	–
1.0	$1.91e-11$	$2.20e-16$	$2.20e-16$	$1.09e-11$

RES Output 8. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$8.84e-04$	–	–	–
0.1	$8.57e-04$	1.00	–	–
0.5	$9.39e-01$	$4.09e-05$	$1.18e-08$	–
1.0	$2.07e-03$	$6.66e-15$	$2.20e-16$	$4.62e-12$

RES Output 9. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$2.20e-16$	–	–
0.5	$5.35e-08$	$2.04e-08$	$2.20e-16$	–
1.0	$1.08e-06$	$2.73e-12$	$2.20e-16$	1.00

RES Output 9. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.16e-14$	–	–	–
0.1	$2.20e-16$	$3.12e-14$	–	–
0.5	$2.20e-16$	1.00	$2.20e-16$	–
1.0	$9.43e-13$	$1.07e-01$	$2.20e-16$	$2.98e-01$

RES Output 9. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.35e-14$	–	–	–
0.1	$2.20e-16$	$1.60e-09$	–	–
0.5	$8.00e-10$	$1.42e-02$	$2.20e-16$	–
1.0	$1.48e-06$	$6.81e-05$	$2.20e-16$	$6.21e-01$

RES Output 10. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.55e-08$	–	–	–
0.1	$2.20e-16$	$1.20e-07$	–	–
0.5	$2.76e-05$	1.00	$8.75e-04$	–
1.0	$3.74e-02$	1.00	$5.39e-09$	$4.29e-01$

RES Output 10. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.69e-03$	–	–	–
0.1	$2.20e-16$	$2.40e-08$	–	–
0.5	$2.46e-03$	1.00	$1.86e-05$	–
1.0	1.00	1.00	$4.10e-08$	$3.59e-01$

RES Output 10. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.16e-09$	–	–	–
0.1	$2.20e-16$	$2.01e-06$	–	–
0.5	$6.62e-03$	$8.79e-01$	$8.23e-07$	–
1.0	1.00	$1.08e-06$	$1.02e-13$	$1.91e-02$

RES Output 11. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.67e-07$	–	–	–
0.1	$2.20e-16$	$1.39e-05$	–	–
0.5	$1.60e-09$	1.00	$4.29e-04$	–
1.0	$1.19e-02$	$1.19e-02$	$4.23e-10$	$2.92e-04$

RES Output 11. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$1.09e-04$	–	–
0.5	$2.20e-16$	1.00	$2.48e-08$	–
1.0	$1.64e-13$	$8.65e-01$	$2.42e-09$	1.00

RES Output 11. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.24e-12$	–	–	–
0.1	$2.20e-16$	$3.78e-11$	–	–
0.5	$1.01e-06$	$2.44e-02$	$2.20e-16$	–
1.0	$4.07e-04$	$1.65e-05$	$2.20e-16$	$4.68e-01$

RES Output 12. Low Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.94e-09$	–	–	–
0.1	$1.03e-11$	1.00	–	–
0.5	$7.16e-08$	1.00	1.00	–
1.0	$6.91e-06$	$1.80e-01$	$2.10e-02$	1.00

RES Output 12. Medium Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$1.69e-05$	–	–
0.5	$2.07e-04$	$2.75e-08$	$2.20e-16$	–
1.0	$5.49e-02$	$2.20e-16$	$2.20e-16$	$1.63e-11$

RES Output 12. High Quality

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.20e-16$	–	–	–
0.1	$2.20e-16$	$1.01e-14$	–	–
0.5	$3.08e-04$	$2.20e-16$	$2.20e-16$	–
1.0	$2.64e-13$	$2.20e-16$	$2.20e-16$	$1.07e-05$

Table D.15.: Pairwise Wilcoxon rank sum test unpaired with Bonferroni correction for assessing differences in performance due to different α configurations, with different RES outputs. Evaluations corresponds to those in Table C.9 where differences were significant. Micro-grid population is $40,000$.

RES Output 1. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.50e-08$	–	–	–
0.1	$< 2e-16$	$6.30e-10$	–	–
0.5	$< 2e-16$	$< 2e-16$	0.00027	–
1.0	$< 2e-16$	$2.20e-04$	0.86522	$8.70e-10$

RES Output 1. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$8.80e-08$	–	–	–
0.1	$< 2e-16$	$1.10e-10$	–	–
0.5	$< 2e-16$	$< 2e-16$	0.678	–
1.0	$< 2e-16$	$1.10e-06$	$2.00e-03$	$3.30e-08$

RES Output 1. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$6.00e-08$	–	–	–
0.1	$< 2e-16$	$2.30e-09$	–	–
0.5	$< 2e-16$	$2.30e-06$	1	–
1.0	$1.30e-13$	$2.88e-01$	$7.10e-05$	0.00012

RES Output 2. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$< 2e-16$	–	–
0.5	$< 2e-16$	0.083	$1.30e-12$	–
1.0	$< 2e-16$	0.584	$< 2e-16$	1

RES Output2. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.20e-14$	–	–	–
0.1	$< 2e-16$	$3.40e-12$	–	–
0.5	$< 2e-16$	1	$4.60e-11$	–
1.0	$5.10e-14$	$3.10e-02$	$< 2e-16$	$1.00e-05$

RES Output 2. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.5e-14$	–	–	–
0.1	$< 2e-16$	$3.7e-05$	–	–
0.5	$< 2e-16$	0.0829	$4.0e-11$	–
1.0	$< 2e-16$	0.0072	$3.4e-10$	0.1460

RES Output 3. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.2e-14$	–	–	–
0.1	$7.1e-15$	0.035	–	–
0.5	$2.8e-11$	0.357	$3.8e-16$	–
1.0	$2.0e-09$	$1.1e-06$	$< 2e-16$	$4.2e-05$

RES Output 3. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	1	–	–
0.5	$< 2e-16$	$3.50e-09$	$< 2e-16$	–
1.0	$6.50e-14$	$< 2e-16$	$< 2e-16$	$7.10e-10$

RES Output 3. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$5.10e-12$	–	–	–
0.1	$< 2e-16$	$3.70e-03$	–	–
0.5	$< 2e-16$	$8.47e-02$	0.0647	–
1.0	$1.90e-15$	1.00	$5.80e-08$	0.0004

RES Output 4. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.0001	–	–	–
0.1	$8.10e-06$	1	–	–
0.5	1	$3.10e-09$	$< 2e-16$	–
1.0	0.9934	$1.20e-14$	$< 2e-16$	0.0021

RES Output 4. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	0.0041	–	–
0.5	0.0028	$2.6e-16$	$< 2e-16$	–
1.0	1	$< 2e-16$	$< 2e-16$	$2.5e-05$

RES Output 4. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.0e-07$	–	–	–
0.1	0.5588	0.1239	–	–
0.5	0.1181	$1.4e-08$	$1.1e-11$	–
1.0	0.0017	$1.6e-10$	$< 2e-16$	0.0282

RES Output 5. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$3.1e-09$	–	–
0.5	$< 2e-16$	$3.6e-13$	$1.5e-11$	–
1.0	$7.6e-09$	1	0.00071	$1.6e-15$

RES Output 5. Meidum Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$1.0e-06$	–	–
0.5	$6.5e-13$	1.000	$1.0e-11$	–
1.0	$6.9e-07$	$3.4e-06$	$< 2e-16$	0.014

RES Output 5. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$5.4e-11$	–	–
0.5	0.0295	$1.9e-10$	$< 2e-16$	–
1.0	0.0092	$< 2e-16$	$< 2e-16$	$1.4e-09$

RES Output 6. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.4e-11$	–	–	–
0.1	$< 2e-16$	$3.9e-07$	–	–
0.5	$< 2e-16$	$2.5e-05$	1	–
1.0	$< 2e-16$	1	$4.3e-12$	$1.1e-11$

RES Output 6. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$7.7e-15$	–	–	–
0.1	$1.4e-15$	1.000	–	–
0.5	0.072	$< 2e-16$	$< 2e-16$	–
1.0	$6.0e-07$	$< 2e-16$	$< 2e-16$	$< 2e-16$

RES Output 6. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$2.5e-10$	–	–
0.5	0.02	$< 2e-16$	$< 2e-16$	–
1.0	1.00	$< 2e-16$	$< 2e-16$	$< 2e-16$

RES Output 7. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$1.4e-06$	–	–	–
0.1	$< 2e-16$	1.00	–	–
0.5	$1.4e-08$	1.00	$9.2e-06$	–
1.0	1.00	$1.2e-06$	$< 2e-16$	$4.5e-10$

RES Output 7. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$3.8e-07$	–	–	–
0.1	$7.0e-16$	0.00014	–	–
0.5	$2.6e-09$	100.000	0.00011	–
1.0	0.07823	0.00107	$7.8e-14$	0.00010

RES Output 7. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.2e-12$	–	–	–
0.1	$< 2e-16$	$1.9e-06$	–	–
0.5	0.0012	$3.5e-07$	$< 2e-16$	–
1.0	0.2660	$< 2e-16$	$< 2e-16$	$1.3e-09$

RES Output 8. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00224	–	–	–
0.1	100.000	0.26431	–	–
0.5	0.00018	$< 2e-16$	$< 2e-16$	–
1.0	$1.2e-09$	$< 2e-16$	$< 2e-16$	$4.1e-16$

RES Output 8. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$8.5e-06$	–	–	–
0.1	0.0021	0.7468	–	–
0.5	$8.4e-09$	$1.8e-12$	$1.3e-15$	–
1.0	$2.3e-12$	$9.3e-16$	$< 2e-16$	$< 2e-16$

RES Output 8. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	0.00025	–	–	–
0.1	0.00098	100.000	–	–
0.5	0.27961	0.00327	$3.3e-05$	–
1.0	0.01448	$< 2e-16$	$< 2e-16$	$< 2e-16$

RES Output 9. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$< 2e-16$	–	–
0.5	$5.7e-08$	$1.6e-12$	$< 2e-16$	–
1.0	$5.9e-06$	$7.7e-15$	$< 2e-16$	1

RES Output 9. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$2.1e-15$	–	–
0.5	$< 2e-16$	100.000	$< 2e-16$	–
1.0	$2.2e-12$	0.00094	$< 2e-16$	0.00181

RES Output 9. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$2.7e-14$	–	–	–
0.1	$< 2e-16$	$1.4e-10$	–	–
0.5	$3.3e-11$	0.0058	$< 2e-16$	–
1.0	$5.1e-07$	$1.3e-05$	$< 2e-16$	0.3031

RES Output 10. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.0e-11$	–	–	–
0.1	$< 2e-16$	$6.1e-07$	–	–
0.5	$1.3e-05$	0.771	0.013	–
1.0	0.068	1.000	$1.9e-08$	0.239

RES Output 10. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$5.9e-07$	–	–	–
0.1	$< 2e-16$	$1.4e-08$	–	–
0.5	0.0062	10.000	$9.6e-06$	–
1.0	10.000	0.0020	$2.3e-10$	0.0060

RES Output 10. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.1e-12$	–	–	–
0.1	$< 2e-16$	$9.4e-08$	–	–
0.5	0.0076	1	$4.3e-07$	–
1.0	0.0727	$3.9e-08$	$4.6e-15$	0.0010

RES Output 11. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.8e-10$	–	–	–
0.1	$< 2e-16$	$6.9e-07$	–	–
0.5	$3.5e-12$	10.000	$3.7e-06$	–
1.0	0.0089	0.0022	$7.4e-11$	$6.9e-06$

RES Output 11. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$1.7e-09$	–	–
0.5	$< 2e-16$	1.000	$9.8e-13$	–
1.0	$< 2e-16$	0.429	$< 2e-16$	0.077

RES Output 11. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$1.7e-15$	–	–
0.5	$7.4e-13$	0.0019	$< 2e-16$	–
1.0	$2.4e-11$	$9.1e-10$	$< 2e-16$	0.4766

RES Output 12. Low Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$4.0e-11$	–	–	–
0.1	$4.5e-13$	1.00	–	–
0.5	$1.7e-07$	1	0.9735	–
1.0	$1.3e-06$	0.2314	0.0069	1

RES Output 12. Medium Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$1.4e-06$	–	–
0.5	0.00039	$2.1e-12$	$< 2e-16$	–
1.0	$2.9e-05$	$< 2e-16$	$< 2e-16$	$< 2e-16$

RES Output 12. High Quality.

	0.01	**0.05**	**0.1**	**0.5**
0.05	$< 2e-16$	–	–	–
0.1	$< 2e-16$	$1.1e-15$	–	–
0.5	0.00052	$< 2e-16$	$< 2e-16$	–
1.0	$< 2e-16$	$< 2e-16$	$< 2e-16$	$1.1e-10$

Table D.16.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing scalability between SLC, CLP and NLC. Evaluations corresponds to those in Table C.10 where differences are significant. Continues in Table D.17.

RES Output 1. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 1. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 1. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 1. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 2. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 2. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 2. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 2. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 3. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 3. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 3. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 3. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 4. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 4. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 4. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 4. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 5. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 5. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 5. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 5. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 6. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 6. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 6. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 6. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 7. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

Table D.17.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing scalability between SLC, CLP and NLC. Evaluations corresponds to those in Table C.10 where differences are significant. Continuation from Table D.16.

RES Output 7. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 7. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 7. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 8. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 8. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 8. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output8. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 9. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 9. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 9. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 9. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 10. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 10. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 10. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 5. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 11. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 11. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 11. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 11. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 12. 40 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 12. 400 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 12. 4.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

RES Output 12. 40.000 **Households**

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.20e-16$	$2.20e-16$

Table D.18.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing the effect of dynamism in the performance of SLC, CLP and NLC. Evaluations corresponds to those in Table C.11 where differences are significant. Continues in Table D.19.

RES Output 1. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$5.9e-12$	$2.2e-16$

RES Output 1. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$6.3e-16$	$2.2e-16$

RES Output 1.High Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 2. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$1.5e-09$

RES Output 2. High Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$1.7e-11$	$2.2e-16$

RES Output 3. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 3. High Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 4. High Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$3.0e-01$	$2.2e-16$

RES Output 5. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 5. High Flexibility

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 6.High Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 7. Low Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 7. Medium Quality

	CLP	**NLC**
NLC	$2.20e-16$	–
SLC	$2.8e-07$	$2.2e-16$

Table D.19.: Pairwise Wilcoxon rank-sum test unpaired with Bonferroni correction for assessing the effect of dynamism in the performance of SLC, CLP and NLC. Evaluations corresponds to those in Table C.11 where differences are significant. Continuation from Table D.19.

RES Output 7. High Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$1.8e-13$	$2.2e-16$

RES Output 8. Low Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. Medium Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 8. High Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. Low Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. Medium Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 9. High Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$3.1e-14$	$2.2e-16$

RES Output 10. Low Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$1.4e-13$	$2.2e-16$

RES Output 10. Medium Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$6.2e-16$

RES Output 10. High Flexibility

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.9e-13$

RES Output 11. Low Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$9.8e-06$	$2.2e-16$

RES Output 11. Medium Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 11.High Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. Low Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$4.7e-02$	$2.2e-16$

RES Output 12. Medium Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

RES Output 12. High Quality

	CLP	NLC
NLC	$2.20e-16$	–
SLC	$2.2e-16$	$2.2e-16$

Table D.20.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.13 for each RES output. Continues in Table D.21.

