Techno-socio-economic analysis of the impact of dynamic electricity price components on households and low-voltage grids in Germany

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Hauptreferent:	Prof. Dr. rer. pol. Martin Wietschel
Korreferent:	Prof. Dr. rer. pol. Christof Weinhardt

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Abstract

The accelerated electrification of the heating and transportation sectors, coupled with the increased share of renewable electricity generation, presents significant challenges for low-voltage grids. Electricity consumption is required to become more flexible to balance the increased load and the more volatile electricity generation. In Germany, substantial flexibility potential is emerging in the residential sector with by the adoption of electric vehicles (EVs), heat pumps (HPs), and PV battery storage systems (PV-BSSs). One option to utilize this flexibility is the implementation of dynamic electricity price components, with prices based on time of use or demand to encourage households to shift or reduce their load. The primary components considered are electricity procurement and retail – represented by dynamic electricity retail tariffs (DETs) – and grid charges. While households in Germany are free to choose their electricity retail tariff and decide whether to utilize their flexibility, grid charges remain subject to regulation.

This dissertation examines the influence of dynamic electricity price components on the flexibility utilization by households, their effects on electricity consumption behavior and the low-voltage grids. It addresses the possibility of higher grid utilization and the potential for reducing or deferring the need for grid reinforcement.

The techno-socio-economic model *EVaTar*, developed to answer the research questions systematically, represents a novel approach in this field. Its modular design allows for a comprehensive analysis of the economic impacts of DETs and different grid charge designs on households equipped with various flexible technologies and the impacts on grid utilization and reinforcement needs. Central to the methodological development is the consideration of household decision-making behavior regarding the choice of electricity retail tariffs and investment decisions in a home energy management system (HEMS). An integrated approach is employed, considering the interplay between the grid charge design and utility-side electricity retail tariffs, incentives for renewable energy generation, as well as household decisions on electricity retail tariffs and flexibility utilization.

Results show that flexible EV charging can reduce future household electricity prices. From a user perspective, the financial viability of flexibility utilization depends on offsetting the costs associated with HEMS and smart meters with the cost savings achieved from flexible energy use. DETs offer substantial financial benefits, particularly for households with an EV. Households with a HP may find it more profitable to increase their self-consumption with a HEMS, depending on the additional costs of metering point operation. The integration of a PV system or PV-BSS further enhances the cost-effectiveness of DETs for households with an EV or a HP.
From a grid perspective, leveraging household flexibility can contribute to increasing grid utilization and decreasing or deferring grid reinforcement needs. This is primarily due to the heterogeneous decisions of households. These include the choice of either static or dynamic electricity retail tariffs, and their decisions regarding the investment in a HEMS. In addition, the implementation of grid charge designs

with a capacity subscription can enhance the potential for cost savings resulting from flexible energy use, thereby promoting broader flexibility utilization among households and further reducing the need for grid reinforcement.

This thesis was carried out as part of my research at the Fraunhofer Institute for Systems and Innovation Research (ISI) and the Fraunhofer Research Institution for Energy Infrastructures and Geothermal Systems (IEG) under the supervision of Prof. Dr. Martin Wietschel at the Institute for Industrial Production (IIP) at the Karlsruhe Institute of Technology (KIT).

Kurzfassung

Die beschleunigte Elektrifizierung des Wärme- und Verkehrssektors in Verbindung mit dem steigenden Anteil der Stromerzeugung aus erneuerbaren Energien stellt die Niederspannungsnetze vor erhebliche Herausforderungen. Der Stromverbrauch muss flexibler gestaltet werden, um die gestiegene Last und die volatilere Stromerzeugung auszugleichen. In Deutschland entsteht ein erhebliches Flexibilitätspotenzial im Haushaltssektor durch den Einsatz von Elektrofahrzeugen, Wärmepumpen und PV-Batteriespeichersystemen (PV-BSS). Eine Möglichkeit, diese Flexibilität zu nutzen, besteht in der Einführung dynamischer Strompreiskomponenten. Diese Preise werden nach der Nutzungszeit oder der Nachfrage bestimmt, um die Haushalte zu veranlassen, ihre Last zu verschieben oder zu reduzieren. Die primären Komponenten, die in Betracht gezogen werden, sind Beschaffung, Vertrieb und Marge – dargestellt durch dynamische Stromtarife (DETs) – sowie Netzentgelte. Während Haushalte in Deutschland ihren Stromtarif frei wählen und entscheiden können, ob sie ihre Flexibilität nutzen möchten, unterliegen die Netzentgelte der Regulierung.

Die vorliegende Dissertation untersucht den Einfluss dynamischer Strompreiskomponenten auf die Flexibilitätsnutzung durch Haushalte, deren Auswirkungen auf das Stromverbrauchsverhalten sowie Niederspannungsnetze. Dabei wird die Möglichkeit einer höheren Netzauslastung sowie das Potenzial zur Verringerung oder Aufschiebung von Netzverstärkungsbedarfen erörtert.

Das techno-sozio-ökonomische Modell *EVaTar*, welches zur systematischen Beantwortung der Forschungsfragen entwickelt wurde, stellt einen innovativen Ansatz in diesem Bereich dar. Der modulare Aufbau des Modells ermöglicht eine umfassende Analyse der ökonomischen Auswirkungen von DETs und unterschiedlicher Netzentgeltsystematiken auf Haushalte die mit verschiedenen flexiblen Technologien ausgestattet sind, sowie der Auswirkungen auf die Netzauslastung und Netzverstärkungsbedarfe. Im Zentrum der methodischen Entwicklung steht die Berücksichtigung des Entscheidungsverhaltens von Haushalten hinsichtlich der Wahl von Stromtarifen und Investitionen in ein Hausenergiemanagementsystem (HEMS). Im Rahmen der Untersuchung wird ein integrierter Ansatz verfolgt, der das Zusammenspiel zwischen der Netzentgeltsystematik und den versorgungsseitigen Stromtarifen, den Anreizen für die Erzeugung erneuerbarer Energien sowie den Entscheidungen der Haushalte bezüglich der Stromtarifwahl und Flexibilitätsnutzung berücksichtigt.

Die Ergebnisse zeigen, dass das flexible Laden von Elektrofahrzeugen dazu beitragen kann, die zukünftigen Strompreise für Haushalte zu senken. Aus Nutzersicht ist die finanzielle Tragfähigkeit der Flexibilitätsnutzung jedoch davon abhängig, ob die mit HEMS und intelligenten Zählern verbundenen Kosten durch die erzielten Kosteneinsparungen kompensiert werden können. DETs bieten insbesondere für Haushalte mit einem Elektrofahrzeug erhebliche finanzielle Vorteile. Für Haushalte mit einer Wärmepumpe kann es je nach den zusätzlichen Kosten für die Nutzung eines intelligenten Zählers rentabler sein, ihren Eigenverbrauch mit einem HEMS zu erhöhen. Die Integration einer PV-Anlage oder eines PV-BSS steigert die Kosteneffizienz von DETs für Haushalte mit einem Elektrofahrzeug oder einer Wärmepumpe

zusätzlich.
Aus Netzperspektive kann die Nutzung der Flexibilität der Haushalte dazu beitragen, die Netzauslastung zu erhöhen und den Bedarf an Netzverstärkung zu verringern oder zu verschieben. Dies ist in erster Linie auf die heterogenen Entscheidungen der Haushalte zurückzuführen. Dazu gehören die Wahl zwischen statischen und dynamischen Stromtarifen sowie die Entscheidung über die Investition in ein HEMS. Des Weiteren kann die Implementierung von Netzentgeltsystematiken mit einem Kapazitätsabonnement das Potential für Kosteneinsparungen durch flexible Energienutzung erhöhen. Dadurch wird eine breitere Nutzung der Flexibilität durch die Haushalte gefördert und der Bedarf an Netzverstärkung weiter verringert.

Die vorliegende Arbeit entstand im Rahmen meiner Forschungsarbeit am Fraunhofer-Institut für System- und Innovationsforschung (ISI) und an der Fraunhofer-Einrichtung für Energieinfrastrukturen und Geothermische Systeme (IEG) unter der Betreuung von Prof. Dr. Martin Wietschel am Institut für Industrielle Produktion (IIP) des Karlsruher Instituts für Technologie (KIT).

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Abbreviations

ABM	Agent-Based Modeling
BEV	Battery Electric Vehicle
BSS	Battery Storage System
CAP	Grid charge design with capacity subscription
CAP-VOL	Grid charge design with capacity subscription and volumetric charge
CBC	Choice-Based Conjoint
COP	Coefficient of Performance
CPP	Critical Peak Pricing
CVM	Contingent Valuation Method
DA	Day-Ahead
DA-RTP	Day-Ahead Real Time Pricing
DCM	Discrete Choice Model
DET	Dynamic Electricity Retail Tariff
DP	Dynamic Programming
DR	Demand Response
DSO	Distribution System Operator
DT	Dynamic Tariff
EnWG	Energiewirtschaftsgesetz
EU	European Union
EV	Electric Vehicle
GCD	Grid Charge Design
HEMS	Home Energy Management System
HOL	Hours with Overload
HP	Heat Pump
HS	Heat Storage
iMSys	Intelligent Metering System
LP	Linear Programming
LV	Low-voltage
MPC	Model Predictive Control
MFH	Multi-Family Home

MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MV	Medium-voltage
NEP	Network Development Plan (Netzentwicklungsplan)
NLP	Non-linear Programming
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
PV-BSS	PV Battery Storage System
RE	Renewable Energy
RTP	Real Time Pricing
SC	Self-Consumption
SFH	Single- and Two-Family Home
SOC	State of Charge
ToU	Time of Use
VOL	Volumetric grid charge design
V2H	Vehicle to Home
WACC	Weighted Average Cost of Capital
WTP	Willingness to Pay
WTPM	Willingness to Pay More

Part I

1 Introduction

1.1 Background and motivation

The escalating climate crisis demands a decisive global response, primarily through the reduction of greenhouse gas emissions [1]. International agreements, such as the Paris Agreement [2], which introduced the 1.5/2°C target, alongside the recent agreement at COP28 [3], highlight the global commitment to transitioning away from fossil fuels. Within the European context, the EU's Green Deal reiterates these environmental targets [4], taking measures including increasing energy efficiency [5], direct utilization of renewable sources, and the use of renewable energies for generating electricity [6]. At the national level, Germany has updated the Climate Protection Act [7] in 2021, setting ambitious goals to reduce greenhouse gas emissions by at least 65% by 2030 and achieve net-zero emissions by 2045. Besides the developments in energy efficiency, two significant changes are evident which help achieve these ambitious targets. Firstly, there is a shift away from fossil energy carriers in electricity generation towards renewable energy sources [8, 9]. Secondly, there is an increase in electrification in the heating and transport sectors [8], and in the industry [10]. These two developments, among others, are central to global efforts to combat the climate crisis. They are leading to significant changes in energy consumption and generation patterns, subsequently resulting in new requirements for power grids.

On the energy consumption side, a substantial increase in electric vehicles (EVs) and heat pumps (HPs) within the next years is anticipated [11, 12]. This trend is projected to significantly increase the load on low-voltage (LV) grids, which could have profound impacts [13, 14]. Concurrently, on the energy supply side, the rising share of renewable energy sources leads to an increasingly volatile electricity generation [15]. In low-voltage grids this is driven by an increasing number of rooftop photovoltaic (PV) systems. These dynamics in energy consumption and generation increase the risk of grid congestion, potentially leading to the need for grid reinforcement in low-voltage grids [16, 11]. Given the lengthy and expensive nature of grid reinforcement processes from planning to operation [17], finding both interim and permanent solutions to mitigate or defer these needs is essential.

Enhancing flexibility in electricity consumption through demand response (DR) mechanisms can balance the increased load against the more volatile electricity generation. In low-voltage grids, this includes leveraging the substantial flexibility potential that is developing with the uptake of so-called „micro-flexibilities“, including EVs, HPs, and PV battery storage systems (PV-BSSs) [11]. Dynamic electricity price components as one option of price-driven DR mechanisms play a crucial role in this context [18]. They are designed to provide price signals that incentivize residential consumers to adjust their energy usage to reduce peak loads and enhance overall system stability [19]. One advantage of this is that they are implemented „behind the meter“ [20], which means that all decisions on load shifting or shedding are made on the consumer side. The distribution system operator (DSO) only sees the result of these decisions, allowing for fewer external interventions and enabling more informed consumer decisions on electricity usage with the aid of smart meters.

Electricity retail tariffs for household consumers in Germany and throughout the European Union consist of several price components, including costs for electricity procurement and retail and several fiscal and non-fiscal charges like grid charges. These price components create a foundation for price incentives through DR mechanisms. The two price components that account for the largest proportion of the electricity price are the component for electricity procurement and retail, which represents approximately 38.9% of the electricity price for residential consumers in Germany in 2022, and grid charges, which account for a share of 21.8% in Germany [21]. On a European level, grid charges constituted an even higher average share of 28.3% in 2021 [22]. These figures highlight the particular interest in these two components when discussing dynamic electricity price components for residential consumers.

Various design options exist for dynamic electricity retail tariffs (DETs) – representing the electricity price component of electricity procurement and retail – and grid charges, which are chosen based on the desired effect on flexibility utilization. DETs aim to better balance load and generation, facilitating the integration of electricity from renewable energy sources with low marginal costs. Grid charge designs (GCDs) are intended to integrate load and generation into the power grid, preventing grid congestion and optimizing grid utilization.

Enabling technologies such as home energy management systems (HEMSs) or smart meters, are pivotal in leveraging dynamic electricity price components. These systems enable an automated response to dynamic pricing signals and actively control and optimize energy consumption within households. By applying control strategies, they manage the operation of various devices, including EVs, HPs, and PV-BSSs. Integrating a HEMS with a smart meter enhances the effectiveness of dynamic electricity price components, making it a crucial element for residential consumers to manage their flexible technologies intelligently and cost-effectively. From an alternative perspective, the uptake of technologies such as EVs, HPs, and PV-BSSs delivers a use case for HEMS and smart meters to be used sensibly. Research underscores the importance of automated load shifting in motivating consumers to actively engage in dynamic pricing models [23]. This automation simplifies flexibility utilization in response to dynamic pricing signals for consumers, reducing both complexity and effort. As a result, it helps preventing response fatigue and enhances consumer engagement [24], playing a critical role in the successful adoption of dynamic electricity price components.

In Germany, households can select their electricity supplier, which gives them the freedom to decide whether to utilize a DET. Moreover, consumers are free in their investment decisions regarding a HEMS and in utilizing their flexibility. In contrast, the GCD is subject to regulation, limiting the choices available to consumers in this regard. The combination of free choices and regulatory influences significantly impacts the effects of DETs and GCDs. Potential cost savings associated with DETs are dependent on different aspects. Households exhibit a high degree of heterogeneity with regard to their household load profiles, heat demand, transportation patterns, and other variables, which are influenced by a range of socio-demographic and technical factors [25, 26, 27, 28]. The availability of flexible technologies and generation units further contributes to this heterogeneity. Financial benefits represent the most commonly identified motivation for households to utilize their flexibility and, consequently, opt for a DET and invest in a HEMS [24]. However, these decisions are also influenced by other behavioral drivers [24], leading to heterogeneous decision-making [29].

Despite existing research on the impacts of dynamic electricity price components on grid utilization and reinforcement needs, gaps in literature remain in understanding the impact of household heterogeneity and decision-making behavior on flexibility utilization, from both the user and distribution grid perspective. In addition, the interaction between the free choice of tariff by households (including DETs) and the simultaneous implementation of various GCDs has not yet been investigated. These gaps in literature limit the depth and applicability of conclusions that can be drawn from current studies, highlighting the need for further research.

This dissertation aims to address these gaps by focusing on the impact of dynamic electricity price components on residential consumers and grid reinforcement needs. It explores the potential of higher grid utilization and the possibility of reducing or deferring grid reinforcement needs. Looking at both the user and the distribution grid perspective and accounting for technological, economical, and sociological aspects, direct addressees of the research are political decision-makers concerned with the design of future German energy systems, electricity suppliers, HEMS providers, and residential consumers.

To comprehensively address this research topic, a techno-socio-economic, model-based approach is developed. The user perspective is considered first in order to determine which grid load and flexibility potential can be utilized in low-voltage grids in the future. While existing research provides insights into the impacts of dynamic electricity price components on the distribution grid level, this dissertation extends the investigation by considering effects of household heterogeneity, the free choice of tariff, and investment decisions in a HEMS on grid utilization and reinforcement needs, aiming to align the findings more closely with real-world scenarios. Including these aspects is a crucial aspect of understanding and designing future energy policies.

1.2 Research questions

The primary objective of this dissertation is to provide a comprehensive understanding of the impact of dynamic electricity price components on residential consumers and distribution grids in Germany. Specifically, it investigates the potential for higher grid utilization and assesses whether grid reinforcement needs can be reduced or deferred, with a particular focus on the years 2030 and 2035. The novelty of this research lies in its exploration of previously under-examined aspects: the inclusion of household heterogeneity, decision-making behavior regarding tariff choices and the decision to invest in a HEMS, along with the impact of simultaneously available dynamic electricity price components. Households are heterogeneous, displaying a wide array of differences in behavior and characteristics that are crucial for the analyses conducted in this dissertation. This heterogeneity is reflected in differences in household load profiles, heat demands, transportation habits, available flexible technologies, and in the decision-making behavior regarding the choice of electricity retail tariffs and decisions to invest in a HEMS. These variations are influenced by a range of socio-demographic and technical factors, influencing each households' flexibility potential and how they respond to dynamic electricity price components. In this context, the term „household heterogeneity" is used to specifically consider these elements within the dissertation.

Despite the existing body of knowledge, several research gaps remain to be assessed. The research is designed to systematically answer the following key research questions that bridge both content and methodological gaps identified in the existing literature[1]. The focus is on two main perspectives: the user perspective (Research question I) and the distribution grid perspective (Research question II).

Research question I: From a user perspective – What is the influence of dynamic electricity price components on flexibility utilization considering the heterogeneity of residential consumers?

This dissertation investigates the impact of two key electricity price components on the flexibility utilization of residential consumers: the price component for electricity procurement and retail, represented by DETs, and the price component of grid charges, represented by GCDs. Both electricity price components have different design options. The most commonly discussed time-varying forms of DETs include Time of Use (ToU) tariffs, where each period of the day is assigned to a specific price level [30], and Real Time Pricing (RTP) which sets different price levels for each hour based on wholesale electricity market prices [31]. For GCDs, two main design components are seen: a volumetric tariff charged per kWh of energy used, and a capacity-based tariff charged by the power draw or feed-in. These components are flexible in design and can be combined in a GCD [32]. A more detailed examination of design options can be found in Section 8.1.2 in Publication IV.

Three aspects have been identified in the literature that need to be considered on the user level to subsequently analyze the grid impact of dynamic electricity price components: (1) the economic effects on households equipped with flexible technologies, such as EVs, HPs, and PV-BSSs, (2) the impact of these price components on households' tariff choices and their decisions to invest in a HEMS, and (3) their effects on the load curves of these households.

To comprehensively address these aspects, several interconnected subquestions are considered. Subquestion I.1 examines the impact of the ongoing electrification and adoption of flexible technologies on the overall electricity prices for residential consumers in Germany, with a specific focus on EV charging. Subquestion I.2 considers the impact on flexibility utilization when the electricity price component for electricity procurement and retail is assumed to be dynamic, exploring the specific impact of DETs. Lastly, Subquestion I.3 builds on this by incorporating different GCDs, examining the interaction with DETs and the combined effect on flexibility utilization. This approach ensures a thorough exploration of how dynamic electricity price components impact economic conditions, tariff choices and decisions to invest in a HEMS, and load curves of households.

Subquestion I.1: Focusing on electric vehicles – What impact will flexible EV charging have on future household electricity prices?

EVs are a central topic in discussions about flexibility options in the residential sector [11]. Extensive research has been conducted on integrating EVs into the power system, showing that flexible charging of EVs can positively impact grid load and facilitate the integration of electricity from renewable sources, while also offering potential cost savings for EV owners (for example in Refs. [33, 34, 35, 36, 37, 38, 39, 40, 41, 42]). Key findings from various studies highlight the benefits of controlled charging strategies

[1] It should be noted that the description of the state of the art is intentionally concise here. More detailed analyses are available in the referenced sections of Publications I to IV.

that adapt charging times to grid demands or electricity prices. For a detailed examination of the existing literature and a more in-depth discussion on the state of the art regarding EV integration, please refer to Section 5.2 in Publication I.

Despite these valuable insights, a common limitation of previous studies is their focus on singular impacts – often examining effects on grid charges or electricity generation costs separately. This approach overlooks the combined influence these factors have on overall retail electricity prices for residential consumers. To provide a comprehensive understanding of the financial implications for households, it is essential to assess how flexible EV charging can affect specific grid charges in low-voltage grids and how it interacts with the broader dynamics of the electricity market. Subquestion I.1 builds upon the state of the art by addressing these gaps, thus offering a holistic view of the economic impacts of flexible EV charging on household electricity expenses.

Subquestion I.2: ***Under which conditions are dynamic electricity retail tariffs the most economic option for residential consumers, and how do these conditions affect household decisions?***

For residential consumers to adopt DETs, one of the most critical aspects is the economic viability of utilizing their flexibility [24]. Although the economic aspects of various DET designs have been extensively explored in literature (e.g., Refs. [41, 40, 43, 44, 45]), significant research gaps remain, particularly the overlooked issue of household heterogeneity and decision-making behavior regarding the tariff choices and decisions to invest in a HEMS. For a detailed analysis on the research gaps see Table 7.3, Publication III. For a more comprehensive analysis of the economic aspects in literature, refer to Section 7.1.3 in Publication III.

Current research mostly limits its focus to one or two technology combinations, such as EVs or HPs paired with PV systems or PV-BSSs (e.g., Refs. [40, 46, 47]). These studies indicate that the impact of DETs can vary greatly depending on the specific technologies available within a household. There is a clear need for broader analysis that includes a wider array of technology combinations and accounts for the diverse load profiles across different households. This allows for a better understanding of the potential synergies and interactions between technologies when responding to DETs, highlighting the need for an extensive evaluation of how these technologies influence flexibility usage and the economic appeal of DETs.

Many studies evaluate financial benefits for households with flexible technologies achievable through DETs based on a scenario without explicit flexibility utilization (for instance, see Refs. [48, 46, 47]). This approach potentially leads to an overestimation of savings for households with a PV system, as flexibility can also be utilized in households via a HEMS to solely enhance self-consumption. A detailed comparison is thus essential to determine whether DETs provide additional financial benefits over optimizing self-consumption to minimize costs. Moreover, the comparison should extend to examining how flexibility usage differs between these strategies.

The majority of existing research assumes that households already have a HEMS and a smart meter. This research primarily focuses on the potential for cost savings through reduced variable electricity costs, which are calculated by subtracting the feed-in remuneration from the annual unit rate costs (e.g., Refs. [49, 43, 45]). However, the practical adoption of DETs and the installation of HEMSs largely hinges on whether the financial benefits can offset the initial and operating costs associated with these technologies. This includes expenses for metering point operation and the investment in HEMS. Therefore, it is crucial to assess under what conditions the savings from DETs and HEMSs can offset these additional costs.

Looking beyond purely financial aspects, research exists on behavioral drivers of households regarding the adoption of new technologies. The studies show that aspects such as effort [50], data-privacy concerns [51], or perceived usefulness [52] influence household decisions. These insights into household decision-making behavior have yet to be considered in a model-based approach regarding households' tariff choices and decisions to invest in a HEMS. Including the decision-making behavior provides a more realistic evaluation of flexibility utilization and is essential for the impact analysis for dynamic electricity price components on low-voltage grids.

Subquestion I.3: ***How do different grid charge designs influence households' tariff choices and decisions to invest in a HEMS?***

After exploring the electricity price component of electricity procurement and retail, particularly focusing on DETs and consumer choices, the focus is shifted to GCDs. The current GCD for residential consumers in Germany uses volumetric grid charges, which has been widely criticized. Critics argue that this model does not adequately reflect grid costs, which are primarily driven by peak demand or feed-in, especially in light of challenges posed by the ongoing energy transition [53, 32]. Consequently, there is a notable shift towards capacity-based GCDs in various European countries [54, 55], and other GCDs, considered to better align with actual grid costs, are analyzed in the literature (for instance, see Refs. [56, 57, 58, 59, 60]).

Despite the shift in GCDs, the potential for conflicting price signals between dynamic grid charges and DETs has been only minimally addressed in existing research [61]. This gap highlights the need for a more in-depth examination of how changes in GCD might influence cost savings through flexibility utilization and subsequently affect residential consumers' tariff choices and decisions to invest in a HEMS. This subquestion, therefore, sets the focus on the interplay between DETs and GCDs and its impact on household decisions. For a more detailed analysis on the state of the art refer to Section 8.1.2 in Publication IV.

Research question II: **From a distribution grid perspective – Which dynamic electricity price components enable efficient grid use, considering residential consumers' tariff choices and HEMS investment decisions?**

In the context of the ongoing energy transition, both in terms of how electricity is generated and used, achieving efficient grid use is crucial. This efficiency involves „minimizing costs and environmental impacts while maximizing system reliability, resilience, flexibility, and stability“ [62] and is key to utilize infrastructure in a cost-optimized manner, considering both the overall economic perspective and the perspective of the individual consumer. Subquestion II.1 explores the effect of greater market availability of DETs on low-voltage grids. Subsequently, Subquestion II.2 assesses various GCDs and their effectiveness in reducing grid reinforcement needs, including the decision-making behavior of households regarding DETs and HEMSs.

Subquestion II.1: ***What is the impact of dynamic electricity retail tariffs on distribution grids, considering electricity tariff choices and HEMS investment decisions of residential consumers?***

Studies on the impact of DETs on low-voltage grids mainly apply a single type of DET across all households in a grid area, overlooking the fact that consumers in Germany and the European Union have the freedom to choose their electricity retail tariffs (e.g., Refs. [63, 64, 65, 66]). Additionally, these studies make fixed assumptions about the share of households implementing a HEMS and utilizing flexibility (for instance, see Refs. [65, 64, 66]), thereby neglecting the decision-making behavior of households. The majority of these studies show an increase in grid load due to high simultaneity when all households react to the same pricing signal (e.g., Refs. [65, 64, 66]). For a more detailed analysis, please refer to Section 6.1.1 in Publication II. Given the heterogeneous decision-making behavior of households, it is possible that these high simultaneity scenarios may not occur in reality. Consequently, Subquestion II.1 aims to integrate the analysis of electricity tariff choices and investment decisions regarding a HEMS into a more comprehensive and realistic examination of the impact of DETs on grid utilization and efficiency.

Subquestion II.2: ***Which grid charge designs are effective in enhancing grid utilization and reducing grid reinforcement needs, considering residential consumers' tariff choices and HEMS investment decisions?***

While numerous studies have investigated the impact of different GCDs on low-voltage grids and grid reinforcement needs [11, 60, 59], as well as the effects of different GCDs under a day-ahead real time pricing (DA-RTP) tariff [67, 59, 68], no comprehensive study has been found exploring the interplay between DETs and GCDs and its effect on household tariff choices and decisions to invest in a HEMS, and the subsequent effects on low-voltage grid utilization and grid reinforcement needs. This gap in literature is significant as it can lead to an inaccurate assessment of the effectiveness of distinct GCDs. Addressing this issue requires an understanding of how GCDs interact with DETs and how these interactions influence households' tariff choices and HEMS investment decisions. This approach is vital for assessing the potential reduction in grid reinforcement needs and more efficient grid use through various GCDs. For a comprehensive literature analysis, refer to Section 8.1 in Publication IV.

1.3 Structure of the thesis

Section 1 outlines the research gaps and resulting research questions. Section 2 summarizes the methodological approach and introduces the developed model, called *EVaTar*, used in three of the four scientific publications. Sections 5 to 8 contain the aforementioned publications. Section 3 presents a synthesis of the results, addressing the research questions and presenting methodological achievements. Section 4 presents a summary of the key findings, along with the conclusions drawn. It also provides a critical assessment of the work and an outlook for further research. At a superordinate level, Sections 1 to 4 serve as the framework chapter in Part I of the dissertation, and the scientific publications in Sections 5-8, that form the core of this dissertation, constitute Part II. Figure 1.1 gives an overview of the cumulative dissertation's content structure and how the research questions and publications connect.

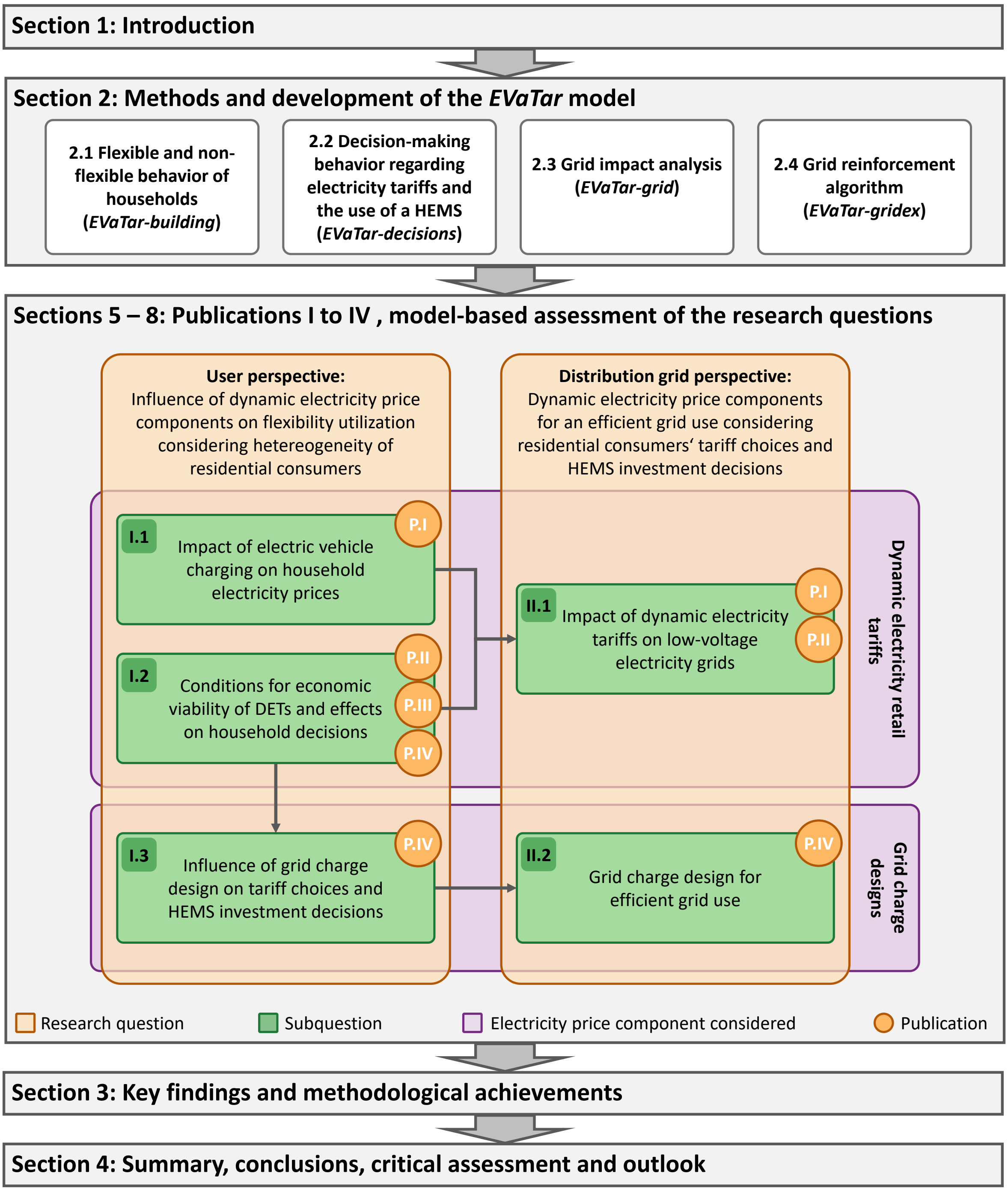

Figure 1.1: Overall structure of the thesis and overview of the research questions and the according publications (P.I to P.IV) included in this thesis.

The four stand-alone scientific publications in Part II have been published in internationally recognized scientific journals. The following provides a brief overview of my contributions to each publication and its content.

Publication I:

*M. Kühnbach, **J. Stute**, T. Gnann, M. Wietschel, S. Marwitz, and M. Klobasa (2020): „Impact of electric vehicles: Will German households pay less for electricity?“, Energy Strategy Reviews, Vol. 32, Article No. 100568*

Publication I (Section 5) focuses on the effects of advancing electrification in the household sector on household electricity prices, with a specific emphasis on EVs. Four analysis steps are conducted, including the coupling of four different models. First, the diffusion of EVs with different charging powers is determined for 2030. Second, the effects of uncontrolled and controlled EV charging on electricity generation costs and, subsequently, the electricity cost component of electricity procurement and retail are investigated. Third, the impacts on the distribution grid and specific grid charges are determined. Last, the effects on electricity generation costs and specific grid charges are combined, and the overall effect on household electricity prices can be derived.

My contribution: I conceptualized the analysis on the distribution grid and specific grid charges together with S. Marwitz. I performed the formal analysis for the low-voltage grid using the FLEX-GOLD model developed by S. Marwitz, managed data curation, and developed and implemented the methodology for utilizing the aggregated EV profiles from the system level in the low-voltage analysis, breaking them down to determine charging times of individual EVs. Additionally, I wrote a substantial part of the first draft of the manuscript, namely the literature analysis of the implications of EVs for electricity grids (Section 3.2), the formal description of the methodological approach for low-voltage grid analysis (Section 3.3), the description of the assumptions for EVs in a suburban low-voltage grid (Section 4.2), the analysis of the results on the influence of EVs on grid charges (Section 5.5), and parts of the discussion and conclusion section. Furthermore, I was substantially involved in the overall design of the manuscript and the development of the research gap and supported the conceptualization, formal analysis, and visualization. Additionally, I edited and reviewed the manuscript together with the co-authors.

Publication II:

***J. Stute** and M. Kühnbach (2023): „Dynamic pricing and the flexible consumer – Investigating grid and financial implications: A case study for Germany“, Energy Strategy Reviews, Vol. 45, Article No. 100987*

Publication II (Section 6) introduces the implementation of the decision-making behavior of households regarding the choice of electricity retail tariff and the investment decision regarding a HEMS within the *EVaTar* model. A range of DETs already available on the market in Germany is considered. An analysis of how various tariff structures affect the financial viability of DETs for households with flexible technologies is conducted. Subsequently, load flow calculations are carried out for a low-voltage grid area to assess the effects of DETs on low-voltage grids in a comprehensive and more realistic setting.

My contribution: I developed the research questions of the publication conducting a comprehensive literature analysis. I conceptualized the research framework including the curation and preparation of input data. Furthermore, I developed the methodology and implemented the *EVaTar-building*, *EVaTar-decisions*, and *EVaTar-grid* modules used within the publication. I further conducted the formal analysis of the results, validated the results, and developed the visualization. I drafted the manuscript and included reviews and edits from the co-author and was involved in the acquisition of the research projects that supported the work.

Publication III:

***J. Stute**, S. Pelka, M. Kühnbach, and M. Klobasa (2024): „Assessing the conditions for economic viability of dynamic electricity retail tariffs for households“, Advances in Applied Energy, Vol. 14, Article No. 100174*

Publication III (Section 7) considers household heterogeneity, the costs of HEMS and metering point operation of smart meters, the impact of price trends and the differences between types of households with flexible technologies. Three different operational strategies are compared within the analysis: no explicit flexibility utilization, utilization of flexibility via a HEMS to increase self-consumption, and utilization of flexibility via a HEMS, a smart meter, and DETs to minimize electricity purchase costs. Maximum tolerable costs for HEMS and metering point operation are derived from the results.