RES Output 1

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$							
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−
4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	1.0	−
40.000	6.5e − 05	6.5e − 05	1.0	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	2.1e − 01	1.2e − 03

RES Output 2

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−
4.000	6.5e − 05	7.8e − 04	−	4.000	6.5e − 05	6.3e − 03	−	4.000	6.5e − 05	2.6e − 04	−	4.000	6.5e − 05	6.3e − 03	−	4.000	6.5e − 05	2.3e − 02	−	4.000	6.5e − 05	1.0	−
40.000	6.5e − 05	1.3e − 04	6.3e − 01	40.000	6.5e − 05	1.9e − 03	1.0	40.000	6.5e − 05	6.5e − 05	1.0	40.000	6.5e − 05	4.4e − 03	1.0	40.000	6.5e − 05	9.0e − 03	1.0	40.000	6.5e − 05	1.0	2.6e − 04

RES Output 3

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	6.5e − 05	−	−	400	2.6e − 04	−	−	400	6.5e − 05	−	−	400	1.3e − 04	−	−	400	6.5e − 05	−	−	400	1.7e − 02	−	−
4.000	6.5e − 05	1.0	−	4.000	6.5e − 05	1.0	−	4.000	6.5e − 05	2.1e − 01	−	4.000	6.5e − 05	1.0	−	4.000	6.5e − 05	1.0	−	4.000	9.0e − 03	1.0	−
40.000	6.5e − 05	1.0	1.3e − 04	40.000	6.5e − 05	1.0	1.0	40.000	6.5e − 05	1.0	4.5e − 01	40.000	6.5e − 05	1.0	1.0	40.000	6.5e − 05	1.0	2.6e − 01	40.000	9.0e − 03	1.0	6.3e − 03

RES Output 4

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	1.2e − 03	−	−	400	6.5e − 05	−	−	400	4.1e − 02	−	−	400	6.5e − 05	−	−	400	1.2e − 03	−	−	400	1.7e − 01	−	−
4.000	6.5e − 05	5.4e − 02	−	4.000	6.5e − 05	1.4e − 01	−	4.000	1.3e − 02	9.9e − 01	−	4.000	6.5e − 05	1.0	−	4.000	1.3e − 04	1.0	−	4.000	1.0	3.8e − 01	−
40.000	6.5e − 05	1.7e − 02	1.0	40.000	6.5e − 05	1.4e − 01	6.3e − 01	40.000	2.3e − 02	1.0	5.4e − 01	40.000	6.5e − 05	1.0	2.6e − 01	40.000	6.5e − 05	1.0	1.0	40.000	1.0	9.0e − 03	1.7e − 02

RES Output 5

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−	400	6.5e − 05	−	−
4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	6.5e − 05	−	4.000	6.5e − 05	3.1e − 01	−
40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	6.5e − 05	6.5e − 05	40.000	6.5e − 05	1.4e − 01	6.5e − 05

RES Output 6

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	1.39e − 01	−	−	400	4.10e − 02	−	−	400	3.78e − 01	−	−	400	4.35e − 03	−	−	400	4.10e − 02	−	−	400	2.13e − 01	−	−
4.000	3.12e − 02	2.13e − 01	−	4.000	1.95e − 03	1.00	−	4.000	4.52e − 01	1.00	−	4.000	6.50e − 05	1.00	−	4.000	4.35e − 03	1.00	−	4.000	8.59e − 01	1.25e − 02	−
40.000	9.03e − 03	1.39e − 01	2.60e − 01	40.000	2.92e − 03	9.93e − 01	1.00	40.000	2.60e − 01	1.00	1.00	40.000	6.50e − 05	1.00	1.00	40.000	2.33e − 02	1.00	6.31e − 01	40.000	8.59e − 01	9.03e − 03	2.60e − 04

Table D.21.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.13 for each RES output. Continuation from Table D.20.

RES Output 7

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–
4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	1.00	–
40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	1.00	$1.11e-01$

RES Output 8

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$4.10e-02$	–	–	400	$1.39e-01$	–	–	400	$1.11e-01$	–	–	400	1.00	–	–	400	$7.38e-01$	–	–	400	1.00	–	–
4.000	$9.03e-03$	$6.31e-01$	–	4.000	$1.95e-03$	1.00	–	4.000	$1.39e-01$	$8.59e-01$	–	4.000	1.00	1.00	–	4.000	$8.59e-01$	1.00	–	4.000	1.00	$1.39e-01$	–
40.000	$9.03e-03$	$8.59e-01$	1.00	40.000	$2.60e-04$	1.00	1.00	40.000	$1.39e-01$	$8.59e-01$	1.00	40.000	1.00	1.00	1.00	40.000	$8.59e-01$	$3.15e-01$	1.00	40.000	$8.59e-01$	$1.11e-01$	1.00

RES Output 9

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–
4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$9.03e-03$	–
40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$2.92e-03$	40.000	$6.50e-05$	$6.50e-05$	$2.33e-02$	40.000	$6.50e-05$	$4.10e-02$	$1.73e-02$

RES Output 10

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$1.30e-04$	–	–	400	$2.92e-03$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–
4.000	$6.50e-05$	1.00	–	4.000	$6.50e-05$	$6.90e-02$	–	4.000	$6.50e-05$	1.00	–	4.000	$6.50e-05$	1.00	–	4.000	$6.50e-05$	1.00	–	4.000	$6.50e-05$	1.00	–
40.000	$6.50e-05$	1.00	1.00	40.000	$6.50e-05$	$1.73e-02$	1.00	40.000	$6.50e-05$	$8.59e-01$	1.00	40.000	$6.50e-05$	$8.59e-01$	1.00	40.000	$6.50e-05$	1.00	$6.31e-01$	40.000	$6.50e-05$	1.00	$1.11e-01$

RES Output 11

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–
4.000	$6.50e-05$	$2.60e-04$	–	4.000	$6.50e-05$	$4.55e-04$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	1.00	–
40.000	$6.50e-05$	$6.50e-05$	$8.59e-01$	40.000	$6.50e-05$	$6.50e-05$	$7.38e-01$	40.000	$6.50e-05$	$6.50e-05$	1.00	40.000	$6.50e-05$	$6.50e-05$	$1.11e-01$	40.000	$6.50e-05$	$6.50e-05$	$6.90e-02$	40.000	$6.50e-05$	1.00	$8.59e-01$

RES Output 12

$\alpha = 1.0$				$\alpha = 0.5$				$\alpha = 0.1$				$\alpha = 0.05$				$\alpha = 0.01$				$\alpha = 0.0$			
	40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000		40	400	4.000
400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–	400	$6.50e-05$	–	–
4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.50e-05$	–	4.000	$6.50e-05$	$6.30e-03$	–
40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	$6.50e-05$	$6.50e-05$	40.000	$6.50e-05$	1.00	$6.50e-05$

Table D.22.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different α configurations within groups specified in Table C.14 for each RES output. Continues in Table D.23.

RES Output 1

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$5.8e-02$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	$2.3e-02$	–	–	–	**0.05**	$1.6e-04$	$1.6e-04$	–	–	–
0.1	$6.5e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$5.8e-02$	1.0	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$6.5e-04$	–	–
0.5	$1.0e-01$	$1.1e-02$	1.0	$1.0e-01$	–	**0.5**	$1.6e-04$	$1.1e-02$	$3.2e-04$	$2.3e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	$7.3e-03$	1.0	$2.3e-02$	1.0	**1.0**	$1.6e-04$	$1.9e-03$	$1.6e-04$	$3.2e-04$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.1e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 2

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$5.8e-02$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	1.0	$5.3e-01$	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–
0.1	1.0	$5.8e-02$	1.0	–	–	**0.1**	$1.6e-04$	$9.5e-01$	$2.2e-01$	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$1.3e-01$	$2.8e-01$	–	–
0.5	$7.9e-01$	$6.5e-04$	$3.5e-01$	$9.5e-01$	–	**0.5**	$1.6e-04$	$1.3e-01$	$1.6e-02$	1.0	–	**0.5**	$1.6e-04$	$3.1e-03$	$6.5e-04$	$6.5e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	$3.5e-01$	$3.2e-04$	$1.3e-01$	$1.0e-01$	1.0	**1.0**	$6.5e-04$	$1.9e-03$	$6.5e-04$	$7.8e-02$	$1.3e-01$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.0e-01$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.9e-03$

RES Output 3

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	1.0	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	1.0	1.0	–	–	–	**0.05**	$3.2e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–
0.1	1.0	1.0	1.0	–	–	**0.1**	$3.2e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–
0.5	1.0	1.0	1.0	1.0	–	**0.5**	$1.1e-02$	$5.3e-01$	1.0	1.0	–	**0.5**	$1.6e-04$	$1.0e-01$	$1.7e-01$	$5.8e-02$	–	**0.5**	$1.6e-04$	$3.2e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	1.0	1.0	1.0	1.0	**1.0**	$2.3e-02$	$2.2e-01$	$5.3e-01$	1.0	1.0	**1.0**	$1.6e-04$	$6.5e-04$	$3.1e-03$	$1.9e-03$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 4

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$1.3e-01$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	1.0	$5.3e-01$	–	–	–	**0.05**	$3.2e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–
0.1	1.0	1.0	1.0	–	–	**0.1**	$1.1e-03$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–
0.5	1.0	$1.3e-01$	1.0	1.0	–	**0.5**	$4.9e-03$	$4.3e-02$	$1.3e-01$	1.0	–	**0.5**	$1.6e-04$	$1.9e-03$	$6.5e-04$	$1.6e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$6.5e-04$	–
1.0	1.0	$4.9e-03$	$4.3e-01$	$5.3e-01$	1.0	**1.0**	1.0	$1.6e-04$	$1.1e-03$	$1.6e-02$	1.0	**1.0**	$1.6e-04$	$3.2e-04$	$1.6e-04$	$6.5e-04$	$4.3e-02$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 5

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$1.9e-03$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$2.8e-01$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	$2.3e-02$	–	–	–	**0.05**	$1.6e-04$	$3.2e-04$	–	–	–
0.1	$7.9e-01$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$5.3e-01$	1.0	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$6.5e-01$	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$3.1e-02$	–	–
0.5	1.0	$1.6e-04$	$1.9e-03$	$3.1e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-02$	$4.9e-03$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	$1.6e-04$	$6.5e-04$	$7.8e-02$	1.0	**1.0**	$2.3e-02$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.1e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.9e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 6

40 households						**400 households**						**4.000 households**						**40.000 households**					
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$1.9e-03$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$2.8e-01$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	$2.3e-02$	–	–	–	**0.05**	$1.6e-04$	$3.2e-04$	–	–	–
0.1	$7.9e-01$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$5.3e-01$	1.0	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$6.5e-01$	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$3.1e-02$	–	–
0.5	1.0	$1.6e-04$	$1.9e-03$	$3.1e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-02$	$4.9e-03$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	$1.6e-04$	$6.5e-04$	$7.8e-02$	1.0	**1.0**	$2.3e-02$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.1e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.9e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

Table D.23.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different α configurations within groups specified in Table C.14 for each RES output. Continuation from Table D.22.

RES Output 7

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$1.0e-01$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$1.3e-01$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	$2.2e-01$	–	–	–	**0.05**	$1.6e-04$	$5.3e-01$	–	–	–
0.1	$1.6e-02$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$1.7e-01$	$9.5e-01$	–	–	**0.1**	$1.6e-04$	$4.3e-02$	$1.7e-01$	–	–	**0.1**	$1.6e-04$	$6.5e-04$	$1.1e-02$	–	–
0.5	1.0	1.0	$3.5e-01$	$2.8e-01$	–	**0.5**	$1.6e-04$	$1.1e-03$	$1.9e-03$	$5.8e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$3.2e-04$	$7.3e-03$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	$2.3e-02$	$1.1e-02$	$1.6e-04$	1.0	**1.0**	$3.1e-03$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.3e-01$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.3e-01$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.9e-03$

RES Output 8

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	1.0	–	–	–	–	**0.01**	1.0	–	–	–	–	**0.01**	$3.1e-02$	–	–	–	–	**0.01**	$3.2e-04$	–	–	–	–
0.05	1.0	1.0	–	–	–	**0.05**	1.0	1.0	–	–	–	**0.05**	1.0	$4.3e-01$	–	–	–	**0.05**	$1.1e-03$	1.0	–	–	–
0.1	$6.5e-01$	1.0	1.0	–	–	**0.1**	1.0	1.0	1.0	–	–	**0.1**	1.0	$7.9e-01$	1.0	–	–	**0.1**	$1.1e-03$	$5.3e-01$	1.0	–	–
0.5	$5.8e-02$	1.0	1.0	1.0	–	**0.5**	$1.0e-01$	$1.7e-01$	1.0	$5.8e-02$	–	**0.5**	$1.3e-01$	$1.6e-04$	$5.8e-02$	$4.3e-02$	–	**0.5**	$4.3e-02$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	$3.1e-03$	$1.7e-01$	$2.8e-01$	1.0	$7.9e-01$	**1.0**	$3.1e-03$	$7.3e-03$	$3.1e-02$	$1.1e-02$	$7.9e-01$	**1.0**	$3.1e-02$	$3.2e-04$	$7.3e-03$	$7.3e-03$	$7.9e-01$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$6.5e-04$

RES Output 9

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$7.3e-03$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	$2.2e-01$	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–	**0.05**	$1.6e-04$	1.0	–	–	–
0.1	$3.1e-03$	1.0	$4.3e-01$	–	–	**0.1**	$1.6e-04$	$5.8e-02$	1.0	–	–	**0.1**	$1.6e-04$	$4.3e-01$	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–
0.5	$7.3e-03$	1.0	$3.1e-02$	1.0	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.9e-03$	$1.9e-03$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	$5.8e-02$	$3.5e-01$	$1.1e-02$	1.0	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$6.5e-04$	$6.5e-04$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$7.8e-02$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 10

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	1.0	–	–	–	–	**0.01**	$3.2e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	1.0	1.0	–	–	–	**0.05**	$2.2e-01$	$5.3e-01$	–	–	–	**0.05**	$1.6e-04$	$3.1e-02$	–	–	–	**0.05**	$1.6e-04$	$1.6e-04$	–	–	–
0.1	$1.3e-01$	1.0	1.0	–	–	**0.1**	$7.3e-03$	$7.8e-02$	1.0	–	–	**0.1**	$1.6e-04$	$3.1e-02$	$9.5e-01$	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$3.2e-04$	–	–
0.5	1.0	1.0	1.0	1.0	–	**0.5**	1.0	$1.1e-03$	1.0	$1.7e-01$	–	**0.5**	$1.6e-04$	$1.6e-04$	$6.5e-04$	$3.1e-02$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	$9.5e-01$	1.0	1.0	1.0	1.0	**1.0**	1.0	$1.9e-03$	1.0	1.0	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$3.1e-03$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.1e-03$

RES Output 11

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$5.3e-01$	–	–	–	–	**0.01**	$6.5e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$9.5e-01$	1.0	–	–	–	**0.05**	$7.3e-03$	1.0	–	–	–	**0.05**	$1.6e-04$	$6.5e-01$	–	–	–	**0.05**	$1.6e-04$	$1.6e-04$	–	–	–
0.1	1.0	1.0	1.0	–	–	**0.1**	$7.3e-03$	1.0	1.0	–	–	**0.1**	$1.6e-04$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$1.6e-04$	$1.6e-02$	–	–
0.5	1.0	1.0	1.0	1.0	–	**0.5**	$7.9e-01$	$1.0e-01$	$9.5e-01$	$9.5e-01$	–	**0.5**	$1.6e-04$	$1.6e-04$	$3.2e-04$	$6.5e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	1.0	1.0	1.0	1.0	1.0	**1.0**	$3.5e-01$	$2.3e-02$	$2.2e-01$	$2.2e-01$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$3.2e-04$	1.0	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

RES Output 12

	40 households						**400 households**						**4.000 households**						**40.000 households**				
	0.0	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**		**0.0**	**0.01**	**0.05**	**0.1**	**0.5**
0.01	$3.1e-03$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–	**0.01**	$1.6e-04$	–	–	–	–
0.05	$1.9e-03$	1.0	–	–	–	**0.05**	$1.6e-04$	$1.0e-01$	–	–	–	**0.05**	$1.6e-04$	$7.9e-01$	–	–	–	**0.05**	$1.6e-04$	$1.6e-04$	–	–	–
0.1	$2.3e-02$	1.0	1.0	–	–	**0.1**	$1.6e-04$	$2.8e-01$	1.0	–	–	**0.1**	$1.6e-04$	$1.1e-03$	$1.3e-01$	–	–	**0.1**	$1.6e-04$	$1.6e-04$	1.0	–	–
0.5	1.0	$1.7e-01$	$2.8e-01$	1.0	–	**0.5**	$1.6e-04$	$1.6e-04$	$6.5e-04$	$6.5e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–	**0.5**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	–
1.0	$5.3e-01$	$1.6e-04$	$3.2e-04$	$1.1e-03$	$5.8e-02$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$3.1e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$4.9e-03$	**1.0**	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$	$1.6e-04$

Table D.24.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.15 for each RES output. Continues in Table D.25.

RES Output 1

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0

RES Output 2

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$5.7e-01$

RES Output 3

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	1.0	$-$	**SLC-FK**	1.0	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	1.0	1.0	**SLC-FKd**	$5.2e-02$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0

RES Output 4

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$4.3e-03$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	$5.2e-02$	1.0	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$1.3e-04$	**SLC-FKd**	$1.9e-04$	$3.2e-05$

RES Output 5

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$8.6e-02$	**SLC-FKd**	$1.9e-04$	$2.1e-02$	**SLC-FKd**	$1.9e-04$	1.0

RES Output 6

40 Households			400 Households			4.000 Households			40.000 Households		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$	**SLC-FK**	$1.9e-04$	$-$
SLC-FKd	$1.9e-04$	$4.3e-01$	**SLC-FKd**	$1.9e-04$	$1.1e-01$	**SLC-FKd**	$1.9e-04$	$3.2e-05$	**SLC-FKd**	$1.9e-04$	$3.2e-05$

Table D.25.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences as a consequence of different population sizes within groups specified in Table C.15 for each RES output. Continuation in Table D.24.