My contribution: I developed the research questions of the publication conducting a comprehensive literature analysis. I conceptualized the research framework and curated and prepared the input data. Furthermore, I developed the methodology and further developed the *EVaTar-building* module used within the publication and implemented the electricity price manipulation. Additionally, I performed the comprehensive analysis and complex visualization of the results. I drafted the manuscript and included reviews and edits from the co-authors and was involved in the acquisition of the research projects that supported the work.

Publication IV:

***J. Stute** and M. Klobasa (2024): „How do dynamic electricity tariffs and different grid charge designs interact? – Implications for residential consumers and grid reinforcement requirements“, Energy Policy, Vol. 189, Article No. 114062*

Publication IV (Section 8) focuses on the interplay of DETs and different GCDs. A range of volumetric and capacity-based GCDs are considered. The study explores how these GCDs influence tariff choices of households and their decisions to utilize flexibility via a HEMS. These decisions are then considered when analyzing the GCDs' effectiveness in mitigating grid reinforcement needs and associated costs.

My contribution: I conceptualized the study, defined the scope, and formulated the research questions based on a comprehensive literature analysis. I further developed the *EVaTar-building* module by adding the possibility of different GCDs and developed and implemented the methodology for the grid reinforcement analysis within the *EVaTar-gridex* module. I conceptualized the research framework, conducted the data curation, prepared the necessary input data, and performed the formal analysis. I also validated the results. Additionally, I wrote the first draft of all parts of the manuscript apart from the conclusions section, which was drafted by the co-author after joint drawing of conclusions. I further included reviews and edits from the co-author and was involved in the acquisition of the research projects that supported the work.

2 Methods

The research questions analyzed in this thesis (refer to Section 1.2) are addressed through the development of the *EVaTar* („**E**fficient **Va**riable **Tar**iffs“) model. This innovative model bridges a significant methodological gap by combining techno-economic modeling of household flexibility utilization with socio-economic modeling of household decision-making, and including these elements into distribution grid modeling that includes the analysis of grid reinforcement needs and associated costs. This integration forms a comprehensive interdisciplinary techno-socio-economic analysis. The model is organized into four distinct modules, each designed to explore different aspects of the central research topic and enable a systematic approach to analysis:

1. *EVaTar-building*: This module analyzes the flexibility utilization of households equipped with various flexible technologies. It depicts households along with their electricity demand and generation profiles, implementing various strategies for flexibility deployment. Different DETs and GCDs can be analyzed. The module is described in more detail in Section 2.1 and Publication III.

2. *EVaTar-decisions*: The second module focuses on depicting the not purely rational decision-making behavior of households regarding their choices of electricity retail tariffs and the acquisition and use of HEMSs. Each household is presented with a range of static and dynamic electricity retail tariffs, from which they select the most suitable option. The module is further detailed in Section 2.2, as well as in Publications II and IV.

3. *EVaTar-grid*: To evaluate the impact of households' tariff choices and decisions to use a HEMS on grid utilization, in this third module, flexible and non-flexible households along with their load and generation profiles are distributed across the nodes of low-voltage grids. Power flow calculations are then performed to evaluate the resulting grid load. Further information on this module is provided in Section 2.3 and Publication II.

4. *EVaTar-gridex*: The final module addresses grid reinforcement needs and associated costs. It utilizes the results from the third module and evaluates grid restriction violations to determine and analyze necessary grid reinforcement measures and associated costs through a heuristic grid reinforcement algorithm. The methodology is explained in detail in Section 2.4 and Publication IV.

Figure 2.1 provides an initial overview of the modeling requirements, the four modules and their connection points, the methodological approaches employed, and the results obtained. The subsequent sections outline these aspects in further detail.

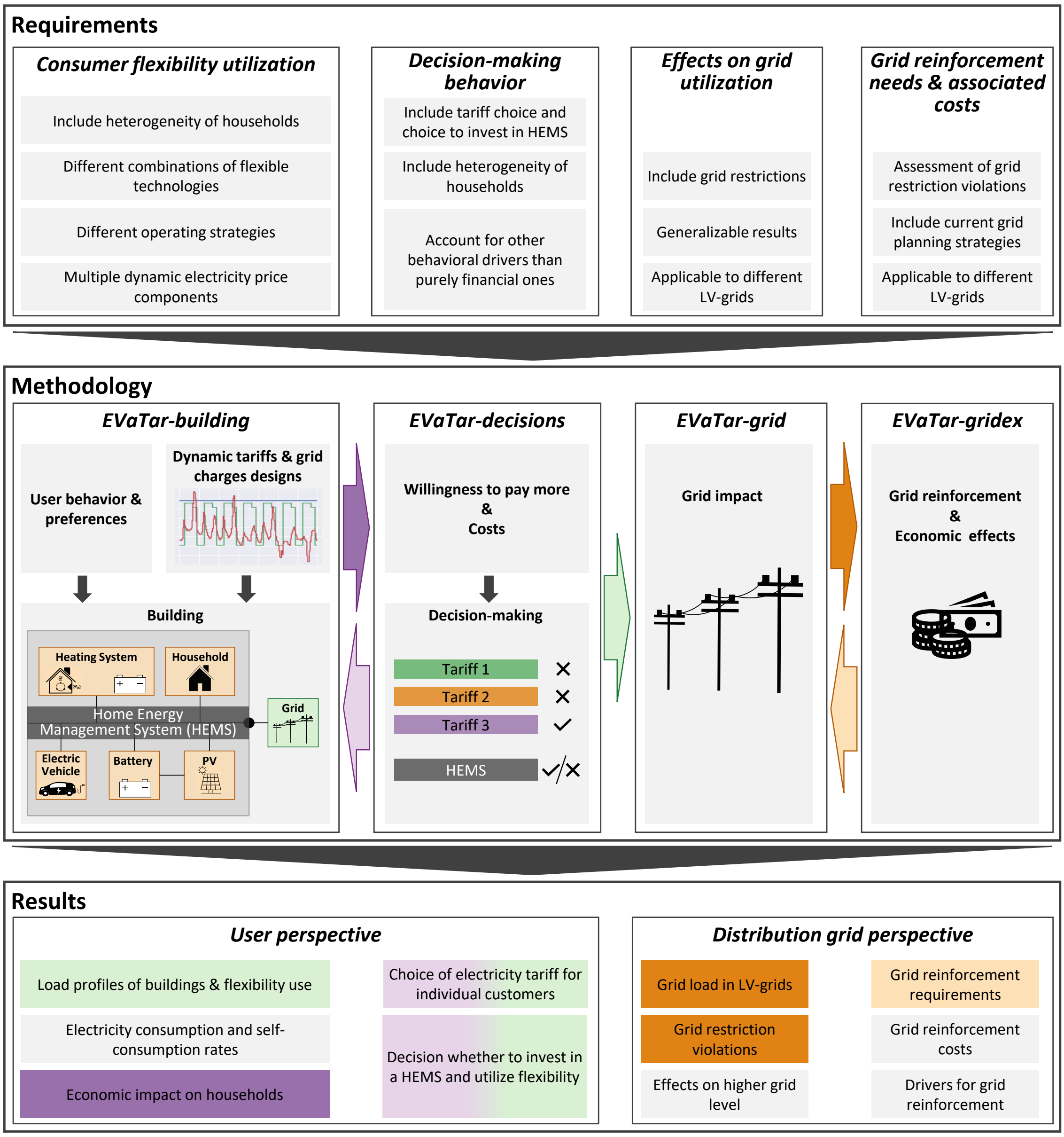

Figure 2.1: Modeling requirements, schematic representation of the model *EVaTar* and its four modules, and overview of results that can be obtained.

2.1 Flexible and non-flexible behavior of households (*EVaTar-building*)

The first module serves as the foundation for the model-based assessment of the impact of dynamic electricity price components on residential consumers and grid reinforcement needs. A detailed description of the *EVaTar-building* module was published in Publication III. In the following, the modeling requirements, the implementation and results obtained from the module are described.

2.1.1 Modeling requirements regarding the heterogeneity of households, operational strategies for flexibility, and electricity price components

To allow for a comprehensive evaluation of how dynamic electricity price components impact flexibility utilization from both a user and a distribution grid perspective, while considering the heterogeneity of residential consumers, the results obtained from the module must be applicable across all other modules. The requirements concerning household heterogeneity and available flexible technologies, the operational strategies for utilizing flexibility, and the electricity price components under consideration are specified in the following.

2.1.1.1 Household heterogeneity and available flexible technologies

To effectively account for the heterogeneity of households, the model must incorporate a wide variety of individual household profiles and include user preferences. It must include relevant data, such as heterogeneous household load profiles, various EV driving and availability patterns, and heat demand profiles for heat pumps, among others. Additionally, the module must allow for the representation of different combinations of flexible assets to explore potential synergies and interactions between technologies. Given that analyzing heterogeneous households involves handling substantial amounts of input data, the model needs to allow for parallel computation. This enables the simultaneous processing of multiple households, significantly reducing computation time. Furthermore, a robust database setup is required to manage both the input and output data efficiently.

Several critical factors must be considered when selecting household-related data for the model to address the research questions effectively. These include the types of flexible technologies to be depicted, the temporal resolution, the duration of the time intervals under consideration, and the degree of household heterogeneity[1]. These requirements are described in more detail below, followed by a brief examination of the representativeness of the data utilized in Publications II to IV, which represents another important aspect.

Available technologies

As outlined in Section 1, studies have shown that the technology available in a household significantly impacts the financial viability of dynamic electricity tariffs. To fully assess the research questions and understand the impacts of dynamic electricity price components on households and low-voltage grids, it is essential to explore all possible combinations of relevant technologies. The selected technologies include EVs, HPs, PV systems, and PV-BSSs, based on the technologies identified as relevant by the four German transmission system operators (TSOs) within the network development plan [12]. Twelve different variants result from these combinations, as shown in Figure 2.2a. Figure 2.2b provides an exemplary overview of the annual electricity drawn from the grid for these variants, and Figure 7.5 in Publication III gives an exemplary overview of the load profiles for different technology combinations, illustrating variations in household energy usage throughout the day.

[1] Spatial resolution is not explicitly considered here, as a distinction regarding that matter can be indirectly addressed through the input data of individual households.

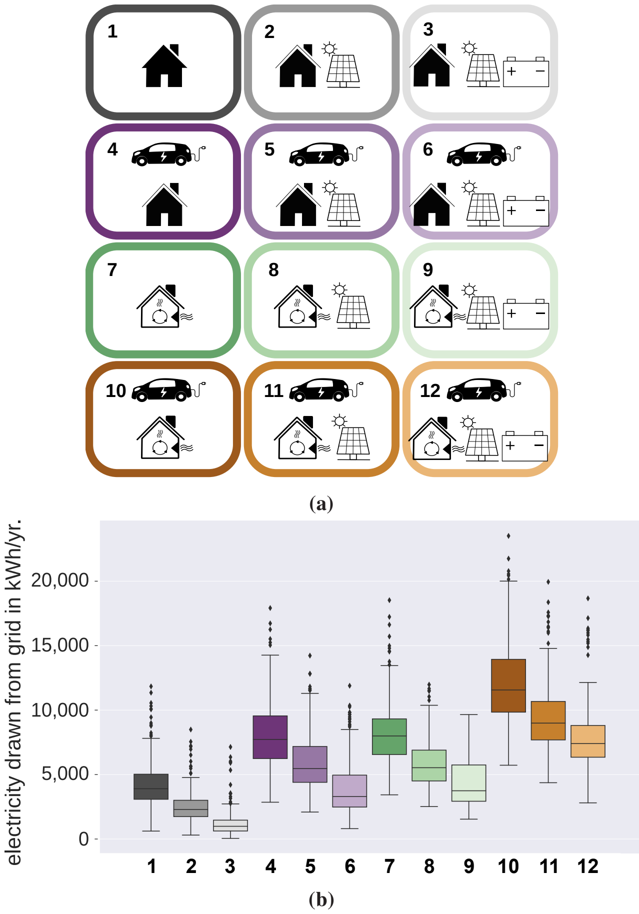

Figure 2.2: (a) Overview of all technology combinations in households considered (– household, – household with a HP, – EV, – PV system, – BSS). (b) Annual electricity withdrawn from the grid when flexibility is not explicitly utilized for the technology combinations considered. Boxplots including all households considered in Publication III [69].

Temporal resolution

The temporal resolution of load and generation data is crucial for evaluating the financial viability of utilizing flexibility and dynamic electricity tariffs in households. Lower time resolutions result in temporal aggregation, smoothing out mismatches between load and generation [70, 71]. For instance, Ayala-Gilardón et al. [70] show a 9% difference in self-consumption rates when comparing 10-second resolution data to hourly resolution. However, most DETs discussed in the literature and available in the market are based on an hourly resolution. Consequently, for modeling flexibility utilization, a maximum time resolution of one hour is required for household load profiles. This resolution, while adequate for assessing economic impacts, is relatively low for analyzing effects on low-voltage grids in Germany, where voltage stability is evaluated using 10-minute averages (DIN EN 50160 [72]). However, Widén et al. [71] demonstrate that the distribution of voltage levels in an low-voltage grid is only minimally affected when comparing hourly resolution to 10-minute resolution. Therefore, an hourly resolution is utilized for the data in Publications II to IV, primarily due to data availability. The model is designed to allow the time resolution to be adjusted freely for each scenario, enabling the analysis of higher temporal resolutions if data becomes available.

Seasonality

Household electricity consumption and generation exhibit significant seasonal variations. For instance, electricity generated by PV systems is generally higher in summer and lower in winter, while household electricity consumption is lower in summer, and heat demand peaks in winter. Given these seasonal dynamics and the inclusion of various energy storage options like PV-BSSs, EVs, and heat storage tanks in the model, it is essential to analyze an entire year. This approach ensures an adequate evaluation of the impacts of flexibility utilization in households.

Individual households

Households exhibit a wide range of electricity consumption patterns, including variations in general household electricity use, HP operation, and EV charging. To accurately model these differences, individual household load profiles, heat demands, and driving behaviors must be considered. Moreover, design parameters such as the installed power of PV systems or the capacity of PV-BSSs also vary by household. Allowing for comprehensive input data and the individual adjustment of installed power and capacities within the model enables addressing the research gaps of including household heterogeneity in terms of load profiles and available flexible technologies.

Representativity of household data

Household data, especially detailed and comprehensive datasets, are scarce. The dataset selected for Publications II to IV, derived from a smart meter field study in Austria and Germany [73], is comprehensive and crucial for the depth and scope of our analysis. It encompasses not only measured, heterogeneous household load profiles but also socio-demographic information, essential for the chosen methodological approach. Using this household data and accounting for representativity allows for a more accurate evaluation of the significance of the results for the considered country or region. Therefore, Table 2.1 compares selected descriptive parameters of the households under consideration with the general population in Germany.

It is noticeable that the sample shows higher average electricity consumption in households with up to two persons compared to the German population. For households with three or more persons, the average electricity consumption aligns more closely with national averages [74]. The sample also features a larger proportion of households with three or more persons and households with children than the cross-section of the population [75]. Additionally, the average age of the primary income earner in the sample is slightly younger than that in the general population [75]. The sample adequately represents living space and social status values of the population [75].

2.1.1.2 Operational strategies of flexible technologies

Different operational strategies for flexible technologies are prevalent in households today and are widely discussed in the literature [40, 43]. To determine if the use of DETs offers additional financial benefits compared to other strategies (addressed in Subquestion I.2), the model needs to represent various operational strategies for comparison. The most commonly discussed operational strategy invovles utilizing a HEMS for cost optimization by leveraging dynamic electricity price components. This is essential to assess the effects of DETs and GCDs. Additionally, utilizing flexibility via a HEMS for

	Sample	**Population**
Floor area	139 m^2	136 m^{2a}
Power consumption		
overall	5,020 kWh/yr.	3,383 kWh/yr.[b]
1 person	3,452 kWh/yr.	2,105 kWh/yr.
2 persons	4,525 kWh/yr.	3,471 kWh/yr.
3 or more persons	5,518 kWh/yr.	5,411 kWh/yr.
Household size		
1 person	7%	19%[a]
2 persons	36%	41%
3 persons	24%	17%
4 or more persons	33%	23%
Social status		
self-employed	3%	9%[c]
employed	63%	56%
unemployed	3%	1%
not gainfully employed	30%	34%
Age		
18-24 years	1%	0%[c]
25-34 years	7%	5%
35-44 years	24%	17%
45-54 years	26%	22%
55-64 years	21%	23%
65-69 years	11%	8%
70-79 years	10%	19%
80+ years	1%	6%
Household type		
living alone	7%	18%[a]
single parent	3%	1%
couples without child	34%	38%
couples with child	48%	21%
other	7%	21%

[a] Statistisches Bundesamt [75], figures refer to 2018
[b] Statistisches Bundesamt [74], figures refer to 2021
[c] Statistisches Bundesamt [75], figures refer to 2018, figures were not available for all adult household members, therefore the numbers refer to the primary income earner.

Table 2.1: Comparison of the descriptive parameters of the analyzed households with the German population.

optimizing self-consumption is also critical to address. For baseline comparison, a scenario with no explicit use of flexibility serves as the reference case. The basic concepts of these three operational strategies are briefly described below.

No explicit use of flexibility

To represent the status quo in Germany and provide a baseline for evaluating the effects of utilizing flexibility, the model must include a reference case with no explicit flexibility utilization.
For **PV battery storage systems**, this includes the currently most common operational strategy in Germany, which is a relay-based system typically used in households without a HEMS. This strategy operates independently of the tariff system. Electricity generated by the PV system is first used to meet

the household's immediate electricity demand, including the demand of the EV and the HP. Excess electricity is then directed to charge the battery storage system (BSS), with any further surplus being fed into the low-voltage grid. When household demand exceeds PV output, energy is drawn from the BSS to meet the demand.
For **electric vehicles**, no explicit use of flexibility includes constant charging. The EV charging process begins as soon as it is plugged in and continues until the EV battery is either fully charged or the EV is driven again.
Lastly, the **heating system** in the reference case operates to continuously meet the heat demand. The heat storage tank is maintained at full capacity to ensure a constant heat supply, even during power outages or technical failures. This approach provides a clear baseline against which to measure the benefits of employing flexible operating strategies.

Use of flexibility for cost optimization through self-consumption

With the introduction and market uptake of HEMSs, a new operational strategy for flexibility utilization has become widely available for households equipped with a PV system or PV-BSS [76]. This strategy focuses on minimizing electricity costs through optimized self-consumption. Households using this strategy typically operate under a static tariff but employ the HEMS to shift the load of the **electric vehicle** and the **heat pump** to periods of high PV generation or to utilize the **battery storage system** more efficiently, allowing for the consumption of self-generated electricity at a later time. This operating strategy is crucial for the model to estimate the potential additional benefits from DETs accurately without mixing it with benefits from increased self-consumption if a PV system or PV-BSS is available.

Incorporating user behavior and preferences is essential when considering the use of a HEMS and the flexible operation of household technologies. This includes minimizing or avoiding loss of comfort related to heating demands and ensuring that the mobility needs tied to EV usage are not restricted. Factors such as travel and standing times of EVs, as well as concerns like range anxiety, must also be taken into account to provide a realistic and effective representation of household energy management.

Use of flexibility for cost optimization through dynamic electricity price components

The final operational strategy involves using flexibility for cost optimization through dynamic electricity price components, widely discussed and partially implemented by HEMS manufacturers in Germany and other countries [76]. This strategy employs a HEMS to minimize electricity costs by responding to price signals for electricity purchase and feed-in remuneration. It includes shifting load of **electric vehicles** and **heat pumps** to periods with lower electricity prices and enhancing self-consumption by aligning consumption with PV generation or utilizing the **battery storage system**. User behavior and preferences must be considered to ensure the strategy does not significantly disrupt comfort or mobility.

2.1.1.3 Electricity price components

To accurately depict various dynamic electricity price components, the model must allow for individual definitions of each component, including electricity procurement and retail, grid charges, and other taxes, levies, and surcharges. This research focuses on DETs and different GCDs, all of which must be represented in the model. The DETs considered are time-varying. For GCDs, both static and time-varying volumetric GCDs and capacity-based GCDs must be depicted. The model must also incorporate additional costs such as standing charges, metering point operation costs, and HEMS investment costs, which influence households' tariff choices and decisions to invest in a HEMS.

2.1.2 Implementation of the *EVaTar-building* module

The *EVaTar-building* module is developed to evaluate both the technical and economic impacts on household electricity consumption under various static and dynamic electricity prices, and GCDs. The basis of the module is the household (or building) itself with its electricity demand, which is considered inflexible. Additionally, the household can be equipped with various technologies such as an EV, a heating system consisting of a HP and an additional heat storage tank, a PV system, or a PV-BSS. Those technologies offer flexibility in terms of load-shifting potential. During the initial setup, households with different flexible and inflexible technologies are configured, processed individually with parallelization to speed up computation time. Input and output data are stored in two separate PostgreSQL databases which allow for simultaneous reading and writing operations, enhancing computational efficiency.

To map the three strategies for flexibility deployment - (a) no explicit use of flexibility, (b) flexibility utilization to enhance self-consumption using a HEMS, and (c) flexibility utilization to minimize electricity purchase costs through the use of DETs using a HEMS - two methodological approaches are required. The choice of the methodological approaches is driven by the specific requirements of each operational strategy.

A simulation suffices for scenarios where flexibility is not explicitly used, capturing predictable load patterns, such as EV charging upon arrival, HP operation based on thermal demand, and relay-based operation of PV-BSSs. In contrast, more complex scenarios that involve optimizing electricity purchase costs through self-consumption or dynamic electricity price components require a more sophisticated approach.

Several modeling approaches have been used in literature to depict household flexibility utilization, which are considered for their suitability. Table 2.2 provides a concise overview. For more information, please refer to the references given for each approach.

Each methodological approach comes with unique advantages and trade-offs. While linear programming (LP) and non-linear programming (NLP) are straightforward, they may lack the complexity needed for dynamic systems. Dynamic programming (DP) excels at breaking down large problems into manageable subproblems but faces scalability issues due to the curse of dimensionality. More advanced techniques like mixed-integer non-linear programming (MINLP) and stochastic models effectively handle complex dynamics and uncertainties but require significant computational resources. Model predictive control (MPC) provides real-time control, robust programming prioritizes reliability under uncertainty, and heuristics offer scalability at the expense of optimal accuracy. After careful consideration, mixed-integer linear programming (MILP) was selected for its ability to balance optimality and computational feasibility, offering robust solutions that can handle discrete decisions and linear relationships effectively across complex scenarios. This makes MILP the best choice for achieving a mix of complexity, accuracy, and computational efficiency required within this module. The general representation of the flexible

Methodological approach	Short description	Examples for use in literature
Linear Programming (LP)	Offers a straightforward modeling approach but is limited because it cannot handle non-linearities or binary decisions inherent in the flexible technologies considered [77, 78].	[79, 80]
Mixed-Integer Linear Programming (MILP)	Balances the handling of discrete decisions and linear relationships, suitable for complex scenarios with multiple decision variables. MILP provides global optimality and robustness in solutions but can be computationally demanding for large systems [78, 81].	[82, 83, 84, 85]
Non-Linear Programming (NLP) and Mixed-Integer Non-Linear Programming (MINLP)	These methods can model more realistic, complex scenarios but often result in increased computational burden and difficulty in finding global optimal solutions [86, 81].	[87, 88]
Dynamic Programming (DP)	Large complex problems are broken down into smaller subproblems, and problems are solved recursively [89]. DP can become computationally infeasible as the number of state variables increases and shows scalability issues for large problems [89].	[90, 91]
Model Predictive Control (MPC)	Effective for real-time control based on a rolling horizon principle [92]. It requires advanced forecasting models [78].	[93, 94, 95]
Stochastic Programming	Handles uncertainty in parameters like electricity prices and PV generation effectively. Can be complex to solve due to the probabilistic nature of inputs and knowledge about probability distribution function is required [96, 81].	[97, 98, 99]
Robust Programming	Uncertainty is included in parameters and variables without knowledge about probability distribution by considering intervals of parameter values. This can lead to an increased conservativeness (worst case assumptions) in solutions [100, 81].	[101, 102]
Heuristics and Metaheuristics	These methods provide quicker, often near-optimal solutions, suitable for large-scale problems where exact methods might be impractical, but they do not guarantee the best solution [78, 81, 103, 104].	[105, 106]

Table 2.2: Overview on methodological approaches used in literature for modeling household flexibility utilization.

technologies within the module and the specific implementation of the simulation and optimization approaches are described below.

2.1.2.1 General representation of flexible technologies

Within this section, the fundamental aspects of the module that are common to both the simulation and the optimization approaches are described. A schematic representation of a household with all technology options considered within the module is given in Figure 7.3 in Publication III.

The household is connected to the low-voltage grid via its grid connection point. The energy drawn from the grid $E^t_{\text{grid, building}}$ to supply the household energy demand at time step t consists of the electricity demand of the inflexible load of a household, the EV charging process, and the heating system minus the energy provided by the PV system and the BSS (Equation 2.1):

$$E^t_{\text{grid, building}} = E^t_{\text{H}} + \alpha_{\text{EV}} \cdot E^t_{\text{EV}} + \alpha_{\text{HP}} \cdot E^t_{\text{HP, el}} - \alpha_{\text{PV}} \cdot E^t_{\text{PV, building}} - \alpha_{\text{BSS}} \cdot E^t_{\text{BSS}}, \quad \forall t \in T \tag{2.1}$$

with:

t	Time step
T	Set of all time steps
α	Binary variable denoting the presence or absence of a specific technology
E_{H}	Inflexible electricity demand of the household in kWh
E_{EV}	Energy demand of the charging process of the EV in kWh
$E_{\text{HP, el}}$	Electrical energy demand of the HP in kWh
$E_{\text{PV, building}}$	Energy supplied to the building by the PV system in kWh
E_{BSS}	Energy supplied to the building by the BSS in kWh

PV system

The power output from the PV system $P^t_{\text{PV, generation}}$ at time step t can be separated into three different power flows as specified in Equation 2.2):

$$P^t_{\text{PV, generation}} = P^t_{\text{PV, building}} + P^t_{\text{PV, BSS}} + P^t_{\text{PV, grid}}, \qquad \forall t \in T \tag{2.2}$$

with:

$P^t_{\text{PV, building}}$	Power flow from the PV system to the household in kW
$P^t_{\text{PV, BSS}}$	Power flow from the PV system to the BSS in kW
$P^t_{\text{PV, grid}}$	Power flow from the PV system to the grid in kW

Battery storage system

The BSS can be charged solely by the PV system within the module. It can supply the charged energy to cover the building's energy requirements.

The amount of energy stored in the battery E^t_{BSS} at time step t is defined in Equation 2.3. This considers the battery's self-discharge, the energy charged during the charging process, and the energy discharged when supplying power to the building, each adjusted for respective efficiency factors.

$$E^t_{\text{BSS}} = (1 - q_{\text{losses, BSS}}) \cdot E^{t-1}_{\text{BSS}} + P^t_{\text{PV, BSS}} \cdot \eta_{\text{BSS, charge}} \cdot \Delta t - P^t_{\text{BSS}} \cdot \frac{1}{\eta_{\text{BSS, discharge}}} \cdot \Delta t, \qquad \forall t \in T \tag{2.3}$$

with:

P^t_{BSS}	Power flow from the battery to the building in kW
$\eta_{\text{BSS, charge}}$	Charging efficiency factor of the BSS
$\eta_{\text{BSS, discharge}}$	Discharging efficiency factor of the BSS
$q_{\text{losses, BSS}}$	Self-discharge rate of the BSS in %/Δt

The power flow to and from the BSS is restricted to the maximum charging and discharging power of the battery system $P_{\text{BSS, max, ch}}$ and $P_{\text{BSS, max, dis}}$, respectively (Equations 2.4 and 2.5). The energy stored in the battery is limited by the maximum usable capacity $E_{\text{BSS, max}}$ (Equation 2.6).

$$0 \leq P^t_{\text{PV, BSS}} \leq P_{\text{BSS, max, ch}}, \qquad \forall t \in T \tag{2.4}$$

$$P_{\text{BSS, max, dis}} \leq P^t_{\text{BSS}} \leq 0, \qquad \forall t \in T \tag{2.5}$$

$$0 \leq E^t_{\text{BSS}} \leq E_{\text{BSS, max}}, \qquad \forall t \in T \tag{2.6}$$

Electric vehicle

Electric vehicles are represented as mobile battery storage units, indicating that the EV battery cannot be constantly used as a resource for flexibility. Households are allocated driving profiles, each with its associated energy demand $E^t_{\text{EV, demand}}$. The availability of a vehicle at time step t at its home location, denoted as f^t_{avail}, is predetermined exogenously.

The amount of energy stored in the EV battery E^t_{EV} at time step t is calculated by factoring in the battery's self-discharge, the energy added during the charging process (considering charging efficiency), and the energy used while driving (Equation 2.7).

$$E^t_{\text{EV}} = (1 - q_{\text{losses, EV}}) \cdot E^{t-1}_{\text{EV}} + P^t_{\text{EV}} \cdot \Delta t \cdot \eta_{\text{EV, charge}} - E^t_{\text{EV, demand}}, \qquad \forall t \in T \tag{2.7}$$

with:

P_{EV}	Charging power in kW
$\eta_{\text{EV, charge}}$	Charging efficiency of the EV battery
$q_{\text{losses, EV}}$	Self-discharge rate of the EV battery in %/Δt

The charging power is restricted to the maximum charging power $P_{\text{EV, max, ch}}$ of the EV battery (Equation 2.8), and the energy stored in the EV battery is limited by the maximum usable capacity $E_{\text{EV, max}}$ (Equation 2.9).

$$0 \leq P^t_{\text{EV}} \leq P_{\text{EV, max, ch}}, \qquad \forall t \in T \tag{2.8}$$

$$0 \leq E^t_{\text{EV}} \leq E_{\text{EV, max}}, \qquad \forall t \in T \tag{2.9}$$

Heating system

A building's heating system within the model consists of two main components: the HP, which can be air-to-water or brine-to-water, and a heat storage tank. The heat demand of the building $\dot{Q}^t_{\text{heat demand}}$ must be met at each time step t (Equation 2.10). Heat can be supplied to the building by both the HP and the heat storage tank. The HP can further supply the heat storage tank. The required electric power consumption of the HP $P^t_{\text{HP, el}}$ is determined according to Equation 2.11.

$$\dot{Q}^t_{\text{heat demand}} = \dot{Q}^t_{\text{HP, building}} + \dot{Q}^t_{\text{HS, building}}, \qquad \forall t \in T \tag{2.10}$$

$$P^t_{\text{HP, el}} = \frac{\dot{Q}^t_{\text{HP, th}}}{\text{COP}^t} = \frac{\dot{Q}^t_{\text{HP, building}} + \dot{Q}^t_{\text{HP, HS}}}{\text{COP}^t}, \qquad \forall t \in T \tag{2.11}$$

with:

$\dot{Q}_{\text{HP, building}}$	Thermal power flow from the HP to the building in kW_{th}
$\dot{Q}_{\text{HS, building}}$	Thermal power flow from the heat storage tank to the building in kW_{th}
$\dot{Q}^t_{\text{HP, HS}}$	Thermal power flow from the HP to the heat storage tank in kW_{th}
$\dot{Q}^t_{\text{HP, th}}$	Thermal power output of the HP in kW_{th}
COP^t	Coefficient of performance (COP) at time step t

A heating curve is implemented within the heating system, which leads to a flow temperature T^t_{high} dependent on the ambient temperature T^t_{amb} (Equation 2.12):

$$T^t_{\text{high}} = T_{\text{room}} + (T_{\text{high, max}} - T_{\text{room}}) \cdot \left(\frac{T_{\text{room}} - T^t_{\text{amb}}}{T_{\text{room}} - T_{\text{amb, norm}}} \right)^{\frac{1}{n}}, \qquad \forall t \in T \tag{2.12}$$

with:

T_{room}	Target room temperature, maintained consistently by the heating system in K
$T_{\text{high, max}}$	Technically maximum achievable flow temperature of the HP in K
$T_{\text{amb, norm}}$	Norm outside temperature for the specific location in K
n	Radiator exponent

The COP is temperature-dependent, which is especially important for air-to-water HPs. Additionally, efficiency losses for air-to-water HPs due to icing at ambient temperatures below 2°C are accounted for by reducing the COP for low temperatures by a factor f_{icing}. The COP equals to (Equation 2.13):

$$COP^t = \begin{cases} \eta_{\text{COP}} \cdot \frac{T^t_{\text{high}}}{T^t_{\text{high}} - T^t_{\text{amb}}} & T^t_{\text{amb}} > T_{\text{icing}} \\ \eta_{\text{COP}} \cdot \frac{T^t_{\text{high}}}{T^t_{\text{high}} - T^t_{\text{amb}}} \cdot (1 - f_{\text{icing}}) & T^t_{\text{amb}} \leq T_{\text{icing}} \end{cases}, \qquad \forall t \in T \tag{2.13}$$

with:

η_{COP}	Quality grade of the HP type
T_{icing}	Temperature threshold below which icing can occur in K

Due to the temperature-dependent COP, the maximum possible thermal power output $\dot{Q}^t_{\text{max, th}}$ is also variable. It can be calculated with additional information on the nominal coefficient of performance COP_{nom} and the nominal power output $\dot{Q}_{\text{nom, th}}$ of the HP (Equation 2.14):

$$\dot{Q}^t_{\text{max, th}} = \frac{\text{COP}^t}{\text{COP}_{\text{nom}}} \cdot \dot{Q}_{\text{nom, th}}, \qquad \forall t \in T \tag{2.14}$$

The appropriate sizing of the HP is determined endogenously using information on the heating demand per square meter, which depends to a great extent on the construction year, the refurbishment state, the living space of the building, and the norm outside temperature. First, the heat demand at norm outside temperature $\dot{Q}_{\text{amb, norm}}$ is determined based on the resulting heat demand curve and the ambient temperature time series (Equation 2.15).

$$\dot{Q}_{\text{amb, norm}} = (T_{\text{amb, norm}} - T_{20^\circ\text{C}}) \cdot \frac{\dot{Q}_{\text{th},20^\circ\text{C}} - \dot{Q}_{\text{th},T_{\text{min}}}}{T_{20^\circ\text{C}} - T_{\text{min}}} \tag{2.15}$$

with:

T_{min}	Minimal outside temperature of the time series in K
$\dot{Q}_{\text{th},20^\circ\text{C}}$	Heat demand at an ambient temperature of 20°C in kW_{th}
$\dot{Q}_{\text{th},T_{\text{min}}}$	Heat demand at T_{min} in kW_{th}

The maximum thermal power output $\dot{Q}_{\text{HP, th, max}}$ of the HP is then fixed using a flexibility factor $f_{\text{HP, flexibility}}$ that allows for more flexible use of the HP also in times of low ambient temperatures (Equation 2.16).

$$\dot{Q}_{\text{HP, th, max}} = f_{\text{HP, flexibility}} \cdot \dot{Q}_{\text{amb, norm}}, \qquad \text{with } f_{\text{HP, flexibility}} \geq 1 \tag{2.16}$$

The heat storage tank is another important component of the heating system when talking about flexibility. It is represented in a simplified manner considering the thermal power flow from the storage to the building, the thermal power flow from the HP to the storage, and the standby losses $q_{\text{losses, HS}}$ of the heat storage tank. The stored energy in the heat storage tank Q^t_{HS} at time step t is defined as (Equation 2.17):

$$Q^t_{\text{HS}} = (1 - q_{\text{losses, HS}}) \cdot Q^{t-1}_{\text{HS}} + \dot{Q}^t_{\text{HP, HS}} \cdot \Delta t - \dot{Q}^t_{\text{HS, building}} \cdot \Delta t, \qquad \forall t \in T \tag{2.17}$$

2.1.2.2 No explicit flexibility utilization – a simulation model

A simulation model is implemented for the operational strategy of no explicit flexibility utilization. It includes the inflexible demand for household appliances, a PV-first operational strategy for BSSs, immediate charging upon arrival for EVs, and demand-driven operation of HPs, all described in detail below.

PV battery storage system – relay-based operation

The PV-BSS follows a relay-based PV-first operational strategy. The BSS is charged if there is an excess of PV generation in time step t after supplying the household load, EV charging process, and HP, and the maximum capacity is not reached yet (Equations 2.18 to 2.20). The resulting power flow to the BSS is subject to the restrictions regarding its maximum charging power and maximum capacity (see Equations 2.4 and 2.6).

$$P^t_{\text{PV, BSS}} = \begin{cases} P^t_{\text{res}} & P^t_{\text{res}} < P_{\text{BSS, max, ch}} \wedge P^t_{\text{res}} \cdot \Delta t \leq E^t_{\text{empty}} < E_{\text{BSS, max}} \\ P_{\text{BSS, max, ch}} & P^t_{\text{res}} \geq P_{\text{BSS, max, ch}} \wedge P^t_{\text{res}} \cdot \Delta t \leq E^t_{\text{BSS, cap}} < E_{\text{BSS, max}} \\ \frac{E^t_{\text{BSS, cap}}}{\Delta t} & E^t_{\text{BSS, avail cap}} \leq P^t_{\text{res}} < E_{\text{BSS, max}} \\ 0 & E^t_{\text{BSS, cap}} = E_{\text{BSS, max}} \end{cases}, \quad \forall t \in T \tag{2.18}$$

with:

$$P^t_{\text{res}} = P^t_{\text{PV, generation}} - (P^t_{\text{H}} + P^t_{\text{EV}} + P^t_{\text{HP, el}}) \geq 0, \qquad \forall t \in T \tag{2.19}$$

$$E^t_{\text{BSS, cap}} = E_{\text{BSS, max}} - E^{t-1}_{\text{BSS}}, \qquad \forall t \in T \tag{2.20}$$

The BSS is discharged whenever the PV system cannot meet the power demand of the building (Equations 2.21 and 2.22). The resulting power flow from the BSS is restricted by the maximum discharging power (see Equation 2.5) and the energy stored in the battery at time step t.

$$P^t_{\text{BSS}} = \begin{cases} P^t_{\text{res}} & P^t_{\text{res}} > P_{\text{BSS, max, dis}} \wedge 0 < |P^t_{\text{res}} \cdot \Delta t| \leq E^{t-1}_{\text{BSS}} \\ P_{\text{BSS, max, dis}} & P^t_{\text{res}} \leq P_{\text{BSS, max, dis}} \wedge 0 < |P^t_{\text{res}} \cdot \Delta t| \leq E^{t-1}_{\text{BSS}} \\ \frac{E^{t-1}_{\text{BSS}}}{\Delta t} & 0 < E^{t-1}_{\text{BSS}} \leq |P^t_{\text{res}} \cdot \Delta t| \\ 0 & E^{t-1}_{\text{BSS}} = 0 \end{cases}, \quad \forall t \in T \tag{2.21}$$

with:

$$P^t_{\text{res}} = P^t_{\text{PV, generation}} - (P^t_{\text{H}} + P^t_{\text{EV}} + P^t_{\text{HP, el}}) < 0, \qquad \forall t \in T \tag{2.22}$$

Electric vehicle – charging upon arrival

Within the simulation, immediate charging upon arrival for EVs is considered. The battery of the EV is charged until the EV is driven again or it is fully charged (Equations 2.23 and 2.24). The charging power is restricted by the available battery capacity (see Equation 2.9).

$$P^t_{\text{EV}} = \begin{cases} P_{\text{EV, max, ch}} & P_{\text{EV, max, ch}} \cdot \Delta t \leq E^t_{\text{EV, cap}} \wedge f^t_{\text{avail}} = 1 \\ \frac{E^t_{\text{EV, cap}}}{\Delta t} & P_{\text{EV, max, ch}} \cdot \Delta t > E^t_{\text{EV, cap}} \wedge f^t_{\text{avail}} = 1 \\ 0 & E^{t-1}_{\text{EV}} = E_{\text{EV, max}} \wedge f^t_{\text{avail}} = 1 \end{cases}, \quad \forall t \in T \tag{2.23}$$

with:

$$E^t_{\text{EV, cap}} = E_{\text{EV, max}} - E^{t-1}_{\text{EV}}, \qquad \forall t \in T \tag{2.24}$$

Heating system – following the heat demand

The electrical load of the HP can be derived from the equations shown in Section 2.1.2.1. The heat storage tank is kept fully charged throughout the heating period to ensure heating in case of a blackout or other technical issues. The power flow from the heat storage tank to the building and from the HP to the heat storage tank is defined in Equations 2.25 and 2.26:

$$\dot{Q}^t_{\text{HP, HS}} = \dot{Q}^t_{\text{max, th}} - \dot{Q}^t_{\text{HP, building}}, \qquad \forall t \in T \tag{2.25}$$

$$\dot{Q}^t_{\text{HS, building}} = \dot{Q}^t_{\text{heat demand}} - \dot{Q}^t_{\text{HP, building}}, \qquad \forall t \in T \tag{2.26}$$

2.1.2.3 Explicit flexibility utilization – an optimization model

Within the *EVaTar-building* module, a MILP model is implemented to depict the use of a HEMS. The objective function (Equation 2.27) incorporates the electricity costs for electricity withdrawn from the grid and the feed-in remuneration for the electricity supplied to the grid from the PV system.

$$\min \sum_{t=0}^{t_{max}} \left(E^t_{\text{grid, building}} \cdot c^t_{\text{electricity price}} - E^t_{\text{PV, grid}} \cdot c_{\text{feed-in}} \right), \qquad \forall t \in T \tag{2.27}$$

with:

$E_{\text{grid, building}}$	Amount of energy drawn from the grid in kWh
$E_{\text{PV, grid}}$	Energy fed into the grid from the PV system in kWh
$c_{\text{electricity price}}$	Electricity price in €ct/kWh
$c_{\text{feed-in}}$	Feed-in remuneration in €ct/kWh

In order to maximize the cost savings through self-consumption using a HEMS, the accuracy of the load and feed-in forecasts is of great importance [107, 108, 109]. The model utilizes a rolling horizon approach to account for forecast uncertainties in load, generation, and electricity prices (see Figure 2.3). This approach involves a horizon spanning over n time steps, within which it performs an optimization. The results from the first m time steps are then fixed. After that, the horizon moves m time steps forward. This methodology enables the model to account for potential forecast inaccuracies or changes in the load, generation, and electricity price predictions.

Battery storage system – increasing self-consumption

The BSS is incorporated into the HEMS, which allows for a more flexible and predictive use. Within the MILP model, several constraints are implemented for the battery operation. First, power flow from the battery to the building is restricted to only meet the demand (see Equation 2.28).

$$P^t_{\text{BSS}} \leq P^t_{\text{H}} + P^t_{\text{EV}} + P^t_{\text{HP, el}} - P^t_{\text{PV, building}}, \forall t \in T \tag{2.28}$$

Furthermore, the energy level or state of charge (SOC) of the battery has to be the same for the first and the last time step considered (Equation 2.29).

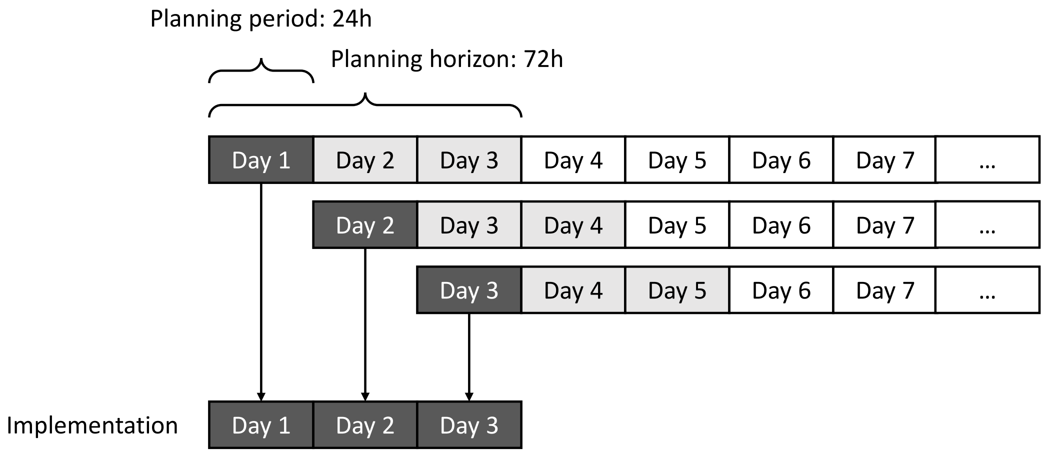

Figure 2.3: Schematic representation of the rolling horizon approach used for the optimization in *EVaTar-building*. The time intervals given in the figure are exemplary and can be adjusted freely.

$$E_{\text{BSS}}^{t=0} \stackrel{!}{=} E_{\text{BSS}}^{t_{\max}} \tag{2.29}$$

Additionally, the battery cannot be charged and discharged simultaneously. This constraint is implemented using a binary flag variable f_{BSS} and a BigM variable (Equations 2.30 and 2.31).

$$P_{\text{PV, BSS}}^{t} \leq f_{\text{BSS}} \cdot \text{BigM}, \qquad \forall t \in T \tag{2.30}$$

$$P_{\text{BSS}}^{t} \leq (1 - f_{\text{BSS}}) \cdot \text{BigM}, \qquad \forall t \in T \tag{2.31}$$

Electric vehicle – controlled charging

Integrating the EV into the building's HEMS allows for controlled charging. User preferences regarding the charging process are implemented into the MILP model, including the minimum energy stored in the EV battery (or minimum desired range) at the time of departure $E_{\text{EV, departure, min}}$ (see Equation 2.32), as well as the critical minimum energy level $E_{\text{EV, ch, min}}$, at which charging of the vehicle should be initiated (refer to Equation 2.33).

$$E_{\text{EV}}^{t} \geq E_{\text{EV, departure, min}}, \qquad \forall t \in T \quad \text{where} f_{\text{avail}}^{t-1} = 1 \wedge f_{\text{avail}}^{t} = 0 \tag{2.32}$$

$$E_{\text{EV, ch, min}} \leq E_{\text{EV}}^{t} \leq E_{\text{EV, max}}, \qquad \forall t \in T \tag{2.33}$$

A further constraint is set, so that the EV can only be charged when it is available at the home location (Equation 2.34).

$$0 \leq P_{\text{EV}}^{t} \leq P_{\text{EV, max, ch}} \cdot f_{\text{avail}}^{t}, \qquad \forall t \in T \tag{2.34}$$

Additionally, as with the BSS, the energy stored in the EV battery must be equal for the first and last time step considered (Equation 2.35).

$$E_{\text{EV}}^{t=0} \stackrel{!}{=} E_{\text{EV}}^{t_{\max}} \tag{2.35}$$

Heating system – heat storage tank for flexibility

When integrating the heating system into the HEMS, the heat storage can be utilized to provide flexibility. A strategic shift in when the HP is operated is possible, adhering to the constraint of meeting the household's heat demand (see Equation 2.10).

For the heat storage, as before for the BSS and the EV, the energy stored must be the same for the first and last time step considered (Equation 2.36).

$$E_{\text{HS}}^{t=0} \stackrel{!}{=} E_{\text{HS}}^{t_{\max}} \tag{2.36}$$

2.1.2.4 Depiction of different electricity price components

The electricity price seen by a household is broken down into various components. For the price component of electricity procurement and retail, both static and dynamic electricity prices are captured through a time series. Similarly, the grid charge component includes a time series for both static and time-varying volumetric charges. Additionally, the model incorporates parameters for a capacity-based GCD using a step function for capacity subscription, which depend on the maximum power drawn from or supplied to the grid during a specific period p. In the MILP model, a new constraint is added to limit the maximum grid connection capacity of a household. Due to differing planning horizons in the rolling horizon approach and the period used to evaluate capacity subscription levels, the most cost-effective subscription choice is not integrated directly into the objective function. Instead, this choice is determined through an iterative process across each specified period of the capacity subscription, starting at the lowest power level. If no feasible solution is found, the model progresses to the next higher level and repeats this until a feasible solution is reached. The total electricity costs at this power level are then compared to the costs at the next higher level to assess if a higher subscription level would yield further savings. This evaluation continues until no additional economic gains are achieved from higher power level subscriptions. More information on the implementation of grid charges is detailed in Publication IV. Other electricity price components are adjustable, assuming static values. The total variable electricity costs C_{variable} of a household are determined as follows (Equation 2.37):

$$C_{\text{variable}} = \sum_{t=0}^{t_{\max}} \left(E_{\text{grid, building}}^{t} \cdot c_{\text{electricity price}}^{t} - E_{\text{PV, grid}}^{t} \cdot c_{\text{feed-in}}\right) + \sum_{p=0}^{p_{\max}} C_{\text{gc cap}}^{p}, \quad \forall t \in T, \forall p \in P \tag{2.37}$$

with:

$C_{\text{gc cap}}^{p}$ Grid charges paid for the capacity subscription level during period p in €ct/kW

2.1.3 Results from the *EVaTar-building* module

Results derived from the first module allow for an assessment of the conditions for economic feasibility of DETs (Subquestion I.2) and of the influence of different GCDs on household decision-making (Subquestion I.3), building the basis for the analysis on the distribution grid level (Research question II). They include the resulting load profiles of each building for the operational strategies considered. Results further include the residual load profile of the building and individual load profiles of each available technology. Furthermore, annually aggregated results, allowing for the analysis of the economic effects of flexibility utilization, are stored in the database. Results include, among others, the annual electricity consumption of each technology and the household as a whole, electricity fed into the grid, self-consumption rates, received feed-in remuneration, unit rate costs, paid grid charges and overall electricity costs.

2.2 Decision-making behavior regarding electricity retail tariffs and the use of a HEMS (*EVaTar-decisions*)

The *EVaTar-decisions* module integrates household decision-making behavior concerning electricity retail tariffs and the acquisition of a HEMS to utilize flexibility. The inclusion of these two in research overlooked aspects (see Section 1.2) is essential in providing a comprehensive understanding of the impact of dynamic electricity price components on low-voltage grids and addressing the research questions effectively. The following sections outline the modeling requirements, describe the selected methodological approach, and present the results that can be obtained from the module.

2.2.1 Modeling requirements regarding the depiction of household decision-making

Household decisions when adopting novel „green" technologies[2], are not purely monetary but are influenced by other behavioral drivers, such as data-privacy concerns [51], cognitive biases [52], perceived usefulness, and hedonic motivation [110], among others. The goal of the module *EVaTar-decisions* is to include these social and psychological drivers alongside the technical and economical aspects and to consider household heterogeneity. Since individual households' attitudes and behavioral data are challenging to determine and data availability is generally low, the module must be able to map heterogeneity while being widely applicable. Another requirement is the easy integration with the *EVaTar-building* module, allowing for direct use of its results.

[2] „Novel green consumer technologies comprise emerging technologies that have a significantly lower environmental footprint than current technologies or that help to lower the footprint of current consumption." [51]

2.2.2 Implementation of the *EVaTar-decisions* module

Different methodological approaches are considered for modeling the decision-making behavior of households. Conventional discrete choice models (DCMs), based on the assumption of rational utility-maximizing behavior, split the utility into observable and non-observable variables. The non-observable variables can be interpreted as a lack of information [111]. Therefore, the discrete choice in DCMs is described through the probability of a household choosing a specific option (i.e., an electricity retail tariff). To correctly estimate the utility of different choices for households, DCMs require detailed and specific information about the preferences and choices of individuals, which can be obtained via well-designed household surveys that accurately capture choice scenarios. A DCM with a purely economic focus has been used in literature to depict the choice of electricity tariff of rational residential consumers in Norway [112]. Although DCMs are valuable for detailed analysis of rational choices, they lack the capability to fully capture irrational decision-making behaviors often observed in real-world scenarios. Behavioral economics models address this by incorporating the non-rational behavior of household decision-making behavior, providing a more nuanced understanding of household choices [113]. However, these models require detailed and complex data collection, which can be resource-intensive. Data collection can be done by survey instruments or experimental designs [114]. Agent-based modeling (ABM) offers another alternative, simulating complex interactions at an individual level. It is useful for understanding how individual decisions can scale up to societal trends. Yet, the high sensitivity to initial conditions and parameter settings in ABMs limits their predictive accuracy [115]. To balance detailed behavioral insights with comprehensive economic analyses and accounting for data availability and broad applicability, an approach is chosen that combines the willingness to pay more (WTPM) with the „diffusion of innovations“ theory of E. Rogers [116]. This approach effectively combines behavioral and economic data. It has previously been used in literature to model the market diffusion of PV-BSSs, while incorporating household heterogeneity [117].

Non-economic behavioral drivers of households as described above can be reflected in a consumer's willingness to pay (WTP) or willingness to pay more (WTPM) for new technologies. These measures depict how non-economic factors shape household decisions on adopting new technologies, translating complex behavioral influences into quantifiable economic terms. The WTP has been studied in literature for different aspects, such as renewable energy [118], EVs [119], innovative heating and cooling systems [120], or PV systems [121, 122]. WTP or WTPM are typically determined through household surveys using methods like the contingent valuation method (CVM) [123] or choice-based conjoint (CBC) experiments [124], which provide insights into the economic impact of behavioral drivers on technology adoption.

Studies show, that the WTP for green technologies and renewable energy is positively correlated with variables such as opinion leadership [122], income level [123, 121], and educational level [123, 121], while a negative correlation exists with age [123, 121]. Moreover, a study by Pelka et al. [50] suggests that households possessing one or more flexible technologies – referred to as first-movers – exhibit more favorable attitudes towards new technological applications like DR services. This relationship underscores the role of innovativeness in household decision-making behavior. These findings align with the adopter categories defined in Rogers' „diffusion of innovations“ theory [116], which classifies consumers into five categories based on their innovativeness[3]: innovators, early adopters, early majority, late majority, and laggards [116]. These categories are described using the mean value and standard deviation of the adoption curve, typically following a normal distribution (see Figure 6.3 in Publication II). Each adopter category exhibits distinct characteristics and values that can be generalized and categorized into three types [116][4]:

- **Socio-economic status:** Including, among others, formal education, which is higher among the earlier adopter categories, and variables defining the social status, such as income or possession of wealth, which also tend to be higher for earlier adopters.
- **Personality values:** Including the ability to deal with abstractions, a favorable attitude toward change, the ability to cope with uncertainty and risk, and a favorable attitude toward science, all of which are higher for the earlier adopter categories.
- **Communication behavior:** Including active information seeking about innovations, opinion leadership, and contact with change agents, which again, are higher for earlier adopters.

Connecting the adopter categories and the WTP or WTPM, innovators, known for their high innovativeness and willingness to take risks, typically exhibit the highest WTP/WTPM, eagerly adopting new technologies. Following them are the early adopters, who are also quick to embrace new technologies but slightly less risk-taking than innovators. They maintain substantial opinion leadership but have a moderately lower WTP/WTPM. The early majority, making up one-third of adopters, shows more cautious behavior, resulting in longer adoption times and correspondingly lower WTP/WTPM. In contrast, the late majority adopts technologies later than the average, often requiring additional persuasion and proof of benefits. Lastly, laggards, who are traditionally conservative and focused on maintaining existing practices, are the last to adopt new technologies, typically resistant to change and showing the lowest WTP/WTPM.

The *EVaTar-decisions* module, which was introduced in Publication II, utilizes the relative WTPM, expressed as a percentage, to model household decision-making regarding their choice of electricity retail tariffs and investments in HEMS. This approach allows the module to accommodate various adopter categories and behavioral drivers. A positive WTPM indicates that a household is willing to incur higher costs, either to adopt dynamic electricity tariffs or to invest in a HEMS, seeing the added value or benefits as justifying the extra expense. Conversely, a negative WTPM suggests that the household requires a certain level of cost savings to consider switching to dynamic tariffs or investing in HEMS. The adaptability of the *EVaTar-decisions* module to incorporate various household segmentation strategies, such as demographic, technical or behavioral aspects based on available data, further enhances its applicability.

In the first step of the concrete implementation, household data and their assignment to one of the adopter categories and the according WTPM are prepared. In a second step, all possible combinations of electricity retail tariffs – both static and dynamic – with or without a HEMS are computed using the *EVaTar-building* module, and annual variable electricity costs C_{variable} (see Equation 2.37) for each

[3] Innovativeness is defined as „the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system“ [116]

[4] For a comprehensive list of characteristics, see [116], chapter 7, p. 287 ff.

tariff and HEMS combination n are derived for each household. These are then used in the *EVaTar-decisions* module, where all additional costs are incorporated, including standing charges $C_{\text{standing charges}}$, metering point operation costs C_{metering}, and the annualized capital expenditure for a HEMS C_{HEMS}. This comprehensive aggregation of costs allows for a thorough financial assessment of the overall electricity costs $C^n_{\text{electricity costs}}$ for each tariff and HEMS combination n as detailed in Equation 2.38.

$$C^n_{\text{electricity costs}} = C^n_{\text{variable}} + C^n_{\text{standing charges}} + C^n_{\text{metering}} + C^n_{\text{HEMS}} \tag{2.38}$$

In the final step, the WTPM values of the adopter categories are integrated. With this, the module determines the option n_{min} that results in the lowest perceived costs (including the WTPM) for each household, which is the option the household chooses within the model (see Equation 2.39).

$$n_{\text{min}} = \underset{n \in \text{N}}{\arg\min} \left(C^n_{\text{electricity costs}} \cdot (1 - \text{WTPM}) \right) \tag{2.39}$$

2.2.3 Results from the *EVaTar-decisions* module

The *EVaTar-decisions* module allows for an evaluation of households' electricity retail tariff choices and their decisions to invest in a HEMS. With this, the influence of dynamic electricity price components in form of DETs and GCDs on flexibility utilization (Subquestions I.2 and I.3) can be assessed more comprehensively, as it adds to a purely economic-driven assessment and includes household heterogeneity. Additionally, the decisions of each household obtained from the module and the according load and generation profiles from the *EVaTar-building* module can be used to determine the input data for the *EVaTar-grid* and *EVaTar-gridex* modules, assessing which dynamic electricity price components enable efficient grid use (Research question II) in a more comprehensive and novel way. The *EVaTar-grid* and *EVaTar-gridex* modules are described in the following.

2.3 Grid impact (*EVaTar-grid*)

The *EVaTar-grid* module is developed to comprehensively analyze the impact of dynamic electricity price components on low-voltage grids. This analysis entails evaluating grid conditions and identifying any potential grid restriction violations. It incorporates household heterogeneity and decision-making behavior, which are crucial for understanding the impact of DETs on low-voltage grids (Subquestion II.1). The subsequent sections detail the modeling requirements, explain the implementation, and describe the results obtainable from the module.

2.3.1 Modeling requirements regarding the grid impact assessment of residential flexibility

To effectively analyze the impact of dynamic electricity price components on low-voltage grids, comprehensive power flow calculations are necessary. These calculations help evaluate grid conditions and establish whether grid restrictions are violated. Essential input data include household load and generation profiles, the requirements of which were already discussed in Section 2.1.1 when looking at the *EVaTar-building* module. The seamless integration of results from the two preceding modules needs to be ensured. Additionally, detailed electrical models incorporating all relevant parameters required to conduct power flow calculations of low-voltage grids are needed.

Given the heterogeneity of low-voltage grids, it is necessary to analyze a variety of grid structures to allow for better generalizability of the results and draw conclusions applicable for an entire region or country. The scarcity of openly available data on real low-voltage grids poses a challenge, which is mitigated by using representative grid models derived from actual grid data. These models are classified based on geographic aspects, urbanization characteristics, or electrical parameters [125]. Representative grids further allow to account for heterogeneity while keeping the number of low-voltage grids for analyses low. Publications II to IV specifically focus on single- and two-family houses (SFHs) for flexibility utilization until 2035. Within these buildings, households can more easily navigate and implement necessary changes. Unlike multi-family houses (MFHs), which often face regulatory hurdles, SFHs have greater autonomy and the space needed for installations like EV charging stations or heat storage. SFHs, primarily located in rural and suburban areas, are expected to adopt flexible technologies more rapidly because of fewer regulatory constraints and better adaptability [11]. Representative grids reflecting these urbanization characteristics are required to address the research questions adequately.

2.3.2 Implementation of the *EVaTar-grid* module

Power flow calculations are critical for evaluating grid stability and identifying grid restriction violations in low-voltage grids. The choice of tool for these calculations is influenced by the need for an open-source solution implemented in Python. Therefore, the widely recognized pandapower tool is incorporated [126, 127]. Pandapower is designed for the automated static and quasi-static analysis and optimization of balanced power systems [126] and allows for convenient integration of the load and generation profiles from the *EVaTar-building* module. It offers a range of electrical components in its standard-type library, but other components are also easily included. With a broad selection of low-voltage grid models already formatted for pandapower, it meets the requirements to effectively address the research questions.

Various representative low-voltage grids are used in the publications. In Publication I, a suburban grid based on [128] is used for the analysis because studies show that users of EVs or those interested in buying one tend to live in small towns or rural surroundings [129, 130, 131]. For the same reason, another suburban grid, the „Vorstadt Kabel 1“ grid from Ref. [132] forms the basis for the analysis in Publication II. In Publication IV, a broader analysis is conducted, and all low-voltage grids from the SimBench dataset [133, 134] are analyzed, which includes three urban, two suburban, and one urban grid. More information on the analyzed low-voltage grids can be found in the corresponding publications.

The distribution of households and their flexible assets can significantly impact grid load. Therefore, households are randomly assigned to grid connection points in each low-voltage grid. This randomization is repeated across multiple iterations for robust results. While this method helps in minimizing biases and ensuring diverse configurations, it inherently excludes neighborhood effects – interactions that could occur when households influence each other's investment decisions regarding flexible technologies due to spatial or social proximity. However, for scenarios targeting 2035, such effects are expected to become less critical, as the widespread adoption of technologies such as EVs and HPs likely leads to a more uniform distribution of energy demand and flexibility across residential areas. Due to the high number of power flow analyses when different representative low-voltage grids and multiple iterations are analyzed, parallelization is implemented for the individual processes.

2.3.3 Results from the *EVaTar-grid* module

Results from the power flow calculations are analyzed regarding grid utilization and violations of grid restrictions. This includes both the extent and duration of grid restriction violations such as voltage band violations and thermal overloads of transformers and lines. Additionally, the impact of household flexibility utilization on higher grid levels is assessed, providing comprehensive data to analyze the effectiveness of dynamic electricity price components and residential flexibility in managing grid impacts (Subquestion II.1).

2.4 Grid reinforcement (*EVaTar-gridex*)

The *EVaTar-gridex* module, introduced in Publication IV, is implemented to analyze the effectiveness of different GCDs in reducing grid reinforcement needs while accounting for household heterogeneity and decision-making behavior (Subquestion II.2). This module goes beyond analyzing grid utilization and violations of grid restrictions by also determining grid reinforcement requirements and estimating associated grid investments. The subsequent sections specify the modeling requirements, discuss the chosen methodological approach, and provide insights into obtainable results.

2.4.1 Modeling requirements for determining grid reinforcement needs and costs

Grid restrictions are in place with the intention of maintaining grid stability, operational efficiency and protecting grid equipment and end users. Grid reinforcement needs occur when grid restrictions are violated. In low-voltage grids, these include thermal overloads of transformers and lines or voltage band violations. While real-world grid planning varies by specific low-voltage grid and the responsible DSO, the model-based analysis of these needs requires automation due to multiple iterations and various considered low-voltage grids (refer to Section 2.3). A trade-off is required, allowing for reasonable computation times while reflecting real-world grid planning processes accurately. Adaptability and broad applicability are essential to account for the heterogeneity of low-voltage grids and varying grid planning approaches by DSOs. Parallelization is necessary to reduce computation times.

For input data requirements such as load and generation profiles or electrical models of low-voltage grids, please refer to Sections 2.1.1 and 2.3.1.

2.4.2 Implementation of the *EVaTar-gridex* module

In the domain of distribution grid reinforcement planning, various methodological approaches are documented in the literature [135]. Prominent methods include mathematical formulations such as mixed-integer linear programming [136], non-linear programming [137], dynamic programming [138], and second-order cone programming [139]. These approaches aim to identify the global optimum for grid reinforcement problems. However, the intrinsic non-linear and non-convex nature of these problems – largely due to grid losses and the radial configuration of low-voltage grids – necessitates simplifications in constraints, reductions in solution spaces, or linearizations, complicating the models and reducing their adaptability to evolving conditions [135, 140]. Given the complexities involved, heuristic and meta-heuristic methods such as genetic algorithms [141], particle swarm optimization [142], and tabu search [143] are frequently used. These methods excel in handling complex problems to find near-optimal solutions efficiently, suitable for expansive solution spaces that are challenging for mathematical models. However, these meta-heuristics can be computationally demanding [140].

Given the array of methodological choices, a heuristic optimization approach is selected for the *EVaTar-gridex* module. This decision is driven by the heuristic method's alignment with the practical demands of grid planning, striking an optimal balance between computational efficiency and analytical precision. This method allows for quick adjustments and seamless integration of new grid optimization or reinforcement strategies. It is based on established grid reinforcement algorithms documented in Refs. [16, 144] and refined in consultation with DSOs to reflect current strategies in low-voltage grid planning.

A flow chart outlining the algorithm is presented in Figure 2.4. Initially, a power flow calculation is performed for the considered grid. If thermal overloads or voltage band violations are identified, the grid reinforcement algorithm is initiated. Violations of grid restrictions are addressed in the following order:

1. Thermal overload of a transformer
2. Voltage band violations
3. Thermal overload of cables and overhead lines

A standard type library for transformers and cables/overhead lines is defined beforehand, including the permissible equipment for the given low-voltage grid. The individual parts are explained below.

Thermal overload of a transformer

The transformer loading, representing the thermal load, is defined as the ratio of the flow current to the rated current of the transformer. Higher transformer loading leads to higher resistive losses. It is therefore kept within a permissible range for operational efficiency and to prevent damage or premature ageing effects on operating equipment. The transformer loading threshold at which a thermal overload occurs can be adjusted to align with the specific scenario being analyzed. As an example, this threshold is set at 100% in Publication IV. If a thermal overload of a transformer is detected, the existing transformer is replaced with one of the next higher apparent power from the standard type library, which also has a higher rated current. Subsequent power flow calculations are then performed to verify if the overload has been effectively resolved. If the overload persists, the process of replacing the transformer with the next higher capacity model from the standard type library continues. This step is repeated until the overload is either resolved or the highest capacity transformer available in the library has been reached without resolving the overload. In the latter case, an additional transformer of the same type is installed in parallel, as detailed in Figure 8.2a in Publication IV.

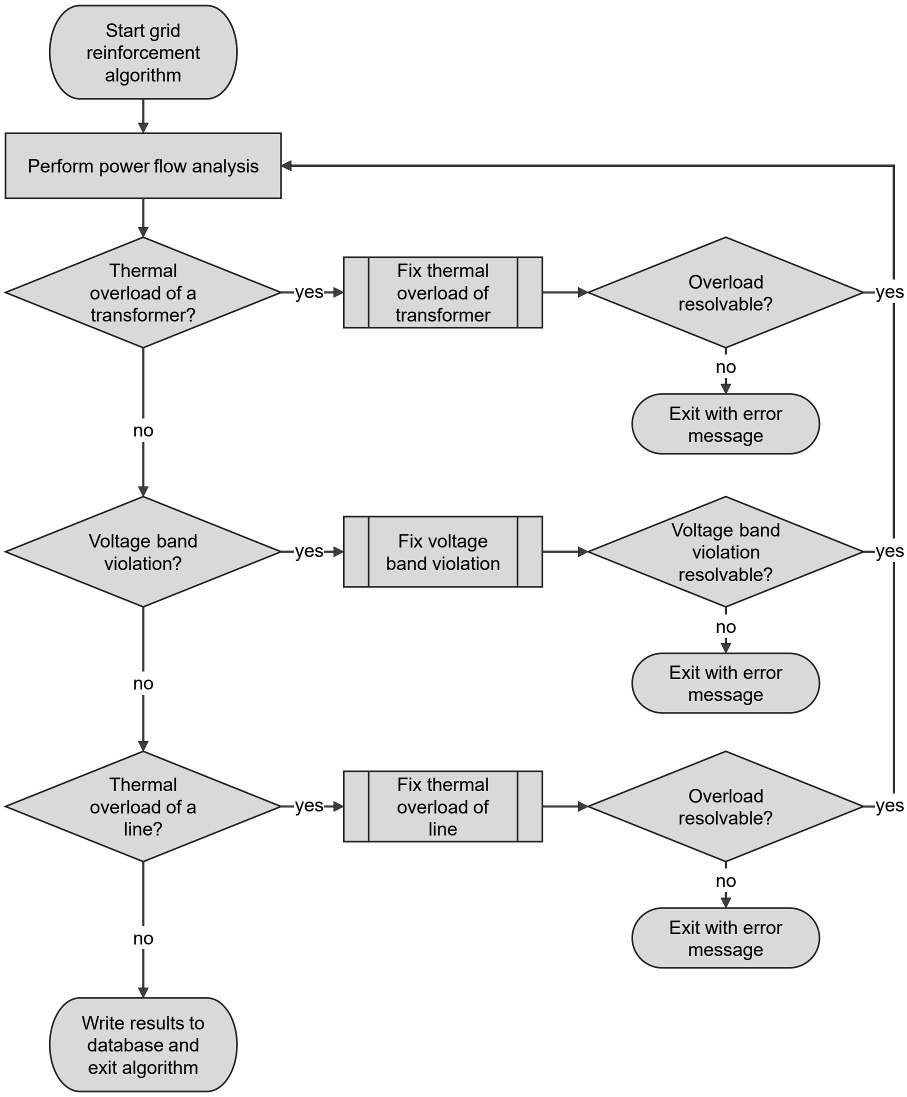

Figure 2.4: Simplified flow chart of the grid reinforcement algorithm within the *EVaTar-gridex* module.

Voltage band violation

The requirements for the voltage in low-voltage grids in Germany are defined in DIN EN 50160 [72]. The permissible voltage band range is defined jointly for the MV and low-voltage network levels. The quantitative allocation to the individual grid levels is carried out individually by the DSOs. In the module, the permissible voltage band for the low-voltage grid is adjustable based on the specific scenario under consideration. For instance, in Publication IV, it is set to $\pm 5\%$. If the voltage exceeds or drops below this predefined band, a feeder separation strategy is implemented. This involves dividing the grid feeder into two separate ones at approximately two-thirds of the distance from the violating grid node to the transformer. This results in a reduction of the power flow through the longitudinal impedance of the lines, thereby reducing the voltage drop. In grids with multiple transformers, the transformer closest to the node of violation is selected, or in case different grid zones are defined, the transformer in the relevant zone is chosen (see Figure 8.2b in Publication IV). Following this separation, power flow calculations are carried out to determine if the voltage band violation has been resolved. If the violation persists, further feeder separations are performed. This iterative process continues until the violation is fully resolved.

Thermal overload of a line

The line loading, indicative of the thermal load, is defined as the ratio between the current flowing through the line and the line's rated current. As with transformer loading, increased line loading results in greater resistive losses. Maintaining loading within an acceptable range is crucial for operational efficiency and to avoid damage or premature aging of the equipment. The maximum permissible line loading is customizable based on the scenario under consideration. For instance, in Publication IV, it is set at 100%. Initially, in the event of a thermal overload on a line, a parallel line of the same type is constructed. The distribution of the load and the current flowing through each individual line serves to decrease line loading. As DSOs are moving away from using copper cables, this step is omitted if the overload occurs on a copper cable. If the subsequent power flow analysis shows that the overload remains unresolved even with the addition of a parallel line, then either the parallel lines or the copper cable are replaced with a line of a higher cross-section, which has a higher rated current (see Figure 8.2c in Publication IV). As revealed through discussions with DSOs, typically, NAYY-J 4x150 mm^2 (or NAYY-J 4x240 mm^2) cables are used for these replacements. This replacement process is repeated iteratively until the overload issue is fully resolved.