RES Output 7

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$6.5e-01$	**SLC-FKd**	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	1.0

RES Output 8

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$5.2e-02$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$2.7e-01$	**SLC-FKd**	$1.9e-04$	$6.5e-05$	**SLC-FKd**	$1.9e-04$	$3.2e-05$

RES Output 9

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$2.3e-01$	**SLC-FKd**	$1.9e-04$	$9.4e-01$	**SLC-FKd**	$1.9e-04$	1.0

RES Output 10

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–	**SLC-FK**	$1.9e-04$	–
SLC-FKd	$1.9e-04$	1.0	**SLC-FKd**	$1.9e-04$	$1.9e-01$	**SLC-FKd**	$1.9e-04$	$8.4e-01$	**SLC-FKd**	$1.9e-04$	$4.3e-01$

RES Output 11

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$3.2e-05$	–	**SLC-FK**	$6.2e-04$	–	**SLC-FK**	$3.2e-03$	–	**SLC-FK**	$6.5e-05$	–
SLC-FKd	$3.2e-05$	1.0	**SLC-FKd**	$1.3e-04$	1.0	**SLC-FKd**	$1.2e-02$	$8.4e-01$	**SLC-FKd**	$3.2e-05$	1.0

RES Output 12

40 Households			**400 Households**			**4.000 Households**			**40.000 Households**		
	CLP-FK	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**		**CLP-FK**	**SLC-FK**
SLC-FK	$3.2e-05$	–	**SLC-FK**	$3.2e-05$	–	**SLC-FK**	$3.2e-05$	–	**SLC-FK**	$1.9e-04$	–
SLC-FKd	$3.2e-05$	1.0	**SLC-FKd**	$3.2e-05$	1.0	**SLC-FKd**	$3.2e-05$	1.0	**SLC-FKd**	$1.9e-04$	1.0

Table D.26.: Pairwise comparison with unpaired Wilcoxon rank sum test with Bonferroni. Post-hoc analysis for assessing significant differences between load scheduling strategies with different household load composition. Tests are performed in cases where significant differences are found within groups in Table C.16 for each RES output.

RES Output 1. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.0345

RES Output 1. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	1

RES Output 2. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	1

RES Output 2. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	1

RES Output 3. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.6527

RES Output 3. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	1

RES Output 4. Only Washing Machines.

	CLP-FK	SLC-FK
SLC-FK	0.0864	–
SLC-FKd	0.0256	1

RES Output 4. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.0086

RES Output 4. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	0.0001

RES Output 5. Only Washing Machines.

	CLP-FK	SLC-FK
SLC-FK	0.0697	–
SLC-FKd	0.0205	0.5709

RES Output 5. No EVs.

	CLP-FK	SLC-FK
SLC-FK	0.1064	–
SLC-FKd	0.0441	0.9450

RES Output 5. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	0.0205

RES Output 6. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.0002

RES Output 6. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	$3.25e-05$

RES Output 7. No EVs.

	CLP-FK	SLC-FK
SLC-FK	0.0556	–
SLC-FKd	0.0697	1

RES Output 7. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	1

RES Output 8. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.0205

RES Output 8. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	$6.50e-05$

RES Output 9. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	0.7424

RES Output 9. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	0.9450

RES Output 10. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	1

RES Output 10. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0002	–
SLC-FKd	0.0002	0.8396

RES Output 11. No EVs.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	1

RES Output 11. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	0.0032	–
SLC-FKd	0.0117	0.8396

RES Output 12. Only Washing Machine.

	CLP-FK	SLC-FK
SLC-FK	0.0268	–
SLC-FKd	0.0015	0.3154

RES Output 12. No EVs.

	CLP-FK	SLC-FK
SLC-FK	0.0086	–
SLC-FKd	0.0010	1

RES Output 12. All Appliances.

	CLP-FK	SLC-FK
SLC-FK	$3.25e-05$	–
SLC-FKd	$3.25e-05$	1

E. Summaries of Performance

Table E.1.: Summary of the results of the analysis of the scalability of SLC. Continues at Table E.2.

RES Output	Statistic									α											
		1.0				0.5				0.1				0.05				0.01			
		Population				**Population**				**Population**				**Population**				**Population**			
		40	400	4, 000	40, 000	40	400	4, 000	40, 000	40	400	4, 000	40, 000	40	400	4, 000	40, 000	40	400	4, 000	40, 000
1	**Min.**	17.5%	8.1%	6.9%	7.4%	18.1%	7.5%	6.6%	6.9%	17.8%	8.0%	6.4%	6.3%	18.0%	8.3%	7.2%	7.2%	18.5%	9.5%	8.1%	8.4%
	1st Qu.	20.9%	10.5%	8.8%	8.6%	21.1%	10.2%	8.1%	7.8%	21.3%	10.2%	8.2%	7.8%	21.7%	10.7%	9.2%	9.0%	22.0%	11.5%	10.0%	9.7%
	Median	22.2%	11.1%	9.2%	9.0%	22.2%	10.8%	8.7%	8.4%	22.7%	10.7%	9.0%	8.7%	23.1%	11.6%	9.9%	9.7%	23.6%	12.3%	10.7%	10.5%
	3rd Qu.	23.8%	11.8%	9.8%	9.5%	23.6%	11.4%	9.2%	8.9%	24.1%	11.4%	9.6%	9.3%	24.7%	12.5%	10.5%	10.3%	25.0%	13.1%	11.3%	11.1%
	Max.	29.7%	14.9%	11.7%	11.5%	27.5%	13.5%	11.1%	10.9%	29.1%	13.8%	11.1%	10.3%	30.5%	15.3%	11.6%	11.0%	31.3%	19.8%	17.0%	16.6%
2	**Min.**	19.9%	12.0%	12.0%	12.4%	19.2%	11.8%	11.0%	11.5%	19.0%	10.6%	10.8%	11.1%	18.3%	11.8%	11.9%	11.9%	19.4%	12.7%	12.8%	13.2%
	1st Qu.	23.3%	14.5%	13.7%	13.7%	23.4%	14.3%	13.4%	13.4%	23.2%	13.3%	12.1%	12.0%	23.6%	14.6%	13.3%	13.1%	24.8%	16.1%	14.9%	14.8%
	Median	24.8%	15.1%	14.2%	14.1%	24.8%	15.2%	13.9%	13.9%	24.9%	14.2%	12.7%	12.6%	25.3%	15.4%	14.0%	13.9%	26.6%	16.9%	15.6%	15.5%
	3rd Qu.	26.4%	16.0%	14.6%	14.5%	26.4%	16.0%	14.4%	14.3%	26.9%	15.2%	13.5%	13.3%	27.4%	16.5%	15.0%	14.7%	28.1%	18.1%	16.4%	16.1%
	Max.	32.4%	19.4%	18.4%	17.7%	32.6%	19.4%	18.5%	18.1%	33.0%	25.9%	22.8%	21.3%	34.5%	24.0%	23.8%	23.0%	38.5%	27.4%	24.8%	24.3%
3	**Min.**	20.7%	14.5%	16.5%	16.6%	20.2%	14.5%	15.7%	16.5%	20.7%	13.8%	14.9%	15.8%	21.1%	14.9%	14.8%	15.1%	20.6%	14.6%	14.8%	15.2%
	1st Qu.	25.5%	17.9%	17.7%	17.5%	25.3%	17.8%	17.2%	17.1%	24.3%	17.2%	16.6%	16.4%	24.9%	17.3%	16.5%	16.3%	26.3%	18.8%	18.5%	18.4%
	Median	27.4%	18.9%	18.1%	17.9%	27.1%	18.8%	17.6%	17.5%	26.5%	18.2%	17.1%	17.0%	26.6%	18.5%	17.4%	17.2%	28.3%	20.5%	19.7%	19.5%
	3rd Qu.	29.5%	19.9%	18.6%	18.3%	28.9%	19.7%	18.2%	17.9%	28.3%	19.1%	17.6%	17.3%	29.0%	19.5%	18.3%	18.1%	30.7%	21.7%	20.8%	20.8%
	Max.	37.5%	22.6%	20.3%	19.2%	38.5%	22.8%	19.4%	18.9%	36.2%	21.8%	18.9%	18.6%	36.0%	24.1%	20.7%	20.4%	39.2%	26.2%	23.1%	22.6%
4	**Min.**	20.6%	20.1%	21.9%	22.4%	21.4%	18.5%	20.5%	21.3%	19.8%	17.7%	19.2%	19.5%	17.2%	16.0%	19.0%	19.5%	20.3%	16.4%	18.9%	19.6%
	1st Qu.	27.5%	23.0%	23.1%	23.1%	27.3%	22.2%	22.4%	22.4%	25.4%	21.0%	21.0%	21.0%	25.4%	21.0%	20.7%	20.8%	26.2%	21.8%	21.9%	21.8%
	Median	30.2%	24.0%	23.6%	23.5%	29.3%	23.6%	23.1%	23.0%	27.9%	22.0%	21.6%	21.5%	27.8%	22.3%	21.6%	21.5%	28.8%	23.7%	23.3%	23.2%
	3rd Qu.	32.8%	25.3%	24.2%	24.1%	32.1%	24.8%	24.0%	24.0%	30.2%	23.2%	22.3%	22.4%	30.4%	23.7%	22.8%	22.5%	31.0%	25.2%	24.5%	24.4%
	Max.	42.6%	28.2%	27.5%	27.1%	40.3%	28.7%	27.3%	27.0%	41.3%	26.6%	24.8%	24.7%	38.0%	29.5%	26.9%	26.6%	38.8%	30.7%	28.8%	28.6%
5	**Min.**	17.8%	8.1%	7.5%	7.6%	16.7%	8.0%	6.9%	7.1%	15.6%	6.9%	5.5%	6.0%	17.9%	7.3%	6.4%	6.3%	16.1%	8.2%	7.4%	7.7%
	1st Qu.	20.4%	10.3%	8.8%	8.8%	20.7%	9.7%	7.9%	7.8%	20.5%	9.2%	7.2%	7.0%	20.9%	9.6%	7.9%	7.8%	21.1%	10.6%	9.3%	9.2%
	Median	21.7%	11.1%	9.6%	9.3%	21.8%	10.5%	8.6%	8.5%	21.9%	9.9%	8.0%	8.0%	22.5%	10.5%	8.9%	8.9%	22.6%	11.3%	10.1%	10.0%
	3rd Qu.	23.2%	12.0%	10.5%	10.1%	23.2%	11.2%	9.5%	9.2%	23.2%	10.8%	8.7%	8.6%	23.8%	11.4%	9.5%	9.2%	24.4%	12.2%	10.8%	10.6%
	Max.	29.3%	14.2%	13.6%	12.9%	29.7%	15.2%	12.6%	12.4%	29.9%	13.5%	10.2%	10.0%	28.6%	13.8%	10.6%	10.1%	28.4%	14.3%	12.0%	11.4%
6	**Min.**	21.8%	18.3%	18.9%	19.4%	20.4%	15.5%	17.9%	18.6%	18.0%	15.0%	15.5%	15.9%	18.0%	14.5%	15.1%	15.8%	19.1%	15.0%	16.5%	17.0%
	1st Qu.	27.3%	20.6%	20.6%	20.6%	26.5%	20.0%	19.7%	19.7%	24.6%	18.0%	17.3%	17.2%	25.2%	18.5%	17.4%	17.4%	26.3%	20.2%	19.7%	19.6%
	Median	29.4%	21.6%	21.1%	21.0%	28.6%	20.9%	20.2%	20.2%	26.6%	19.3%	18.0%	17.9%	27.5%	19.6%	18.9%	18.7%	28.7%	21.9%	21.3%	21.3%
	3rd Qu.	31.5%	22.8%	21.5%	21.4%	31.0%	22.0%	20.8%	20.6%	29.4%	20.6%	19.6%	19.7%	30.0%	21.3%	20.2%	20.3%	30.9%	23.2%	22.2%	22.1%
	Max.	42.6%	27.0%	22.8%	22.3%	40.1%	24.8%	22.6%	21.8%	37.7%	24.2%	22.0%	21.8%	38.6%	26.5%	23.9%	23.0%	40.9%	27.2%	25.0%	24.5%

Table E.2.: Summary of the results of the analysis of the scability of SLC. Continuation from Table E.1.

RES Output	Statistic	α																			
		1.0				0.5				0.1				0.05				0.01			
		Population				**Population**				**Population**				**Population**				**Population**			
		40	400	4,000	40,000	40	400	4,000	40,000	40	400	4,000	40,000	40	400	4,000	40,000	40	400	4,000	40,000
	Min.	14.4%	9.2%	7.6%	7.8%	17.3%	8.1%	6.7%	6.9%	17.0%	7.4%	5.4%	5.4%	17.2%	7.6%	6.2%	6.2%	17.1%	8.3%	7.2%	7.3%
	1st Qu.	20.9%	10.7%	9.1%	8.9%	20.8%	10.3%	8.2%	7.9%	20.8%	9.2%	7.1%	6.9%	20.9%	9.7%	7.6%	7.3%	21.6%	10.6%	8.8%	8.5%
7	**Median**	22.1%	11.4%	9.7%	9.7%	22.1%	10.9%	8.8%	8.7%	22.0%	10.0%	7.8%	7.5%	22.2%	10.6%	8.7%	8.5%	23.0%	11.8%	10.0%	9.6%
	3rd Qu.	23.2%	12.0%	10.4%	10.3%	23.4%	11.6%	9.7%	9.7%	23.7%	10.8%	8.6%	8.4%	23.6%	11.5%	9.6%	9.4%	24.6%	13.0%	11.2%	11.0%
	Max.	28.0%	14.3%	12.7%	11.5%	29.6%	14.9%	12.2%	11.3%	28.5%	14.8%	13.4%	12.7%	28.6%	16.7%	15.0%	14.4%	30.2%	18.6%	16.8%	15.9%
	Min.	25.7%	28.0%	29.9%	30.7%	25.3%	25.9%	29.1%	29.8%	21.7%	23.3%	26.8%	27.0%	24.0%	22.6%	25.6%	26.2%	18.5%	23.8%	25.9%	26.5%
	1st Qu.	35.6%	31.1%	31.2%	31.3%	34.3%	30.4%	30.4%	30.4%	31.5%	28.3%	28.1%	28.0%	31.8%	27.9%	27.3%	27.3%	31.8%	28.6%	28.3%	28.3%
8	**Median**	37.9%	32.0%	31.6%	31.5%	36.6%	31.5%	30.9%	30.8%	34.6%	29.7%	29.1%	28.8%	34.5%	29.4%	28.6%	28.5%	34.7%	30.1%	29.8%	30.0%
	3rd Qu.	41.0%	33.1%	32.0%	31.8%	39.7%	32.6%	31.4%	31.2%	37.2%	31.4%	30.2%	30.3%	37.5%	31.1%	30.7%	30.7%	37.6%	32.3%	31.7%	31.6%
	Max.	50.1%	36.6%	33.0%	32.4%	47.3%	35.1%	32.7%	31.9%	45.5%	35.1%	33.3%	32.2%	46.0%	37.1%	34.0%	32.8%	50.6%	36.8%	35.2%	34.5%
	Min.	18.7%	9.9%	9.5%	9.3%	18.9%	8.6%	8.0%	8.0%	15.5%	8.3%	7.2%	7.4%	18.0%	9.5%	8.1%	8.4%	18.1%	9.7%	9.6%	9.8%
	1st Qu.	21.6%	11.6%	10.3%	10.1%	21.6%	11.4%	10.2%	10.1%	21.4%	10.5%	8.3%	8.0%	22.3%	11.4%	9.4%	9.3%	22.7%	12.5%	10.7%	10.5%
9	**Median**	23.1%	12.2%	10.7%	10.5%	22.8%	12.1%	10.6%	10.4%	22.7%	11.1%	8.8%	8.4%	23.7%	12.2%	10.1%	9.8%	24.2%	13.3%	11.6%	11.2%
	3rd Qu.	24.4%	12.9%	11.2%	11.1%	24.3%	12.8%	11.0%	10.7%	24.2%	12.0%	9.5%	9.3%	25.2%	13.0%	10.9%	10.6%	25.8%	14.2%	12.2%	11.9%
	Max.	29.0%	14.7%	12.7%	12.3%	28.3%	14.4%	12.7%	12.3%	28.9%	16.2%	12.3%	12.0%	29.4%	15.4%	13.1%	12.1%	31.7%	17.7%	14.9%	14.7%
	Min.	18.9%	12.1%	12.5%	13.2%	19.2%	12.8%	12.6%	13.1%	18.4%	12.2%	12.8%	12.9%	19.2%	12.7%	13.5%	13.7%	20.2%	13.9%	14.1%	14.6%
	1st Qu.	23.1%	15.4%	14.8%	14.7%	23.2%	15.3%	14.5%	14.3%	23.3%	15.0%	14.1%	14.0%	24.1%	15.7%	14.9%	14.8%	24.9%	16.4%	15.6%	15.5%
10	**Median**	25.1%	16.6%	16.2%	16.3%	25.2%	16.4%	15.6%	15.6%	25.5%	16.0%	14.7%	14.6%	26.0%	16.7%	15.4%	15.3%	26.5%	17.4%	16.2%	16.0%
	3rd Qu.	27.2%	17.7%	17.1%	17.1%	27.0%	17.5%	16.5%	16.3%	27.4%	17.1%	15.3%	15.2%	27.7%	17.9%	16.0%	15.8%	28.8%	18.5%	16.8%	16.7%
	Max.	33.5%	20.3%	19.2%	18.8%	34.4%	20.9%	19.0%	18.8%	35.4%	21.0%	17.5%	16.6%	33.7%	21.7%	19.1%	18.8%	37.1%	24.9%	22.4%	22.0%
	Min.	17.4%	8.4%	7.1%	7.5%	16.8%	8.0%	6.9%	7.4%	16.4%	7.7%	6.6%	6.8%	17.1%	7.7%	6.5%	6.8%	17.2%	8.1%	7.1%	7.8%
	1st Qu.	20.5%	10.2%	8.3%	8.1%	20.7%	10.1%	8.2%	8.0%	20.8%	9.6%	7.5%	7.3%	21.1%	9.9%	8.1%	7.9%	21.5%	10.8%	9.1%	9.0%
11	**Median**	21.9%	11.0%	8.9%	8.5%	22.0%	10.8%	8.7%	8.5%	22.4%	10.2%	8.1%	7.7%	22.5%	10.8%	8.6%	8.3%	23.1%	11.8%	9.8%	9.5%
	3rd Qu.	23.3%	12.0%	9.8%	9.7%	23.8%	11.5%	9.5%	9.3%	23.6%	11.2%	8.7%	8.2%	24.0%	11.8%	9.4%	9.1%	24.7%	12.8%	10.6%	10.5%
	Max.	29.6%	15.3%	12.4%	11.1%	29.4%	13.9%	11.0%	10.4%	29.5%	15.0%	10.9%	10.6%	30.4%	15.1%	11.7%	10.6%	33.9%	15.8%	13.3%	12.3%
	Min.	17.5%	8.8%	7.7%	7.9%	16.7%	8.9%	7.5%	7.8%	16.8%	7.0%	5.6%	5.2%	17.2%	7.1%	6.2%	5.9%	16.8%	8.1%	6.9%	7.5%
	1st Qu.	20.9%	10.7%	9.1%	9.0%	20.9%	10.4%	8.6%	8.3%	20.5%	9.1%	6.8%	6.5%	20.9%	9.5%	7.5%	7.2%	21.3%	10.4%	8.6%	8.5%
12	**Median**	22.2%	11.3%	9.6%	9.6%	22.1%	11.0%	9.1%	8.8%	21.7%	10.0%	7.7%	7.5%	22.4%	10.2%	8.2%	8.0%	22.7%	11.4%	9.4%	9.0%
	3rd Qu.	23.5%	11.9%	10.1%	9.9%	23.5%	11.7%	9.6%	9.4%	23.3%	10.9%	8.9%	8.6%	23.6%	11.2%	9.1%	9.0%	24.0%	12.3%	10.5%	10.4%
	Max.	28.4%	14.5%	12.5%	12.1%	28.1%	14.4%	12.4%	12.2%	27.5%	13.7%	12.2%	11.7%	27.2%	14.8%	12.3%	11.9%	32.3%	16.0%	12.8%	12.1%