If all violations of the grid restrictions have been successfully resolved, the process is successfully completed. In the rare case that no solution is achieved, the algorithm terminates and an error message is issued.

2.4.3 Results from the *EVaTar-gridex* module

When the grid reinforcement algorithm is completed successfully, a comprehensive list of the implemented grid reinforcement measures and their associated costs is stored into a PostgreSQL database, along with the results from both the original grid setup's power flow and the power flow incorporating all grid reinforcement measures. Specifically, transformer-related expenditures are categorized into two main areas: the cost of the transformer itself and the investment in the MV/LV local substation. For line construction incurred by resolving voltage band violations or thermal overloads, various cost components are considered, including the cost of materials, labor expenses, external services, and additional overhead surcharges. The proportion of in-house labor differs among DSOs, leading to the consideration of an average total construction cost for cables or overhead lines. Cost assumptions derived from discussions with DSOs can be found in Section 8.3.6 in Publication IV. The individual measures and their costs are aggregated for each low-voltage grid, enabling a detailed comparison of grid reinforcement needs and associated expenses across various scenarios and grids. This analysis is crucial for assessing the impacts of different DETs and GCDs (Subquestion II.2).

3 Key findings and methodological achievements

This section entails a summary of the key findings of the dissertation based on the results presented in Publications I to IV (Section 3.1), and a brief compilation of the methodological achievements of the dissertation (Section 3.2), addressing both the content and methodological delta elaborated in Section 1.

3.1 Key findings

This section summarizes the key findings of the dissertation as addressed across Publications I to IV, based on the initial research questions outlined in Section 1.2. Each finding correlates to in-depth analyses which are detailed in the respective journal publications referenced from Sections 5 to 8.

3.1.1 Research question I: From a user perspective – What is the influence of dynamic electricity price components on flexibility utilization considering the heterogeneity of residential consumers?

This fundamental research question focuses on the residential consumer perspective and is addressed in all four journal publications. The findings reveal that dynamic electricity price components significantly affect flexibility utilization, contigent on several variables such as available flexible technologies, additional costs of enabling technologies, and household decision-making behavior. Three specific subquestions are considered to get a comprehensive view.

3.1.1.1 Subquestion I.1: Focusing on electric vehicles – What impact will flexible EV charging have on future household electricity prices?

To address this subquestion, Publication I investigates the economic implications of flexible EV charging on future household electricity prices, considering both the price component for electricity procurement and retail and grid charges. The comprehensive analysis utilizes four distinct models. The ALADIN model [28, 145, 146] is used initially to forecast EV diffusion and charging behavior in 2030 across various charging powers (3.7 kW, 11 kW, and 22 kW). The eLOAD model [147, 148] projects the system load for 2030 and examines the impact of controlled EV charging. The MiPU model [149] determines changes in power plant dispatch and the average volume-weighted marginal electricity generation costs, constituting the electricity cost components for electricity procurement and retail. Finally, the FLEX-GOLD model [128] analyzes low-voltage grid loads to estimate grid investments and changes in specific grid charges.

The publication examines the considered charging powers for uncontrolled and controlled charging at the system level. Controlled charging includes a price signal that reflects the system's residual load. The low-voltage grid analysis considers various local EV penetration rates (share of households with an EV in the low-voltage grid) ranging from 5% to 30%.

On the system level, with a fixed generation park, additional electricity demand from EVs increases the deployment of power plants with higher marginal costs (gas, coal, lignite). Hence, the average volume-weighted marginal electricity generation costs increase up to 6.1% with uncontrolled charging (refer to Table 5.1, Publication I). Controlled charging mitigates this increase by 2.3 percentage points due to better utilization of cheaper electricity from renewable sources.

On the infrastructure side, the additional electricity demand of EVs raises overall grid utilization, which can reduce specific grid charges. Grid investments are largely passed on to end users via grid charges. Specific grid charges are determined by the total amount of energy distributed in a grid area. Therefore, higher EV penetration rates – and thus higher electricity demand – within the low-voltage grid result in more significant reductions of specific grid charges. With grid reinforcement needs being avoided through controlled EV charging, specific grid charges decrease for all EV penetration rates and charging powers (refer to Figure 5.10, Publication I). This decrease in specific grid charges outweighs the increase in electricity generation costs, resulting in an overall household electricity price reduction of up to 3.7% (refer to Figure 5.11, Publication I). In the case of uncontrolled charging, grid reinforcement measures are required for charging powers above 3.7 kW, as the maximum power drawn from the grid increases. The associated grid investments have a cost-increasing effect on specific grid charges. However, the cost-decreasing effects of the increased grid utilization mentioned above offset the cost-increasing effect for EV penetration rates above 5%. Therefore, an overall electricity price reduction of up to 2.5% can be seen for uncontrolled charging when grid reinforcement is necessary (refer to Figure 5.11, Publication I).

In response to Subquestion I.1, applying controlled charging by aligning EV charging times with low-cost electricity supply periods not only mitigates the increase in generation costs but also leads to overall reductions in household electricity prices in 2030 by optimizing grid investments and utilization (refer to Figures 5.10 and 5.11, Publication I). Uncontrolled charging, while requiring some grid reinforcement for higher EV charging powers, still shows potential for reducing overall electricity costs.

3.1.1.2 Subquestion I.2: Under which conditions are dynamic electricity retail tariffs the most economic option for residential consumers, and how do these conditions affect household decisions?

Publications II to IV offer a thorough analysis of the conditions under which DETs are the most economical choice for residential consumers. This analysis also explores how these conditions influence household decisions, leveraging insights from the *EVaTar-building* and *EVaTar-decisions* modules. Before key findings regarding Subquestion I.2 are presented, the differences in scenarios and assumptions made within the three publications are described to enable a better understanding of the results.

Differences in the scenarios and assumptions made in the three Publications

Publication II focuses on market-available DETs, considering standing charges and metering point operation costs. In addition to a static tariff, DETs examined include a 3-tier ToU tariff and a DA-RTP tariff[1]. The tariffs under consideration exhibit different annual average values. The DA-RTP tariff has the lowest average value, followed by the ToU tariff. The static tariff exhibits the highest average value. Publication III explores three distinct electricity price scenarios under a DA-RTP tariff, reflecting market dynamics during the 2022/2023 energy crisis as an example of higher price levels and price spreads. Publication IV considers a static, a 3-tier ToU, and a DA-RTP tariff, all set to the same average value. Key parameters of the tariffs considered within Publications II to IV are summarized in Table 3.1.

All three publications consider a HEMS investment (including installation) of €1,500[2], which translates to a 167 €/year annuity with an assumed lifetime of 10 years and an interest rate of 2%. Publications II and III assume that metering point operation costs for a smart meter only occur upon adopting a DET. By contrast, Publication IV assumes that all households are already equipped with a smart meter in 2035, independent of their tariff choice. Therefore, metering point operation costs occur for all households, regardless of their decision on flexibility utilization. For the assumed annual metering point operation costs and standing charges within the Publications, refer to Table 3.2.

In Publication III, the focus is on the economic effects on households using the *EVaTar-building* module. In Publications II and IV, the economic assessment is broadened by applying the *EVaTar-decisions* module, thereby including the decision-making behavior described in Section 2.2.

Publication No.	Scenario	Mean value	Min. value	Max. value	Standard deviation	PV feed-in remuneration
		in €ct/kWh	in €ct/kWh	in €ct/kWh	in €ct/kWh	in €ct/kWh
II	static	29.87	29.87	29.87	0.00	8.56
	ToU	27.81	25.09	29.60	2.11	8.56
	DA-RTP	26.80	11.60	36.77	1.85	8.56
III	DA-RTP, low	22.60	7.40	32.60	1.80	3.62
	DA-RTP, medium	30.20	4.40	48.30	6.20	9.71
	DA-RTP, high	37.80	1.50	91.90	10.70	15.81
IV	static	32.27	32.27	32.27	0.00	8.20
	ToU	32.27	30.50	33.54	1.38	8.20
	DA-RTP	32.27	10.04	59.84	6.53	8.20

Table 3.1: Comparison of the electricity price scenarios within Publications II to IV [150, 69, 151].

Publication No.	Scenario	Standing charge in €/year	Metering point operation in €/year
II	static	141.84	–
	ToU	187.44	90.00
	DA-RTP	104.76	65.28
III	DA-RTP, low	57.60	90.00
	DA-RTP, medium	57.60	90.00
	DA-RTP, high	57.60	90.00
IV	static	58.00	60.00
	ToU	58.00	60.00
	DA-RTP	58.00	60.00

Table 3.2: Comparison of the metering point operation costs and standing charges within Publications II to IV [150, 69, 151].

1 For a description of the two tariff schemes, refer to Figure 6.1 in Publication II.
2 All costs within the analysis are given in $€_{2019}$.

Households' tariff choices across the publications and scenarios

Table 3.3 provides an overview of the households' tariff choices and decisions on flexibility utilization across the publications. The results from Publications II to IV consistently show significant financial benefits for households that utilize their flexibility under the DA-RTP tariff. In analyzing market-available electricity retail tariffs, average cost savings through the DA-RTP tariff range from 11.7% to 16.5%. This leads to more than 90% of households with flexible assets choosing this tariff (Publication II). In scenarios where electricity prices are rising and becoming more volatile, absolute cost savings increase. This allows households to more easily cover additional costs associated with investing in a HEMS and metering point operation. Consequently, the proportion of households benefiting from DA-RTP tariffs increases significantly from 3.9% to 62.5% compared to a low price scenario (Publication III). Different GCDs influence the attractiveness of DETs, with the share of households choosing a DA-RTP tariff in combination with utilizing their flexibility ranging from 52.0% to 64.2% (Publication IV).

Although ToU tariffs also offer cost savings, they are generally less beneficial than DA-RTP tariffs for households with flexible assets. However, up to 19.5% of households would choose a ToU tariff in combination with utilizing their flexibility under a critical peak pricing GCD. Interestingly, 10.9% of households not utilizing flexibility under a volumetric GCD find ToU tariffs most attractive, particularly due to their higher electricity consumption in off-peak hours (9 p.m to 6 a.m., Publication IV).

In a low price scenario, the financial benefits of utilizing DETs are diminished by the additional costs of metering point operation. As a result, a large share of 48% of households opt for a static tariff combined with a HEMS to enhance their self-consumption (Publication III).

	Flexible households			Inflexible households		
	Static	ToU	DA-RTP	Static	ToU	DA-RTP
Publication II						
Status quo scenario	0.0%	0.0%	4.8%	95.2%	x	x
Low 2035 scenario	0.0%	0.0%	35.6%	64.4%	x	x
Medium 2035 scenario	2.1%	0.0%	48.6%	49.3%	x	x
High 2035 scenario	4.8%	0.0%	63.0%	32.2%	x	x
Publication III						
Low price scenario	44.8%	x	3.5%	51.6%	x	x
Medium price scenario	26.1%	x	43.7%	30.2%	x	x
High price scenario	21.4%	x	56.3%	22.4%	x	x
Publication IV						
VOL GCD	1.0%	11.2%	55.0%	21.7%	10.9%	0.2%
CAP GCD	1.1%	8.9%	64.2%	16.8%	8.9%	0.2%
CAP-VOL GCD	1.1%	10.5%	62.3%	16.8%	9.1%	0.2%
CPP GCD	3.5%	19.5%	52.0%	19.3%	5.6%	0.2%

Table 3.3: Overview of the tariff choices of households in Publications II to IV [150, 69, 151]. Remarks: In Publications II and IV, the decision-making behavior is included, whereas in Publication III, it is not included; „x“ marks cases that are not applicable for the considered Publication; For Publication III, static tariff and flexible households refers to households choosing to increase their self-consumption; Inflexible households are defined as households without flexible technologies in Publication II, households not utilizing their flexibility in Publications III and IV.

The publications highlight three main factors that affect the economic feasibility of DETs for households and represent the research gaps identified in Section 1.2: the flexible technologies available in a household, the comparison of flexibility utilization under a DET with the case of increasing self-consumption, and the additional costs associated with flexibility utilization, including HEMS investment and metering point operation costs. The implications of all three factors are discussed in the following.

Impact of available technologies on flexibility usage and financial attractiveness of DETs

Publications II to IV provide critical insights into how different technologies impact the flexibility usage and economic benefits of DETs for residential consumers. The studies focus particularly on the interaction between technology availability, DETs like DA-RTP and ToU tariffs, and the associated cost savings.

The analysis shows that explicit flexibility utilization is crucial to avoid increased electricity costs with a DA-RTP tariff, as household electricity consumption (including flexible assets) correlates with high prices (Publication IV). Households with only a PV-BSS can bridge high electricity price periods even without explicit flexibility utilization and can therefore still benefit from the DA-RTP tariff. In contrast, under a ToU tariff, households with a HP can achieve savings without explicit flexibility utilization due to the higher heat demand in the evening hours in the off-peak period of the ToU tariff (refer to Figure 8.5, Publication IV).

Implementation of a HEMS allows for load to be shifted to periods with lower prices. Under the DA-RTP tariff, this leads to cost savings for all households except those solely with a HP. Under the ToU tariff, cost savings can be observed for all households except those solely with an EV. The ToU tariff generally offers higher benefits for households with a HP, also when a PV system or PV-BSS is included, as it exhibits longer low price periods from evening to early morning. With this, the flexibility of the heat storage tank can be used in the early morning hours to reduce electricity cost for the morning heat demand peak (Publication IV).

Households with an EV show significant cost-saving potential: Households with an EV exhibit significant potential for cost savings under DETs when combined with a HEMS. EV availability at the charging point typically aligns well with low electricity prices at night and EVs can shift their load over a longer period, enhancing the cost-saving potential. Achievable savings in variable electricity costs (combination of unit rate costs and feed-in remuneration) are highest under a DA-RTP tariff. In combination with a PV-BSS, annual variable electricity cost savings of up to 821%[3] are possible in a high price scenario (refer to Table 7.7, Publication III). Including additional costs such as standing charges, metering point operation costs, and the investment in a HEMS shows that potential cost savings remain substantial with 30.4% (Publication IV). The DA-RTP tariff is more advantageous for households with an EV and households with both an EV and a HP. Looking at average cost savings normalized to household electricity consumption, households with an EV (with and without further flexible technologies) can reach average savings between 3.3 €ct/kWh and 5.1 €ct/kWh (Publication II).

Households with a HP have lower cost savings potential: Households with a HP have inherently lower flexibility in shifting the load over a longer period, as heat demand is comparably steady over the course of the day and the heat storage has a lower capacity and higher standby losses than an EV battery. However, these household can still achieve notable savings, especially when combined with a PV-BSS. Under a DA-RTP, average variable electricity cost savings can go as high as 485% (refer to Table 7.7, Publication III). When additional costs are considered, savings go as high as 9.7% (Publication IV). Higher cost

[3] For households with a PV system or PV-BSS, relative cost savings can be notably high as variable electricity costs are relatively low in the no-flex case.

savings of up to 13.1% is seen in households with a HP and a PV system under a ToU tariff by utilizing self-generated electricity from the PV system during daytime and charging the heat storage tank in the early morning hours during the off-peak period to meet the heat demand in the morning hours before PV generation is available. Average cost savings normalized to the electricity consumption of households with a HP are in the range from 4.7 €ct/kWh to 4.9 €ct/kWh, varying with the penetration of flexible technologies (refer to Figure 6.8, Publication II). It is important to note that the group of households with a HP in this publication includes all technology combinations where a HP is present. More precisely, within this group, between 28.6% and 98.6% of households also have an EV. The overall flexibility potential is highest when all considered flexible technologies are available, resulting in higher average cost savings for scenarios with a larger proportion of households with a HP also having an EV and a PV-BSS.

Households with both an EV and a HP offer more flexibility: When both an EV and a HP are present in a household, the savings potential increases due to the combined flexibility potential. Households with an EV, a HP, and a PV system exhibit highest absolute savings under a DA-RTP tariff with average savings in variable electricity cost of up to €879 (72%) in a high price scenario (Publication III). Including additional costs, cost savings for the same technology combination are around 21.6% under a DA-RTP tariff scheme and around 18.1% under the ToU tariff scheme (Publication IV).

Households with a PV-system or PV-BSS increase cost savings for EVs and HPs: Households equipped solely with a PV-BSS do not benefit from flexibility utilization through DETs, as these households exhibit lower unit rate costs due to higher self-consumption rates and, therefore cost savings do not offset the HEMS investment (Publication IV). However, the presence of a PV system or a PV-BSS significantly increases the economic benefits for all households with other flexible technologies (Publications II to IV). This stems from low-cost electricity generated by the PV system and additional flexibility potential form the BSS.

Considering the addressed research gap, focusing on the impact of available technologies on the flexibility usage and financial attractiveness of DETs for residential consumers, the findings show that the presence of an EV, a HP, and a PV-BSS, along with implementing a HEMS, significantly affects the cost-effectiveness of dynamic versus static electricity retail tariffs. This observation highlights the importance of the strategic offering of HEMSs which integrate multiple flexible technologies within a household.

Analysis of the potential additional benefits of DETs when compared to self-consumption optimization through HEMS in households with PV systems and differences in flexibility usage

Publication III thoroughly investigates the financial advantages of DETs over pure self-consumption optimization through a HEMS in households equipped with a PV system or PV-BSS. It assesses how flexibility usage varies between these two operational strategies – self-consumption optimization (SC-flex) and dynamic tariff optimization (DT-flex).

Differences in flexibility utilization: Figure 7.5 and Table 7.5 in Publication III give an overview of the differences between the SC-flex (self-consumption) and the DT-flex (dynamic tariff) cases. For households with an EV and a PV system or PV-BSS, the SC-flex case exhibits a shift of load from evening to morning. The EV is charged right before departure, minimizing standing losses and self-generated electricity is used during daytime. In contrast, in the DT-flex case, the EV is mostly charged during night and early morning when electricity prices are lowest. For households with a HP, both the SC-flex and DT-flex cases exhibit a shift of load to utilize PV generation when available. The main difference in flexibility utilization lies in the timing of load shifts: in the SC-flex case, consumption is shifted from morning and late evening hours mainly to evening hours, while in the DT-flex case, load is shifted to early morning hours. The HP follows the electricity price, but the effect is smaller than with an EV, as storage capacity is limited. For households with solely a HP, load from the HP gets shifted to early morning hours in the DT-flex case due to lower electricity prices and to early afternoon due to higher efficiency (higher COP with higher outside temperature). Households with both an EV and a HP show combined effects. The effects for EVs predominate, as EV charging powers are, on average, higher than the power drawn by the HP.

Self-consumption rates: Flexibility utilization can enhance the efficiency of HP operation by shifting load to times with a higher COP. This can lead to a reduction in electricity consumption in households with solely a HP by up to 10.9% in the DT-flex case. With a PV system present, self-consumption rates increase when flexibility is utilized. Using a DA-RTP tariff in the DT-flex case generally shows lower self-consumption rates compared to the SC-flex case from solely maximizing self-consumption to also exploiting low electricity prices. When comparing available technologies individually, households with an EV exhibit higher self-consumption rates than those with a HP, as the EV is used throughout the year while the HP is only used during the heating period. The highest average self-consumption rate over all households occurs in households equipped with an EV, a HP, and a PV-BSS, reaching up to 62.1%. While self-consumption rates in a low price scenario are quite similar between the SC-flex and the DT-flex cases, the self-consumption rate in the DT-flex case decreases with higher electricity price scenarios as price incentives increase (refer to Figure 7.6, Publication III). In these scenarios, electricity prices occasionally drop below the feed-in remuneration, prompting a shift in flexibility utilization. Households shift their load to periods with lower electricity prices rather than using periods of high self-generation, opting instead to feed self-generated electricity back into the grid.

Cost savings in variable electricity costs: In the SC-flex case, no change in self-consumption rates can be observed between electricity price scenarios. However, due to the change in the ratio between the static tariff and the feed-in remuneration, changes in variable electricity cost savings occur (see Section 7.2.1.2 in Publication III for more details on the methodology). Households with an EV can realize greater cost savings in both the SC-flex and DT-flex cases in low and medium price scenarios due to achieving better alignment of charging with PV generation and low tariff periods when flexibility is utilized. Households with a HP and a PV system achieve greater financial gains in a high price scenario in the SC-flex case. However, for all other technology combinations in a high price scenario, the DT-flex case generally leads to greater variable electricity cost savings than the SC-flex case (refer to Table 7.7, Publication III). Notably, for households equipped with an EV and a PV-BSS, cost savings in the DT-flex case are more than twice as high compared to the SC-flex case.

Including additional costs in financial evaluation: When additional costs are considered (HEMS, metering point operation, standing charges), optimizing self-consumption without using a DET is more financially viable for households with a HP and a PV system or PV-BSS. This is because additional variable electricity cost savings through using a DET do not offset the additional costs for metering point operation (Publication III). Conversely, a large share of households with an EV (85.4%) can offset additional costs and gain greater benefits from using a DET, especially when combined with a PV system or PV-BSS, which enhances flexibility potential. This effect can also be seen for households with both a HP and an EV.

Addressing the research gap, the decision between DETs and self-consumption optimization depends to a large part on the specific technological setup of a household, prevailing electricity price scenarios, and the costs associated with implementing flexibility solutions like HEMS. DETs offer substantial potential savings for households capable of adjusting consumption to price signals, particularly those with an EV and a PV system. However, optimizing self-consumption remains a viable strategy for households with a HP due to additional cost savings when using a DET not compensating for metering point operation costs.

Analysis of the conditions under which savings gained through DETs and HEMS offset additional costs associated with metering point operation and HEMS

This crucial aspect is thoroughly examined in Publications II and III. Market-available DETs can lead to substantial cost savings for households utilizing flexibility in combination with DETs. These savings are partly facilitated by lower average electricity prices of DETs compared to static tariffs, providing a beneficial offset against the costs associated with HEMS and metering point operation (Publication II). The range of potenital savings ranges between 3.5 €ct/kWh and 4.9 €ct/kWh (refer to Figure 6.8, Publication II). However, households with low overall electricity consumption, typically in the adopter category of Late Majority, do not achieve sufficient benefits from flexibility utilization to decide to utilize their flexibility. This is attributable to their inherent low electricity costs and a low WTPM. DETs become particularly appealing in high price scenarios where absolute cost savings for households increase, thus likely offsetting additional costs (Publication III). 85.4% of households would profit from DETs even when considering additional costs in a high price scenario. As mentioned before, in the medium and high price scenario of Publication III, for households with a HP and a PV system additional cost savings through a DET do not offset the added costs for metering point operation, making optimizing self-consumption financially more beneficial. In case smart meters become obligatory for all households, the financial incentive of DETs for households with a HP could improve. For households with an EV and a HP in the same electricity price scenarios, 93.7% and 99.4%, respectively, would still achieve cost savings from DETs when additional costs are included.

In a further analysis, the maximum tolerable costs for HEMS and metering point operation are analyzed (Publication III). They are defined in a way that 75% of households would still profit from utilizing their flexibility. Both the SC-flex and DT-flex cases are analyzed separately. With the DA-RTP tariff used in the DT-flex case, households with an EV set the maximum tolerable costs at around €50 per year in the low price scenario. In the medium and high price scenarios, as absolute cost savings increase, households with a HP set the maximum tolerable costs at €97 and €111, respectively. In the SC-flex case, households with a HP show higher absolute cost savings, therefore households with an EV and a PV-BSS set the maximum tolerable costs in all electricity price scenarios. These range between €126 and €145 per year. For a more detailed analysis, refer to Table 7.8 in Publication III.

In addressing the research gap, it becomes apparent that for cost savings from DETs and HEMS to offset additional costs associated with metering point operation and HEMS investment, there are two critical levers: the average value and price spreads of the electricity price influencing potential cost savings and the height of additional costs. Importantly, the maximum tolerable costs vary depending on the technology combination, allowing HEMS providers to tailor their pricing strategies accordingly. In contrast, the limit for metering point operation costs is currently set at a uniform level depending on the annual electricity consumption, leaving less room for maneuver.

3.1.1.3 Subquestion I.3: How do different grid charge designs influence households' tariff choices and decisions to invest in a HEMS?

Additionally to examining potential cost savings for households through DETs within the existing GCD in Germany, it is crucial to explore how alternative GCDs influence households' choices of electricity tariffs and decisions to utilize flexibility via a HEMS. This research is essential for understanding the interplay of GCDs and DETs in facilitating flexibility utilization. It is addressed in Publication IV with results obtained from the *EVaTar-building* and *EVaTar-decisions* modules. Within the publication, four widely discussed grid tariff structures from the literature are considered:

1. VOL: a volumetric grid charge design, representing the status quo in Germany
2. CAP: a grid charge design with monthly capacity subscription
3. CAP-VOL: a hybrid GCD with a volumetric part and a capacity subscription part
4. CPP: a critical peak price GCD with a volumetric base price and a volumetric price for peak hours

The parameters of each GCD are configured in a manner that ensures that the DSOs revenues from grid charges remain consistent across all GCDs. For further details on the GCDs considered, please refer to Sections 8.2.4 and 8.3.4 in Publication IV.

Households with an EV or a HP face significant increases in grid charges under the capacity-based GCDs (CAP and CAP-VOL) if flexibility is not explicitly utilized, primarily due to their high power demands. The introduction of a HEMS can mitigate increased grid charges by managing the maximum power draw, independent of the electricity tariff chosen. Households with a PV system or a PV-BSS benefit from unit rate prices occasionally falling below the feed-in remuneration under the CAP or CAP-VOL GCDs, which changes how flexibility is utilized, i.e., self-generated electricity from the PV system is supplied to the grid instead of being used within a household and EV charging is shifted to periods with lower electricity prices. The VOL GCD, currently in place in Germany, exhibits the lowest incentive for utilizing flexibility, with 67.2% of households investing in a HEMS. This adoption rate increases under the CAP and CAP-VOL GCDs, reaching 74.1% and 73.8%, respectively. The highest share of households investing in a HEMS can be seen under the CPP GCD with 74.9%. However, the CPP GCD shows the least compatibility with the DA-RTP tariff due to price signal conflicts. Households show a higher preference for the ToU tariff under the CPP GCD (19.5%), as the ToU tariff exhibits consecutive hours with the same price level, allowing for easier circumvention of peak hours of grid charges. Additionally, a share of 3.5% of households chooses exclusively to optimize their self-consumption and grid charges in conjunction with a static tariff. Households utilizing their flexibility demonstrate higher engagement with the DA-RTP tariff under the capacity-based GCDs (CAP and CAP-VOL), with adoption rates of 64.2% and 62.3%, respectively. These GCDs have a capacity-based price component which lessens price conflicts with volumetric electricity retail tariffs.

Under all GCDs considered, a certain share of households opts for a DET without explicitly utilizing flexibility. This share is highest under the VOL GCD, with 11.1%. The most attractive tariff in this case is the ToU tariff, chosen by 10.9% of households, as especially households with a HP profit from off-peak periods.

In response to Subquestion I.3, results show that capacity-based GCDs substantially increase the incentive for households to utilize flexibility through DETs by up to 7.7 percentage points. This increase can potentially enhance Germany's overall flexibility potential by a considerable amount[4].

One key observation is that the GCD influences the decision to utilize flexibility through a HEMS. However, once this decision is made, the tariff choice of a household has little impact on the annual grid charges paid. This finding implies better planning security for DSOs.

3.1.2 Research question II: From a distribution grid perspective – Which dynamic electricity price components enable efficient grid use, considering residential consumers' tariff choices and HEMS investment decisions?

Shifting focus from individual households to the distribution grid level, dynamic electricity price components are seen as a key instrument in incentivizing efficient grid use. Therefore, this research question explores two main aspects. The first aspect, considered in Subquestion II.1, is the impact of DETs on low-voltage grid utilization and grid reinforcement requirements. The second aspect, covered by Subquestion II.2, is the influence of various grid charge designs on grid reinforcement needs. For both subquestions, the analysis incorporates consumers' tariff choices and the decision to invest in a HEMS and utilize flexibility. The aspects are evaluated by using all four modules of the *EVaTar* model, ensuring a comprehensive evaluation.

3.1.2.1 Subquestion II.1: What is the impact of dynamic electricity retail tariffs on distribution grids, considering electricity tariff choices and HEMS investment decisions of residential consumers?

This subquestion is addressed through findings from Publications I and II, focusing on the effects of DETs on the grid load of individual households and the cumulative impact within predefined low-voltage grids.

Grid load of individual households

Publication II quantitatively analyzes the change in various parameters between households not explicitly utilizing their flexibility and those that invest in a HEMS and opt for DETs (refer to Figure 6.7, Publication II). Key parameters analyzed include maximum feed-in power, maximum power withdrawn from the grid, and load variability, obtained from the *EVaTar-building* module.

No substantial changes in the maximum feed-in power are observed. Notably, households utilizing a HEMS and opting for a DET exhibit an 11% increase in maximum power withdrawn from the grid

[4] Considering the high penetration rates considered within Publication IV: with an assumed flexibility potential of 11 kW per household, a 12 GW difference in overall flexibility potential in Germany in 2035 would arise (1,104,000 SFHs difference between VOL and CAP, 11 kW per SFH).

under the ToU tariff and approximately 15% under the DA-RTP tariff. The greater increase for the DA-RTP tariff stems from the electricity price profile having individual hours with low electricity prices, whereas in the ToU tariff case, several consecutive hours exhibit the same price level. Among household technology groups, the increase is more pronounced in households with a HP (with and without further flexible technologies), with a 17% increase in the ToU tariff case and a 20% increase in the DA-RTP tariff case. This is due to the higher power demand, as within this household group 98.6% of households also have an EV. Additionally, variability in load profiles, indicative of load continuity, increases up to 27% in these households, highlighting the significant shifts in electricity consumption driven by DETs. PV-BSSs can use cheaper electricity from the PV system in a time-delayed manner, reducing the energy withdrawn from the grid during peak hours. Therefore, for households with a PV-BSS, the increase in variability is substantially lower, at around 9% for the ToU tariff and 11% for the DA-RTP tariff.

Cumulative effects on low-voltage grids

Publication I applies the FLEX-GOLD model [128] to analyze the impact of various EV penetration rates on grid utilization and infrastructure requirements. The study contrasts scenarios of uncontrolled versus controlled EV charging. Results demonstrate that controlled charging under a DET based on the residual load of the system can significantly mitigate the need for grid reinforcement at higher charging powers of 11kW and 22kW. This effect can be observed for all penetration rates considered. The charging processes of EVs are mostly shifted from evening hours, where inflexible household demand is high, to early morning hours, where inflexible demand is lower, therefore achieving a reduction in grid load. Additionally, higher grid utilization is achieved, as the overall electricity consumption with the considered low-voltage grid increases with the diffusion of EVs.

Further analysis in Publication II examines how consumer electricity tariff choices and the decision to invest in a HEMS influence grid performance in a rural low-voltage grid. The study compares a scenario with a static tariff for all households to one where the free choice of tariff is considered. The analysis is conducted for a status quo diffusion scenario and three future technology diffusion scenarios set in 2035. The scenario considering the free choice of tariff and investment decisions in HEMSs exhibits mixing effects in the cumulative load curves of all households when households employ different electricity tariffs and operational strategies for flexibility utilization. Findings from the *EVaTar-grid* module show that while load-side flexibility only minimally affects maximum positive voltage deviations driven by PV generation, it substantially improves load-driven voltage drops. This effect is more pronounced in scenarios with widespread technology adoption, as the aforementioned mixing-effects increase. Simultaneously, the number of hours with voltage band violations increases when households can choose their tariff, suggesting improved grid utilization once the grid is reinforced. Additionally, enhancements are observed in the thermal load of lines and the transformer. The maximum active power drawn from the higher grid level can be reduced substantially (by up to 11% in the medium diffusion scenario). This reduction can positively impact the higher grid level and, with the current GCD in Germany, can reduce grid charges within the low-voltage grid due to lower upstream grid charges.

In response to Subquestion II.1, residential flexibility, when responding to DETs, can positively impact load-dominated low-voltage grids. The heterogeneity in consumer behavior, particularly in tariff choices and HEMS investment decisions, introduces beneficial mixing effects regarding the coincidental occurrence of peak loads of individual households.

3.1.2.2 Subquestion II.2: Which grid charge designs are effective in enhancing grid utilization and reducing grid reinforcement needs, considering residential consumers' tariff choices and HEMS investment decisions?

Publication IV examines the impact of various grid charge designs (presented in Section 3.1.1.3) on grid reinforcement requirements and costs. Applying the *EVaTar-gridex* module alongside all other *EVaTar* modules, the study evaluates the impacts across six diverse low-voltage grids: one urban, two suburban, and three rural, reflecting a broad spectrum of grid scenarios. Capacity-based GCDs (CAP and CAP-VOL) are particularly effective in reducing individual peak loads. This is especially the case in households with EVs, which show a substantial decrease in peak load when compared to the case without flexibility utilization (refer to Table 8.10, Publication IV). Households with a HP, unless combined with a PV-BSS, show only marginal reductions in peak load. This difference comes from the inherent lower flexibility potential of the heating system during cold periods compared to BSSs or EVs.

Figure 8.9 in Publication IV displays the resulting grid reinforcement costs for all grids and GCDs considered. The analysis indicates that the CPP GCD does not reduce the need for grid reinforcement in the low-voltage grids with the given parameters. A higher spatial and temporal resolution would be necessary to achieve a reduction, which would require more data. GCDs with capacity subscription, CAP and CAP-VOL, lead to increased grid utilization and substantial cost reductions in grid reinforcement across the examined grids. This can be attributed to the higher percentage of households utilizing their flexibility under these GCDs. Savings range from 14% to 88% compared to the current volumetric GCD, with the greatest reductions observed in suburban grids („LV semiurb 4“ and „LV semiurb 5“) and the lowest reductions seen in the urban grid. The savings within the suburban grids are primarily attributed to decreased needs for transformer reinforcement and, in the „LV semiurb 5“ grid, additionally to reduced grid reinforcement needs to address voltage band violations.

In response to Subquestion II.2, the findings underscore the effectiveness of capacity-based GCDs in reducing grid reinforcement needs. These GCDs also demonstrate a higher incentive for residential consumers to utilize flexibility.

3.2 Methodological achievements

This dissertation's methodological achievements can be summarized into the following key aspects, demonstrating the comprehensive approach taken from household flexibility utilization to grid reinforcement requirements.

Modular representation of the entire „chain“, from household flexibility utilization to grid reinforcement requirements

The *EVaTar* model with its four modules enables a step-wise, comprehensive, consistent and interdisciplinary analysis of the effects of dynamic electricity price components on the entire „chain“ from households to grid reinforcement requirements. The interdisciplinary integration of the techno-socio-economic model provides a robust and comprehensive framework for understanding the complex impacts of dynamic electricity price components on residential consumers and distribution grids. This is achieved through a modular approach involving different perspectives:

Household perspective: Two modules are implemented, analyzing how heterogeneous households with various flexible technologies respond to DETs and different GCDs (*EVaTar-building* module), including their decision-making behavior regarding the tariff choices and decisions to invest in a HEMS (*EVaTar-decisions* module). This allows to determine the flexibility utilization of each household.

Distribution grid perspective: Two modules are implemented, assessing the impacts of consumer decisions regarding flexibility use on the impact grid utilization (*EVaTar-grid* module) and the requirements and associated costs for grid reinforcement (*EVaTar-gridex* module).

This modular setup allows for a detailed examination of each aspect, ensuring clarity in the understanding of the contribution of each component. Furthermore, the flexibility and adaptability of the modular setup facilitates the adaptation of the model to new research questions.

Creating a more accurate representation of household flexibility

To address the research questions posed in Section 1.2, modeling the technical and temporal aspects of demand-side flexibility of households and their flexible assets is required. The *EVaTar-building* module was implemented, offering an advanced depiction of demand-side flexibility by considering the crucial aspect of household heterogeneity and the technical characteristics of various flexible assets, such as EVs, HPs, and PV-BSSs. Key features include:

Household heterogeneity: The module includes all possible combinations of flexible technologies within households. Additionally, various measured household load profiles are used as input data. Individual driving profiles and the heat demand are assigned to the households based on socio-demographic data within Publications II to IV.

Realistic behavioral models: Demand-side flexibility of EVs is restricted by their availability at a charging location and other behavioral factors. The range anxiety of EV users is incorporated, expressed as a minimum SOC that must be reached before the EV is driven again and a minimum SOC, at which the charging process must be started at the latest. These aspects are important not to overestimate flexibility potential of EVs. Including the results of a specially designed household survey in the scenarios for realistic assumptions enhances the approaches seen in literature. A combination of an outside temperature dependent COP for air-to-water HPs and automated adjustment of the flow temperature depending on weather conditions via a heating curve is implemented. This advanced approach helps prevent an overestimation of HP flexibility potential.

Rolling horizon approach: This approach enhances the model's realism regarding HEMS utilization by integrating potential forecasting errors and allowing for dynamic re-planning. This approach, already existing in literature, complements the whole model by enhancing its accuracy and applicability. Additionally, the flexible definition of horizon and planning intervals allows for analysis of model predictive control for flexibility utilization.

Comparison of operational strategies: By evaluating different strategies for electricity cost minimization, the module allows for comprehensive assessment of the financial benefits of DETs against no flexibility use and self-consumption optimization. This approach is a valuable addition to research (see Publication III) to estimate the additional financial benefits of DETs accurately, as their attractiveness can be overestimated without a comparison to the increased self-consumption case.

Although individual aspects of this modeling approach have been used in literature before, the *EVaTar-building* module is the first to combine and extend them for greater precision. It incorporates real-world data from household surveys, accounts for household heterogeneity, considers all combinations of flexible technologies, and compares different operational strategies for flexibility use. This comprehensive integration makes the *EVaTar-building* module uniquely holistic in its analysis.

Including the households' decision-making behavior regarding the choice of tariff and the decision to invest in a HEMS

The *EVaTar-decisions* module integrates behavioral aspects into the decision-making process of households regarding their tariff choices and decisions to invest in a HEMS. This determination of the share of households utilizing their flexibility and their tariff choices, based on results from the *EVaTar-building* module, enables drawing a clearer picture of the effects of residential flexibility on low-voltage grids. The approach has been proven to shed new light on the impact of dynamic electricity price components on low-voltage grids in Publications II and IV. A noteworthy aspect of the chosen approach is its flexibility in household segmentation. Unlike methods rigidly confined to predefined categories, this model can adapt to various data sets, enabling the use of alternative groupings such as demographic, technical or behavioral segments based on available data.

Consideration of the interplay between DETs and GCDs

Recognizing the simultaneous influence of DETs and GCDs on residential consumers' tariff choices and flexibility utilization, the *EVaTar-building* and *EVaTar-decisions* modules allow for the explicit analysis of this aspect. Subsequently, the *EVaTar-grid* and *EVaTar-gridex* modules facilitate a techno-economic evaluation of the impacts on low-voltage grids, factoring in technical constraints and planning principles of the grid infrastructure. Publication IV addresses the interplay between DET adoption, flexibility utilization, and different GCDs. The results demonstrate the importance of this analysis, as otherwise, the impact of GCDs on low-voltage grid reinforcement requirements could be misestimated.

Grid reinforcement algorithm adapted to today's planning structures

Reflecting current engineering practices and DSO strategies, the *EVaTar-gridex* module incorporates an updated heuristic grid reinforcement algorithm that aligns with modern predictive grid planning principles. This update, based on discussions with German DSOs, is crucial for making the research applicable to current and future grid management challenges.

Modern planning practices now favor the immediate installation of larger cable diameters rather than incremental upgrades, reflecting a forward-looking approach to infrastructure requirements. The transformer reinforcement strategy prioritizes replacing existing transformers with higher apparent power units rather than adding parallel transformers, aligning with current grid planning principles of efficiency and cost-effectiveness. These strategic adaptations ensure that the grid reinforcement algorithm aligns with the predictive grid planning of DSOs, enabling practical and forward-looking recommendations

4 Summary, conclusions, critical assessment, and outlook

Dynamic electricity price components are a much-discussed option for leveraging household flexibility. This flexibility is essential for integrating fluctuating renewable energy sources and distributed loads, particularly from the electrification of the heating and transport sectors. Residential electricity prices consist of several components, two of which are mainly discussed to become dynamic: electricity procurement and retail, and grid charges.

The design of these price components must incorporate financial incentives that not only provide cost savings, thereby motivating households to utilize their flexibility, but also promote the desired behavioral changes in household electricity demand. These changes are critical for integrating renewable electricity and relieving the burden on local distribution grids by reducing or deferring grid reinforcement needs. Additionally, grid charges should be designed to recover grid costs in a cost-reflective manner. Importantly, households in Germany are free to choose their electricity suppliers and consequently their electricity retail tariffs. They can also decide whether to utilize their flexibility. This freedom of choice and the heterogeneous decision-making behavior of households play a crucial role in the overall impact of DETs and GCDs on low-voltage grids and must therefore be considered.

This dissertation aims to provide a more comprehensive understanding of how dynamic electricity price components affect residential consumers and grid reinforcement needs in Germany, both currently and looking ahead to 2030 and 2035. This understanding is further enhanced by accounting for heterogeneity of household and their diverse decision-making behavior regarding electricity retail tariff choices and decisions to invest in a HEMS. The objective is to determine whether dynamic electricity price components can lead to better grid utilization and potentially reduce or defer grid reinforcement needs, thus promoting more efficient grid use.

In the following sections, a summary is presented and conclusions are drawn in Section 4.1. Subsequently, the results are critically assessed and future research directions are suggested in Section 4.2.

4.1 Summary and Conclusions

The research questions are addressed through the development of the techno-socio-economic *EVaTar* („**E**fficient **Va**riable **Tar**iffs“) model, which consists of four distinct modules. Each module focuses on a specific aspect of the impact assessment of dynamic electricity price components. This interdisciplinary and modular approach allows for in-depth examination of each aspect, ensuring a comprehensive understanding of the implications for residential consumers and grid reinforcement needs in Germany.

The first module, *EVaTar-building*, depicts residential consumers' inflexible and flexible electricity demand and generation. It uses both a MILP optimization and a simulation model to analyze the effects of various dynamic and static electricity price components on load characteristics and financial aspects of households. Three operational strategies are examined: no explicit use of flexibility, optimizing self-consumption using a HEMS, and minimizing electricity costs using a HEMS in combination with a DET. This module incorporates household heterogeneity, empirical data from household surveys, and a wide range of flexible technologies and their combinations, thereby facilitating a more realistic representation of household flexibility. Moreover, it allows for the analysis of how different technologies and price components interact. This enables an analysis of the interplay of DETs and different GCDs on both household and low-voltage grid levels. The comprehensive integration of all aspects allows for a uniquely holistic analysis.

The second module, *EVaTar-decisions*, extends this economic analysis by incorporating the decision-making behavior of residential consumers regarding their electricity retail tariff choices and decisions to invest in a HEMS. The decision-making behavior is not purely based on financial aspects [51, 52, 110]. Therefore, this module considers both financial and other behavioral drivers of households, offering new insights into the impact of dynamic electricity price components on low-voltage grids.

The third module, *EVaTar-grid*, expands the analysis from the individual consumers' perspective to the distribution grid perspective. It employs automated power flow calculations of low-voltage grids to assess the technical impacts of dynamic electricity price components and household decision-making behavior on grid utilization and stability.

The final module, *EVaTar-gridex*, includes a grid reinforcement algorithm to analyze grid reinforcement needs and associated costs under various scenarios. This algorithm has been adapted to align with current engineering and planning principles, reflecting modern practices of predictive grid planning, such as the immediate installation of larger cable diameters and strategic transformer replacements. This ensures that the model reflects the current grid planning practices of DSOs.

Based on the synthesis of the key findings of the four publications and the methodological achievements of this dissertation (see Chapter 3), several conclusions and recommendations are formulated.

Impact of the additional electricity demand of EVs and HPs, and flexibility utilization on household electricity prices

The results show that the projected increase in electricity demand from EVs will result in higher marginal electricity generation costs if the power generation park is assumed to be fixed. Nevertheless, the additional demand also leads to increased grid utilization, which reduces specific grid charges. This decreasing effect outweighs the increased cost of electricity generation, thus reducing household electricity prices by up to 3.7% (Publication I). These results are valid if grid reinforcement needs are kept to a minimum or entirely avoided, for instance, through the implementation of controlled charging. When the additional electricity demand of HPs and EVs is considered collectively, grid utilization can be further enhanced and specific grid charges can be reduced if the additional electricity demand of HPs and EVs outweighs the grid utilization decreasing effect of higher self-consumption through PV-BSSs [152]. **The decreasing effect on specific grid charges of the additional electricity demand of EVs and HPs, especially when flexibility is utilized to reduce grid reinforcement needs, can contribute to a more objective debate in the public discussion.**

Conditions for the economic viability of DETs

Modeling results of market-available DETs show substantial potential cost savings for households with flexible technologies, despite the additional costs for acquiring a HEMS and metering point operation of smart meters. Over 90% of flexible households potentially opt for a DET, considering household decision-making behavior (Publication II). However, several factors influence cost savings through DETs and the decision to utilize flexibility:

- *Future electricity prices and price spreads:* The share of households achieving cost savings through flexibility utilization under a DA-RTP tariff increases from 3.5% to 56.3% when moving from a low to a high price scenario with higher price levels and spreads (Publication III).
- *Available flexible technologies:* Households with an EV and a PV-BSS show the highest average cost savings potential under a DA-RTP tariff, up to 30.4%, when all additional costs are considered (Publication IV). For households with a HP, average cost savings reach up to 9.7% with an additional PV-BSS (Publication IV). The presence of both an EV and a HP increases flexibility potential further. A PV system or PV-BSS significantly enhances the attractiveness of flexibility utilization via a HEMS combined with a DET or for self-consumption (Publication III).
- *Costs associated with metering point operation and HEMS investment:* In a high price scenario, costs of up to €111 per year would incentivize 75% of households to utilize their flexibility and opt for a DET (Publication III). These costs reduce to €50 per year in a low price scenario.
- *Operational strategy of flexible technologies:* Comparing the operational strategy of flexibility utilization via a HEMS combined with a DET and self-consumption optimization, results show that even though DETs offer cost savings for a large share of households, optimizing self-consumption is a financially more attractive option for households with a HP (Publication III).

While the upper price limit of metering point operation is regulated by law [153] and has been reduced since 2024 [154], HEMS purchase costs are set by manufacturers and vary depending on the manufacturer [76]. However, information on future purchase and installation costs is scarce. **The maximum tolerable costs for HEMS and metering point operation that would incentivize 75% of households to utilize their flexibility vary depending on available flexible technologies. This gives HEMS providers the opportunity to set prices based on the integrated technologies.**

In addition to financial considerations, residential consumers also weigh non-financial factors when making decisions about utilizing flexibility, which were considered within the analyses. One of the main non-financial considerations is the effort required to respond to DETs [50, 24]. **It is essential that HEMS manufacturers, policymakers, and electricity suppliers consider both the economic viability and the effort required from residential consumers. This is crucial to ensure the attractiveness and diffusion of DETs and HEMS. Moreover, for DETs to be mutually profitable for suppliers and residential consumers, suppliers must share financial gains with consumers. This can help incentivize the initial investment in a HEMS and the adoption of DETs.**

Results on the impact of flexible technologies on potential cost savings through DETs in future scenarios show that DETs are financially attractive, especially for households with an EV and a HP. Households with this technology combination also show a higher affinity for demand response services [50]. At the same time, DETs could facilitate faster diffusion of flexible technologies due to anticipated cost savings. **The future penetration rates of EVs and HPs will ensure high flexibility provision through price incentives for the energy system. Nevertheless, it is important to note that the short-term contribution to flexibility provision should not be overestimated due to the currently low penetration rates and, thus, lower flexibility potential.**

The analyses presented in this dissertation consistently demonstrate that the installation of a PV rooftop system enhances the attractiveness of utilizing flexibility. Concurrently, the installation of PV systems results in an increase in renewable electricity generation within the system. **The enhanced attractiveness of utilizing flexibility when adding a PV rooftop system suggests that further incentives for PV installation, alongside accelerated adoption of smart meters, are crucial for enabling and incentivizing households to adjust their electricity demand flexibly. It is of particular importance that incentives for PV installation ensure the utilization of flexibility by subsidized households.**

While DETs often present a financially profitable option, they may not always be the optimal financial choice for households, especially those with a HP. Optimizing self-consumption via a HEMS is financially more attractive for these households. **A comparison of the financial benefits of DETs with a conservative operational strategy of no explicit flexibility utilization and an operational strategy optimizing self-consumption via a HEMS is valuable for market actors offering DETs to assess the attractiveness of their business model for households and for residential consumers to identify the financially optimal option for themselves.**

As the penetration rates of HP increase, the flexibility of HPs will become particularly crucial in winter, as high simultaneity in heating is expected. It is therefore essential to provide incentives to households with a HP to become flexible and react to price signals. Results show that with low price incentives, flexibility of heating systems with an air-to-water HP is employed to utilize self-generated electricity from the PV system. This includes shifting load to midday, where the outside temperature-dependent COP is typically highest, rather than responding to the lowest electricity prices of a day. **To effectively prevent high simultaneity in heating through price incentives, it is necessary to ensure that the price level and spreads are sufficiently high. This is to counter the tendency of flexible use of air-to-water HPs to utilize self-generated electricity and shift load to midday, rather than responding to electricity prices.**

Market-available DETs can financially benefit households equipped with a HP, an EV, and a PV-BSS when utilizing their flexibility with a HEMS. Implementing enabling technologies to react to pricing signals and optimize household electricity demand is the first step in preparing for future GCDs. However, acquiring a HEMS that integrates all components is currently challenging due to the lack of universally implemented communication standards. **A HEMS should ideally integrate all existing and future flexible technologies in a household, requiring the implementation of communication standards. It is essential to ensure the controllability of flexible technologies from the outset, in order to accommodate potential changes in GCD and regulations (such as § 14a of the Energy Industry Act (EnWG), or Redispatch 3.0).**

Influence of different GCDs on households' tariff choices and decisions to invest in a HEMS

The influence of GCDs on households' tariff choices and their decisions to invest in a HEMS is a crucial aspect of this thesis. Results demonstrate that a capacity-based GCD with a capacity subscription can significantly increase the share of households deciding to utilize their flexibility from 67.2% to 74.1%

compared to a volumetric GCD. Similarly, the share of households opting for a DET (with or without flexibility utilization) increases from 77.3% to 82.2%. Additionally, the DA-RTP tariff becomes more attractive, while the ToU tariff is chosen less frequently.

Regarding the decision-making behavior of households, results show that despite potential cost savings, some households do not utilize their flexibility. This is because they tend to have a lower electricity consumption than others, which in turn leads to an overall lower cost saving potential. These households, often slower in adopting new technologies and requiring higher economic incentives to do so[1], present an additional flexibility potential if activated. Improving the acceptance and willingness to pay or pay more of these households could lead to overall decreasing electricity prices for all households. This is due to the fact that it would increase the share of flexibility utilization, as shown by the results for the scenario in which EV users in 2030 engage in controlled charging. This, in turn, would result in a reduction in household electricity prices of up to 3.7%. **Efforts should be made to enhance the acceptance and WTP or WTPM of households that require greater financial incentives for adopting new technologies and to increase the number of households utilizing their flexibility, e.g., through the implementation of information campaigns.**

The analysis of different GCDs in combination with future wholesale electricity prices, and grid charges scaled to today's revenues of DSOs shows that GCDs influence households' decisions to utilize their flexibility and their tariff choice. However, once a household utilizes its flexibility, the annual grid charges remain mostly the same if it switches to another tariff. In 2035, where average wholesale electricity prices are expected to be below 100 €/MWh [155] and with expected rising grid charges due to grid reinforcement needs, grid incentives of alternative GCDs will be even more prevalent for households with flexible technologies. **Revenue planning for DSOs is simplified, as knowing whether a household is flexible is sufficient to estimate revenues without additional information on the electricity retail tariff used**[2].

Impact of DETs on distribution grids when considering residential consumers' decision-making behavior

It is anticipated that grid restriction violations and, consequently, grid reinforcement needs will increase in the near future due to the integration of distributed renewable electricity generation and the increasing grid load resulting from the growing adoption of EVs and HPs. Discussions and research to mitigate these needs include dynamic electricity prices. In current literature, it is often assumed that all households in a grid area use the same tariff. This assumption leads to high simultaneity of load, further increasing grid load. Nevertheless, the incorporation of both static and dynamic electricity prices, in addition to the households' free choice of tariff and their HEMS investment decisions, reveals a notable increase in grid utilization and a significant reduction in grid restriction violations in load-driven low-voltage grids (Publication II). Consequently, the need for grid reinforcement is also expected to be reduced. **The findings of the analyses in this dissertation suggest that distribution grid planning should be updated to include a more realistic picture of residential flexibility. This should be done by**

[1] Specifically, households falling into the Late Majority and Laggards adopter categories, with a lower WTPM.

[2] This only applies to the comparison between electricity retail tariffs, not to possible changes in electricity consumption due to rising overall electricity costs as seen in the energy crisis [156].

considering the free tariff choices of households, the investment decisions of HEMS, and future electricity tariffs, all of which impact the simultaneity of EV charging and HP usage.

Results show that grid reinforcement needs due to EV charging can be mitigated or even prevented if controlled charging is applied or if the charging power of home charging points is kept below 11kW. This is because grid reinforcement needs are driven by home charging points with higher EV charging power (Publication I). **In order to limit the necessity grid reinforcement as a consequence of EV charging, it is recommended that controlled or flexible charging of EVs and the limitation of charging power be incentivized in accordance with increasing EV penetration rates. This approach could also bridge lengthy network planning and reinforcement processes. It is also necessary to consider whether the costs of grid reinforcement in low-voltage grids resulting from high EV charging powers should be distributed among all consumers or whether they should primarily be borne by users of EVs with these high charging powers.**

The research findings highlight the potential of market-based dynamic electricity prices in mitigating grid reinforcement needs. Notwithstanding the fact that the price signal is not based on grid load, this approach can still be somewhat effective (Publications I and II). It is, however, important to note that as the share of EVs, HPs and PV-BSSs, increases, and as more households become responsive to DETs, the effectiveness of this strategy is limited. Market-based DETs can not completely and reliably prevent grid congestion in low-voltage grids. **In addition to the market availability of DETs, which facilitate the integration of electricity generated by renewable sources, the research highlights the need for adjusting the electricity price component grid charges. This component, in which the regulator establishes the framework and the DSOs configure the details, should be modified to effectively mitigate grid reinforcement needs and to more accurately reflect the contribution of individual consumers to incurred grid costs. This policy change is crucial in the context of the rising penetration rates of EVs and HPs.**

GCDs effective in reducing grid reinforcement needs and incentivizing flexibility utilization

The current GCD with a volumetric charge and the mostly static electricity retail tariffs for households result in the under-utilization of low-cost energy during high renewable energy feed-in periods. This leads to higher electricity prices for households due to higher overall generation costs and increasing grid charges. **The GCD should be adjusted to support the integration of renewable energy through DETs and residential flexibility while maintaining stable grid conditions, limiting grid reinforcement needs, and reflecting the contribution of individual consumers to incurred grid costs.**

The analysis of GCDs and their efficacy in reducing grid reinforcement needs, while considering residential consumers' tariff choices and HEMS investment decisions, reveals that GCDs which more accurately reflect the contribution of individual consumers to incurred grid costs, such as capacity-based GCDs, provide incentives for a larger percentage of households to utilize their flexibility. This leads to substantially reduced grid reinforcement needs and costs and facilitates the integration of renewable energy generation (Publication IV). These GCDs encompass a GCD with a capacity subscription and a combined GCD with both a capacity subscription and a volumetric charge. In comparison to the current purely volumetric GCD in Germany, grid reinforcement costs can be reduced by 14% to 89%, with the degree of reduction varying depending on the low-voltage grid (Publication IV). The effects are most pronounced in suburban grids. Results show that a capacity-based GCD has similar effects on grid reinforcement needs as a combined GCD with capacity-based and volumetric components. The volumetric component additionally encourages energy conservation. Sophisticated, complex, and dynamic GCDs that reflect the current grid status are increasingly facilitated by DSOs, which are currently developing their distribution grids toward better grid load measurement. **When designing a GCD for residential consumers, consideration should be given to combined GCDs, as the benefits of different designs can be united. It is recommended that a GCD with a capacity-based component be considered to effectively mitigate grid reinforcement needs and associated costs, thus reducing both economic costs and costs for individual households.**

Methodological considerations

In conclusion, the results of this thesis demonstrate that the ongoing debate on residential consumer flexibility and the impact of dynamic electricity price components on grid reinforcement needs and costs must consider the intricate interplay between the GCD and utility-side electricity retail tariffs (dynamic and static), incentives for renewable energy generation, the use of flexibility, as well as consumers' tariff and flexibility decisions. Otherwise, the effects of consumer flexibility might not be estimated correctly, and, for instance, in the case of new GCDs, they could fail to achieve their intended outcome.

4.2 Critical assessment and outlook

Different modeling approaches and input data are used in this dissertation to assess the impact of dynamic electricity price components on flexible consumers and distribution grids. Certain simplifications are made within the model, as modeling real systems is a trade-off between a realistic depiction of the system and model complexity, computational capability, and the capability to assess the research questions investigated. Furthermore, as some level of data uncertainty is inherent in modeling approaches, specific limitations regarding the input data are acknowledged. Therefore, when evaluating the results, it is essential to consider the structural characteristics and limitations of the different approaches and the data used.

Flexible and non-flexible behavior of households

Within the module *EVaTar-building*, a MILP model is implemented to depict the function of the HEMS. Forecast uncertainties are addressed by implementing a rolling horizon scheme, thereby providing a more nuanced and realistic assessment of the benefits and limitations of dynamic electricity price components. In real-world applications, the successful use of HEMS depends on forecasts of the key input variables such as PV generation, electricity demand, heat demand, or driving and availability profiles of EVs [157]. Future research could therefore include an MPC-based HEMS, which can easily be implemented as the planning period and planning horizon (see Figure 2.3) within the module can be set freely.

The potential repercussions of flexibility utilization in households on the spot market and electricity generation park are not addressed in the analyses of Publications II to IV. This is considered an adequate basis for the underlying research, which focuses on individual low-voltage grids or the economic effects of DETs on residential consumers. However, Publication I demonstrates that flexibility utilization affects electricity generation costs and grid charges, and can result in reduced household electricity prices. Future analyses should include this aspect, as the reduced electricity prices could reduce the share of households utilizing their flexibility.

To ensure the reliability of the results, despite the limitations of the input data, a variety of strategies are employed. Real electricity prices are subject to a multitude of factors, including the increase in renewable energies, the decommissioning of fossil fuel plants, and the electricity market design. To address this aspect, electricity price scenarios covering a wide range of potential future market prices and tariffs for residential consumers are analyzed in depth throughout the publications (see Table 3.1). These scenarios are based on market-available tariffs, the trends observed on the day-ahead spot market, the results from an electricity market model, and the predictions of future prices, anticipating future trends. In addition, various penetration rate scenarios are considered in the publications. Future research should incorporate new developments such as national or international targets for renewable energy expansion, electrification of the heating and transport sectors, technological advancements, market trends, and consumer adoption rates, should they arise. Furthermore, whole-year profiles are used to model households' energy consumption and generation, capturing seasonal variations in household electricity demand and PV generation. This approach allows for a more comprehensive and accurate depiction of year-round dynamics of household flexibility utilization. However, only one weather year is considered, neglecting year-to-year weather variations. Additionally, the PV systems within the analyses were all considered to be southwards facing with a tilt of 35°. PV generation depends on multiple factors such as annual global radiation which varies throughout Germany [158], system orientation and tilt [159]. These aspects could affect self-consumption levels of PV systems and PV-BSSs. Including multiple weather scenarios and different PV system configurations and corresponding PV generation profiles in future analyses would allow for an even better understanding of the impacts of dynamic electricity price components.

A broad set of household load profiles (refer to Section 2.1.1.1) is used in Publications II to IV, reflecting the heterogeneity of households, thus reducing the influence of peculiarities of a single household on overall results. Additionally, the driving and availability profiles of EVs and the heat demand are matched to each household individually, using socio-demographic data. However, the household load profiles considered are from 2009 to 2010, and household technologies have since changed. It is anticipated that they will continue to evolve in the future, with potential impacts on household electricity demand. Examples of factors influencing demand include the adoption of more efficient lighting, an increase in IT equipment, the use of air conditioning, shifts in working hours, and a larger share of home office hours. As the majority of households' electricity demand can be attributed to EVs and HPs, the household load profiles are considered sufficient for the analyses. A comparison of the profiles with the population of Germany shows a higher proportion of households with children. In order to enhance the analyses, representative input data and accounting for changes in household load profiles and overall electricity consumption could be considered.

SFHs have private parking spaces available and are therefore likely to invest in private charging infrastructure [160]. Therefore, private charging is seen as the most critical charging case for the underlying scenarios in Publications II to IV, focusing on SFHs. However, other charging opportunities such as charging at work or public charging will play an essential role in the future [160]. As charging infrastructure is continuously built in Germany, the applicability of the results can be broadened by including these other charging opportunities. Furthermore, only one EV per household was considered within the publications. However, there are various potential scenarios for mobility in Germany that could be explored in future work. For instance, while the current trend indicates an increase in the number of EVs per household [161], other scenarios such as a shift towards shared mobility or and increased use of public transportation could also impact household mobility patterns. Examplarily, with multiple EVs within one household, PV-BSSs and DETs could become even more beneficial, and capacity-based GCDs could have a higher influence on EV charging.

For HPs, the energy demand for heating varies by region, construction year, and refurbishment state of the building. The chosen final energy demand for heating within the publications was 236 kWh/m^{2}a in Publication II (corresponding to a building built between 1949-1978 [162]), and 100 kWh/m^{2}a in Publications III and IV (corresponding to a building from 1995-2001 with an improved standard [162])[3]. Future developments with lower heat demands could influence cost savings potential through flexible HP utilization. Yousefi et al. [45], for instance, see higher cost savings potential through HEMS and a ToU tariff in well-insulated buildings than in less insulated buildings. Furthermore, while air-to-water HPs were considered within the analyses due to their market share (87% in 2022 [164]), other types such as brine-to-water and water-to-water HPs should be analyzed in future work due to their potential better response to price incentives (COP not dependent on ambient-temperature). The adoption of these HP types is also supported by the funding directive „Richtlinie für die Bundesförderung für effiziente Gebäude – Einzelmaßnahmen (BEG EM)“ [165] in Germany, potentially increasing their market share.

Decision-making behavior regarding the choice of electricity retail tariff and the investment in a HEMS

The *EVaTar-decisions* module incorporates the free choice of tariff and the investment decision regarding a HEMS. A trade-off is made between accuracy, data availability, and model complexity. Despite not depicting the actual decision-making process of each household, utilizing a combination of the WTPM and adopter categories from the „diffusion of innovations“ theory by Rogers [116] provides a good estimate of household decisions. Future work could extend the module to include a threshold for minimum cost savings required before switching tariffs, obtained via household surveys. A lack of data was identified regarding the WTPM for DETs and the investment in a HEMS, which should be explicitly determined for future work. This could be done by household surveys for other household segmentations than the adopter categories. For instance, a segmentation by available flexible technologies or the households' attitude towards sustainability could be chosen, which can easily be implemented within the module. Other behavioral drivers that have been demonstrated to be significant in the field, such as effort [50], could be incorporated into the decision-making process in a more explicit manner. Additionally, the frequency with which households are confronted with tariff changes could be included in the analysis.

Grid impact and grid reinforcement needs

The grid utilization and grid reinforcement analysis with the *EVaTar-grid* and *EVaTar-gridex* modules are based on representative low-voltage grids. Various low-voltage grids are analyzed, with random placement of households within the grid combined with multiple iterations to reflect uncertainties in the distribution of flexible technologies. A critical limitation of the grid analyses is the temporal resolution of load and generation profiles. Hourly profiles are used due to data availability, whereas voltage quality in low-voltage grids in Germany is evaluated based on 10-minute mean values in accordance with DIN

[3] For comparison: the average final energy demand for SFHs in Germany is around 190 kWh/m^{2}a [163]

EN 50160 [72]. However, Ref. [71] shows that the distribution of voltage levels in a low-voltage grid is only affected minimally with hourly resolution compared to 10-minute resolution, and the results of the grid analyses are used and interpreted comparatively. Therefore, the derived conclusions are assumed to be valid. Nevertheless, future research should include data with higher temporal resolution, if available.

Grid reinforcement decisions within the grid reinforcement algorithm are made based on grid restriction violations. Additional securities in dimensioning grid equipment can be considered in grid planning that could, in reality, lead to higher grid reinforcement costs, e.g., transformers in low-voltage grids can be dimensioned for a maximum loading of 50% to tolerate grid interconnections during maintenance work. Sensitivity analyses could address these aspects. Moreover, the analysis solely focused on grid reinforcement, overlooking the potential for grid optimization measures. Although this approach provides a worst-case estimation for grid reinforcement needs, future work could include grid optimization measures, which could be incorporated into the algorithm. Additionally, the most rapid diffusion of flexible technologies is predicted to be in suburban areas with high shares of SFHs, and there are still regulatory obstacles to the utilization of flexibility in multi-family homes (MFHs). Therefore, the publications focus on SFHs. However, in future analyses that go beyond 2035, MFHs, charging at work, and other variations should be considered. Furthermore, repercussions on specific grid charges due to changes in energy transported within a low-voltage grid and grid reinforcement costs are neglected in Publications II to IV. However, Publication I shows a positive impact of EV charging on specific grid charges, whereas [166] shows a negative impact of PV-BSSs and increased self-consumption. This negative impact is, however, outweighed by the effect of EV charging if EV diffusion is higher than PV-BSS diffusion. Similar results are shown in [57]. These aspects should be considered in future work. Also, § 14a of the German Energy Industry Act (EnWG) [167] allows for lower specific grid charges for controllable assets. A simplification was made, assuming one electricity price for households and their flexible technologies, based on extensive discussions regarding § 14a EnWG and the prospect of new regulation. The new regulation from 1.1.2024 now allows households to choose being controllable by the DSO or receive a value for permissible electricity consumption [168]. Additionally, DSOs are now allowed to implement time-varying volumetric grid charges. These developments provide additional incentives for flexibility utilization via a HEMS.

Future work should include a broader range of variations and combinations of DETs and GCDs. DSOs are currently developing their distribution grids towards improved grid load measurement, thereby enabling GCDs based on the current grid status. However, the selected modeling approach does not include a feedback loop or direct integration from the *EVaTar-grid* and *EVaTar-gridex* modules to the *EVaTar-building* or *EVaTar-decisions* modules. This integration would be necessary for assessing grid state-based GCDs. The financial impact of this GCD is difficult to predict for households. For an analysis within the *EVaTar* model, households' decisions regarding their tariff choices and HEMS investment would have to be determined in advance. It would then be possible to integrate the *EVaTar-building* and *EVaTar-grid* modules to determine how flexibility is utilized with grid charges based on the grid status. Subsequently, the *EVaTar-gridex* module could be used to assess the need for grid reinforcement. Additionally, the economic impact on households and their changes in tariff decisions and flexibility utilization could be examined using the *EVaTar-decisions* module. This, in turn, would impact the grid load and, thus, the grid state-based grid charges, showing the matter's complexity.

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Part II

5 Publication I: Impact of electric vehicles: Will German households pay less for electricity?

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[Start of Publication I]

Impact of electric vehicles: Will German households pay less for electricity?

Matthias Kühnbach[a,*], Judith Stute[b], Till Gnann[a], Martin Wietschel[a], Simon Marwitz[c], Marian Klobasa [a]

[*] Corresponding author.
[a] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139, Karlsruhe, Germany
[b] Fraunhofer Institution for Energy Infrastructures and Geothermal Systems, Breslauer Strasse 48, 76139, Karlsruhe, Germany
[c] TransnetBW GmbH, Osloer Str. 15-17, 70173, Stuttgart, Germany

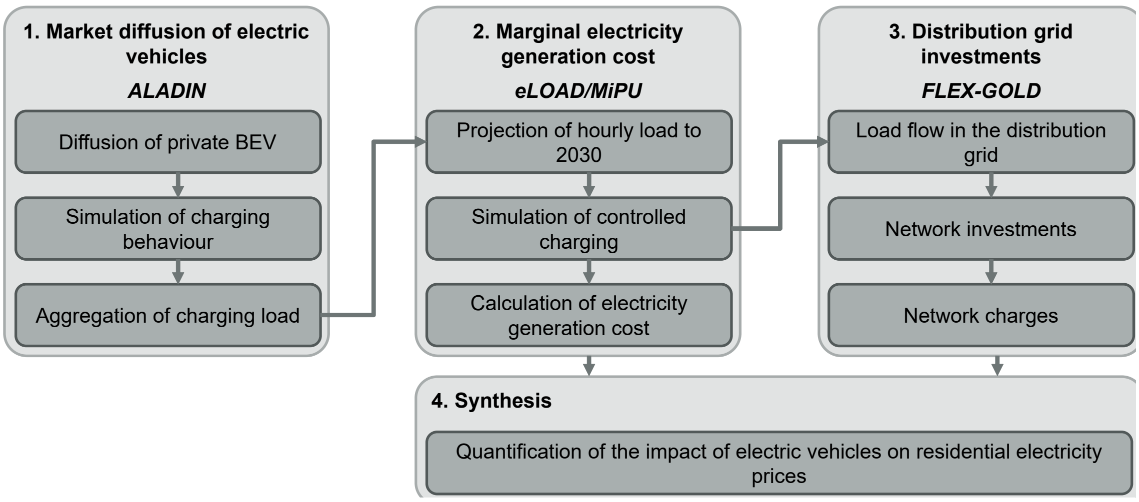
Highlights

- Assessment of the influence of electric vehicles on the household electricity price.
- Demand projection and simulation of controlled charging of private electric vehicles.
- Analysis of impacts of EVs on electricity generation and distribution grid for 2030.
- Grid investments occur if high charging power and uncontrolled charging coincide.
- Rising electricity generation costs overcompensated by falling grid charges.

Abstract

High energy efficiencies imply that electric mobility is regarded as an important technological option to reduce greenhouse gas emissions from the transport sector. However, electric vehicles (EVs) also have impacts on electricity grids and electricity generation. Hence, this paper explores how private EVs affect residential electricity prices in Germany. We examine effects of EVs on electricity generation, the contribution of controlled charging and impacts on distribution grid grids. We show that in 2030, private EVs can reduce the electricity prices for households since at distribution grid level, the additional electricity demand increases the overall utilisation of the grid and lowers specific costs. Because the additional load of EVs leads to an increased usage of power plants with higher variable costs, there is the opposite effect on electricity generation costs, although limited by controlled charging. Overall, the effect of rising electricity generation costs is usually overcompensated by falling specific grid charges.

Graphical Abstract



Keywords

Electric vehicles; Household electricity price; Distribution grid expansion modelling; Demand response modelling;

5.1 Introduction

At present, significant growth rates for electric vehicles (EVs) are being recorded worldwide [1]. As a consequence, renewable electricity (RE), especially wind and photovoltaic (PV), can be used to meet mobility requirements, while simultaneously reducing greenhouse gas emissions and the dependency on import of energy carriers [2, 3, 4]. At the same time, pure battery EVs (BEVs) are now able to meet today's mobility demands since vehicles with larger batteries are sold [5].

An additional net electricity demand[1] of around 12 TWh can be calculated for 2030 given a market penetration of approx. 4 million EVs[2] in Germany; the country's total net electricity demand in 2016 was about 525 TWh [6]. The substitution of conventional fuels (petrol and diesel) by electrical power and the resulting increasing demand for electricity give rise to questions about the impacts of e-mobility on the electricity system as a whole. The additional demand for electricity must be met by the installed generation capacity in order to maintain the security of supply. At the same time, it can be assumed that there are also relevant local effects due to EV charging, in particular at distribution grid level.