Table E.3.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of 40 households. Continues in Table E.4.

RES Output	**Statistic**	**Forecast Category**								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
	Min.	17.9%	7.3%	18.5%	18.8%	7.4%	18.5%	17.5%	7.3%	19.3%
	1st Qu.	20.4%	9.0%	23.9%	21.0%	9.3%	23.9%	20.9%	9.0%	23.7%
1	**Median**	22.3%	9.9%	25.4%	21.8%	9.9%	25.4%	22.3%	9.8%	26.0%
	3rd Qu.	24.4%	11.9%	27.6%	23.1%	11.5%	27.6%	23.9%	10.9%	27.8%
	Max.	29.7%	24.3%	32.6%	26.2%	18.2%	32.6%	27.4%	19.4%	34.7%
	Min.	19.2%	8.3%	21.9%	19.8%	7.9%	21.9%	20.1%	8.2%	21.6%
	1st Qu.	23.2%	10.1%	27.8%	23.6%	10.0%	27.8%	23.3%	10.9%	28.2%
2	**Median**	24.6%	12.0%	30.3%	25.0%	12.0%	30.3%	24.7%	13.2%	30.4%
	3rd Qu.	26.3%	14.2%	32.7%	26.5%	13.9%	32.7%	26.4%	16.0%	32.8%
	Max.	31.8%	19.9%	40.1%	30.3%	20.1%	40.1%	30.5%	23.3%	39.2%
	Min.	20.7%	8.1%	24.0%	21.4%	8.4%	24.0%	21.0%	9.3%	24.8%
	1st Qu.	24.1%	12.4%	28.8%	24.5%	11.9%	28.8%	24.7%	12.9%	28.7%
3	**Median**	26.1%	14.4%	30.9%	26.5%	14.7%	30.9%	26.6%	14.7%	30.6%
	3rd Qu.	27.6%	16.5%	33.8%	29.6%	17.1%	33.8%	28.2%	17.2%	33.5%
	Max.	32.3%	28.4%	42.9%	34.9%	26.5%	42.9%	36.2%	27.0%	40.7%
	Min.	20.3%	8.9%	29.1%	21.2%	9.0%	29.1%	21.2%	7.8%	30.5%
	1st Qu.	24.8%	11.3%	38.2%	24.4%	11.8%	38.2%	25.7%	11.7%	39.0%
4	**Median**	27.1%	13.5%	41.2%	27.6%	14.2%	41.2%	28.3%	13.7%	41.5%
	3rd Qu.	30.2%	15.8%	43.5%	30.6%	16.5%	43.5%	30.1%	15.8%	44.2%
	Max.	36.1%	23.2%	52.1%	35.3%	25.8%	52.1%	35.6%	22.7%	51.3%
	Min.	18.1%	7.9%	16.9%	17.3%	7.6%	16.9%	17.9%	6.5%	17.1%
	1st Qu.	20.6%	9.4%	24.3%	20.3%	8.6%	24.3%	19.9%	8.2%	24.3%
5	**Median**	21.7%	10.7%	26.8%	21.6%	9.7%	26.8%	21.4%	8.9%	26.4%
	3rd Qu.	23.6%	11.8%	28.3%	23.0%	11.0%	28.3%	22.6%	10.2%	28.2%
	Max.	27.2%	18.1%	39.3%	29.9%	17.8%	39.3%	25.9%	14.4%	33.8%
	Min.	21.9%	8.7%	30.0%	20.3%	9.2%	30.0%	18.0%	8.5%	28.2%
	1st Qu.	25.2%	14.3%	35.4%	24.4%	13.1%	35.4%	24.2%	11.9%	36.5%
6	**Median**	27.9%	16.7%	38.8%	25.6%	15.8%	38.8%	26.3%	14.3%	39.4%
	3rd Qu.	31.2%	20.1%	41.9%	29.1%	18.3%	41.9%	28.4%	17.2%	41.5%
	Max.	37.7%	27.5%	48.5%	36.3%	26.4%	48.5%	34.7%	29.2%	47.9%

Table E.4.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of 40 households. Continuation from Table E.3.

RES Output	**Statistic**	**Forecast Category**								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
7	**Min.**	17.7%	7.4%	21.7%	17.3%	7.0%	21.7%	17.8%	7.3%	20.0%
	1st Qu.	20.6%	8.9%	25.9%	20.9%	9.1%	25.9%	20.6%	8.7%	25.6%
	Median	21.7%	9.8%	28.1%	22.1%	10.2%	28.1%	21.9%	9.5%	28.5%
	3rd Qu.	23.7%	10.8%	29.9%	23.2%	11.1%	29.9%	23.5%	10.8%	29.8%
	Max.	28.5%	20.4%	36.6%	27.9%	17.2%	36.6%	26.5%	14.5%	34.8%
8	**Min.**	18.5%	14.9%	44.8%	24.8%	14.9%	44.8%	25.5%	14.9%	44.1%
	1st Qu.	30.9%	20.3%	50.5%	31.5%	20.7%	50.5%	31.7%	21.1%	49.5%
	Median	33.8%	23.8%	53.6%	34.3%	23.4%	53.6%	34.5%	23.6%	51.7%
	3rd Qu.	36.4%	26.9%	55.9%	37.1%	27.7%	55.9%	36.8%	26.8%	55.2%
	Max.	47.9%	40.4%	65.9%	43.5%	41.7%	65.9%	42.4%	33.3%	63.6%
9	**Min.**	17.8%	7.3%	19.7%	19.4%	7.1%	19.7%	18.0%	6.8%	19.9%
	1st Qu.	20.7%	8.8%	24.5%	21.4%	8.9%	24.5%	21.4%	9.4%	23.8%
	Median	22.6%	10.0%	25.9%	23.0%	9.5%	25.9%	22.4%	10.6%	25.8%
	3rd Qu.	23.9%	11.2%	28.1%	24.4%	10.7%	28.1%	23.9%	12.8%	28.1%
	Max.	28.9%	20.5%	33.1%	27.0%	18.0%	33.1%	28.9%	19.6%	35.6%
10	**Min.**	19.8%	9.3%	20.1%	19.2%	8.3%	20.1%	19.1%	8.7%	18.5%
	1st Qu.	22.5%	12.2%	25.5%	23.2%	11.6%	25.5%	23.5%	13.1%	25.7%
	Median	24.6%	13.8%	27.4%	25.1%	14.1%	27.4%	25.3%	15.9%	27.6%
	3rd Qu.	26.5%	16.9%	29.9%	27.1%	16.9%	29.9%	26.9%	18.4%	29.5%
	Max.	33.5%	26.5%	38.1%	34.0%	29.8%	38.1%	32.0%	28.8%	33.6%
11	**Min.**	17.4%	8.5%	19.5%	17.5%	7.6%	19.5%	17.4%	7.3%	18.3%
	1st Qu.	20.7%	10.6%	23.8%	20.5%	9.1%	23.8%	20.5%	8.4%	23.6%
	Median	22.2%	12.3%	26.2%	21.9%	9.9%	26.2%	21.8%	9.2%	26.1%
	3rd Qu.	23.3%	14.6%	28.3%	23.2%	11.1%	28.3%	23.1%	10.7%	28.3%
	Max.	27.5%	23.8%	33.7%	27.2%	16.8%	33.7%	29.6%	18.1%	34.2%
12	**Min.**	18.2%	7.6%	20.8%	16.8%	7.1%	20.8%	17.4%	7.4%	22.5%
	1st Qu.	20.9%	10.4%	26.4%	20.3%	9.1%	26.4%	20.3%	8.3%	25.0%
	Median	22.2%	11.8%	28.6%	21.7%	9.8%	28.6%	21.5%	9.0%	27.5%
	3rd Qu.	23.6%	13.2%	29.6%	23.2%	10.7%	29.6%	22.9%	9.8%	29.5%
	Max.	26.5%	18.3%	35.7%	27.5%	19.6%	35.7%	27.0%	13.9%	34.6%

Table E.5.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of 400 households. Continues in Table E.6.

RES Output	**Statistic**	**Forecast Category**								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
1	**Min.**	7.8%	2.4%	12.6%	7.5%	2.4%	12.6%	8.1%	2.4%	11.7%
	1st Qu.	10.2%	3.7%	14.3%	10.1%	3.6%	14.3%	10.5%	3.3%	14.8%
	Median	10.8%	6.1%	15.4%	10.7%	5.4%	15.4%	11.2%	4.6%	15.5%
	3rd Qu.	11.4%	7.5%	16.4%	11.3%	6.5%	16.4%	12.0%	5.3%	16.5%
	Max.	13.5%	12.7%	18.2%	12.9%	10.2%	18.2%	14.6%	10.7%	19.3%
2	**Min.**	10.8%	4.8%	17.3%	11.2%	3.9%	17.3%	10.6%	4.4%	19.0%
	1st Qu.	13.5%	7.5%	21.0%	13.1%	7.5%	21.0%	13.3%	8.3%	21.0%
	Median	14.2%	8.6%	21.8%	14.9%	8.7%	21.8%	14.5%	10.2%	21.7%
	3rd Qu.	15.0%	9.7%	22.6%	15.4%	9.8%	22.6%	15.3%	12.2%	22.4%
	Max.	17.2%	13.4%	24.3%	25.9%	13.9%	24.3%	19.9%	15.8%	25.2%
3	**Min.**	14.4%	5.9%	20.9%	15.1%	9.1%	20.9%	13.8%	7.7%	21.8%
	1st Qu.	16.7%	11.5%	23.4%	17.3%	11.0%	23.4%	17.9%	11.1%	24.0%
	Median	17.7%	12.6%	24.5%	18.1%	12.4%	24.5%	18.5%	12.3%	25.0%
	3rd Qu.	18.8%	13.8%	25.4%	19.1%	13.6%	25.4%	19.4%	13.7%	26.0%
	Max.	20.8%	19.1%	28.6%	20.8%	17.2%	28.6%	21.8%	18.5%	29.2%
4	**Min.**	18.6%	5.3%	34.8%	17.7%	5.4%	34.8%	16.0%	5.5%	34.9%
	1st Qu.	21.3%	8.3%	37.4%	20.3%	8.7%	37.4%	20.8%	9.0%	36.8%
	Median	22.4%	9.7%	38.3%	21.5%	9.6%	38.3%	22.4%	9.8%	38.1%
	3rd Qu.	23.4%	11.1%	39.3%	22.6%	10.8%	39.3%	24.0%	10.8%	39.3%
	Max.	26.6%	14.1%	41.7%	25.0%	13.9%	41.7%	28.2%	13.3%	41.5%
5	**Min.**	8.0%	4.6%	14.4%	6.9%	3.5%	14.4%	7.6%	1.6%	15.2%
	1st Qu.	9.4%	6.5%	17.4%	8.9%	4.4%	17.4%	8.8%	2.0%	17.2%
	Median	10.4%	7.6%	18.3%	9.8%	5.5%	18.3%	9.5%	2.5%	17.9%
	3rd Qu.	11.1%	8.4%	19.3%	10.6%	6.6%	19.3%	10.2%	2.9%	18.7%
	Max.	15.2%	12.2%	21.8%	13.5%	9.5%	21.8%	11.9%	4.1%	20.8%
6	**Min.**	16.5%	10.9%	31.8%	15.1%	10.2%	31.8%	16.0%	9.2%	31.4%
	1st Qu.	19.2%	13.1%	34.6%	17.4%	12.2%	34.6%	17.5%	11.8%	34.3%
	Median	20.6%	14.0%	35.3%	18.8%	13.3%	35.3%	18.8%	12.9%	35.3%
	3rd Qu.	22.0%	14.9%	36.3%	20.0%	14.3%	36.3%	19.8%	14.0%	36.4%
	Max.	24.2%	19.0%	39.3%	23.6%	17.2%	39.3%	22.6%	17.9%	37.9%

Table E.6.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of 400 households. Continuation from Table E.5.

RES Output	Statistic	Forecast Category								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
	Min.	7.4%	1.9%	15.7%	7.5%	1.9%	15.7%	7.7%	1.7%	16.0%
	1st Qu.	9.1%	3.5%	19.0%	9.4%	3.6%	19.0%	9.3%	3.5%	19.2%
7	**Median**	10.1%	5.1%	20.0%	10.4%	5.9%	20.0%	9.8%	5.0%	20.0%
	3rd Qu.	10.8%	6.6%	20.7%	11.3%	8.6%	20.7%	10.2%	6.1%	20.9%
	Max.	14.8%	12.2%	24.5%	14.8%	10.8%	24.5%	12.6%	11.0%	25.3%
	Min.	25.1%	19.2%	47.0%	22.6%	18.2%	47.0%	25.0%	18.3%	48.1%
	1st Qu.	27.4%	21.5%	50.3%	27.8%	21.3%	50.3%	28.4%	21.1%	50.2%
8	**Median**	29.0%	22.5%	51.2%	29.7%	22.3%	51.2%	29.9%	22.3%	51.4%
	3rd Qu.	30.3%	23.5%	52.2%	31.5%	23.3%	52.2%	31.5%	23.4%	52.5%
	Max.	33.2%	25.7%	54.6%	37.1%	25.6%	54.6%	37.1%	26.6%	55.2%
	Min.	8.3%	3.0%	13.0%	9.0%	2.7%	13.0%	8.7%	2.5%	13.6%
	1st Qu.	10.2%	3.6%	15.1%	10.7%	3.6%	15.1%	10.4%	4.9%	15.1%
9	**Median**	10.9%	5.9%	15.9%	11.6%	5.1%	15.9%	11.3%	6.8%	16.1%
	3rd Qu.	11.6%	7.6%	16.8%	12.4%	6.0%	16.8%	12.1%	8.0%	16.9%
	Max.	13.4%	10.2%	19.0%	16.2%	10.1%	19.0%	14.7%	12.9%	20.0%
	Min.	12.5%	5.5%	15.7%	12.2%	6.4%	15.7%	13.8%	5.5%	15.2%
	1st Qu.	14.4%	9.7%	17.6%	15.0%	9.4%	17.6%	15.5%	10.5%	17.6%
10	**Median**	15.6%	11.7%	18.3%	16.0%	11.1%	18.3%	16.6%	12.4%	18.5%
	3rd Qu.	16.5%	13.0%	19.0%	17.1%	12.8%	19.0%	17.6%	14.4%	19.2%
	Max.	20.5%	19.9%	21.0%	19.9%	16.7%	21.0%	21.0%	18.4%	23.3%
	Min.	8.4%	5.8%	13.6%	8.0%	3.9%	13.6%	7.7%	2.0%	13.3%
	1st Qu.	10.0%	7.7%	15.5%	9.6%	4.5%	15.5%	9.0%	2.8%	15.3%
11	**Median**	10.9%	10.2%	16.4%	10.3%	5.4%	16.4%	9.8%	3.5%	16.4%
	3rd Qu.	11.6%	12.1%	17.2%	10.9%	6.0%	17.2%	10.6%	4.0%	17.4%
	Max.	15.0%	15.8%	21.2%	12.9%	8.7%	21.2%	12.9%	8.3%	20.7%
	Min.	8.6%	5.9%	16.8%	7.5%	3.0%	16.8%	7.0%	1.7%	16.5%
	1st Qu.	10.2%	7.5%	19.0%	9.4%	4.9%	19.0%	8.5%	2.1%	18.7%
12	**Median**	11.1%	8.9%	19.9%	10.0%	5.5%	19.9%	9.0%	2.5%	19.7%
	3rd Qu.	12.0%	10.5%	21.0%	10.6%	6.2%	21.0%	9.7%	2.9%	20.8%
	Max.	13.7%	12.9%	23.1%	12.5%	7.9%	23.1%	11.2%	4.3%	22.7%

Table E.7.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of $40,000$ households. Continues in Table E.8.

RES Output	**Statistic**	**Forecast Category**								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
1	**Min.**	7.1%	2.4%	13.7%	6.9%	2.5%	13.7%	7.6%	3.0%	13.6%
	1st Qu.	7.9%	3.7%	14.0%	7.4%	3.5%	14.0%	8.6%	3.3%	13.9%
	Median	8.4%	6.3%	14.1%	8.3%	5.4%	14.1%	9.1%	4.8%	14.1%
	3rd Qu.	8.8%	8.1%	14.2%	8.7%	6.3%	14.2%	9.8%	5.3%	14.2%
	Max.	9.8%	11.6%	14.4%	9.9%	10.1%	14.4%	11.5%	8.7%	14.5%
2	**Min.**	11.5%	6.3%	20.3%	11.2%	6.3%	20.3%	11.1%	6.2%	20.2%
	1st Qu.	12.2%	7.3%	20.6%	11.6%	6.7%	20.6%	12.1%	7.2%	20.6%
	Median	12.7%	8.5%	20.7%	13.3%	8.4%	20.7%	13.1%	10.1%	20.7%
	3rd Qu.	13.2%	9.5%	20.8%	13.3%	9.6%	20.8%	13.3%	12.5%	20.8%
	Max.	14.1%	11.1%	21.1%	21.3%	11.6%	21.1%	16.6%	14.0%	21.1%
3	**Min.**	15.9%	11.8%	23.4%	16.0%	11.7%	23.4%	15.9%	11.9%	23.4%
	1st Qu.	16.2%	12.2%	23.7%	16.6%	12.1%	23.7%	16.4%	12.2%	23.7%
	Median	16.6%	12.4%	23.8%	17.2%	12.4%	23.8%	17.3%	12.4%	23.9%
	3rd Qu.	17.0%	12.5%	23.9%	17.7%	12.5%	23.9%	18.0%	12.5%	24.0%
	Max.	17.6%	13.2%	24.3%	19.4%	14.0%	24.3%	18.6%	12.9%	24.2%
4	**Min.**	19.5%	7.6%	37.6%	19.5%	7.9%	37.6%	20.1%	7.7%	37.7%
	1st Qu.	20.2%	8.1%	37.9%	20.8%	8.4%	37.9%	20.8%	8.2%	38.0%
	Median	21.9%	9.1%	38.0%	21.2%	8.9%	38.0%	21.9%	8.9%	38.0%
	3rd Qu.	22.9%	10.3%	38.1%	21.6%	9.0%	38.1%	24.0%	9.4%	38.2%
	Max.	26.6%	11.7%	38.4%	23.0%	11.5%	38.4%	24.9%	11.0%	38.4%
5	**Min.**	7.1%	5.8%	16.7%	6.0%	3.6%	16.7%	6.1%	1.6%	16.6%
	1st Qu.	7.4%	6.7%	16.9%	7.1%	4.7%	16.9%	6.7%	1.7%	16.9%
	Median	8.2%	7.8%	17.0%	7.7%	5.8%	17.0%	7.1%	2.4%	17.0%
	3rd Qu.	8.0%	8.5%	17.1%	8.6%	7.4%	17.1%	7.4%	2.8%	17.1%
	Max.	11.8%	10.7%	17.4%	9.5%	8.0%	17.4%	8.7%	3.4%	17.4%
6	**Min.**	18.6%	12.6%	34.4%	15.8%	12.6%	34.4%	16.6%	12.3%	34.6%
	1st Qu.	19.2%	13.4%	34.8%	16.4%	13.1%	34.8%	17.2%	12.6%	34.8%
	Median	19.8%	13.9%	34.9%	17.7%	13.3%	34.9%	17.5%	12.7%	34.9%
	3rd Qu.	20.8%	14.4%	35.0%	18.8%	13.4%	35.0%	17.9%	12.8%	35.0%
	Max.	21.8%	15.8%	35.3%	20.6%	14.5%	35.3%	18.4%	13.2%	35.3%

Table E.8.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of 40, 000 households. Continuation from Table E.7.

RES Output	Statistic	Forecast Category								
		Low Quality			Medium Quality			High Quality		
		Strategy			Strategy			Strategy		
		SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC
	Min.	5.4%	1.7%	18.8%	6.2%	1.9%	18.8%	5.8%	1.7%	18.9%
	1st Qu.	6.9%	3.6%	19.1%	7.2%	2.9%	19.1%	6.7%	2.1%	19.1%
7	**Median**	7.7%	4.9%	19.2%	8.2%	5.6%	19.2%	7.2%	4.6%	19.2%
	3rd Qu.	8.6%	6.2%	19.3%	8.5%	8.5%	19.3%	7.8%	5.7%	19.3%
	Max.	9.1%	11.3%	19.6%	12.7%	9.5%	19.6%	8.7%	10.0%	19.6%
	Min.	26.2%	21.9%	50.8%	26.7%	21.8%	50.8%	27.5%	21.8%	50.8%
	1st Qu.	27.3%	22.2%	51.0%	27.3%	22.1%	51.0%	28.0%	22.2%	51.1%
8	**Median**	28.5%	22.4%	51.1%	29.0%	22.3%	51.1%	29.5%	22.4%	51.2%
	3rd Qu.	30.1%	22.5%	51.3%	29.8%	22.4%	51.3%	30.9%	22.5%	51.3%
	Max.	31.6%	22.9%	51.5%	32.8%	22.8%	51.5%	32.2%	22.9%	51.4%
	Min.	7.7%	3.0%	13.5%	7.7%	2.6%	13.5%	7.4%	3.1%	13.6%
	1st Qu.	8.0%	3.3%	13.9%	8.3%	3.0%	13.9%	7.7%	4.6%	13.9%
9	**Median**	8.4%	5.7%	14.0%	9.1%	4.5%	14.0%	8.8%	6.6%	14.0%
	3rd Qu.	9.0%	7.7%	14.1%	9.8%	5.9%	14.1%	9.2%	8.1%	14.0%
	Max.	9.5%	9.3%	14.4%	10.9%	7.9%	14.4%	12.0%	12.1%	14.4%
	Min.	12.9%	9.0%	16.4%	13.6%	9.0%	16.4%	13.5%	9.3%	16.2%
	1st Qu.	13.5%	9.9%	16.7%	14.3%	9.5%	16.7%	14.3%	10.0%	16.7%
10	**Median**	14.3%	11.5%	16.8%	14.7%	10.6%	16.8%	15.0%	11.9%	16.7%
	3rd Qu.	15.0%	12.1%	16.9%	15.0%	11.6%	16.9%	15.5%	14.2%	16.9%
	Max.	16.1%	17.9%	17.2%	16.6%	14.5%	17.2%	16.6%	14.8%	17.1%
	Min.	7.3%	6.2%	14.7%	6.9%	3.9%	14.7%	6.8%	2.1%	14.8%
	1st Qu.	7.9%	6.9%	15.0%	7.3%	4.2%	15.0%	7.1%	2.3%	15.0%
11	**Median**	8.7%	10.5%	15.1%	7.7%	5.3%	15.1%	7.4%	2.7%	15.1%
	3rd Qu.	9.1%	12.9%	15.2%	8.0%	5.2%	15.2%	7.6%	3.0%	15.2%
	Max.	10.6%	14.6%	15.5%	8.7%	8.5%	15.5%	8.2%	3.3%	15.6%
	Min.	7.6%	7.1%	18.5%	6.2%	3.0%	18.5%	5.2%	1.6%	18.6%
	1st Qu.	8.6%	8.0%	18.9%	6.8%	5.6%	18.9%	5.7%	2.0%	18.9%
12	**Median**	9.2%	9.2%	19.0%	7.4%	5.6%	19.0%	6.3%	2.3%	19.0%
	3rd Qu.	9.6%	10.4%	19.1%	8.0%	6.1%	19.1%	6.6%	2.8%	19.1%
	Max.	11.7%	12.3%	19.3%	8.6%	6.5%	19.3%	7.5%	3.1%	19.3%

Table E.9.: Summary of the results of the performance tolerance to dynamism of SLC. Continues in Table E.10.

RES Output	**Statistic**	α														
		1.0			0.5			0.1			0.05			0.01		
		Forecast Category			**Forecast Category**			**Forecast Category**			**Forecast Category**			**Forecast Category**		
		Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
	Min.	7.2%	6.9%	7.7%	7.3%	6.6%	7.1%	7.2%	6.4%	7.0%	7.9%	7.2%	7.5%	8.8%	8.1%	8.6%
	1st Qu.	8.7%	8.7%	8.8%	8.2%	7.9%	7.9%	8.5%	8.2%	7.6%	9.3%	9.3%	8.7%	10.1%	10.0%	9.6%
1	**Median**	9.2%	9.2%	9.3%	8.6%	8.7%	8.7%	9.3%	8.8%	8.7%	10.0%	9.8%	9.8%	10.7%	10.7%	10.8%
	3rd Qu.	9.9%	9.6%	9.9%	9.2%	9.1%	9.3%	9.8%	9.5%	9.4%	10.5%	10.5%	10.5%	11.1%	11.6%	11.2%
	Max.	11.1%	10.6%	11.7%	10.1%	10.3%	11.1%	10.9%	10.8%	11.1%	11.2%	11.6%	11.4%	12.7%	12.9%	17.0%
	Min.	12.0%	13.0%	12.4%	11.0%	12.5%	12.3%	11.0%	10.8%	10.8%	12.2%	11.9%	11.9%	14.3%	12.8%	13.7%
	1st Qu.	13.4%	13.9%	13.9%	13.3%	13.4%	13.7%	12.1%	12.0%	12.2%	13.4%	13.5%	12.8%	14.9%	14.9%	14.7%
2	**Median**	13.9%	14.3%	14.4%	13.7%	13.9%	14.2%	12.7%	12.6%	12.7%	14.1%	14.1%	13.8%	15.5%	15.5%	15.7%
	3rd Qu.	14.2%	14.8%	14.8%	14.2%	14.4%	14.6%	13.5%	13.5%	13.7%	15.0%	15.0%	14.8%	16.4%	16.2%	17.2%
	Max.	14.8%	18.4%	15.8%	15.3%	18.5%	15.4%	14.9%	22.8%	16.9%	15.8%	23.8%	18.5%	17.1%	24.8%	19.5%
	Min.	16.5%	17.1%	16.5%	15.7%	16.2%	15.8%	14.9%	15.4%	15.6%	15.0%	15.3%	14.8%	15.6%	16.1%	14.8%
	1st Qu.	17.5%	17.8%	17.6%	17.0%	17.4%	17.3%	16.4%	16.8%	16.8%	16.3%	16.7%	16.5%	18.2%	18.6%	19.2%
3	**Median**	17.9%	18.3%	18.1%	17.4%	17.9%	17.7%	16.9%	17.2%	17.5%	17.3%	17.2%	18.7%	19.5%	19.1%	20.7%
	3rd Qu.	18.4%	18.7%	18.7%	18.0%	18.3%	18.2%	17.2%	17.6%	18.1%	17.7%	17.8%	19.4%	20.3%	20.4%	21.4%
	Max.	19.8%	20.3%	19.7%	19.4%	19.3%	19.1%	18.3%	18.7%	18.9%	18.6%	19.7%	20.7%	21.4%	21.8%	23.1%
	Min.	21.9%	22.1%	22.0%	20.5%	21.0%	21.4%	19.7%	19.3%	19.2%	19.0%	19.7%	19.5%	18.9%	20.9%	20.1%
	1st Qu.	23.2%	23.0%	23.2%	22.4%	22.3%	22.4%	21.0%	20.7%	21.6%	20.5%	21.0%	20.7%	21.6%	22.6%	21.7%
4	**Median**	23.6%	23.6%	23.7%	23.2%	22.8%	23.2%	21.5%	21.1%	22.2%	21.4%	21.8%	21.3%	23.2%	23.7%	22.2%
	3rd Qu.	24.2%	24.2%	24.3%	23.9%	23.7%	24.1%	21.9%	21.9%	22.7%	22.8%	22.5%	23.8%	24.5%	24.4%	25.2%
	Max.	27.5%	25.3%	25.6%	27.3%	25.4%	25.3%	24.8%	23.5%	24.1%	26.9%	23.8%	25.4%	28.8%	25.6%	27.0%
	Min.	7.5%	7.5%	7.8%	6.9%	7.4%	7.1%	7.8%	5.7%	5.5%	8.3%	6.4%	6.7%	8.8%	7.9%	7.4%
	1st Qu.	8.6%	8.9%	9.1%	7.5%	8.4%	8.3%	8.4%	7.2%	6.9%	8.9%	7.8%	7.4%	9.9%	9.7%	8.6%
5	**Median**	9.2%	9.8%	9.7%	7.9%	9.0%	8.9%	8.8%	7.7%	7.2%	9.3%	9.0%	7.9%	10.2%	10.6%	9.2%
	3rd Qu.	10.2%	10.6%	10.6%	8.5%	9.7%	9.5%	9.2%	8.6%	7.7%	9.7%	9.7%	8.6%	10.7%	11.1%	9.8%
	Max.	13.4%	13.6%	11.7%	12.6%	12.4%	11.0%	10.1%	10.2%	9.1%	10.6%	10.6%	10.5%	12.0%	11.8%	11.2%
	Min.	18.9%	19.9%	19.7%	17.9%	18.3%	19.2%	17.3%	15.5%	16.1%	17.0%	15.1%	16.3%	19.5%	16.5%	19.1%
	1st Qu.	20.2%	20.9%	20.7%	19.1%	20.0%	20.0%	19.1%	16.8%	17.2%	19.8%	16.6%	17.7%	21.5%	18.6%	20.0%
6	**Median**	20.8%	21.2%	21.0%	19.7%	20.5%	20.2%	19.9%	17.3%	17.7%	20.9%	17.2%	18.3%	22.4%	19.3%	21.0%
	3rd Qu.	21.5%	21.6%	21.3%	20.8%	21.0%	20.7%	20.6%	18.0%	18.1%	22.0%	18.8%	19.4%	23.3%	21.6%	21.8%
	Max.	22.8%	22.7%	22.8%	22.6%	21.9%	21.5%	22.0%	20.5%	19.3%	23.9%	21.2%	20.4%	25.0%	22.7%	23.2%

Table E.10.: Summary of the results of the performance tolerance to dynamism of SLC. Continuation from Table E.9.