In this study, we combine different energy system models in order to quantify the aspects mentioned and make a holistic assessment of the impacts of private EVs on the electricity system. The electricity price for households is used as an indicator of the cost effects. We thereby examine the following specific questions:

Demand-side:

- How is the load due to charging EVs distributed with hourly resolution and considering different charging powers?

Supply-side:

- What impacts do EVs have on the hourly electricity demand and therefore on electricity generation costs?
- To what extent does controlled charging lead to a reduction of the electricity generation costs?

Distribution grid:

- What influence does charging EVs have on investments in grid expansion in distribution grids and on the resulting grid charge?

We link four models to chart the influence of EVs on the electricity price for households in Germany: The market diffusion model *ALADIN* simulates the future diffusion of EVs and their charging behaviour. Its output then enters the simulation model *eLOAD*, which projects the system load of relevant drivers for 2030. *eLOAD* can also simulate the use of controlled charging of EVs. In the next step, the total hourly electricity demand (system load) is transferred to the electricity market model *MiPU*, which determines the minimum-cost power plant dispatch. In parallel, the *FLEX-GOLD* model calculates the load in a low-voltage grid and determines grid investments. In the final step, household electricity prices are calculated based on the models' results for the assumed scenarios with regard to charging power and local EV penetration rates.

This paper is structured as follows: In the next section, we discuss the existing literature. We then describe the applied method and the models used. Section 5.4 contains the framework conditions, i.e., a market diffusion scenario for EVs, the assumed charging behaviour of users of EVs, and the assumed influence of different charging powers on mobility. Based on the developed case study, we simulate the possible effects of EVs on electricity generation prices and grid charges in Section 5.5. We examine two scenarios

[1] Electricity production without self-consumption from power plant, including grid losses and charging losses (in addition to consumption while driving).

[2] Both BEVs and plug-in hybrid electric vehicles (PHEVs).

with controlled and uncontrolled charging, each with three different cases of charging powers of the EVs. Then, we analyse the impacts on the overall electricity price for households. We draw conclusions in the final section.

5.2 Background

The literature on integrating EVs into the electricity system relevant for this paper can be divided into three different streams: The interaction of EVs with volatile RE and the resulting charging strategies, impacts on the electricity supply side and greenhouse gas emissions, as well as local electricity grid effects.

In the first stream, controlled charging of EVs, in more general terms (i.e., for the whole demand side) also referred to as demand response (DR) [7], and its implications on the electricity system is investigated: Dallinger et al. [8] examine the interactions between volatile RE and the charging process of EVs for Germany and California (also for 2030). They simulated different charging strategies – variable time-of-use tariffs and dynamic real-time pricing tariffs – to analyse what advantages these have for integrating RE. It was shown that uncontrolled charging of EVs results in a load peak in the evening, while controlled charging and real-time pricing, in particular, reduce this peak and integrate additional RE by shifting the charging process to hours with negative residual load[3] [8]. Jochem et al. [9] calculate the effects of EVs in Germany, above all against the backdrop of greenhouse gas emissions. They analyse four different metrics to quantify the CO_2 emissions of EVs, which includes calculating an hourly electricity merit order curve. The authors conclude that it is possible for EVs to cut CO_2 emissions, but that, in addition to the calculation approach used, the country's supply portfolio and the possibility for controlled charging have a strong influence on the results [9]. Lund and Kempton [10] describe similar results with regard to reducing CO_2 emissions in a scenario based on the Danish energy system. As well as the already mentioned charging strategies, they additionally take into account charging at night and the vehicle-to-grid concept, where electricity is fed back into the grid from the vehicle battery. The latter was identified as the most favourable option for integrating RE alongside real-time pricing (referred to as "intelligent charging" in this study) [10]. However, some studies (e.g. Refs. [11, 12, 13]) also take a critical view of vehicle-to-grid concepts because of the associated high battery degradation.

While the cited studies mainly focus on the systemic benefits of EVs in general, and on controlling the charging process in particular, other studies are already developing economic approaches to incentivise charging behaviour that is beneficial to the system as a whole, for instance by participating in system services (e.g. Refs. [14, 15]).

A large number of studies have already considered the consequences of a high penetration of the electricity market by EVs. While EVs are only used within a power plant deployment model as a medium to address further issues, e.g., CO_2 emissions, in Refs. [8, 9, 10], others explicitly address future impacts of EVs on power plant dispatch and electricity prices in Germany [13, 16, 17], Denmark [18] as well as Sweden, Norway, Denmark and Germany [11].

[3] Residual load in this context as well as in the context of our paper is defined as total hourly electricity demand minus electricity generation from volatile RE.

Taljegard et al. [11], who combine a generation capacity investment model with a power plant dispatch model, demonstrate that particularly for a high share of EVs, system costs due to investments in generation technologies increase. The simulations by Hanemann and Bruckner [13] show that the additional demand due to EVs leads to increased demand peaks and correspondingly to an increase in the marginal costs of electricity generation. Controlled charging dampens this effect. By shifting the load to hours with a low electricity price, technologies with low variable costs, especially lignite-powered plants, achieve higher full-load hours in the analysed studies [9, 11, 13, 17]. This results in lower prices than in the uncontrolled case.

While the influence of EVs on prices is consistent in the studies we found, it must be noted that the impact of controlled charging on CO_2 emissions seems less clear and less comparable. According to Göransson et al. [18], controlled charging reduces CO_2 emissions, while Schill and Gerbaulet [17] report increasing emissions (due to an increased use of lignite). Jochem et al. [9] observe no effect at all (case "annual average mix"). The resulting differences are most likely induced by the respective framework scenario (e.g., Göransson et al. look at Denmark, Jochem et al. and Schill and Gerbaulet at Germany) or the features and parameterisation of the models: Schill and Gerbaulet [17] and Jochem et al. [9] both use existing but different scenarios for capacity expansion, i.e., the structure of the electricity system cannot be adapted to the new conditions due to the diffusion of EVs and do not consider cross-border flows. However, Jochem et al. [9] uses a power flow model, i.e. the electricity grid is modelled in high detail, while other aspects such as ramping of power plants are not considered. Hanemann et al. [16] demonstrate that depending on the underlying CO_2 price and resulting fuel switches, effects of controlled charging on emissions can be either positive or negative. Additionally, all papers possess slight differences regarding the diffusion of EVs and the modelling of controlled charging and the consideration of flexibility options.

The implications of EVs for electricity grids, especially low-voltage grids, are unclear as well. This is probably due to the heterogeneity of low-voltage grids in terms of age and settlement structure. One study on the impacts of the diffusion of PHEV in Ontario, Canada, calculated that penetration up to 10.5% has hardly any effect on the stability of the power grids [19]. Meanwhile, in a case study for a generic distribution grid in Great Britain, Papadopoulos et al. [20] arrive at the result that sporadic overloads occur at transformers at this level of penetration, but that voltage range deviations are only present to a large extent if the local stock of vehicles has higher shares of EVs.

Other studies have analysed the influence EVs might have on grid expansion in Germany. These studies generally vary in their methodological approach and distribution grid configuration or supply region and the market penetration rates of EVs. Nobis [21] concludes that no problems should occur at local grid transformers if charging powers at home are limited to 3.7 kW, even with 100% market penetration of EVs. Lower levels of market penetration permit a much higher charging power. The study emphasises the positive role of reactive power control for integrating EVs into electricity grids.

Liu [22] concludes that the configuration of the German medium-voltage grids and their subordinate low-voltage grids is generally sufficient in small towns. As a result, EVs cause hardly any technical problems here. If the grids in larger towns or rural areas have weak points, grid reinforcement measures should be deployed. If an overload occurs at a local transformer, its annual lifetime consumption increases significantly. This can, according to Liu [22], only be eliminated if the batteries of EVs can be charged in a controlled manner.

Friedl et al. [23] point out that controlling the charging of EVs means that hardly any grid investments are needed up to 2030 in Germany, even when assuming higher market penetration rates of EVs.

While it can be assumed that the impacts of EVs on electricity grids depend heavily on the local framework conditions, the positive effect of controlled charging to avoid grid congestion seems very clear-cut (see Refs. [20, 24]).

Various studies deal specifically with the demand for additional grid investments that may be caused by charging EVs. Robinius et al. [25] quantify the investments in all grid levels at around 17.5 billion EUR for Germany if 50% of passenger cars were electrified (approx. 20 million vehicles)[4]. A study by Oliver Wyman [23] calculates the investments required only for the distribution grids for the same rate of electrification at 11 billion EUR with uncontrolled charging of the vehicles. A recent study by McKinsey [26] also highlights the possible high investments in distribution grids due to EVs.

Overall, studies cover many aspects with regard to the impact of the diffusion of EVs into the electricity system. Yet, they have in common that they focus solely on one electricity cost component at a time. To the best of our knowledge, so far, there has been no analysis of what impacts EVs might have on the retail electricity price as a whole. This requires a holistic analysis of the market diffusion of EVs, the resulting impacts on the merit order of the electricity market and the local implications for low-voltage grids. In this paper, we address this research gap for Germany. We use the development of the German residential electricity price as an indicator for this analysis.

In order to illustrate the individual influencing variables, Fig. 5.1 shows the cost components of the German residential electricity price for the year 2018. They consist of procurement costs, network charges, concession fee, renewable surcharge, taxes and other surcharges. In this paper, we analyse implications of EVs on network charges and procurement costs, which are, apart from the renewable surcharge, the largest components of the household electricity price. Under the current regulations in Germany, all relevant price components are largely variable, i.e., they are calculated based on the kilowatt-hours of electricity consumed. As indicated above, EVs can significantly affect the demand for electricity, and this implies that EVs can exert a strong influence on the different electricity price components. In addition, the load profile of EVs is not distributed evenly throughout the day. This raises the question of how this will affect the electricity generation structure.

While using kilowatt-hours to calculate the procurement of electricity largely corresponds to the real cost structure, this is only the case to a limited extent for the other electricity price components. For example, more than 90% of grid costs are fixed costs. These costs are paid by grid users via the so-called specific grid charge[5], which is billed to consumers through the amount of electricity drawn from the grid. Improved utilisation of the electricity grids due to EVs could lead to a reduction of the specific charges and therefore to a reduction of electricity prices and in turn to economic benefits for electricity consumers.

[4] For BEVs with a battery capacity of 75 kWh.

[5] Network charges for "load-profiled", larger grid users in Germany (>500 kW) comprise a capacity price and a price per kWh according to the German regulation [27]. Users with a lower consumption (e.g., households at the low-voltage level) instead have to pay a price per kWh and a fixed basic rate instead of a power price.

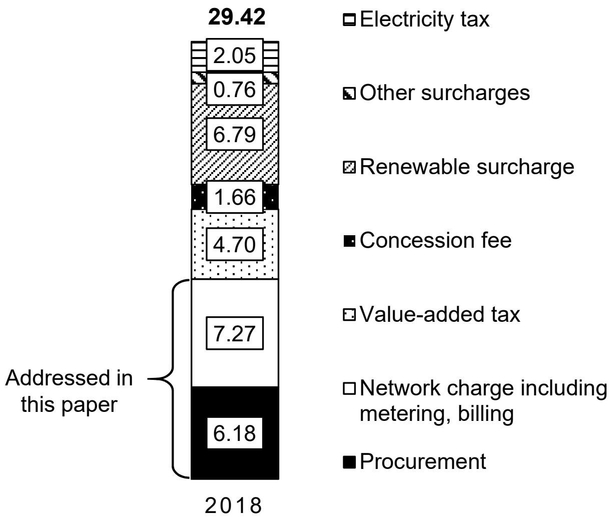


Figure 5.1: Average electricity price for a household in EUR ct/kWh in Germany in 2018 – electricity price for a household with an annual consumption of 3,500 kWh (data from Ref. [27]).

5.3 Methodology

5.3.1 Market diffusion and charging behaviour

The market diffusion model *ALADIN* [28] is used to simulate the EV market diffusion and charging behaviour. *ALADIN* does not use empirical data for charging profiles because, at present, there are not enough representative data available for future charging behaviour with different infrastructure options (at home, at work, public). Instead, *ALADIN* simulates the future diffusion of EVs and their charging behaviour based on driving patterns of conventional vehicles [29, 30]. A detailed description of the model is found in Refs. [31, 32] and left out in this paper as we focus on the impact of EVs on the distribution grid and power generation.

5.3.2 Modelling the influence of electric vehicles on the system load and spot market prices

A comprehensive assessment of the effects of EVs on the electricity system requires analysing their influence on the distribution grid. Beyond local effects, the evaluation must also include the consequences at national level. This concerns the impacts on the structure of total electricity demand and the system load as well as the generation structure and the costs for electricity.

To analyse the effects of EVs at national level, the demand for electricity is modelled with hourly resolution and projected to the year 2030. The first step assumes an uncontrolled load of EVs. In a second step, the charging of EVs is controlled. This approach is able to identify and analyse the impacts on the system load. In parallel, effects on the electricity supply side are quantified by modelling the electricity generation needed to cover the load with and without EVs (for both uncontrolled and controlled charging).

The simulation model *eLOAD* is applied to the process steps listed and coupled with the fundamental model *MiPU*. *eLOAD* ("Energy Load Curve Adjustment Tool") consists of a projection module and a DR/controlled charging module. In the former, the historical system load is disaggregated on the basis of a technology-specific process load curve database with an hourly resolution, and the process load curves are scaled individually using annual, process-specific demand projections for 2030. The process load curves for 2030 are subsequently reaggregated to obtain the system load. This approach implicitly takes into account technological change with structural impacts on the system load. A detailed description of the model is found in Refs. [33, 34].

In the DR module of *eLOAD*, there is the possibility to assume that the load of suitable processes, in our case privately used EVs, is flexible and suitable to optimise its use for controlled charging. *eLOAD*'s DR module has already been presented in Gnann et al. [34]. However, for the sake of consistency but particularly to present the linkage between DR modelling using *eLOAD* and electricity generation modelling with *MiPU*, we consider it necessary to briefly describe this part of the methodology as well.

The total load of EVs is allocated in a mixed-integer cost minimisation. Equation 5.1 shows the objective function for one optimisation interval, in which the costs for the electricity demand $P^{EV}_{ls,i,j}$ of EVs are aggregated and minimised:

$$\min \sum_{i=h_{min}}^{h_{max}} \sum_{j=h_{min}}^{h_{max}} P^{EV}_{ls,i,j} \cdot (p_j - p_i), i \neq j, i, j \in [h_{min}, h_{max}] \tag{5.1}$$

Here, the flexible load $P^{EV}_{ls,i,j}$ (MW), shifted from hour i to hour j depends mainly on the price signal p_j. To calculate implications of DR ex-post and to promote as much load flexibility as possible, we assume that for EVs, load shifting is not associated with additional costs (e.g., activation costs for each load shift or costs due to a consumption increase). We use the residual load, which is calculated endogenously within *eLOAD*, as DR signal p. We further assume that the electricity demand has to be supplied on each day, i.e., loads cannot be shifted from one day to the next. This means, as we use the yearly structure of 2012, that we have 366 optimisation intervals of 24 hours. As long as the vehicles' electricity demand is supplied on time for the next trip, it is assumed that the charging load of each vehicle can be controlled for the entire time interval in which the EV is connected to the grid.

There are no costs associated with shifting loads. However, load adjustments are restricted by load bounds, defined in Equation 5.2 and ensuring that the sum of hourly load (original load in an hour, P^{EV}_i, and load shifted to this hour, $P^{EV}_{ls,j,i}$ minus load shifted away from hour i, $P^{EV}_{ls,i,j}$) stays between the minimum and maximum load P^{EV}_{min} and P^{EV}_{max} (MW), respectively.

$$P^{EV}_{min} \leq P^{EV}_i + \sum_{i=h_{min}}^{h_{max}} P^{EV}_{ls,j,i} - \sum_{i=h_{min}}^{h_{max}} PEV_{ls,i,j} \leq P^{EV}_{max}, \forall i \tag{5.2}$$

Load shifting capacity also depends on the vehicles' storage and the fact that EVs are mobile, which means that three states – connected, mobile and disconnected – and the corresponding vehicle shares for each hour ($vsh_{conn,h}$, $vsh_{mob,h}$, $vsh_{disconn,h}$) are distinguished in order to determine the realistic load shifting potential available.

The available storage capacity for EVs is restricted by the total storage capacity SFL_{max} (MWh) and the minimum storage fill level SFL_{min} multiplied by the share of vehicles in the connected state.

Charging is only possible for vehicles in the connected state. Thus, the storage capacity available for load shifting (see Equation 5.3) depends on charging (planned (P_h^{EV}), and due to load shifting away from ($P_{ls,h,j}^{EV}$) or to an hour ($P_{ls,j,h}^{EV}$)) and additionally on the energy withdrawn from the aggregated available storage (or fed in) if vehicles change from a connected to a mobile state $vex_{conn-mob,h}$ (vehicle exchange vex in MWh). Their storage fill level is then no longer included.

$$SFL_{min} \cdot vsh_{conn,h} \leq \sum_{h=h_{min}}^{i} P_h^{EV} - \sum_{h=h_{min}}^{i} \sum_{j=h_{min}}^{i} P_{ls,j,h}^{EV} - \sum_{h=h_{min}}^{i} vex_{conn-mob,h} \leq SFL_{max} \cdot vsh_{conn,i}, \forall i \tag{5.3}$$

Analogous to Equation 5.3, 5.4 and 5.6 restrict the storage fill level for mobile and disconnected vehicles. In each optimisation interval (24 h), the storage fill level in the mobile case (Equation 5.5) has to be equal to the electricity exchange resulting from the transfer of vehicles from mobile to disconnected $vex_{mob-disconn,h}$ and the discharge load per hour $P_{dis,h}^{EV}$.

$$SFL_{min} \cdot vsh_{mob,h} \leq \sum_{h=h_{min}}^{i} vex_{conn-mob,h} - \sum_{h=h_{min}}^{i} vex_{mob-disconn,h} - \sum_{h=h_{min}}^{i} P_{dis,h}^{EV} \leq SFL_{max} \cdot vsh_{mob,h} \tag{5.4}$$

$$\sum_{h=h_{min}}^{h_{max}} vex_{conn-mob,h} - \sum_{h=h_{min}}^{h_{max}} vex_{mob-disconn,h} - \sum_{h=h_{min}}^{h_{max}} P_{dis,h} = 0 \tag{5.5}$$

$$SFL_{min}(1 - vsh_{conn,h} - vsh_{mob,h}) \leq \sum_{h=h_{min}}^{i} vex_{mob-disconn,h} \leq SFL_{max}(1 - vsh_{conn,h} - vsh_{mob,h}) \tag{5.6}$$

For disconnected vehicles, the energy in storage at the beginning of an optimisation interval again has to be equal to the beginning. Thus, disconnected vehicles are constrained by:

$$\sum_{h=h_{min}}^{h_{max}} vex_{mob-disconn,h} = 0 \tag{5.7}$$

The restrictions Equations 5.8, 5.9 and 5.10 ensure that the available storage capacity is considered for all exchanges between storage groups:

$$-SFL_{max} \cdot vsh_{conn,h} \leq vex_{conn-mob,h} \leq SFL_{max} \cdot vsh_{conn,h} \tag{5.8}$$

$$-SFL_{max} \cdot vsh_{mob,h} \leq vex_{mob-disconn,h} \leq SFL_{max} \cdot vsh_{mob,h} \tag{5.9}$$

$$-SFL_{max}(1 - vsh_{conn,h} - vsh_{mob,h}) \leq vex_{mob-disconn,h} \tag{5.10}$$

This formulation results in a load shifting potential for EVs that takes technical restrictions into account. It generates an adjusted system load, which serves as input for the models *MiPU* and *FLEX-GOLD*.

The fundamental model *MiPU* (Minimal Cost Allocation of Power Units) calculates a merit order within the system boundaries of Germany with hourly resolution. The hourly demand for electricity modelled with *eLOAD* is used as input with and without controlled charging of EVs. This is covered by the available generation technologies, whereby the power plant-specific marginal costs $C^{var}_{k,h}$ of power plant k are calculated for the respective power plant capacity (P_k). The calculation considers the costs for fuel ($p^{fuel}_{k,h}$) and CO_2 allowances (p^{CO2}_h), the type and age of the power plant ($\eta_k(t_{in,k})$) as well as ramp-up times, ramp-up costs ($C^{st}_{k,h}$) and downtimes (see Equation 5.11).

$$C^{var}_{k,h} = \frac{1}{\eta_k} \cdot P_{k,h}(p^{fuel}_{k,h} + p^{CO2}_h \cdot e^{CO2}_k) + C^{st}_{k,h}, \forall k, \forall i \tag{5.11}$$

The demand and the electricity feed-in from PV and wind power are determined exogenously. The price-setting power plant, i.e., the plant with the lowest running costs, is then determined for every hour. This is done by calculating the minimum power plant capacity needed to cover the demand (D), which is transferred from *eLOAD*, minus feed-in from RE (P_{RES}) (see Equation 5.12):

$$\sum_{k=1}^{K} P - k \cdot on_{k,h} \geq D - P_{RES}, \forall h \tag{5.12}$$

Taking default probabilities into consideration, the binary variable $on_{k,h}$ is used to determine whether a power plant is deployable for the hour h in question. The hourly price on the spot market therefore corresponds to the marginal costs of the most expensive power plant needed to cover the load in an hour.

5.3.3 Simulation of the effects on electricity distribution grids and grid charges

Empirical surveys of today's charging behaviour and studies of potential future charging show that the majority of EVs in Germany – 80% - 90% – are charged at home (e.g. Refs. [35, 36]). This raises the question of what effects EVs have on the low-voltage grid (distribution grid).

The investments resulting from grid expansion are passed on to final consumers in the distribution grid through the specific grid charges. The specific grid charges account for about 23% of the electricity price for households and therefore strongly influence this price (see Fig. 5.1). The effects of EVs on the low-voltage grid are analysed using the *FLEX-GOLD* (Flexible Grid and Stakeholders) model. *FLEX-GOLD* conducts load flow calculations of electrical low-voltage grids on a quarter-hourly basis. In order to be able to model the load on the distribution grid in 2030 as realistically as possible, a simulation is carried out of household load profiles, the driving and charging behaviour of EVs and the electricity feed-in from decentralised PV, which, alongside EVs, will determine the grid load in the future. This model also implements an algorithm to depict the grid investments needed if grid overloads occur, for example, due to charging EVs. In line with [37], a distinction is made between voltage-related and thermal overloads. Voltage-related overloads are defined as a voltage deviation at a grid node of more than $\pm$ 4% of the nominal voltage. If there is a voltage-related overload, an additional cable from the local grid

Case		controlled charging	charging power
A	1	no	3.7 kW
	2	no	11 kW
	3	no	22 kW
B	1	yes	3.7 kW
	2	yes	11 kW
	3	yes	22 kW

Table 5.1: Description of cases for uncontrolled and controlled charging and charging power.

transformer to approximately[6] the last third of the overloaded line is installed endogenously. A thermal overload occurs if the electrical power exceeds the nominal power of equipment operated in the grid. In case of a thermal overload, a new cable is added from the local grid transformer to approximately[6] the middle of the overloaded line. The algorithm in detail is publicly accessible (see Ref. [38]).

The weighted average costs of capital (WACC) are determined for the economic assessment of grid investments. These apply a mixed interest rate from the return on equity of the distribution grid operator and the return on borrowed capital. The capital costs are distributed over the lifetime of the used equipment using the annuity method. Changes in the grid charges can then be calculated from this.

5.4 Case study and framework

The analysis is conducted for Germany. The year 2030 is selected for the calculations because the transformation of the energy system and the diffusion of EVs and other sector coupling technologies are already well advanced by then.

We use a set of two cases each containing three different alternatives in terms of charging power in this analysis (see Table 5.1): Case A (i.e., A.1 - A.3), where charging of EVs takes place in an uncontrolled manner and Case B (i.e., B.1 - B.3) in which EV charging is controlled by a DR signal described in Section 5.3.2. For both cases, we focus on EVs with charging possibilities at home and at work, which only differ by the available charging power. The charging powers under consideration are 3.7 kW (Cases A.1 & B.1), 11 kW (Cases A.2 & B.2) and 22 kW (Cases A.3 & B.3). In addition, only privately owned passenger cars are considered when simulating controlled charging of EVs, i.e., fleet vehicles are not taken into account. However, fleet vehicles are included in the projection of the system load. We refer to Ref. [34] for more information on the additional possibility of public charging points as well as other market diffusion parameters.

5.4.1 Assumptions for simulating controlled charging and modelling power plant deployment

The annual demand of specific processes used to model electricity demand and generation as well as the feed-in from RE, the power plants used, and fuel and CO_2 prices are taken from Ref. [39]. Table 5.2 gives an overview on key assumptions for different electricity generation technologies and the price for

[6] Cables are only being added between existing nodes of the grid.

	Installed capacity in GW	Fuel costs
Lignite	9.3	3.7 EUR/MWh_{th}
Hard coal	13.5	14.7 EUR/MWh_{th}
Open cycle gas turbine	5.7	39.6 EUR/MWh_{th}
Combined cycle gas turbine	11.7	39.6 EUR/MWh_{th}
Biomass	8.3	-
Wind onshore	38.3	-
Wind offshore	15	-
PV	52	-
Others (RE + conventional)	7.1	-
CO_2 certificates	-	15.0 EUR/t

Table 5.2: Technology-specific capacity, fuel and carbon prices. Source: [41, 42].

CO_2 certificates. Electricity imports are not considered. See Ref. [40] for the electricity demand in the year 2012, which is used for the projection of the system load.

Furthermore, all scenarios assume that the full load of private EVs is flexible. However, restrictions arise on the one hand due to where the EVs are located and, on the other hand, due to the battery size and charging limits for the charging process. We assume that on average 15 kWh per EV are usable for load shifting, which is equivalent to half of the usable battery capacity of BEVs (90% of 40 kWh) and PHEVs (80% of 10 kWh). We assume that only half of the potential battery capacity is used to still be able to perform all trips per user (cf. [34]). Charging limits are case-specific (see Table 5.1). The electricity demand caused by EV charging is taken from the market diffusion results (Section 5.1). For reasons of consistency, this demand is assumed to be equal for all cases.

For EVs, charging at home and at work is permitted. Conversely, this means that, within the framework of simulating controlled charging, the electricity demand of EVs can be shifted if these are at home or at the workplace as long as the demand for the next trip is covered.

5.4.2 Assumptions for electric vehicles in a suburban low-voltage grid

In the following, the assumptions for household, PV and EV profiles and scenarios are presented and the test grid used is described.

We assume a suburban area with detached houses and an average of 2.5 persons per household. The annual electricity consumption is 5,000 kWh per household [43].

For PV penetration, we assume that 500 MW of PV rooftop capacity will be installed annually in Germany until 2030 [44]. Calculated for the analysed grid, this corresponds to 60 kWp installed PV capacity. It is spread across ten PV systems, each with an installed capacity of 6 kWp [44]. The capacity of each PV system is limited to 70% of the maximum system to comply with the current German Renewable Energy Sources Act [45].

In Section 5.3.1 we model the national penetration of EVs, which is used as input parameter for the calculation of the electricity procurement costs. Nonetheless, independently of the national penetration of EVs in 2030, it is possible that charging of EVs (i.e. ownership of EVs) is very concentrated on individual areas and in consequence on individual grid lines. For this reason, we vary the penetration of EVs in the low-voltage grid in order to depict different penetration scenarios in addition to the cases

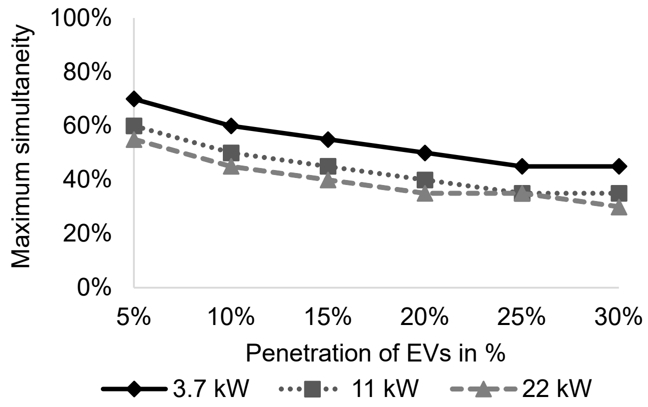


Figure 5.2: Maximum simultaneity for different charging powers and EV penetration (mean value derived from Refs. [21, 46]).

described in Table 1. We define penetration as the proportion of EVs in the analysed grid. We explore scenarios where EVs (including BEVs and PHEVs) account for 5%, 10%, 20% and 30% of all vehicles[7].

The number of EVs present in the grid plays a large role when planning and designing electrical distribution grids. If there is a low number of EVs, simultaneous charging and therefore a high simultaneity of charging processes must be expected. If the number of EVs in the grid increases, diversification effects occur, which reduce the simultaneity factor [46]. The maximum simultaneity factors assumed here are between 30% and 75% depending on charging power and penetration (see Fig. 5.2). The maximum simultaneity is also influenced by the charging power, because different capacities lead to different charging times for the same daily mileage. We also assume that each EV is plugged in once per day at home in the evening after the last trip of the day[8]. To determine the time of charging, the hourly cumulated load profiles of all EVs in Germany from the *eLOAD* model are first converted to quarter-hourly profiles using a spline interpolation. They are then used to determine a probability distribution for whether an EV is currently charging. Based on this distribution and taking into account the maximum simultaneity factors, the charging times of the EVs are determined. The duration of charging depends on the daily distance driven.

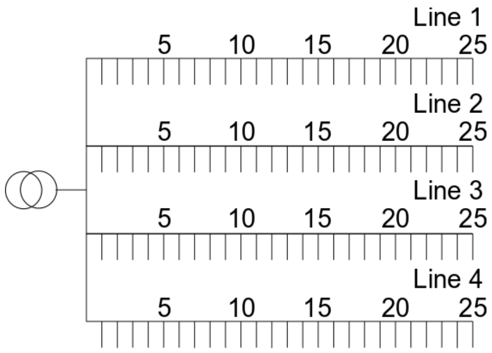
Since a large number of EVs is mainly charged at home in the evening after the last trip of the day on weekdays, there is a high correlation between the households' load peak (19:15) and the maximum load of EVs.

In Case B, we analyse controlled charging of EVs. Under controlled charging, the households' peak load (19:15) and the maximum power consumption of EVs no longer occur in the same time range as in the non-optimised Case A. We assume, in the optimised Case B, the charging load of the EVs is shifted in time but being kept at the same charging point.

The analysis is conducted based on a suburban low-voltage grid in 2030. This type of grid is selected as typical because studies of today's users of EVs or those interested in buying one show that they tend to live in small towns or rural surroundings [47, 48, 49]. Grid structural data from Germany are used for the grid parameters [50]. Each cable is roughly 28 m long. This corresponds to the average length

7 The national penetration rate for EVs in 2030 is approx. 10% (see Section 5.5.1). Local penetration naturally differs from the average national penetration. Therefore, this represents a range of possible local penetration rates for the near future.

8 The simulations assume that charging at the workplace is done in a different low-voltage network. For the load flow calculations, we only consider charging at home.



Grid parameter	Value	Unit
Transformer capacity	630	kVA
Total length of cables	2820	m
Conductor cross-section	150	mm^2
Cable length/household	28	m/HH
Grid lines	4	
Grid nodes	100	
Households	100	
PV systems	10	
EVs	variable	

Figure 5.3: Topology of the suburban grid and the grid parameters used.

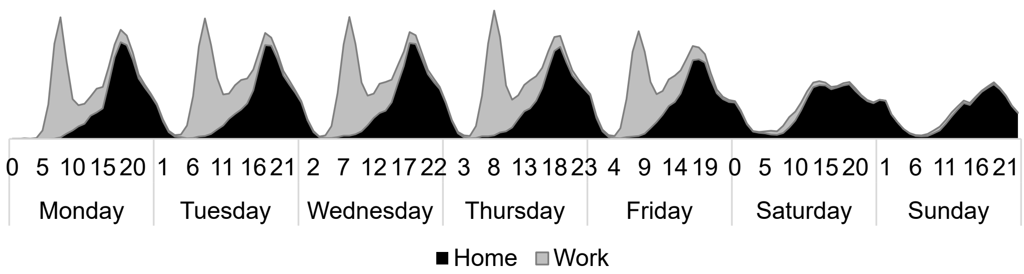


Figure 5.4: Simulated load profile of private EVs in 2030 given charging possibilities at home and at work (here 3.7 kW (Case A.1)).

of low-voltage cables and lines in regions with average population density in Germany [44]. The grid is supplied by a 630 kVA local transformer and consists of four lines, each with 25 nodes. The main grid parameters are summarised in Fig. 5.3.

Every grid node supplies one household (detached house) with electricity. The PV systems and the EVs are assigned stochastically to the nodes. The nodes are connected with each other with NAYY-J cables with a conductor cross-section of 150 mm^2.

For the case examined, it is assumed that the distribution grid operator uses 40% equity capital for the investment with an interest rate of 6.91% (before tax) [51]. The remaining borrowed capital has an interest rate of 2.72% (in accordance with the German Electricity Grid Fee Regulation Ordinance [52]). With the mixed interest rate, the capital costs are spread over 40 years, since this is the minimum regulatory depreciation period for these cables (see Ref. [52]).

5.5 Results

5.5.1 Market diffusion and charging behaviour

The three analysed charging powers in Case A lead to approx. four million EVs in 2030, which corresponds to about 10% of the stock of all passenger cars. These vehicles require 11.6 TWh of electricity in 2030. In addition, this results in a very similar load profile for all analysed charging powers, which is illustrated in Fig. 5.4. The different capacities have hardly any influence on the market diffusion or load profile in the quarter-hourly analysis intervals.

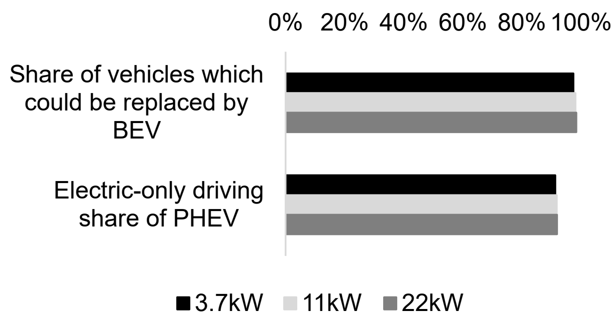


Figure 5.5: Influence of charging power on the use of BEV and PHEV from a technical perspective with assumptions for 2030.

Fig. 5.4 shows the load profile of several vehicles over the course of a week, which is assumed to be representative for a typical vehicle. The black areas show charging at home, the grey ones charging (of privately owned EVs) at work. Charging at home shows a peak in the early evening hours on weekdays, when many cars are charged after work. Charging at work reduces the evening peak on weekdays but creates an additional peak in the morning hours once the vehicles have reached the workplace. At the weekend, the load curve is flatter and spread over the day. We use the aggregated load profile described here as a typical load profile for EVs in the further analyses. The average annual electricity demand of an EV resulting from our model is 2.9 MWh.

The further analyses also clearly show that increasing the charging power does not have any significant influence on the use of a BEV or PHEV. Several thousand driving profiles of vehicles that form the basis of the *ALADIN* model are examined with regard to the technical feasibility of a BEV and with regard to a PHEV's potential share of electric-only driving [29, 30]. It is apparent from Fig. 5.5 that increasing the charging power neither leads to a clear increase in the proportion of vehicles that could be replaced by a BEV nor to an increase in the average share of electric-only driving in PHEVs. Hence, low charging powers are sufficient for everyday mobility needs from a techno-economical perspective.

So-called long-distance transport events are rare and require much higher charging powers (fast charging above 50 kW) [53]. These were not examined in this analysis because they are likely to occur in medium-voltage grids [54].