RES Output	Statistic	α														
		1.0			0.5			0.1			0.05			0.01		
		Forecast Category			**Forecast Category**			**Forecast Category**			**Forecast Category**			**Forecast Category**		
		Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
7	**Min.**	7.8%	7.6%	8.3%	6.8%	6.7%	7.3%	5.4%	5.9%	5.9%	6.2%	6.7%	6.2%	7.2%	7.5%	7.6%
	1st Qu.	9.1%	9.0%	9.2%	8.0%	8.1%	8.2%	7.2%	7.4%	7.0%	7.6%	7.9%	7.5%	8.7%	9.2%	8.6%
	Median	9.6%	9.8%	9.7%	8.6%	9.1%	8.8%	8.1%	8.1%	7.5%	8.8%	9.3%	8.4%	10.0%	10.6%	9.6%
	3rd Qu.	10.3%	10.9%	10.3%	9.5%	9.9%	9.4%	8.8%	8.9%	8.0%	9.8%	9.8%	9.0%	10.8%	11.7%	10.4%
	Max.	11.5%	12.7%	11.8%	10.6%	12.2%	11.4%	9.7%	13.4%	8.9%	11.5%	15.0%	10.3%	13.8%	16.8%	12.6%
8	**Min.**	30.0%	30.0%	29.9%	29.2%	29.1%	29.2%	26.9%	26.8%	26.8%	25.6%	26.3%	26.3%	25.9%	27.2%	27.6%
	1st Qu.	31.3%	31.3%	31.1%	30.4%	30.5%	30.3%	28.0%	28.4%	28.1%	27.1%	27.5%	27.6%	27.6%	28.8%	28.9%
	Median	31.7%	31.6%	31.5%	30.9%	31.0%	30.7%	28.9%	29.1%	29.3%	27.9%	28.7%	29.4%	28.8%	29.8%	30.2%
	3rd Qu.	32.2%	32.0%	31.8%	31.4%	31.4%	31.2%	30.0%	30.2%	30.9%	30.3%	30.1%	31.1%	31.6%	31.0%	32.3%
	Max.	33.0%	32.9%	32.6%	32.7%	32.2%	32.6%	31.6%	32.7%	33.3%	32.0%	34.0%	33.1%	34.1%	35.2%	34.3%
9	**Min.**	9.6%	10.0%	9.5%	8.0%	9.5%	9.1%	7.5%	7.8%	7.2%	8.1%	8.7%	8.2%	9.9%	10.0%	9.6%
	1st Qu.	10.2%	10.5%	10.2%	10.1%	10.5%	10.0%	8.2%	8.6%	8.0%	9.4%	9.8%	9.2%	10.6%	11.2%	10.6%
	Median	10.5%	10.9%	10.6%	10.6%	10.7%	10.5%	8.6%	9.4%	8.6%	9.8%	10.6%	10.0%	11.1%	11.8%	11.9%
	3rd Qu.	11.0%	11.3%	11.3%	10.9%	11.0%	11.0%	9.1%	10.1%	9.6%	10.4%	11.3%	11.0%	11.6%	12.4%	12.5%
	Max.	12.0%	12.2%	12.7%	11.6%	11.8%	12.7%	10.2%	11.5%	12.3%	11.2%	13.1%	12.8%	12.6%	13.9%	14.9%
10	**Min.**	12.5%	12.6%	13.3%	13.0%	12.6%	13.5%	12.8%	13.2%	12.9%	13.6%	13.5%	14.2%	14.1%	14.5%	14.6%
	1st Qu.	14.5%	14.9%	15.9%	14.0%	14.7%	15.1%	13.7%	14.3%	14.4%	14.5%	15.0%	15.3%	15.2%	15.5%	16.1%
	Median	15.1%	16.0%	16.8%	14.7%	15.6%	16.1%	14.2%	14.8%	15.0%	15.0%	15.5%	15.7%	15.9%	16.0%	16.6%
	3rd Qu.	16.8%	16.8%	17.3%	16.4%	16.2%	16.8%	14.8%	15.2%	15.7%	15.5%	16.1%	16.2%	16.5%	16.8%	17.0%
	Max.	19.2%	18.2%	19.1%	18.7%	18.3%	19.0%	16.7%	17.5%	17.0%	18.9%	19.1%	17.6%	22.4%	20.7%	18.7%
11	**Min.**	7.7%	7.1%	7.5%	7.5%	6.9%	7.3%	7.0%	6.6%	6.6%	7.7%	6.5%	6.5%	8.4%	7.1%	7.5%
	1st Qu.	9.0%	8.1%	8.2%	8.9%	8.1%	8.0%	8.3%	7.6%	7.3%	8.8%	7.9%	7.8%	9.5%	9.5%	8.5%
	Median	10.1%	8.7%	8.6%	9.6%	8.7%	8.5%	9.0%	8.0%	7.5%	9.6%	8.5%	8.2%	10.5%	10.1%	9.1%
	3rd Qu.	10.7%	9.2%	9.0%	10.0%	9.1%	8.9%	9.5%	8.4%	7.9%	10.1%	9.1%	8.7%	11.7%	10.6%	9.7%
	Max.	11.5%	12.4%	10.5%	11.0%	10.2%	10.5%	10.9%	9.2%	8.7%	11.7%	10.7%	9.7%	13.3%	12.4%	11.3%
12	**Min.**	7.7%	8.2%	8.1%	7.5%	7.8%	7.8%	7.5%	6.0%	5.6%	6.6%	6.5%	6.2%	7.8%	8.0%	6.9%
	1st Qu.	9.0%	9.3%	8.9%	8.7%	8.5%	8.5%	8.8%	7.0%	6.1%	8.6%	7.6%	6.9%	10.1%	8.9%	8.1%
	Median	9.9%	9.7%	9.3%	9.6%	8.9%	8.9%	9.3%	7.7%	6.5%	9.6%	8.4%	7.5%	10.8%	9.4%	8.5%
	3rd Qu.	10.5%	10.1%	9.6%	10.5%	9.5%	9.3%	10.1%	8.4%	6.9%	10.3%	8.8%	7.9%	11.4%	10.1%	8.9%
	Max.	12.5%	11.1%	10.7%	12.4%	10.2%	10.3%	12.2%	9.0%	8.6%	12.3%	10.5%	8.9%	12.8%	11.3%	10.7%

Table E.11.: Summary of the results of the comparison of the scalability between SLC, CLP and NLC.

RES Output	Statistic	Population											
		40			400			4, 000			40, 00		
		Strategy			Strategy			Strategy			Strategy		
		SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC
	Min.	17.5%	7.3%	17.6%	7.5%	2.4%	11.7%	6.6%	2.3%	12.7%	6.9%	2.4%	13.6%
	1st Qu.	20.8%	9.0%	23.7%	10.2%	3.4%	14.5%	8.3%	3.5%	13.8%	8.1%	3.5%	14.0%
1	**Median**	22.0%	9.9%	25.3%	10.9%	4.6%	15.4%	8.9%	4.9%	14.2%	8.6%	5.0%	14.1%
	3rd Qu.	23.7%	11.5%	27.7%	11.5%	6.6%	16.4%	9.4%	6.5%	14.5%	9.1%	6.7%	14.2%
	Max.	29.7%	24.3%	34.7%	14.6%	12.7%	19.3%	11.7%	11.6%	15.5%	11.5%	11.6%	14.5%
	Min.	19.2%	7.9%	21.6%	10.6%	3.9%	17.3%	10.8%	5.5%	19.2%	11.1%	6.2%	20.2%
	1st Qu.	23.4%	10.2%	28.0%	13.3%	7.6%	21.1%	12.1%	7.2%	20.5%	12.0%	7.1%	20.6%
2	**Median**	24.8%	12.3%	30.6%	14.2%	9.0%	22.0%	12.7%	8.7%	20.8%	12.6%	8.6%	20.7%
	3rd Qu.	26.4%	14.6%	32.9%	15.2%	10.5%	22.9%	13.5%	10.3%	21.1%	13.3%	10.2%	20.8%
	Max.	31.8%	23.3%	40.1%	25.9%	15.8%	26.7%	22.8%	14.3%	22.3%	21.3%	14.0%	21.1%
	Min.	20.7%	8.1%	21.5%	13.8%	5.9%	20.1%	14.9%	10.4%	22.3%	15.9%	11.7%	23.4%
	1st Qu.	24.5%	12.4%	28.6%	17.2%	11.1%	23.6%	16.6%	11.9%	23.6%	16.3%	12.2%	23.7%
3	**Median**	26.4%	14.5%	30.8%	18.2%	12.3%	24.7%	17.2%	12.3%	24.0%	16.9%	12.3%	23.9%
	3rd Qu.	28.4%	16.9%	33.8%	19.1%	13.7%	25.8%	17.7%	12.8%	24.3%	17.5%	12.5%	24.0%
	Max.	36.2%	28.4%	42.9%	21.8%	19.1%	29.2%	19.7%	14.3%	25.2%	19.4%	14.0%	24.3%
	Min.	20.3%	7.8%	29.1%	16.0%	5.3%	34.5%	19.0%	7.2%	36.7%	19.5%	7.6%	37.6%
	1st Qu.	25.2%	11.7%	38.5%	20.8%	8.7%	37.1%	20.6%	8.2%	37.7%	20.7%	8.2%	37.9%
4	**Median**	27.7%	13.8%	41.2%	21.9%	9.7%	38.2%	21.3%	8.8%	38.0%	21.1%	8.6%	38.0%
	3rd Qu.	30.3%	16.0%	43.9%	23.3%	10.9%	39.2%	22.4%	9.5%	38.3%	22.3%	9.3%	38.1%
	Max.	36.1%	25.8%	52.1%	28.2%	14.1%	41.9%	26.9%	12.3%	39.4%	26.6%	11.7%	38.6%
	Min.	17.3%	6.5%	16.9%	6.9%	1.6%	12.9%	5.5%	1.5%	15.8%	6.0%	1.6%	16.6%
	1st Qu.	20.3%	8.7%	24.4%	9.1%	2.9%	17.2%	7.1%	2.9%	16.8%	7.0%	2.8%	16.9%
5	**Median**	21.6%	9.8%	26.7%	9.8%	4.9%	17.9%	7.6%	5.6%	17.1%	7.5%	5.6%	17.0%
	3rd Qu.	23.0%	11.1%	28.6%	10.6%	7.2%	19.0%	8.4%	7.6%	17.4%	8.0%	7.7%	17.1%
	Max.	29.9%	18.1%	39.3%	15.2%	12.2%	21.8%	12.6%	11.0%	18.4%	11.8%	10.7%	17.4%
	Min.	18.0%	8.5%	28.2%	15.1%	9.2%	31.1%	15.1%	11.3%	33.8%	15.8%	12.3%	34.4%
	1st Qu.	24.6%	13.2%	36.2%	17.9%	12.3%	34.4%	17.2%	12.8%	34.7%	17.2%	12.8%	34.8%
6	**Median**	26.6%	15.7%	39.3%	19.2%	13.5%	35.5%	18.3%	13.2%	35.0%	18.1%	13.1%	34.9%
	3rd Qu.	29.4%	18.6%	41.5%	20.7%	14.5%	36.4%	19.4%	13.7%	35.3%	19.3%	13.6%	35.0%
	Max.	37.7%	29.2%	48.5%	24.2%	19.0%	39.3%	22.6%	15.6%	36.4%	21.8%	15.8%	35.4%
	Min.	17.3%	7.0%	20.0%	7.4%	1.7%	15.7%	5.4%	1.7%	17.9%	5.4%	1.7%	18.8%
	1st Qu.	20.6%	8.8%	25.7%	9.2%	3.5%	19.0%	7.1%	3.2%	18.9%	6.9%	2.9%	19.1%
7	**Median**	22.0%	9.8%	28.0%	10.0%	4.3%	20.1%	7.8%	3.8%	19.3%	7.5%	3.8%	19.2%
	3rd Qu.	23.4%	11.0%	29.7%	10.8%	7.0%	20.9%	8.6%	6.8%	19.6%	8.4%	6.7%	19.3%
	Max.	28.5%	20.4%	36.6%	14.8%	12.2%	25.3%	13.4%	11.5%	20.4%	12.7%	11.3%	19.6%
	Min.	18.5%	14.9%	39.3%	22.6%	18.2%	47.0%	25.6%	20.9%	50.0%	26.2%	21.8%	50.7%
	1st Qu.	31.4%	20.6%	50.1%	27.9%	21.3%	50.3%	27.5%	22.0%	50.8%	27.6%	22.2%	51.1%
8	**Median**	34.2%	23.5%	53.1%	29.4%	22.3%	51.4%	28.7%	22.3%	51.1%	28.6%	22.3%	51.1%
	3rd Qu.	36.8%	27.1%	56.0%	31.1%	23.4%	52.4%	30.5%	22.7%	51.4%	30.6%	22.5%	51.3%
	Max.	47.9%	41.7%	65.9%	37.1%	26.6%	55.3%	34.0%	23.9%	52.9%	32.8%	22.9%	51.5%
	Min.	17.8%	6.8%	19.7%	8.3%	2.5%	12.9%	7.2%	2.5%	12.6%	7.4%	2.6%	13.5%
	1st Qu.	21.3%	9.0%	24.4%	10.5%	3.9%	15.1%	8.3%	3.4%	13.9%	8.0%	3.3%	13.9%
9	**Median**	22.6%	9.9%	26.2%	11.1%	5.5%	15.9%	8.8%	5.6%	14.1%	8.4%	5.3%	14.0%
	3rd Qu.	24.1%	11.5%	28.2%	12.0%	7.4%	16.9%	9.5%	7.3%	14.4%	9.3%	7.2%	14.1%
	Max.	28.9%	20.5%	40.4%	16.2%	12.9%	20.0%	12.3%	12.2%	15.2%	12.0%	12.1%	14.4%
	Min.	19.1%	8.3%	18.5%	12.2%	5.5%	15.2%	12.8%	8.3%	15.6%	12.9%	9.0%	16.2%
	1st Qu.	23.0%	11.9%	25.5%	15.0%	9.7%	17.5%	14.1%	9.8%	16.6%	14.0%	9.8%	16.7%
10	**Median**	25.0%	14.5%	27.5%	16.0%	11.2%	18.3%	14.7%	10.5%	16.9%	14.6%	10.3%	16.8%
	3rd Qu.	26.9%	17.6%	29.7%	17.1%	13.7%	19.2%	15.3%	12.5%	17.2%	15.2%	12.2%	16.9%
	Max.	34.0%	29.8%	38.1%	21.0%	19.9%	23.3%	17.5%	18.3%	18.4%	16.6%	17.9%	17.2%
	Min.	17.4%	7.3%	18.3%	7.7%	2.0%	12.6%	6.6%	2.0%	13.7%	6.8%	2.1%	14.5%
	1st Qu.	20.5%	9.1%	23.7%	9.6%	3.9%	15.5%	7.5%	3.0%	14.9%	7.3%	3.0%	15.0%
11	**Median**	21.9%	10.4%	25.9%	10.2%	5.3%	16.3%	8.1%	4.8%	15.2%	7.7%	4.7%	15.1%
	3rd Qu.	23.3%	12.0%	28.1%	11.2%	8.1%	17.3%	8.7%	8.2%	15.5%	8.2%	8.4%	15.2%
	Max.	29.6%	23.8%	36.0%	15.0%	15.8%	21.2%	10.9%	15.0%	16.8%	10.6%	14.6%	15.6%
	Min.	16.8%	7.1%	17.9%	7.0%	1.7%	16.2%	5.6%	1.6%	17.4%	5.2%	1.6%	18.5%
	1st Qu.	20.5%	9.0%	25.4%	9.1%	2.9%	18.8%	6.8%	2.8%	18.8%	6.5%	2.8%	18.9%
12	**Median**	21.7%	10.0%	28.0%	10.0%	5.7%	19.7%	7.7%	5.8%	19.1%	7.5%	5.9%	19.0%
	3rd Qu.	23.3%	11.5%	29.7%	10.9%	7.5%	20.8%	8.9%	7.6%	19.4%	8.6%	8.0%	19.1%
	Max.	27.5%	19.6%	36.5%	13.7%	12.9%	23.1%	12.2%	12.4%	20.2%	11.7%	12.3%	19.4%

Table E.12.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of $4,000$ households. Continues in Table E.13.

		Forecast Category								
RES Output	**Statistic**	**Low Quality**			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
	Min.	7.3%	2.3%	12.8%	6.6%	2.4%	12.8%	7.7%	2.8%	12.7%
	1st Qu.	8.2%	3.5%	13.8%	7.9%	3.5%	13.8%	8.8%	3.3%	13.8%
1	**Median**	8.6%	6.2%	14.2%	8.7%	4.9%	14.2%	9.3%	4.4%	14.2%
	3rd Qu.	9.2%	8.0%	14.5%	9.1%	6.2%	14.5%	9.9%	5.3%	14.4%
	Max.	10.1%	11.6%	15.5%	10.3%	10.3%	15.5%	11.7%	9.1%	15.1%
	Min.	11.0%	6.2%	19.4%	10.8%	6.1%	19.4%	10.8%	5.5%	19.5%
	1st Qu.	12.1%	7.4%	20.5%	12.0%	7.0%	20.5%	12.2%	7.3%	20.5%
2	**Median**	12.7%	8.7%	20.8%	12.6%	8.4%	20.8%	12.7%	10.9%	20.8%
	3rd Qu.	13.5%	9.4%	21.1%	13.5%	9.7%	21.1%	13.7%	12.6%	21.1%
	Max.	14.9%	11.8%	22.3%	22.8%	11.8%	22.3%	16.9%	14.3%	22.0%
	Min.	14.9%	11.0%	22.8%	15.3%	10.4%	22.8%	15.6%	11.2%	22.9%
	1st Qu.	16.4%	11.9%	23.6%	16.7%	11.9%	23.6%	16.8%	12.1%	23.8%
3	**Median**	16.9%	12.2%	24.0%	17.2%	12.2%	24.0%	17.5%	12.4%	24.1%
	3rd Qu.	17.2%	12.7%	24.3%	17.8%	12.7%	24.3%	18.1%	12.8%	24.4%
	Max.	18.3%	14.1%	25.1%	19.7%	14.3%	25.1%	18.9%	13.7%	25.1%
	Min.	19.0%	7.3%	36.7%	19.3%	7.4%	36.7%	19.5%	7.2%	36.9%
	1st Qu.	20.5%	8.0%	37.7%	20.7%	8.3%	37.7%	20.7%	8.2%	37.8%
4	**Median**	21.4%	8.5%	38.0%	21.1%	8.8%	38.0%	21.3%	9.0%	38.0%
	3rd Qu.	22.8%	10.4%	38.3%	21.9%	9.3%	38.3%	23.8%	9.7%	38.3%
	Max.	26.9%	12.3%	39.1%	23.5%	12.2%	39.1%	25.4%	11.7%	39.4%
	Min.	6.9%	5.5%	16.2%	5.7%	3.5%	16.2%	5.5%	1.5%	16.3%
	1st Qu.	7.5%	6.5%	16.9%	7.2%	4.6%	16.9%	6.9%	1.7%	16.7%
5	**Median**	7.9%	7.8%	17.1%	7.7%	5.6%	17.1%	7.2%	2.3%	17.1%
	3rd Qu.	8.5%	8.6%	17.5%	8.6%	7.2%	17.5%	7.7%	2.9%	17.4%
	Max.	12.6%	11.0%	18.4%	10.2%	8.4%	18.4%	9.1%	3.5%	18.1%
	Min.	17.9%	11.8%	33.9%	15.1%	12.0%	33.9%	16.1%	11.3%	33.8%
	1st Qu.	19.1%	13.3%	34.6%	16.6%	13.0%	34.6%	17.2%	12.5%	34.7%
6	**Median**	19.7%	13.8%	35.1%	17.2%	13.3%	35.1%	17.7%	12.8%	34.9%
	3rd Qu.	20.8%	14.5%	35.4%	18.8%	13.7%	35.4%	18.1%	13.1%	35.2%
	Max.	22.6%	15.6%	36.0%	21.2%	14.9%	36.0%	19.3%	14.1%	36.1%

Table E.13.: Summary of the comparison of the performance tolerance to dynamism between SLC, CLP and NLC, with a population size of $4,000$ households. Continuation from Table E.12.

RES Output	**Statistic**	**Forecast Category**								
		Low Quality			**Medium Quality**			**High Quality**		
		Strategy			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
7	**Min.**	5.4%	1.7%	18.0%	5.9%	1.8%	18.0%	5.9%	1.7%	17.9%
	1st Qu.	7.2%	3.6%	18.9%	7.4%	3.2%	18.9%	7.0%	2.4%	19.0%
	Median	8.1%	3.9%	19.3%	8.1%	4.9%	19.3%	7.5%	3.7%	19.4%
	3rd Qu.	8.8%	6.2%	19.6%	8.9%	8.5%	19.6%	8.0%	5.7%	19.6%
	Max.	9.7%	11.5%	20.4%	13.4%	10.0%	20.4%	8.9%	10.7%	20.3%
8	**Min.**	25.6%	21.1%	50.1%	26.3%	21.2%	50.1%	26.8%	20.9%	50.0%
	1st Qu.	27.1%	21.9%	50.9%	27.5%	22.0%	50.9%	28.1%	22.0%	50.8%
	Median	27.9%	22.2%	51.2%	28.7%	22.4%	51.2%	29.3%	22.4%	51.1%
	3rd Qu.	30.3%	22.7%	51.5%	30.1%	22.7%	51.5%	30.9%	22.8%	51.4%
	Max.	32.0%	23.7%	52.9%	34.0%	23.7%	52.9%	33.3%	23.9%	52.5%
9	**Min.**	7.5%	2.6%	13.2%	7.8%	2.5%	13.2%	7.2%	3.0%	12.6%
	1st Qu.	8.2%	3.4%	13.8%	8.6%	3.2%	13.8%	8.0%	4.6%	13.9%
	Median	8.6%	6.0%	14.1%	9.4%	4.1%	14.1%	8.6%	6.7%	14.2%
	3rd Qu.	9.1%	7.6%	14.4%	10.1%	5.7%	14.4%	9.6%	8.1%	14.5%
	Max.	10.2%	9.6%	15.2%	11.5%	8.8%	15.2%	12.3%	12.2%	15.1%
10	**Min.**	12.8%	8.3%	15.8%	13.2%	8.3%	15.8%	12.9%	8.6%	15.7%
	1st Qu.	13.7%	9.9%	16.6%	14.3%	9.4%	16.6%	14.4%	10.1%	16.5%
	Median	14.2%	10.4%	16.9%	14.8%	10.2%	16.9%	15.0%	11.3%	16.8%
	3rd Qu.	14.8%	12.3%	17.1%	15.2%	11.6%	17.1%	15.7%	14.0%	17.3%
	Max.	16.7%	18.3%	17.9%	17.5%	14.9%	17.9%	17.0%	15.8%	18.2%
11	**Min.**	7.0%	6.0%	13.7%	6.6%	3.7%	13.7%	6.6%	2.0%	13.9%
	1st Qu.	8.3%	6.9%	14.9%	7.6%	4.3%	14.9%	7.3%	2.4%	14.9%
	Median	9.0%	10.7%	15.1%	8.0%	4.8%	15.1%	7.5%	2.8%	15.2%
	3rd Qu.	9.5%	12.8%	15.6%	8.4%	5.2%	15.6%	7.9%	3.0%	15.5%
	Max.	10.9%	15.0%	16.8%	9.2%	8.5%	16.8%	8.7%	3.9%	16.2%
12	**Min.**	7.5%	6.8%	17.8%	6.0%	2.8%	17.8%	5.6%	1.6%	17.9%
	1st Qu.	8.8%	7.7%	18.8%	7.0%	5.3%	18.8%	6.1%	2.0%	18.8%
	Median	9.3%	8.6%	19.1%	7.7%	5.8%	19.1%	6.5%	2.4%	19.0%
	3rd Qu.	10.1%	10.4%	19.4%	8.4%	6.1%	19.4%	6.9%	2.7%	19.3%
	Max.	12.2%	12.4%	20.2%	9.0%	6.8%	20.2%	8.6%	3.4%	20.0%

Table E.14.: Summary of the results of the comparison of performance according to different levels of micro-grid load coverage between SLC, CLP and NLC. 40% of the micro-grid load is considered flexible.

Load Coverage	Statistic	RES Output 1			RES Output 2			RES Output 3			RES Output 4			RES Output 5			RES Output 6		
		Strategy			Strategy			Strategy			Strategy			Strategy			Strategy		
		SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC
	Min.	0.0%	0.0%	0.0%	0.3%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1st Qu.	0.1%	0.1%	0.1%	0.3%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
25	**Median**	0.1%	0.1%	0.1%	0.3%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	3rd Qu.	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Max.	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Min.	1.0%	1.0%	2.7%	1.4%	1.4%	4.1%	1.6%	1.0%	4.0%	0.0%	0.0%	6.1%	0.0%	0.0%	0.0%	0.4%	0.4%	1.0%
	1st Qu.	1.1%	1.0%	3.3%	1.5%	1.5%	4.5%	2.6%	1.0%	4.9%	0.1%	0.1%	6.8%	0.0%	0.0%	0.0%	0.4%	0.4%	1.5%
50	**Median**	1.2%	1.1%	3.5%	1.5%	1.5%	4.6%	3.1%	1.1%	5.2%	0.2%	0.1%	7.1%	0.0%	0.0%	0.0%	0.4%	0.4%	1.6%
	3rd Qu.	1.3%	1.1%	3.7%	1.5%	1.5%	4.6%	3.7%	1.1%	5.5%	0.3%	0.1%	7.3%	0.0%	0.0%	0.0%	0.4%	0.4%	1.8%
	Max.	1.8%	1.1%	4.2%	2.6%	1.6%	4.9%	4.6%	1.8%	6.4%	1.3%	0.2%	8.2%	0.0%	0.0%	0.0%	0.4%	0.4%	2.4%
	Min.	3.6%	1.6%	8.4%	3.8%	2.0%	9.9%	14.2%	11.0%	18.3%	12.7%	4.6%	24.5%	0.0%	0.0%	3.7%	8.0%	0.7%	19.0%
	1st Qu.	5.2%	2.4%	9.0%	4.8%	2.1%	10.4%	15.4%	11.6%	18.9%	13.9%	5.5%	25.1%	0.1%	0.0%	4.2%	9.0%	1.1%	19.7%
75	**Median**	5.8%	2.7%	9.2%	5.1%	2.1%	10.6%	15.8%	11.8%	19.2%	14.4%	5.8%	25.3%	0.1%	0.0%	4.4%	9.4%	1.6%	19.9%
	3rd Qu.	6.5%	3.0%	9.4%	5.7%	2.1%	10.8%	16.1%	12.0%	19.4%	14.9%	6.1%	25.5%	0.2%	0.0%	4.6%	9.9%	2.8%	20.1%
	Max.	7.7%	4.0%	10.1%	10.2%	4.5%	11.5%	16.9%	12.7%	20.1%	17.7%	10.5%	26.3%	0.6%	1.3%	5.0%	11.4%	3.9%	20.7%

Load Coverage	Statistic	RES Output 7			RES Output 8			RES Output 9			RES Output 10			RES Output 11			RES Output 12		
		Strategy			Strategy			Strategy			Strategy			Strategy			Strategy		
		SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC	SLC	CLP	NLC
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
	Min.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	1st Qu.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
25	**Median**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	3rd Qu.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Max.	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	Min.	0.0%	0.0%	0.0%	2.7%	0.0%	18.5%	0.5%	0.5%	1.3%	0.8%	0.8%	2.6%	0.1%	0.1%	0.4%	0.1%	0.2%	0.3%
	1st Qu.	0.0%	0.0%	0.0%	3.9%	0.0%	19.4%	0.6%	0.6%	1.4%	0.8%	0.8%	2.6%	0.2%	0.1%	0.5%	0.2%	0.2%	0.4%
50	**Median**	0.0%	0.0%	0.0%	4.3%	0.0%	19.7%	0.6%	0.6%	1.5%	0.8%	0.8%	2.7%	0.2%	0.2%	0.6%	0.2%	0.2%	0.5%
	3rd Qu.	0.0%	0.0%	0.0%	4.7%	0.0%	20.0%	0.6%	0.6%	1.6%	0.8%	0.8%	2.7%	0.2%	0.2%	0.6%	0.3%	0.2%	0.5%
	Max.	0.0%	0.0%	0.0%	5.8%	0.0%	21.0%	0.7%	0.7%	1.8%	0.9%	0.8%	2.8%	0.6%	0.2%	0.7%	0.3%	0.3%	0.8%
	Min.	0.2%	0.2%	4.6%	23.0%	16.9%	38.1%	1.7%	1.1%	5.4%	1.9%	1.3%	5.5%	4.5%	1.2%	6.6%	0.7%	0.5%	6.8%
	1st Qu.	0.3%	0.3%	5.0%	24.3%	17.6%	38.6%	2.6%	1.1%	5.7%	2.3%	1.3%	5.8%	5.9%	2.0%	7.4%	1.2%	0.5%	7.4%
75	**Median**	0.4%	0.3%	5.2%	24.7%	17.8%	38.8%	3.2%	1.2%	5.9%	2.7%	1.3%	5.9%	6.3%	2.3%	7.6%	1.4%	0.5%	7.6%
	3rd Qu.	0.5%	0.3%	5.4%	25.2%	18.0%	38.9%	3.7%	1.2%	6.1%	3.2%	1.8%	6.0%	6.8%	2.9%	7.8%	2.0%	0.6%	7.8%
	Max.	2.3%	0.4%	5.8%	26.6%	18.6%	39.6%	4.9%	2.0%	6.5%	4.2%	3.0%	6.4%	8.2%	4.9%	8.4%	3.1%	3.5%	8.3%

Table E.15.: Summary of the results of the comparison of performance according to different levels of micro-grid load flexibility between SLC, CLP and NLC. A 75% micro-grid load coverage is considered.