5.5.2 Effects of electric vehicles on the system load

An annual electricity demand of 446.4 TWh is assumed for 2030 [39]. Compared to today, this means a slight decrease in total electricity demand due to efficiency increases, especially for lighting in households and the trade, commerce and services sector. As a result, the hourly load decreases slightly, especially between 08:00 and 20:00. As seen in Fig. 5.4, the electricity demand for charging EVs is spread mainly across the period from 06:00 to 22:00. This effect has a corresponding influence on the structure of the system load as shown in Fig. 5.6.

Even when considering charging performed at work, there is an additional increase in the peak load in the evening due to the high proportion of vehicles that are plugged in to charge directly after the last trip of the day. This peak is only slightly lower than the midday load peak. Overall, therefore, EVs alter the shape of the system load compared to today and shift it to hours around midday and in the evening. On average, the system load in 2030 (in Case A) increases by 1.3 GW due to private EVs. The different

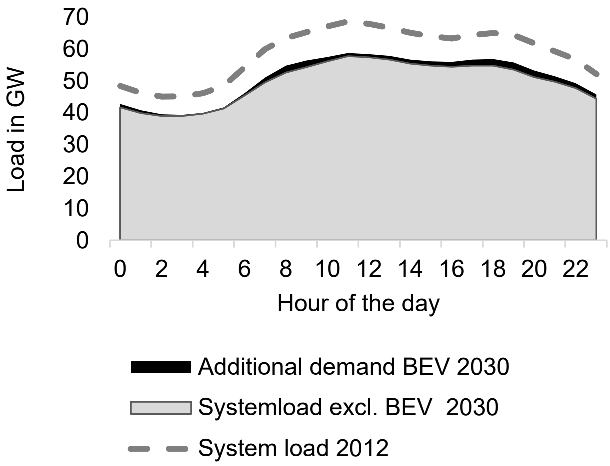


Figure 5.6: Germany's average system load for 2012 (line) and 2030 (area) on an average day. For 2030 the black area shows the load of private EVs (Case A.1).

charging powers analysed in Cases A.1 - A.3 result in negligible differences from the hourly system load perspective.

5.5.3 Controlled charging of electric vehicles

The previous section shows that, already in 2030, EVs represent a perceptible share of total electricity demand. Since, at the same time, EVs also have prolonged downtimes, during which charging power could be shifted, they are suitable for the application of controlled charging. Controlled charging in this paper is modelled in a way that creates an incentive for shifting charging to times of low residual load. Fig. 5.7 shows the aggregated result of optimising the load for Cases B.1 - B.3 (3.7 kW, 11 kW and 22 kW). It illustrates the change in the load of private EVs due to controlled charging. A negative load change results in the morning and from noon to 22:00. Thus, load is shifted away from these hours. Charging takes place instead especially at night between 23:00 and 05:00. This applies to all load levels of Case B.

Comparing Cases B.1 - B.3 shows that, the higher the applied charging power, the more pronounced the change between hours and the more this is concentrated on a smaller number of hours. This is due to the shorter charging duration at a higher charging power. Fig. 5.8 shows the systemic effects of the modified aggregated charging profile: Residual load peaks can be significantly reduced – by a maximum of more than 2 GW.

Controlled charging shifts some parts of the electricity demand into times when the residual load is low or there is even a surplus of RE generation, i.e., a negative residual load. This helps to integrate RE into the system, since they do not have to be dumped due to a surplus of supply in the market[9]. In addition to this, Figs. 5.7 and 5.8 indicate differences resulting from the assumed charging power: Since the flexibility of EVs increases at higher charging power while still complying with the other technical restrictions, phases in which there is a high incentive for load shifting can be better exploited. This leads to higher change rates in the load profile of EVs and thus to higher maximum loads, but can be beneficial from a system perspective, because it smooths the residual load and thus reduces residual load peaks.

[9] In the context of the German Network Development Plan, this – in contrast to grid related curtailment of RE – is called dumped energy [55]

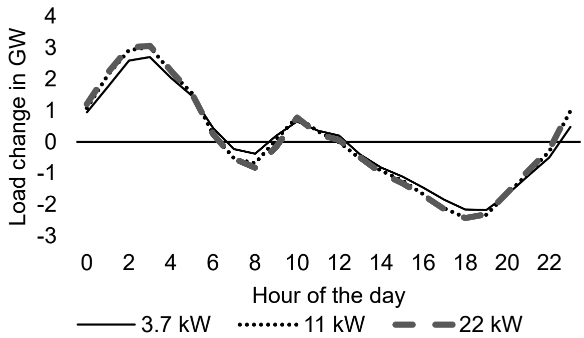


Figure 5.7: Average change in the load of private EVs after controlled charging optimisation and considering charging power in 2030.

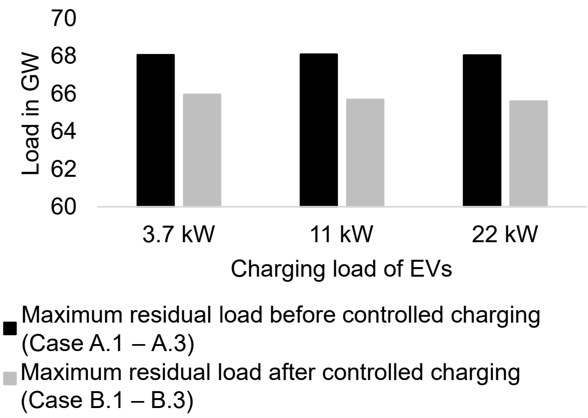


Figure 5.8: Comparison of the maximum residual load of Case A and B for all charging powers considered in 2030.

5.5.4 Effects of electric vehicles on electricity generation costs

In Section 5.5.3, we looked at the effects of EV diffusion on the structure of energy demand. Now, we turn our attention to the perspective of electricity generation.

The diffusion of private EVs – as already demonstrated – initially increases electricity demand by 2.7% by 2030 for the simulated market penetration. This additional energy demand requires additional electricity generation. Again, we point out that the national penetration of EVs used to calculate demand and the associated analyses of electricity generation is about 10% of the stock of passenger cars and is not varied.

Table 5.3 shows the change of the marginal generation costs of the model *MiPU*: For the Cases A.1-3 the average marginal costs of electricity generation increase by around 6% (volume weighted) due to the additional generation needed. If controlled charging is applied (Cases B.1-3), we only observe an increase of the average marginal costs of 3.8%. Overall, the cost increases in all cases also imply that the diffusion of private EVs also has an effect on all electricity consumers.

It is also relevant in this context that, although the marginal costs of electricity generation increase to a similar overall extent in the cases, there are slight differences concerning the increase. The largest increase takes place in Cases A.2 and B.2. The higher charging power (22 kW) in Cases A.3 and B.3 causes the aggregated load profile of all EVs to change so that it is slightly cheaper to purchase electricity.

We conclude that the increase in the marginal costs of electricity generation has a disproportionate impact relative to the additional demand in all cases. This is due to the fact that the uncontrolled load of EVs is not spread equally across the day, but increases disproportionately at certain times, especially around

Case		Average generation costs in EUR/MWh	Change in % (reference: no EVs)
A	1	65.8	+6.0%
	2	65.9	+6.1%
	3	65.8	+6.0%
B	1	64.4	+3.8%
	2	64.5	+3.8%
	3	64.5	+3.8%
Without EVs		62.1	-

Table 5.3: Change of average volume-weighted marginal electricity generation costs due to the diffusion of EVs before (Case A) and after controlled charging (Case B).

	Lignite	Coal	Gas
Increase in electricity generation due to the additional demand of EVs without controlled charging (Case A.1)	3.2%	6.5%	15.2%
Increase in electricity generation due to the additional demand of EVs with controlled charging (Case B.1)	5.7%	5.1%	7.0%
Net effect of controlled charging of private EVs: Case B.1 compared to Case A.1	2.5%	-1.3%	-7.2%

Table 5.4: Impacts of EVs and controlled charging (3.7 kW) of private EVs on electricity generation.

midday and in the evening. As a consequence, power plants with higher marginal costs are increasingly deployed, e.g., gas-powered plants (see Table 5.4). This circumstance leads to correspondingly high average generation costs. Overall, the additional demand of EVs leads to a higher use of all conventional power plants as shown in Table 5.4.

While varying the charging power of EVs between 3.7 kW, 11 kW and 22 kW without DR (Case A.1-3) results in only minor effects on electricity generation costs, controlling their charging, (Case B.1-3) does lead to a noticeable change in the electricity generation structure as highlighted in Table 5.4.

Load shifting from the afternoon and evening into nighttime or early morning hours results in a stabilisation of the system load. Consequently, power plants with higher marginal costs are deployed less frequently, which means a reduction in the electricity generated by gas (-1,830 GWh) and coal-powered plants (-926 GWh) and a higher capacity utilisation of lignite-powered plants (+1,455 GWh). In line with the results described by Hanemann and Bruckner [13], uncontrolled charging increases the marginal costs of electricity generation, especially in peak load hours. When controlled charging (Case B) is applied, the diffusion of EVs increases the marginal costs above all during low-price hours, but overall to a lower extent than is the case for uncontrolled charging (Case A). Our results show that not only average generation costs but also CO_2 emissions decrease due to controlled charging. CO_2 emission savings are particularly high for gas-fired (-10.8%) and hard coal power plants (-3.5%). Despite the increased use of lignite power plants as a result of DR, we observe a slight decrease of CO_2 emissions for this plant type (-0.4%), since more efficient plants are used and ramping is reduced.

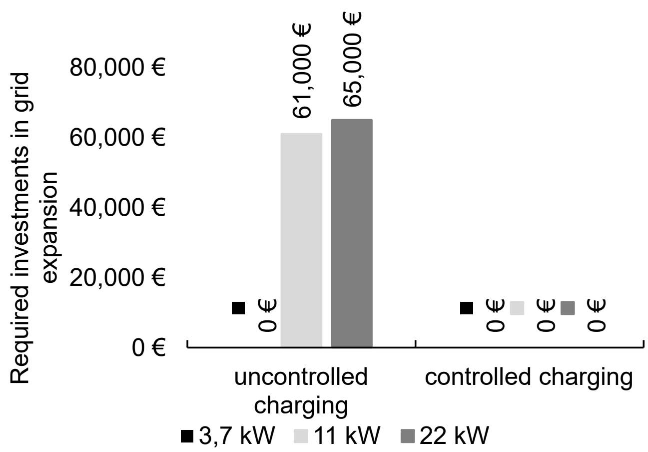


Figure 5.9: Required investments in 2030 for the grid shown in Fig. 5.3 depending on the charging power (valid for all examined rates of local EV penetration).

5.5.5 Influence of electric vehicles on grid charges

In the following, the influence of EVs on grid investments is described first. This is followed by an evaluation of the influence of the additional electricity demand caused by EVs on the refinancing of the existing grid infrastructure.

For Case A.1, no investments in the low-voltage grid are required. With higher charging powers (Cases A.2 & A.3), investments of 61,000-65,000 EUR are required for the analysed grid region for all the examined rates of local EV penetration (see Fig. 5.9). This means investments ranging from 1,800 EUR (EV penetration rate of 30%) to 10,900 EUR (EV penetration rate of 5%) are needed per EV present in the grid. Our results show that rates of local penetration higher than 5% do not increase the need for grid expansion. This is due to the rising diversification effects of a larger number of EVs in the grid and the associated drop in simultaneity. In Cases B.1-3, there is no need for grid expansion and therefore for investments in the analysed distribution grid (see Fig. 5.9).

For the example low-voltage grid selected here, it can be stated that a low charging power (3.7 kW) or controlled charging can avoid investments in the grid.

Investments in the low-voltage grid resulting from grid expansion are largely passed on to the final consumers in a distribution grid via the price charged per kilowatt-hour, which is determined based on their annual electricity consumption (specific grid charges). In spite of possible higher investments in the distribution grids, however, increased grid utilisation actually lowers the grid charges, because these are then distributed across a larger amount of power withdrawn from the grid.

For the defined cases examined here, an additional electricity demand of 13.8 MWh per year occurs in the grid due to EVs if 5% of all vehicles are electric. If 20% of all vehicles are EVs, the demand for electricity increases by 50.5 MWh per year. At a very high degree of penetration (30% EVs), 77.8 MWh per year are needed additionally from the grid. Since a high share of the grid costs are fixed costs and only a very small share is variable, increased utilisation of the grids leads to decreasing specific grid charges.

Fig. 5.10 illustrates the change in the specific grid charges for the analysed scenarios that results from the combination of higher grid utilisation and the required grid expansion due to EVs. There is no need for grid expansion at a charging power of 3.7 kW in the analysed grid. For Case A.1, we observe decreasing

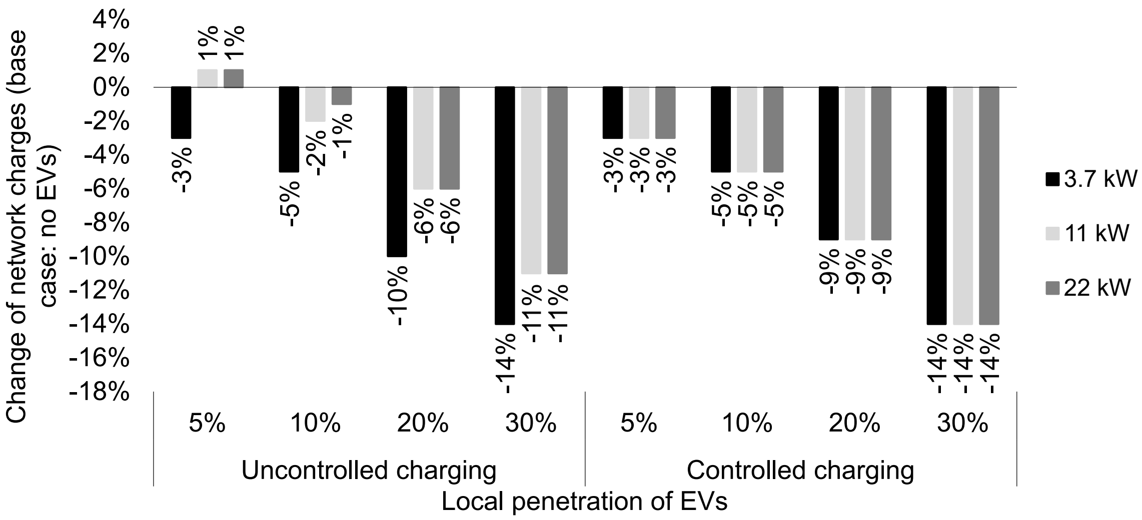


Figure 5.10: Influence of additional electricity demand due to EVs on the grid charge in a suburban grid in 2030.

specific grid charges for all the levels of EV penetration examined. The reductions range from 3% for a penetration rate of 5% EVs up to 14% for a penetration rate of 30% EVs. The same figures are found for Case B with optimised charging times, because there is no need for grid expansion here either – for all the cases and penetration rates analysed. In Case A.2, grid charges increase by 1% for a 5% EV penetration. This increase can also be observed for a even higher charging power of 22 kW (Case A.3). If the proportion of EVs rises to 10%, the specific grid charges decrease by 2% and 1%, respectively, for Cases A.2 and A.3 compared to the reference value. For the higher rates of penetration considered, the grid charges decrease with an increasing share of EVs in the grid by up to 11% (Case A.2), because the improved grid utilisation then outweighs the required grid investments.

Assuming that current regulations apply, we can therefore conclude for the analysed scenarios that the specific grid charges will decrease significantly in almost all cases due to EVs. Due to the declining grid charges, all households without EVs will also pay a lower amount for electricity overall. Although households with EVs require significantly larger amounts of electricity with a corresponding impact on their electricity bill, they also benefit from lower electricity prices.

The results of our study confirm the results of other current studies concerning the need for grid expansion (e.g. Refs. [21, 22, 23]). In addition to the results of these studies, our analysis also considers the effects on grid charges resulting from EVs. As well as the cost-increasing effects of necessary investments, specific cost reductions may also result if grid utilisation is increased. As far as the authors are aware, this effect has hardly been investigated so far.

5.5.6 Synthesis of results: the effects of electric vehicles on household electricity prices

This study explored several effects considering the charging behaviour resulting from the given charging power. On the grid side, we additionally analyse to what extent the diffusion of EVs determines how the grid charges develop, taking into account the proportion of EVs within the described grid area. With regard to electricity generation costs, we analyse how the additional electrical load due to EVs influences the hourly electricity generation costs. Both aspects, the generation costs and the expenditure

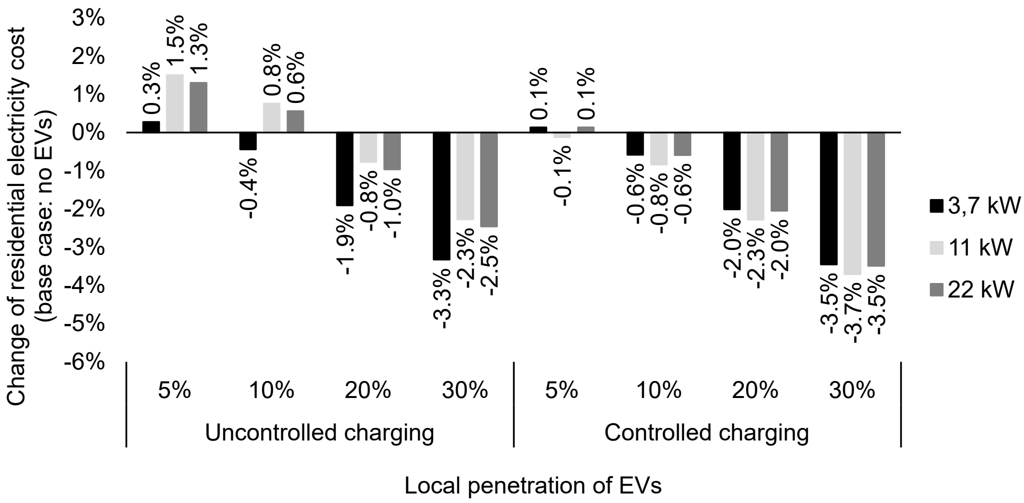


Figure 5.11: Overall change in the electricity price for households, for uncontrolled and controlled charging in 2030.

for grid expansion, were quantified for both controlled and uncontrolled charging. To compare the effects, the change in the electricity price is calculated in cents per kilowatt-hour for household customers (€ct/kWh)[10]. Whereas electricity generation costs increase in all scenarios due to the additional electricity required for EVs, the diffusion of EVs results in locally decreasing grid charges even at a low level of local penetration ($\geq$5%). The overall increase in electricity generation costs, illustrated in detail in Section 5.5.4, is lower than the change in the grid charge if the share of EVs is more than 10% (see Fig. 5.11). This means that rising electricity generation costs are already overcompensated by falling grid charges at a low local diffusion of EVs. As a result, a household without an EV spends up to 3.7% less on electricity than is the case without EVs in the grid. A relative increase in the electricity price is only expected if there is a low local number of EVs.

Overall, it becomes clear that the penetration rate of EVs represents a significant factor for how the electricity price develops. In this context, we emphasise that the total (national) annual electricity demand of EVs remains constant in all the scenarios. The penetration rate is only varied locally in the distribution grid considered. Fig. 5.11 also shows that the reduction of the household electricity price (at a penetration of $\geq$20%) is the lowest in Case A.2 (uncontrolled charging) and is the highest in Case B.2 (controlled charging). This effect, which was already addressed in Section 5.5.4, is due to the charging profile of the EVs in the respective cases.

We emphasise that the charging control of EVs was conducted at national level with the objective of smoothing the national residual load, and that incentive or congestion signals from the analysed distribution grid were not considered. Nevertheless, the results show that controlled charging leads to EVs behaving in a way that benefits the overall system.

[10] This includes the other electricity price components alongside the electricity generation costs and network charge. The basic assumption is that electricity is procured exclusively on the spot market, i.e., at the electricity generation cost calculated. We apply a renewable energy surcharge of 6 ct/kWh. 1.86 ct/kWh is assumed for the distribution costs and profit from electricity generation. This corresponds to the average sales costs assumed for household customers for 2010-2013 [56]. All other price components and the electricity tax are taken from Ref. [57] and assumed to be constant.

5.6 Discussion and conclusions

This study analysed the influence of electric vehicles (EVs) on two important electricity price components, the grid charge for the low-voltage grid and electricity procurement costs, for the price households pay for electricity.

Our study integrates a number of variations: We examined diffusion of EVs, generation costs and grid impacts for an EV charging power of 3.7 kW, 11 kW and 22 kW, with and without controlled charging and varied the local EV penetration in the distribution grid from 5% to 30%. In our view, the high amount of dimensions we chose enhance the robustness of our results. Yet, the four models applied several approximations: The existing scenario we used for the analysis of implications of EVs on the electricity generation costs was designed with a CO_2-reduction pathway of 80% until the year 2050. A more ambitious target would have gone along with more ambitious shares of renewables, leading to lower marginal electricity generation costs but also a higher volatility of generation and thus impacts on the local grid level as well. Political instruments, such as an accelarated coal-phase-out, would also affect the results, since it would improve the market position of gas-fired power plants – reducing CO_2 emissions but supposedly resulting in higher average generation costs. Additionally, as we focussed on the analysis of EVs, controlled charging of EVs was the only source of flexibility considered here. Considering other flexibilities, such as further demand flexibility options, storage, but also the integration of Germany's neighbours (i.e. cross-border electricity transport capacity) into the electricity market model could lead to lower generation costs, decreased CO_2 emissions and decreased volatility and thus could facilitate the integration of EVs into the electricity system. In this respect, studies examining higher shares of RES but also deeper levels of decarbonisation of the demand side and additional sources of flexibility could complement our findings.

Similarly, a much more comprehensive analysis could be conducted that considers all the effects of electric mobility. For example, this would include calculating the effects due to the decline in the demand for petrol and diesel and including the associated losses in tax revenue. This would also include considering the decrease in export expenditures for crude oil and the additional gains in value added and tax revenues from the additional electricity production in Germany. The effects due to changed value creation in automobile production would also have to be considered. Such an overall comprehensive analysis is complex and was beyond the scope of this study. It should be noted, however, that an analysis of comprehensive studies does not reveal a uniform picture and that the effects are strongly determined by the different assumptions. Having pointed that out, the several studies conclude that electric mobility could have positive economic effects on Germany (e.g. Ref. [58]).

With reference to the calculations for the electricity distribution grid, our results show that relevant additional grid investments due to EVs only occur for the analysed supply area if high charging power (11 kW and over) and uncontrolled charging coincide. If charging EVs is controlled, no additional grid investments are needed in the cases examined up to a local penetration of 30% EVs. This finding confirms the results of other studies. However, it must be pointed out that the distribution grids in Germany vary widely in configuration and design, and charging EVs may also result in higher grid investments in individual cases. In addition, local EV penetrations of over 30% could occur in individual cases. The simultaneity of EV charging decreases with higher EV penetrations [21]. Nevertheless, violations of the grid restrictions may occur. Here, too, the effects are strongly dependent on the grid area under consideration. Further investigations into the influence of controlled charging at higher EV penetrations could provide insights here. Also, the future development of battery price and capacity can have large effects on EV market diffusion, but also on the shiftable loads. Higher capacites would allow more users to perform all their driving with a battery electric vehicle and also increase the potentials for load shifting. If the battery price development is not of the same magnitude, this could, however, also have negative effects on market diffusion, since investments would rise and battery electric vehicles could become less attractive. Future studies could analyse this aspect.

As far as the authors are aware, this study is the first to analyse the effect of EVs on both electricity generation and on the grid charge. The latter constitutes the biggest part of the electricity price for German households. Higher electricity sales due to EVs mean much better capacity utilisation of the electricity grid. On the basis of current grid grid regulations, this can significantly reduce the average specific household electricity price (in contrast to the effect on the cost of electricity generation).

If the two effects are taken together, the cost-reducing effects of the grid charge are usually larger and, in sum and depending on the assumed case, the specific electricity price for German households can be reduced by up to 4% in the most favourable case. This might be considered not very relevant, but in the context of the public discussion, in which there are frequent warnings about the possibly high grid investments required by EVs, our study can contribute to a more objective debate.

It can be concluded that controlled charging of EVs should be promoted and incentivised by the regulatory framework. Limiting the charging power can also make sense with a higher market penetration of EVs. In this context, it should also be considered whether the higher grid investments caused by a high charging power (22 kW and above) of households with EVs should be shared across all consumers. Alternatively, it could be discussed whether these costs should be borne solely by the users of the EVs or those with high charging power. However, such considerations should also include possible trade-offs with impacts on the market diffusion of EVs.

Future studies should also include the effects of EVs on the electricity transmission grids and the possible impacts of EVs on the renewable energy surcharge. Complementary studies of distribution grids are also suggested, because such grids are very heterogeneous and the effects of EVs can vary greatly. Furthermore, future research could also consider the influence of possible changes in how the grid charge is configured. A further issue that was not explored here concerns the effects of using public fast charging points on the electrical transmission and distribution grids.

Credit author statement

Matthias Kühnbach: Conceptualization, Methodology, Software, Formal analysis, Visualization, Data curation, Writing – original draft, review & editing. **Judith Stute**: Conceptualization, Methodology, Software, Formal analysis, Visualization, Data curation, Writing – original draft, review & editing. **Till Gnann**: Conceptualization, Methodology, Software, Formal analysis, Visualization, Data curation, Writing – original draft, review & editing, Funding acquisition. **Martin Wietschel**: Conceptualization, Writing – review & editing, Funding acquisition, Supervision. **Simon Marwitz**: Conceptualization, Methodology, Software, Writing – review & editing. **Marian Klobasa**: Writing – review & editing, Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[Start of Publication II]

Dynamic pricing and the flexible consumer – investigating grid and financial implications: a case study for Germany

Judith Stute[1,*] and Matthias Kühnbach[2]

[*] Corresponding author.
[1] Fraunhofer IEG, Research Institution for Energy Infrastructures and Geothermal Systems, Breslauer Str. 48, 76139 Karlsruhe, Germany, corresponding author
[2] Fraunhofer ISE, Institute for Solar Energy Systems, Heidenhofstr. 2, 79110 Freiburg, Germany

Highlights

- Simultaneous availability of several electricity tariffs within a grid area is considered.
- We select dynamic tariffs already available today for our analysis.
- We model decision-making behavior of household customers regarding choice of tariff.
- We analyze effects of dynamic tariffs on a LV grid under free choice of tariff.
- Free choice of tariff leads to lower thermal load and lower voltage band deviations.

Abstract

Due to the ongoing expansion of renewable energies and the increasing energy demand of household consumers, e.g. due to the electrification of the mobility and heating sectors, grid bottlenecks and voltage band violations in low-voltage grids in Germany are expected to occur more frequently in the future. Dynamic pricing, implemented through digitization, is seen as one option to incentivize flexible and responsive electricity use of household consumers. Flexible consumption of household consumers could make grid utilization more efficient. So far, most studies on the effects of dynamic pricing focus on only one tariff for all household consumers within one low-voltage grid, whereas, in reality, households can choose between many different static and dynamic electricity tariffs. As previous studies have shown, the choice of tariff plays a major role in how flexibility is used. To address this research gap, we developed a model which integrates households and their static and flexible consumption and generation units into a home energy management system (HEMS) and minimizes the households' power purchase costs. The model considers a range of dynamic tariffs that are already available today and includes the decision-making of heterogeneous household customers regarding the choice of tariff. Load flow calculations are then used to determine and analyze the effects on a low-voltage grid area. With this methodology including the free choice of tariff we go beyond the state of the art and paint a more realistic picture of the effects of dynamic tariffs on low-voltage grids. Our results show that, even though dynamic tariffs lead to increased peak demand at the level of individual households, peak loads are spread more widely within a grid area as the result of households choosing different tariffs based on economic considerations. Due to these effects, dynamic pricing has positive effects on grid utilization and could reduce the need for grid expansion.

Keywords

Dynamic tariffs, electric vehicles, heat pumps, battery storage systems, distribution grid, flexibility

Abbreviations

BSS, Battery storage system; CPP, Critical-peak-pricing; DA, Day-ahead; EV, Electric vehicle; HEMS, Home energy management system; HP, Heat pump; HS, Heat storage; iMSys, Intelligent metering system; LV, Low-voltage; MFH, Multi family home; MV, Medium-voltage; RTP, Real-time-pricing; SFH, Single family home; ToU, Time-of-use; WTP, Willingness to pay; WTPM, Willingness to pay more.

6.1 Introduction

The energy industry is currently facing major changes, including the expansion of renewable energies and increasing household energy demand due to electric vehicles (EVs), heat pumps (HPs), etc. On the one hand, these changes result in new business models and new ways for household consumers to participate in energy trading, facilitated through digitization, as well as in cost savings through automation in some areas. On the other hand, there will be a significant increase of the load on the electricity distribution grids in Germany [1, 2]. Although grid stability in Germany is very high ($SAIDI_{EnWG}$[1] in low-voltage (LV) grids was 2.11 min in 2020, $ASIDI_{EnWG}$[2] in medium-voltage (MV) grids about 8.62 min [3]), the frequency of grid congestion and voltage band violations could increase sharply given the potential for high simultaneity of EV charging as well as heat demand if appropriate counter-measures are not taken. Those effects could especially increase in MV and LV grids, as this is where most heat pumps as well as most of the charging points for electric vehicles are likely to be found. One promising and in literature much discussed way to handle this increased load and the mentioned simultaneities is to incentivize flexible consumption behavior through dynamic electricity price components („dynamic tariffs“). This could improve the efficiency of use of the distribution grid, so that grid expansion can be delayed or avoided [4, 5, 6]. As cost-reflective pricing is one way to promote the system integration of small-scale power generation plants and flexible loads, regulators, e.g., at EU level, have established the obligation for utilities to offer dynamic tariffs to their customers [7].

Some energy suppliers, therefore, already offer dynamic tariffs for household customers (e.g., „Tibber“[8], „aWATTar“ [9] or „Polarstern“ [10] in Germany). The tariffs available in Germany are two- or three-tier time-of-use (ToU) tariffs and hourly tariffs based on the day-ahead wholesale market price. An overview over these three pricing schemes is given in Fig. 6.1. As the rollout of intelligent metering systems (iMSys) advances and home energy management systems (HEMS) are improving, dynamic tariffs can be offered and used to an even greater extent in the future.

As the framework conditions for the use of dynamic tariffs will continue to improve in the future, the question arises, which effects those tariffs are having on the customer's electricity bill and which flexible consumers will opt for a dynamic tariff. For all consumers having a certain degree of flexibility (e.g., through storage or controllable devices) making use of those tariffs, a change in the individual load profile can be expected. Those changes on individual household level can have a systemic effect on LV distribution grids due to the incentivized use of flexibility.

6.1.1 Literature

Dynamic tariffs for end-users, e.g., based on the wholesale electricity price or on price signals derived from the local grid situation, have been investigated in several existing papers. One major topic is their influence on the load curves of households, electric vehicles, heat pumps, PV home storage systems and other flexible devices. Another important issue is their financial attractiveness for end-users. Going one step further, there is also research on the influence of dynamic tariffs on distribution grids. These three literature strands are relevant for this paper and are presented below.

The effects of dynamic tariffs on household load curves have already been discussed in several studies. Ref. [11] gives a good overview of pilot studies in different countries and reveals that the implementation of ToU tariffs can lower peak demand by about 3-6%. Critical-peak pricing (CPP) can lead to even higher reductions of about 13-20%, or, in combination with enabling technologies, 27-44%. Ref. [12] observed an average peak load reduction of up to 54% for individual households using dynamic pricing schemes.

[1] $SAIDI_{EnWG}$: System Average Interruption Duration Index; Indicates the average supply interruption per connected end consumer within a calendar year. Only unplanned interruptions are included in the calculation.

[2] $ASIDI_{EnWG}$: Average System Interruption Duration Index; Indicates the average supply interruption per connected rated services within a calendar year. Only unplanned interruptions are included in the calculation.

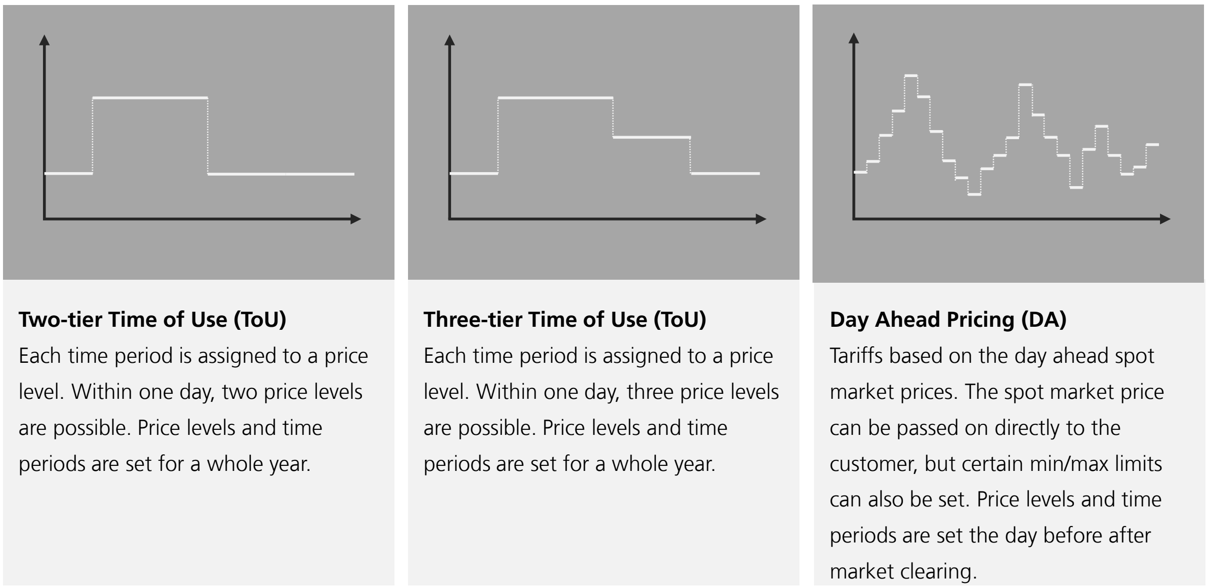


Figure 6.1: Concepts of dynamic tariffs available on the market in Germany.

The financial attractiveness of dynamic tariffs for flexible consumers (end-users with different flexible technologies such as EVs, HPs, or battery storage systems (BSS)) has also already been assessed in several papers: Ali et al. [13] determined potential energy cost savings for direct electric space heating and partial thermal storage using a tariff based on hourly prices of the Nordic day-ahead power market. In Ref. [14], the focus was on smart charging of electric vehicles. The authors found lower charging costs for EV owners using a dynamic tariff. Ref. [15] explored the effect of different dynamic tariff schemes („Economy 7“, which corresponds to a day/night tariff; „time-of-day“ and „wholesale“, a real-time pricing scheme) on the electricity bill and peak load of households, taking into account EVs, vehicle-to-home options, and BSS. The study showed it is possible to reduce a household's electricity bill by up to 85%. At the same time, the peak load increased for all dynamic tariffs considered. A new enhanced ToU (E-ToU) approach was considered in Ref. [16]. This tariff varies for different type days and on energy drawn from the grid. The authors analyzed the effects of the E-ToU tariff on a PV system with BSS considering two options: E-ToU was applied only to power drawn from the grid; and E-ToU was applied to power drawn from and fed into the grid. In the latter case, it was shown that the household peak load could be reduced significantly as could the daily electricity costs (average of summer and winter).

The authors of Ref. [17] analyzed four different EV charging strategies in households with a PV system: direct charging, optimizing self-sufficiency, and optimizing electricity costs with a day-ahead pricing scheme with and without including the PV system. When considering the cost of charging, the best result was for the optimizing self-sufficiency case (35% cheaper than in the direct charging case), followed by the optimizing electricity cost case with PV system (approx. 34.9% reduction of the cost of charging). For both cases of price-optimized charging, the results indicated an increase in the 1% quantile of the aggregated grid load of 184% without PV and 125% with PV. In both cases, it is assumed that all households received the same price signal and used the same charging strategy.