RES Output	**Statistic**	**10% Flexibility**			**20% Flexibility**			**30% Flexibility**			**40% Flexibility**		
		Strategy			**Strategy**			**Strategy**			**Strategy**		
		SLC	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**	**SLC**	**CLP**	**NLC**
32	**Min.**	13.2%	12.5%	14.3%	9.6%	8.5%	11.8%	6.4%	4.5%	10.0%	3.6%	1.6%	8.4%
	1st Qu.	13.5%	12.7%	14.5%	10.3%	8.8%	12.3%	7.5%	5.3%	10.5%	5.2%	2.4%	9.0%
	Median	13.7%	12.8%	14.6%	10.7%	9.0%	12.4%	8.0%	5.5%	10.6%	5.8%	2.7%	9.2%
	3rd Qu.	13.8%	12.9%	14.6%	11.0%	9.1%	12.5%	8.5%	5.7%	10.8%	6.5%	3.0%	9.4%
	Max.	14.4%	13.1%	14.8%	11.6%	9.5%	12.8%	9.7%	6.2%	11.2%	7.7%	4.0%	10.1%
42	**Min.**	10.5%	8.8%	12.2%	7.4%	4.7%	10.6%	4.5%	2.0%	9.9%	3.8%	2.0%	9.9%
	1st Qu.	11.1%	8.9%	12.3%	8.5%	4.9%	11.0%	6.2%	2.1%	10.2%	4.8%	2.1%	10.4%
	Median	11.2%	9.0%	12.4%	8.7%	5.0%	11.1%	6.6%	2.4%	10.4%	5.1%	2.1%	10.6%
	3rd Qu.	11.4%	9.1%	12.4%	9.1%	5.2%	11.2%	7.0%	2.7%	10.5%	5.7%	2.1%	10.8%
	Max.	12.4%	9.9%	12.6%	11.3%	7.1%	11.5%	10.6%	5.1%	10.9%	10.2%	4.5%	11.5%
43	**Min.**	22.6%	21.4%	23.5%	19.5%	17.5%	21.5%	16.9%	14.0%	19.7%	14.2%	11.0%	18.3%
	1st Qu.	22.9%	21.6%	23.7%	20.2%	18.0%	21.9%	17.7%	14.7%	20.4%	15.4%	11.6%	18.9%
	Median	23.0%	21.7%	23.7%	20.4%	18.1%	22.0%	18.0%	14.9%	20.5%	15.8%	11.8%	19.2%
	3rd Qu.	23.1%	21.8%	23.8%	20.5%	18.3%	22.1%	18.3%	15.1%	20.7%	16.1%	12.0%	19.4%
	Max.	23.3%	22.0%	23.9%	20.9%	18.6%	22.4%	18.9%	15.8%	21.3%	16.9%	12.7%	20.1%
70	**Min.**	21.2%	18.7%	25.3%	18.1%	13.6%	24.9%	15.3%	9.0%	24.8%	12.7%	4.6%	24.5%
	1st Qu.	21.7%	18.9%	25.5%	18.7%	13.9%	25.1%	16.1%	9.5%	25.1%	13.9%	5.5%	25.1%
	Median	22.0%	19.0%	25.5%	18.9%	14.1%	25.2%	16.5%	9.7%	25.2%	14.4%	5.8%	25.3%
	3rd Qu.	22.4%	19.2%	25.6%	19.3%	14.2%	25.3%	17.0%	9.9%	25.4%	14.9%	6.1%	25.5%
	Max.	22.8%	20.5%	25.7%	20.4%	16.5%	25.6%	18.7%	13.2%	25.9%	17.7%	10.5%	26.3%
125	**Min.**	5.2%	1.2%	7.2%	1.8%	0.0%	5.5%	0.1%	0.0%	4.2%	0.0%	0.0%	3.7%
	1st Qu.	5.5%	1.5%	7.5%	2.2%	0.0%	5.8%	0.4%	0.0%	4.7%	0.1%	0.0%	4.2%
	Median	5.6%	2.1%	7.5%	2.4%	0.1%	6.0%	0.6%	0.0%	4.9%	0.1%	0.0%	4.4%
	3rd Qu.	5.7%	2.9%	7.6%	2.6%	0.7%	6.1%	0.7%	0.1%	5.1%	0.2%	0.0%	4.6%
	Max.	6.0%	3.4%	7.8%	3.0%	1.7%	6.4%	1.2%	1.5%	5.6%	0.6%	1.3%	5.0%
176	**Min.**	15.9%	13.3%	18.8%	13.3%	8.2%	19.0%	10.6%	3.7%	18.9%	8.0%	0.7%	19.0%
	1st Qu.	16.4%	13.5%	19.1%	13.9%	8.5%	19.2%	11.4%	4.1%	19.4%	9.0%	1.1%	19.7%
	Median	16.6%	13.6%	19.1%	14.1%	8.7%	19.2%	11.8%	4.4%	19.5%	9.4%	1.6%	19.9%
	3rd Qu.	16.7%	13.7%	19.2%	14.4%	8.8%	19.3%	12.1%	5.0%	19.7%	9.9%	2.8%	20.1%
	Max.	17.0%	13.9%	19.3%	15.1%	9.4%	19.6%	13.0%	6.0%	20.0%	11.4%	3.9%	20.7%
242	**Min.**	5.2%	2.1%	7.9%	1.2%	0.0%	5.6%	0.1%	0.1%	4.1%	0.2%	0.2%	4.6%
	1st Qu.	5.9%	2.5%	8.1%	2.1%	0.1%	5.9%	0.5%	0.1%	4.7%	0.3%	0.3%	5.0%
	Median	6.1%	2.8%	8.1%	2.5%	0.2%	6.0%	0.6%	0.1%	4.8%	0.4%	0.3%	5.2%
	3rd Qu.	6.2%	3.2%	8.2%	2.7%	0.5%	6.1%	0.8%	0.1%	5.0%	0.5%	0.3%	5.4%
	Max.	7.2%	4.7%	8.4%	4.5%	1.8%	6.5%	2.9%	0.4%	5.5%	2.3%	0.4%	5.8%
272	**Min.**	34.9%	32.7%	38.8%	31.0%	26.8%	38.5%	26.8%	21.6%	38.4%	23.0%	16.9%	38.1%
	1st Qu.	35.2%	32.9%	38.9%	31.4%	27.3%	38.8%	27.8%	22.2%	38.7%	24.3%	17.6%	38.6%
	Median	35.3%	33.0%	39.0%	31.6%	27.4%	38.9%	28.1%	22.4%	38.8%	24.7%	17.8%	38.8%
	3rd Qu.	35.5%	33.0%	39.0%	31.8%	27.6%	39.0%	28.4%	22.6%	39.0%	25.2%	18.0%	38.9%
	Max.	35.8%	33.2%	39.2%	32.7%	27.9%	39.3%	29.7%	23.2%	39.6%	26.6%	18.6%	39.6%
297	**Min.**	8.6%	7.6%	9.6%	5.4%	3.8%	7.8%	3.3%	1.0%	6.0%	1.7%	1.1%	5.4%
	1st Qu.	9.1%	7.9%	9.7%	6.7%	4.3%	8.0%	4.4%	1.3%	6.6%	2.6%	1.1%	5.7%
	Median	9.3%	7.9%	9.8%	7.0%	4.4%	8.2%	5.0%	1.5%	6.7%	3.2%	1.2%	5.9%
	3rd Qu.	9.4%	8.0%	9.9%	7.2%	4.6%	8.3%	5.3%	2.0%	6.9%	3.7%	1.2%	6.1%
	Max.	9.7%	8.1%	10.1%	7.8%	5.1%	8.5%	6.2%	3.1%	7.2%	4.9%	2.0%	6.5%
347	**Min.**	2.0%	1.2%	3.3%	1.9%	1.0%	3.7%	1.9%	1.1%	4.6%	1.9%	1.3%	5.5%
	1st Qu.	2.3%	1.3%	3.4%	2.2%	1.1%	3.9%	2.2%	1.2%	4.8%	2.3%	1.3%	5.8%
	Median	2.5%	1.4%	3.5%	2.3%	1.1%	3.9%	2.5%	1.2%	4.9%	2.7%	1.3%	5.9%
	3rd Qu.	2.7%	1.6%	3.5%	2.5%	1.2%	4.0%	2.8%	1.4%	5.0%	3.2%	1.8%	6.0%
	Max.	3.3%	2.7%	3.6%	3.2%	1.9%	4.1%	3.6%	2.3%	5.2%	4.2%	3.0%	6.4%
221	**Min.**	13.1%	11.9%	13.6%	10.1%	8.1%	11.1%	7.2%	4.2%	8.5%	4.5%	1.2%	6.6%
	1st Qu.	13.4%	12.1%	13.8%	10.6%	8.5%	11.4%	8.1%	5.0%	9.2%	5.9%	2.0%	7.4%
	Median	13.5%	12.2%	13.9%	10.9%	8.6%	11.5%	8.4%	5.2%	9.4%	6.3%	2.3%	7.6%
	3rd Qu.	13.6%	12.3%	13.9%	11.1%	8.7%	11.7%	8.8%	5.4%	9.5%	6.8%	2.9%	7.8%
	Max.	14.0%	12.5%	14.1%	11.6%	9.2%	11.9%	9.6%	6.4%	10.1%	8.2%	4.9%	8.4%
110	**Min.**	8.4%	4.7%	11.3%	4.2%	0.5%	9.1%	1.3%	0.4%	7.5%	0.7%	0.5%	6.8%
	1st Qu.	9.0%	5.0%	11.6%	5.0%	1.1%	9.4%	2.3%	0.5%	7.9%	1.2%	0.5%	7.4%
	Median	9.3%	5.4%	11.6%	5.3%	1.5%	9.5%	2.7%	0.5%	8.1%	1.4%	0.5%	7.6%
	3rd Qu.	9.4%	6.2%	11.7%	5.6%	2.3%	9.7%	3.3%	0.9%	8.2%	2.0%	0.6%	7.8%
	Max.	9.9%	7.7%	12.1%	6.8%	5.3%	10.0%	4.6%	3.9%	8.9%	3.1%	3.5%	8.3%

Table E.16.: Summary of the results of the comparisons between SLC-FK, SLC-FKd and CLP-FK. Continues in Table E.17.

RES Output	Statistic	40			400			4,000			40,000		
		SLC-FK	SLC-FKd	CLP-FK	SLC-FK	SLC-FKd	CLP-FK	SLC-FK	SLC-FKd	CLP-FK	SLC-FK	SLC-FKd	CLP-FK
1	**Min.**	13.7%	13.0%	9.6%	4.3%	4.3%	2.2%	1.5%	1.5%	0.7%	0.6%	0.6%	0.4%
	1st Qu.	14.3%	14.0%	9.6%	4.5%	4.5%	2.2%	1.6%	1.5%	0.7%	0.6%	0.6%	0.4%
	Median	14.4%	14.2%	9.6%	4.6%	4.6%	2.2%	1.6%	1.6%	0.7%	0.6%	0.7%	0.4%
	3rd Qu.	14.6%	14.8%	9.6%	4.7%	4.8%	2.2%	1.7%	1.6%	0.7%	0.7%	0.7%	0.4%
	Max.	14.9%	15.5%	9.6%	5.9%	5.2%	2.2%	1.7%	1.8%	0.7%	0.7%	0.7%	0.4%
2	**Min.**	14.6%	14.1%	7.8%	7.7%	7.6%	4.3%	6.9%	7.3%	5.3%	7.5%	7.6%	5.6%
	1st Qu.	15.0%	15.1%	7.8%	8.2%	8.1%	4.3%	7.2%	7.5%	5.3%	7.6%	7.7%	5.6%
	Median	15.4%	15.4%	7.8%	8.6%	8.5%	4.3%	7.6%	7.7%	5.3%	7.7%	7.8%	5.6%
	3rd Qu.	15.6%	15.8%	7.8%	8.9%	8.9%	4.3%	7.9%	8.0%	5.3%	7.8%	7.9%	5.6%
	Max.	17.9%	20.9%	7.8%	9.9%	9.9%	4.3%	8.4%	8.1%	5.3%	8.0%	8.0%	5.6%
3	**Min.**	16.3%	16.2%	20.2%	12.4%	12.6%	15.5%	14.0%	13.9%	12.9%	15.0%	14.9%	12.6%
	1st Qu.	18.0%	18.2%	20.2%	13.1%	13.3%	15.5%	14.1%	14.2%	12.9%	15.0%	15.0%	12.6%
	Median	19.8%	19.9%	20.2%	14.8%	14.0%	15.5%	14.4%	14.8%	12.9%	15.1%	15.1%	12.6%
	3rd Qu.	23.0%	22.9%	20.2%	15.9%	15.3%	15.5%	15.1%	15.0%	12.9%	15.1%	15.2%	12.6%
	Max.	25.5%	26.4%	20.2%	17.0%	16.2%	15.5%	15.5%	15.6%	12.9%	15.3%	15.4%	12.6%
4	**Min.**	14.9%	15.7%	16.3%	12.8%	13.0%	7.8%	12.7%	14.7%	8.2%	14.0%	15.1%	7.2%
	1st Qu.	17.1%	16.9%	16.3%	13.6%	13.5%	7.8%	13.6%	15.4%	8.2%	14.2%	15.4%	7.2%
	Median	18.5%	18.3%	16.3%	14.4%	14.1%	7.8%	14.0%	15.7%	8.2%	14.3%	15.5%	7.2%
	3rd Qu.	20.4%	19.6%	16.3%	14.8%	16.0%	7.8%	14.1%	15.9%	8.2%	14.4%	15.7%	7.2%
	Max.	21.5%	20.1%	16.3%	16.6%	17.7%	7.8%	15.0%	16.6%	8.2%	14.5%	16.0%	7.2%
5	**Min.**	13.7%	13.7%	8.6%	4.3%	4.1%	1.1%	1.6%	1.7%	0.5%	0.7%	0.7%	0.5%
	1st Qu.	14.2%	14.2%	8.6%	4.7%	4.6%	1.1%	1.7%	1.7%	0.5%	0.8%	0.8%	0.5%
	Median	14.8%	14.6%	8.6%	4.8%	4.6%	1.1%	1.7%	1.7%	0.5%	0.8%	0.8%	0.5%
	3rd Qu.	15.2%	15.0%	8.6%	4.9%	4.7%	1.1%	1.7%	1.8%	0.5%	0.8%	0.8%	0.5%
	Max.	15.4%	17.2%	8.6%	5.2%	4.8%	1.1%	1.7%	1.8%	0.5%	0.8%	0.8%	0.5%
6	**Min.**	14.9%	15.2%	12.5%	14.2%	15.5%	12.0%	15.8%	17.1%	13.0%	16.2%	17.8%	12.4%
	1st Qu.	16.7%	21.4%	12.5%	14.5%	16.5%	12.0%	15.9%	17.4%	13.0%	16.3%	18.0%	12.4%
	Median	18.4%	23.6%	12.5%	16.2%	17.3%	12.0%	16.2%	17.6%	13.0%	16.4%	18.1%	12.4%
	3rd Qu.	21.6%	25.6%	12.5%	16.6%	18.7%	12.0%	16.5%	18.2%	13.0%	16.5%	18.2%	12.4%
	Max.	28.8%	27.0%	12.5%	19.8%	21.4%	12.0%	16.9%	19.3%	13.0%	16.7%	18.2%	12.4%

Table E.17.: Summary of the results of the comparisons between SLC-FK, SLC-FKd and CLP-FK. Continuation from Table E.16.

RES Output	Statistic	40			400			4,000			40,000		
		SLC-FK	**SLC-FKd**	**CLP-FK**	**SLC-FK**	**SLC-FKd**	**CLP-FK**	**SLC-FK**	**SLC-FKd**	**CLP-FK**	**SLC-FK**	**SLC-FKd**	**CLP-FK**
7	**Min.**	13.5%	13.5%	8.0%	4.8%	4.5%	0.9%	1.8%	1.8%	0.7%	0.9%	0.9%	0.7%
	1st Qu.	14.1%	13.9%	8.0%	4.8%	4.7%	0.9%	1.8%	1.8%	0.7%	1.0%	1.0%	0.7%
	Median	14.7%	14.2%	8.0%	4.9%	4.8%	0.9%	1.9%	1.9%	0.7%	1.1%	1.1%	0.7%
	3rd Qu.	15.2%	14.8%	8.0%	5.0%	5.0%	0.9%	2.0%	2.0%	0.7%	1.1%	1.1%	0.7%
	Max.	15.5%	16.8%	8.0%	5.3%	6.2%	0.9%	2.3%	2.1%	0.7%	1.3%	1.2%	0.7%
8	**Min.**	21.9%	23.5%	23.1%	25.4%	26.3%	21.6%	26.4%	27.7%	22.6%	27.1%	28.0%	22.0%
	1st Qu.	24.9%	26.5%	23.1%	25.6%	27.1%	21.6%	26.9%	28.2%	22.6%	27.4%	28.1%	22.0%
	Median	26.8%	28.0%	23.1%	26.9%	28.2%	21.6%	27.3%	28.4%	22.6%	27.6%	28.3%	22.0%
	3rd Qu.	32.0%	31.1%	23.1%	27.4%	29.6%	21.6%	27.6%	28.7%	22.6%	27.7%	28.5%	22.0%
	Max.	40.4%	38.2%	23.1%	29.9%	30.8%	21.6%	27.8%	29.8%	22.6%	27.9%	28.6%	22.0%
9	**Min.**	13.4%	13.9%	7.3%	4.4%	5.0%	1.1%	2.5%	2.2%	1.1%	2.3%	2.5%	1.4%
	1st Qu.	14.2%	14.6%	7.3%	4.9%	5.2%	1.1%	2.8%	2.6%	1.1%	2.4%	2.6%	1.4%
	Median	15.0%	15.3%	7.3%	5.1%	5.5%	1.1%	3.0%	2.9%	1.1%	2.6%	2.6%	1.4%
	3rd Qu.	15.7%	16.6%	7.3%	5.3%	5.6%	1.1%	3.2%	3.0%	1.1%	2.7%	2.7%	1.4%
	Max.	18.9%	18.6%	7.3%	6.0%	6.7%	1.1%	3.3%	3.2%	1.1%	2.7%	2.7%	1.4%
10	**Min.**	16.0%	14.3%	7.0%	9.9%	9.9%	6.1%	10.1%	9.8%	8.5%	10.7%	10.8%	8.8%
	1st Qu.	16.7%	16.2%	7.0%	10.3%	11.1%	6.1%	10.4%	10.6%	8.5%	10.8%	10.9%	8.8%
	Median	17.9%	17.0%	7.0%	10.5%	12.3%	6.1%	10.7%	11.1%	8.5%	10.9%	10.9%	8.8%
	3rd Qu.	19.3%	19.2%	7.0%	11.1%	13.2%	6.1%	10.8%	11.4%	8.5%	11.0%	11.0%	8.8%
	Max.	24.1%	22.2%	7.0%	13.3%	13.7%	6.1%	11.6%	11.5%	8.5%	11.1%	11.1%	8.8%
11	**Min.**	13.8%	13.7%	6.9%	4.4%	4.9%	0.8%	2.4%	2.3%	1.0%	2.2%	2.6%	1.8%
	1st Qu.	14.3%	14.7%	7.6%	5.1%	5.2%	1.4%	2.9%	2.6%	1.8%	2.6%	2.7%	1.9%
	Median	14.8%	15.1%	8.8%	5.5%	5.3%	2.9%	3.0%	2.7%	2.1%	2.7%	2.7%	2.0%
	3rd Qu.	17.1%	16.0%	10.3%	6.1%	5.6%	3.9%	3.4%	3.2%	2.6%	2.8%	2.8%	2.1%
	Max.	18.9%	21.3%	12.5%	6.9%	7.1%	5.1%	4.1%	4.1%	3.0%	3.0%	3.0%	2.4%
12	**Min.**	13.4%	12.8%	6.0%	4.1%	4.1%	0.7%	1.4%	1.4%	0.2%	0.5%	0.5%	0.2%
	1st Qu.	13.7%	14.3%	6.7%	4.3%	4.2%	0.7%	1.4%	1.5%	0.2%	0.6%	0.6%	0.2%
	Median	14.4%	14.4%	7.3%	4.3%	4.5%	0.8%	1.5%	1.5%	0.3%	0.6%	0.6%	0.2%
	3rd Qu.	14.6%	14.9%	7.6%	4.4%	4.5%	1.1%	1.5%	1.5%	0.3%	0.6%	0.6%	0.2%
	Max.	15.6%	16.6%	9.1%	4.6%	4.7%	1.4%	1.5%	1.5%	0.3%	0.6%	0.6%	0.2%