Venkatesan et al. [4] explored consumer behavior towards demand response by considering different types of consumers. The authors incorporated the different consumer types into an analysis of the IEEE 123 node test feeder, assuming all consumers were given a 24-h real-time pricing (RTP) tariff scheme. They showed that demand response during peak hours helped to boost the node voltages. Ref. [18] considered the effects of time-of-use and time-of-export[3] tariffs for households with batteries and heat pumps. The authors aggregated the load of 100 households to assess the effects on a MV/LV substation level and assumed all households had the same pricing scheme (3-tier ToU). Their results showed the formation of a rebound peak in the evening hours, when all batteries started charging during the off-peak price band. In a second step, the authors examined the effects of staggered off-peak price bands. This helped to reduce the rebound peak in areas with a high number of BSS. Boulaire et al. [19] analyzed the potential benefits of household and community batteries for individual households but also for the transformer of a LV grid using an agent-based model. They considered a 2-tier ToU and a static tariff already available on the market (in Queensland, Australia). Their results showed that a community battery would lead to a slight increase of peak load at the MV/LV transformer. Ref. [20] investigated the impact of a 3-tier ToU tariff combined with a grid tariff with demand charge (€/kW) The technologies considered were electric water heating, PV and BSS. Power flow analysis was conducted for three different residential LV distribution grids. The results showed an increase in line loading of the head feeder of each grid when applying the ToU tariff. The demand charge of the grid tariff was only able to counteract that effect to a small extent. Furthermore, the ToU tariff was shown to have negative effects on the voltage level of the grid nodes. In this paper, as well as in the others described above, it was assumed that all households react to the same tariff within a grid. In Ref. [21][4], households within the CIGRE LV benchmark grid (European configuration) with different technologies such as EVs, heat pumps and PV systems were presented with different price incentives. It was shown that, for all dynamic pricing schemes, there was an increase in grid restriction violations compared to the static tariff case. Again, all household consumers within the grid area were presented with the same tariff scheme for each scenario.

6.1.2 Research gap and research question

Overall, as outlined above, dynamic tariffs appear to be financially attractive for the participants. Researchers have also analyzed the implications of dynamic tariffs for the grid and obtained mixed results. On the one hand, there are positive implications, e.g., the peak demand of households decreases in pilot studies of households without flexible devices. On the other hand, there are negative implications for LV grids if households have a higher share of flexible technologies. A common denominator of the studies presented above is that they model both the attractiveness and the grid implications of tariffs sequentially, i.e., each case study assumes only one type of tariff per scenario. This is, however, not a realistic assumption: In reality, end-users that have selected different tariffs are located within one grid area. The systemic impact of price-responsive pricing is affected by the sum of the tariff choices and the decision-making of all consumers within the grid, not just by the design of a specific tariff or the economic attractiveness of this tariff to an individual consumer. This is due to the fact that, in Germany (and most of Europe), customers are free to choose a tariff and, due to the heterogeneity of households and occupants, it is unlikely that all end-users within a grid area will select the same tariff.

Decision-making behavior within this study refers to the decision to actively use the flexibility of EVs, heat pumps and PV battery storage systems (e.g., via a HEMS). This can be achieved by choosing an electricity contract with a dynamic tariff and benefiting specifically from price differences over the course

[3] A time-of-export tariff offers the possibility to penalize the export of electricity from PV systems in specific hours of the day and to incentivize the export of electricity in other hours of the day.

[4] The first author of this paper also co-authored Ref. [21]

of the day. These decisions are not based on purely financial aspects, but also on personal preferences, knowledge and understanding of the technologies and tariffs offered, and other, sometimes idealistic reasons [22].

Essentially, this means that the perceptions of a tariff's attractiveness will vary because households are heterogeneous both in terms of their demand patterns and the technical equipment they have at their disposal. As a result, different tariffs are likely to coexist within one distribution grid, leading to a different/new grid situation.

These observations give rise to the following research questions:

- Are the dynamic electricity tariffs available on the market today financially attractive to flexible consumers and prosumers?
- When considering the variety of tariffs available to flexible consumers, do dynamic electricity tariffs have a positive impact on the distribution grid after all?

We attempt to answer these research questions by presenting a model-based but more realistic insight into the effects of dynamic tariffs on low-voltage grids. This is achieved by considering the free and thus heterogeneous choice of tariff that household customers have in reality: The model integrates consumer decision-making, gives customers a set of different static and dynamic tariff options, and investigates the cumulated effect their individual decisions have on a low-voltage grid.
The following chapter describes the methodological approach used to answer the questions (Section 6.2). Section 6.3 presents the underlying assumptions of the case study. Section 6.4 gives an overview of the electricity tariffs considered, their effects on the load profiles and decision-making behavior of households, as well as their effects on the distribution grid. The paper finishes by discussing the results (Section 6.5) and presenting the conclusions (Section 6.6).

6.2 Method

Depending on the electric devices available in a household, their flexibility and whether a household has a PV system, dynamic tariffs lead to changes in consumption behavior, i.e., in the load profile of a household. The model *EVaTar* („**E**fficient **Va**riable **Tar**iffs“, developed by the first author) is used to map the reaction of flexible consumers to dynamic tariffs. An overview of the model structure consisting of three modules is shown in Fig. 6.2. The model allows the simulation of inflexible and flexible load shares in households and models a HEMS. Within the HEMS, the household's electricity purchase costs are minimized by optimizing the operation of the BSS, the charging of EVs, and the electricity consumption of heat pumps (*EVaTar-building*). User preferences regarding the charging of EVs can also be mapped (see Section 6.2.1). In addition, the decision-making behavior of household consumers with regard to the choice of electricity tariff is depicted (*EVaTar-decisions*). This considers the electricity procurement costs determined in *EVaTar-building*, investments, and the willingness to pay more (WTPM) of individual groups (see Section 6.2.2).

By coupling this model with the open-source model pandapower [126], it is possible to perform load flow calculations for low-voltage power grids. In this way, the effect of dynamic tariffs and the resulting

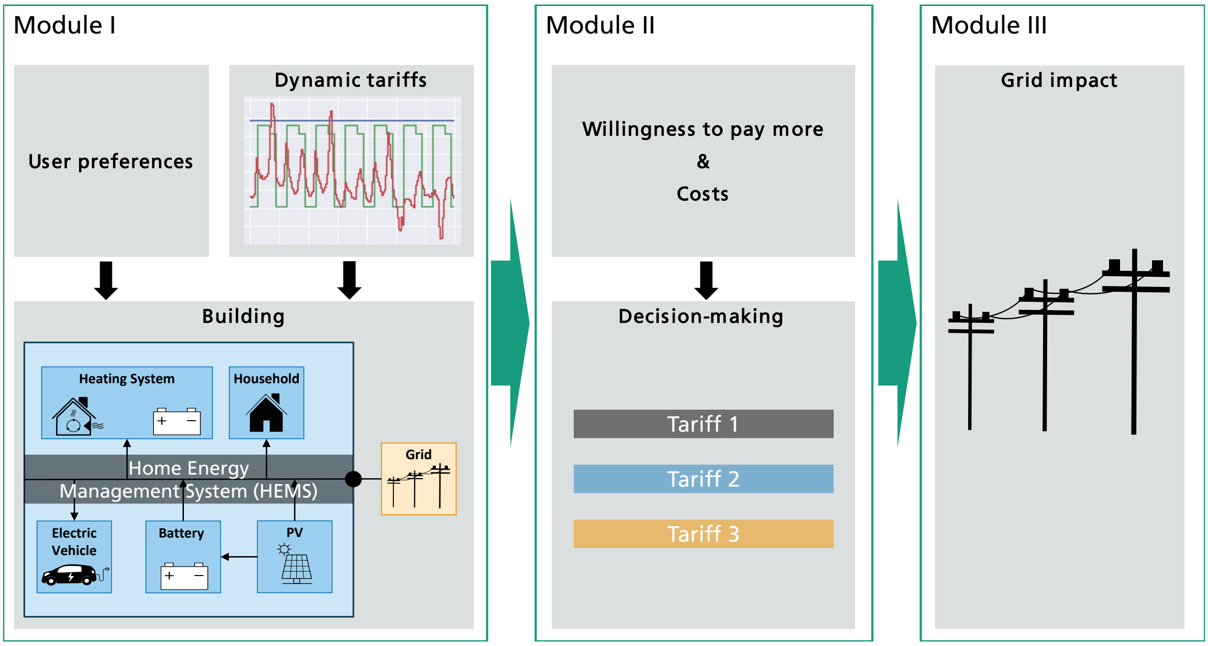


Figure 6.2: Structure of the simulation model *EVaTar* and its modules.

changes in grid load and grid feed-in on the load of the distribution grids can be mapped and investigated (*EVaTar-grid*, see Section 6.2.3).

The individual modules are described below.

6.2.1 Modeling of households (*EVaTar-building*)

Buildings in the model consist of at least one household. In addition, EVs, PV systems and battery storage systems as well as heating systems consisting of a heat pump and a heat storage tank (HS) can be represented. The building is connected to a low-voltage grid and can draw electricity from it or feed electricity generated by a PV system into it. More information on the structure and energy flows of a building within *EVaTar* can be found in Ref. [23].

We assume that the building has a HEMS with perfect foresight that actively intervenes in operating the building and its energy-using technologies in order to minimize the electricity purchase costs. The associated objective function is given in Equation 6.1:

$$\min \sum_{t=0}^{t_{\max}} E^t_{\text{grid, building}} \cdot c^t_{\text{electricity price}} - E^t_{\text{PV, grid}} \cdot c_{\text{feed-in remuneration}} \tag{6.1}$$

Here, $E^t_{\text{grid, building}}$ stands for the energy drawn from the grid in an hour t in kWh. $c^t_{\text{electricity price}}$ is the electricity price applicable in this time unit in €ct/kWh. $E^t_{\text{PV, grid}}$ stands for the energy fed into the grid from the PV system in an hour t in kWh. $c_{\text{feed-in remuneration}}$ stands for the time-independent feed-in remuneration in €ct/kWh. The energy drawn from the grid $E^t_{\text{grid, building}}$ is defined as follows (Equation 6.2):

$$
\begin{aligned}
E^t_{\text{grid, building}} = \\
& E^t_{\text{building, H}} - \alpha^i_{\text{PV}} \cdot E^t_{\text{PV, building}} - \alpha^i_{\text{BSS}} \cdot E^t_{\text{BSS, building}} \\
& + \alpha^i_{\text{EV}} \cdot E^t_{\text{building, EV}} + \alpha^i_{\text{HP}} \cdot E^t_{\text{building, HP}}, \qquad \forall t \in T, \forall i \in I
\end{aligned}
\tag{6.2}
$$

where α represents a binary variable that defines whether a technology is available in the building i; $E^t_{\text{building, H}}$ is the household's inflexible electricity demand in an hour t in kWh; $E^t_{\text{PV, building}}$ represents the energy supplied to the building by the PV system in an hour t in kWh; $E^t_{\text{BSS, building}}$ stands for the energy supplied to the building by the battery storage system in an hour t in kWh; $E^t_{\text{building, EV}}$ is the energy supplied from the building to charge the EV in an hour t in kWh; and $E^t_{\text{building, HP}}$ defines the energy supplied from the building to the heating system in an hour t in kWh.

We considered two different operation strategies of the building:

- *No HEMS, inflexible demand:*
  - Battery storage system: The battery operation is based on simple rules. The electricity from the PV system is first used to meet the electricity demand of the building (including the electricity demand of the EV and the heating system). If a generation surplus remains, it is used to charge the battery storage. Further surpluses are fed into the grid. As soon as the building's electricity demand exceeds PV generation, electricity is drawn from the battery to cover the household's energy demand.
  - Electric vehicle: Continuous charging of the EV is started immediately after arrival until a state of charge of 100% is reached or the EV is driven again.
  - Heating system: The heating system is operated in an inflexible way, so that it meets the heat demand at any given point in time.
- *HEMS, flexible demand:*
  - Battery storage system: The operating strategy allows flexible and predictive operation in terms of dynamic tariffs. This means that the battery system is included in the building's HEMS and thus used to minimize the building's overall energy procurement costs (see Equation 6.1).
  - Electric vehicle: Controlled charging is possible. This means that the EV is integrated into the HEMS. We assume that EV owners can enter their preferences into the HEMS, i.e., they can specify the minimum range or the minimum energy stored in the battery at the time of departure $E_{\text{min, departure}}$ and the minimum energy level $E_{\text{min, charge}}$ at which they want to start charging their vehicle at the latest.
  - Heating system: The heating system is integrated into the HEMS and can supply flexibility using the heat storage tank.

For both operating strategies, the electricity demand of household appliances is considered to be inflexible and is defined exogenously in the form of a household load profile. Furthermore, the PV system can be used within the model to supply the various appliances in the building, charge a battery storage system or feed electricity into the grid. Its generation is also considered to be inflexible.

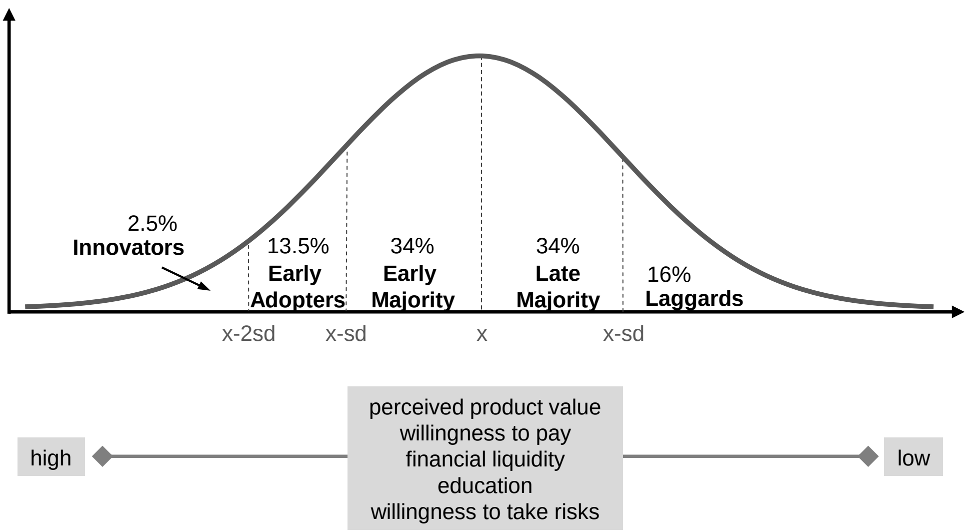


Figure 6.3: Schematic representation of the relationship between types of adopters and their location on the adoption curve with defining characteristics according to Rogers [24].

6.2.2 Decision-making behavior regarding the electricity tariff (*EVaTar-decisions*)

To map the decision-making of flexible consumers regarding the choice of an electricity tariff, one key factor are the financial aspects of dynamic tariffs. In addition to the perception of economic benefits, other behavioral drivers such as perception of environmental values, status and prestige, self-sufficiency or interest in innovative technologies play a key role in the adoption of new technologies. In order to take into account the heterogeneity of households regarding those behavioral drivers of the adoption of new, innovative technologies such as a HEMS, we use the „diffusion of innovations“ theory of E. Rogers [24]. This theory is often used to describe the market diffusion of new technologies and states that consumers can be divided into five adopter categories: innovators, early adopters, early majority, late majority, and laggards. A schematic representation of the relationship between the types of adopters and their location on the technology adoption curve according to Rogers can be seen in Fig. 6.3. The adopter categories differ in their behavioral drivers as well as their willingness to pay (WTP) for non-financial values. The adopter categories are linked to socio-economic characteristics and personal variables (e.g., social status, financial liquidity, education). Innovators are the most innovative and risk-taking adopter category and tend to be quick to adopt new technologies. Furthermore, innovators have the highest WTP and/or WTPM amongst the five adopter categories. Early adopters are also quick to adopt new technologies but less risk-taking than innovators. They do have a high degree of opinion leadership. A significantly longer adoption time can be seen within the category of the early majority. Individuals in the category late majority adopt a new technology later than the average individual in a society. The last category are laggards, who usually tend to be focused on „traditions“ and therefore are last in adopting a new technology. The characteristics and behavioral drivers are usually determined through household surveys. Using these characteristics and variables, each household can be assigned to one of the adopter categories.

Based on the adopter category and the survey results, a WTPM results for each household, which is included in the decision-making behavior. A positive WTPM means that some households are willing to pay more compared to the status quo (for instance static tariff without HEMS) due to their attitude towards new technologies. A negative WTPM means the opposite.

In order to model the decision-making behavior of households regarding the choice of an electricity tariff, we first determine the electricity costs incurred within a year for each available electricity tariff. We assume that all households initially use a static tariff without HEMS. The cost of a dynamic electricity tariff thus includes the capital expenditure for a HEMS, derived from distributing the initial investment to individual years using the annuity method (see Section 6.3.2), in addition to the electricity costs incurred within the timeframe of one year. On top of this purely financial consideration, we include a WTPM for the different adopter groups. With that included, we first find the dynamic tariff which would result in the lowest costs for the household within the year under consideration, taking into account the annualized investment costs for the HEMS C_{HEMS} (Equation 6.3):

$$\min\left(\left(C_{\text{HEMS}}+\begin{bmatrix}C_{\text{electricity costs, tariff 1}}\\ C_{\text{electricity costs, tariff 2}}\\ \vdots\\ C_{\text{electricity costs, tariff n}}\end{bmatrix}\right)\cdot(1-\text{WTPM})\right) \tag{6.3}$$

The overall electricity costs $C_{\text{electricity costs, tariff n}}$ in €/yr. with a tariff n for each household can be calculated as (Equation 6.4):

$$\begin{aligned}C_{\text{electricity costs, tariff n}} = &\sum_{t=0}^{t_{\text{max}}} E^{t}_{\text{grid, building, tariff n}}\cdot c^{t}_{\text{electricity price, tariff n}} - E^{t}_{\text{PV, grid}}\cdot c_{\text{feed-in remuneration, tariff n}}\\ &+C_{\text{standing charges, tariff n}}+C_{\text{metering point operation}}\end{aligned} \tag{6.4}$$

where $C_{\text{standing charges}}$ are the tariff's annual standing charges in €/yr. and $C_{\text{metering point operation}}$ depicts the annual costs for metering point operation in €/yr.

Having determined the dynamic tariff with the lowest costs (including the WTPM), we check whether this option is cheaper than the static tariff option. If it is, the household chooses the dynamic tariff. If the static tariff is cheaper, the household will choose the static tariff and remain inflexible in their electricity consumption.

6.2.3 Modeling the grid impact (*EVaTar-grid*)

After the choice of tariff has been determined for each household, the resulting load and generation profile of each household were used to model the grid impact. Each household is connected to a grid connection point of the distribution grid. Assigning the selected households to grid connection points is randomly based. To obtain more robust results, this random-based assignment was repeated 50 times for each scenario (Fig. 6.3).

A load flow calculation was performed for each of the resulting grid scenarios. The load flow calculations were performed with the open source model pandapower [25]. The results of the load flow calculations

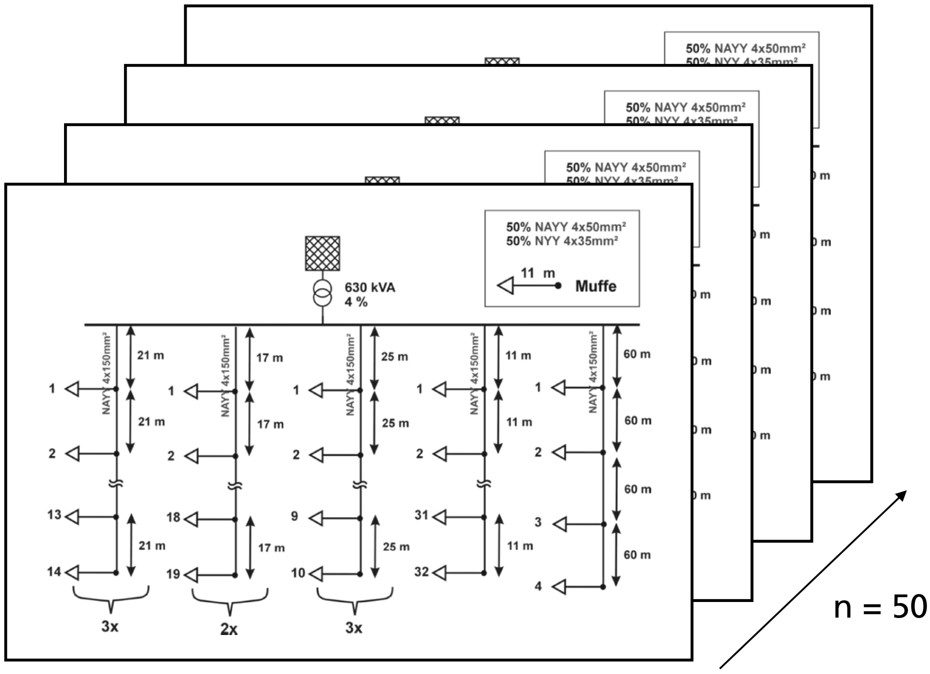


Figure 6.4: Iterations of random-based assignment of households to grid connection points in the representative suburban grid „Vorstadt Kabel 1“ by Kerber [26].

were analyzed regarding the minimum and maximum voltage band deviation, the maximum occurring line and transformer loading as well as the maximum power drawn from the higher grid level.

6.3 Case study

In our case study, a suburban low-voltage grid was selected and defined for the grid analyses. Households with various technology options (EVs, HPs, BSS, PV rooftop systems) are located within this grid and different dynamic tariffs are offered to the household customers. The decision to choose one of the tariffs is determined for each household. Subsequently, the effects on the load profiles of the households as well as on the load of the distribution grid are analyzed using the relevant indicators. For comparison reasons, as a reference we also considered the case where all households have a static tariff. For consistency, we used data for the city of Karlsruhe (Southern Germany) for the year 2019. These include weather data, PV generation time series, heat demand time series, grid charges, and electricity price time series. A more detailed description of the individual aspects of the case study is given below.

6.3.1 Low-voltage grid

The reference grid for our investigations is the suburban grid „Vorstadt Kabel 1“ by Kerber [26]. The grid is defined as a representative grid for suburban areas in Germany [27]. The topology is shown in Fig. 6.4. The grid has 146 grid connection points, to each of which one household (single-family home or two-family home) is connected in our case study.

6.3.2 Households and technologies considered

6.3.2.1 Households

We used load profiles from a sample of more than 300 households from a smart meter field study conducted in Austria and Germany [28] to reflect the heterogeneity of household load profiles.

6.3.2.2 Electric vehicles

For EVs (availability at home and energy demand while driving), we used a dataset [29] computed with the vehicle diffusion model ALADIN [30, 31, 32]. This model uses vehicle usage data from Ref. [33]. EV profiles were assigned to each household based on the socio-demographic data also collected in this field study.

6.3.2.3 PV systems

An optimized sizing of a PV system for a household is out of scope of this study, therefore we assumed an installed capacity of 8.1 kWp for households with a PV system. This corresponds to the average installed capacity of PV systems in Germany in 2017 [34]. To create the PV generation profile for the year 2019 and the city of Karlsruhe, we used the simulation tool Renewables.ninja[5].

6.3.2.4 Battery storage systems

We assumed a battery capacity of 7.8 kWh for households with BSS. This corresponds to the average usable battery capacity installed in Germany (2017) [34]. We chose a fixed value, as the determination of the optimal size of a BSS is out of scope of this study.

6.3.2.5 Heating systems

The size of the heat pump was selected depending on the heated area of the respective building. The size of the heat storage tank was selected so that it can store the energy supplied by the heat pump running at maximum operation for 2 h. A heat demand profile for the year 2019 was taken from „HotMaps“ [38] for the city of Karlsruhe (DE12) and scaled to 236 kWh/m^2/yr. For consistency, we used ambient temperature for the same year (2019) and also for the city of Karlsruhe. Weather data, including ambient temperature, were taken from the Climate Data Center of the German Weather Service (Deutscher Wetterdienst) for station ID 4177 [39].

[5] Renewables.ninja is available at [35]. For more information, please refer to Refs. [36, 37].

Table 6.1: Willingness to pay more of the adopter categories according to Rogers [24] taken from [40].

Innovators	Early Adopters	Early Majority	Late Majority	Laggards
60%	10%	0%	-5%	-10%

6.3.2.6 Home energy management system

The time horizon within the model is one year. Therefore, we annualized the investment in a HEMS. We assumed costs of 1500 € for the HEMS (incl. installation), a lifetime of 10 years and an interest rate of 2%; the resulting annual payment is 167 €/yr.

6.3.3 Willingness to pay more (WTPM)

Within the smart meter field study, the load profiles of households used within this paper were measured as well as two household surveys were conducted. From those surveys, each household was assigned to adopter categories according to Rogers [24] in Ref. [40]. The WTPM for purchasing a PV home storage system was determined for these categories using the given information on the households as well as a market research survey and a prosumer model (Table 6.1). Further information on the households and derived WTPM can be found in Ref. [40]. Due to a lack of data on the WTPM for HEMS and dynamic electricity tariffs, we further assumed that the WTPM for PV battery storage systems is also valid for the purchase of a HEMS.

6.3.4 Technology scenarios

Four different technology penetration scenarios were defined in the case study: a status quo scenario reflecting the current penetration of rooftop PV, home battery storage, EVs, and HPs, and three future scenarios for the year 2035 (Low, Medium and High), which are based on the scenario framework of the German Network Development Plan for Electricity (2021) 2035 [41]. Our Low 2035 scenario corresponds to the scenario NEP A 2035, our Medium 2035 scenario corresponds to the scenario NEP B 2035, and our High 2035 scenario corresponds to the scenario NEP C 2035. For the penetration of PV systems, the installed PV capacity and number of PV systems of 2018 is taken from MaStR[6] database for all PV systems with an installed capacity below 15 kW. The penetration is then calculated for the Status Quo scenario by dividing the number of installed PV systems by the total number of single- and multi-family homes (SFH/MFH) in Germany [42]. For the future scenarios, it is assumed that the average PV system size and the ratio of PV rooftop systems to PV ground-mounted systems is constant. Therefore, we can derive the number of PV systems from the installed PV capacity given in the NEP scenarios. Regarding the penetration rate of BSS and HS, we assume that approximately 90% of all BSS and HS will be installed in SFH/MFH. For EVs, we assume that around 75% of all EVs have private owners. The penetration rates for all four scenarios are shown in Fig. 6.5. A penetration rate of 10% means that 10% of all household within the given grid area do have the according technology.

6 https://www.marktstammdatenregister.de/MaStR, date of data evaluation: 19.8.2021.

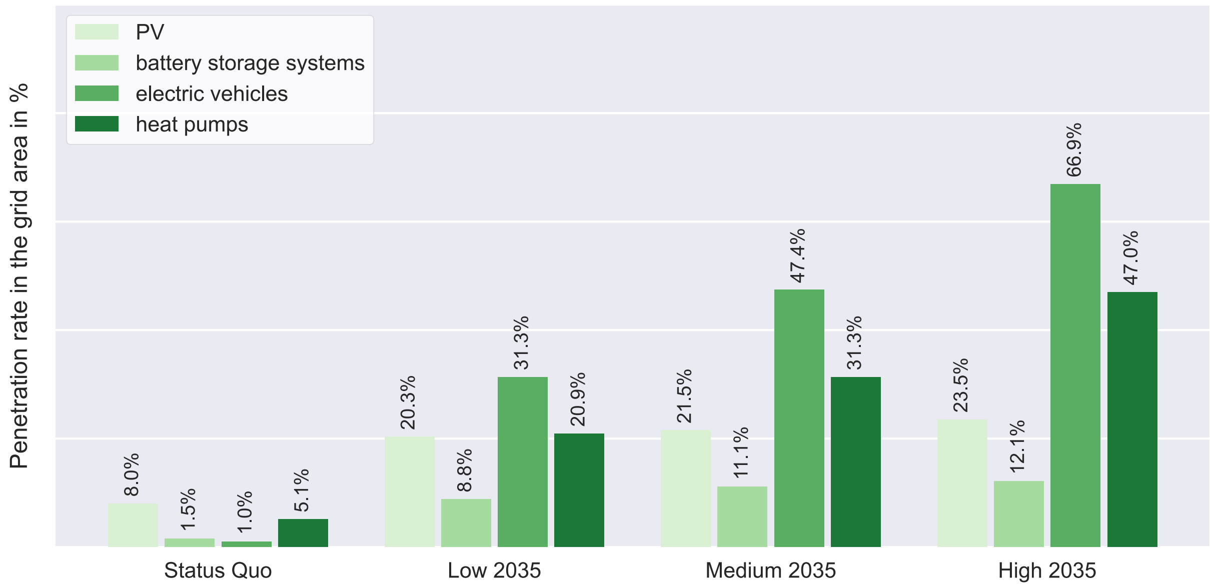
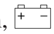
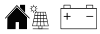
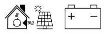


Figure 6.5: Scenarios investigated with regard to the diffusion of technologies in the households considered (based on [41]).

Table 6.2: Number and share of households with different technologies ( – only household,  – PV system,  – BSS,  – EV,  – HS) for all four scenarios (deviations from 100% result from rounding errors.

	Status Quo	Low 2035	Medium 2035	High 2035
	133 (91,1%)	90 (61,6%)	72 (49,3%)	47 (32,2%)
	6 (4,1%)	4 (2,7%)	0 (0%)	0 (0%)
	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	0 (0%)	21 (14,4%)	23 (15,8%)	24 (16,4%)
	0 (0%)	1 (0,7%)	5 (3,4%)	5 (3,4%)
	0 (0%)	0 (0%)	0 (0%)	1 (0,7%)
	1 (0,7%)	2 (1,4%)	3 (2,1%)	1 (0,7%)
	3 (2,1%)	4 (2,7%)	2 (1,4%)	0 (0%)
	1 (0,7%)	0 (0%)	0 (0%)	0 (0%)
	0 (0%)	3 (2,1%)	17 (11,6%)	40 (27,4%)
	1 (0,7%)	8 (5,5%)	8 (5,5%)	11 (7,5%)
	1 (0,7%)	13 (8,9%)	16 (11,0%)	17 (11,6%)

The figure shows a strong increase of EVs and HPs in all scenarios for the year 2035 and large differences between the three scenarios for these technologies. The differences are smaller for PV rooftop systems and battery storage systems.

We assumed that households are more likely to adopt a technology if they belong to a more innovative adopter group. In other words, the group of innovators are quicker to adopt the considered technologies than the group of laggards. As the technologies are being randomly distributed to the households, some households will have more than one of the technologies available. More detailed information is shown in Table 6.2.

6.4 Results

The results of the analyses of the case study scenarios are presented below. First, the investigated tariff structures are presented and compared (Section 6.4.1). Then, the influence of the dynamic electricity

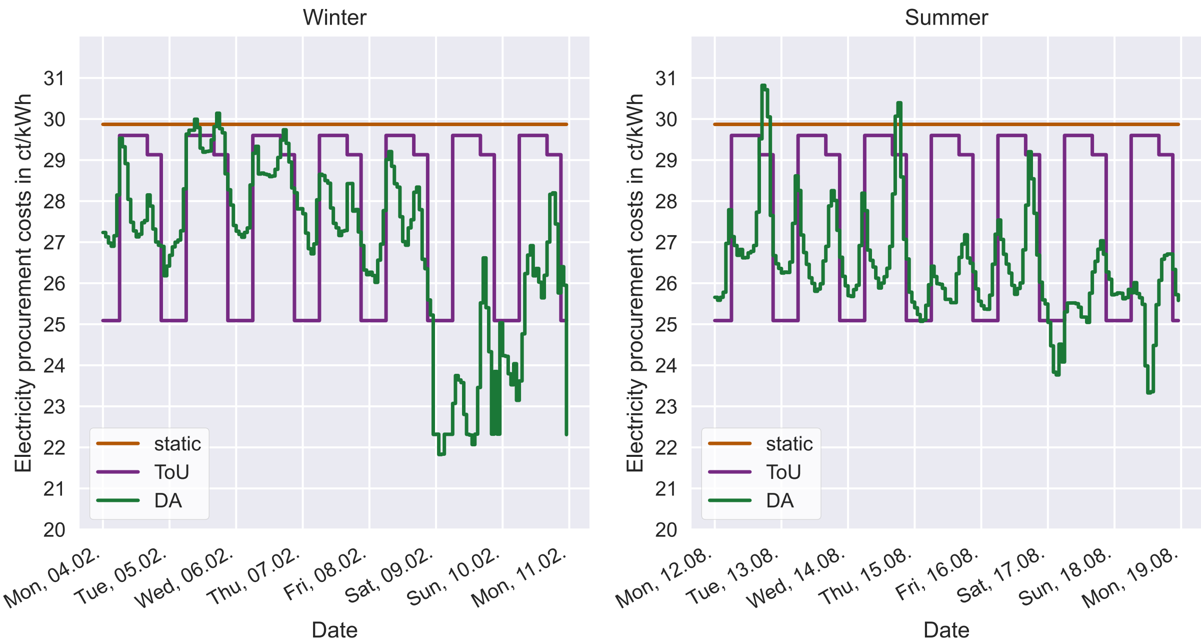


Figure 6.6: Considered electricity tariffs for one example week in winter and one example week in summer (ToU – Time-of-Use tariff, DA – hourly day-ahead tariff).

tariffs on the load profiles of households is considered (Section 6.4.2). Based on this, the possible cost savings of households and the effects on their decision-making behavior are derived (Section 6.4.3). The final aspect is the impact on the grid if households are considered to have a free choice of tariff (Section 6.4.4).

6.4.1 Tariffs

The case study considers dynamic electricity tariffs already available today and includes one static and two dynamic electricity tariffs. The amount of the grid charge component to be paid was adjusted to the Karlsruhe grid area. Fig. 6.6 gives a graphical representation of the tariffs considered for an exemplary week in summer and in winter.

6.4.1.1 Tariffs considered

6.4.1.1.1 Static electricity tariff

The static electricity tariff is composed of a standing charge of 11.82 €/month and the unit rate of 29.87 €ct/kWh.

6.4.1.1.2 3-tier time-of-use tariff (ToU)

We chose the „E.ON SmartStrom Öko“ tariff [43] as our first dynamic tariff. This is a time-of-use tariff with three (time-dependent) price levels for the unit rate. The High Tariff I (HTI) is applied between 6 a.m. and 4 p.m. at a unit rate of 29.60 €ct/kWh. The slightly cheaper High Tariff II (HTII) is applied from 4 p.m. to 9 p.m., at a unit rate of 29.13 €ct/kWh. The Low Tariff is applied between 9 p.m. and 6 a.m., at the unit rate of 25.09 €ct/kWh. The standing charge is 15.62 €/month.

Table 6.3: Overview of the three electricity tariffs considered within this case study.

	Min.	Max.	Mean	Median
Static electricity tariff (static)	29.87 €ct/kWh	29.87 €ct/kWh	29.87 €ct/kWh	29.87 €ct/kWh
3-tier Time-of-Use tariff (ToU)	25.09 €ct/kWh	29.60 €ct/kWh	27.81 €ct/kWh	29.13 €ct/kWh
Hourly day-ahead tariff (DA)	11.60 €ct/kWh	36.77 €ct/kWh	26.80 €ct/kWh	26.84 €ct/kWh

In addition, there are costs for the smart meter (7.50 €/month) plus the annual investment costs for the HEMS (see Section 6.3.2).

6.4.1.1.3 Hourly pricing based on the day-ahead price of EPEX spot DE (DA)

The second dynamic electricity tariff considered is the „HOURLY“ tariff of aWATTar Deutschland GmbH [44], which is based on the day-ahead price of EPEX Spot DE. The unit rate consists of the hourly prices of EPEX Spot DE (limited to max./min. ± 20 €ct/kWh), a flat rate of 0.25 €ct/kWh and all other taxes, levies and charges. The standing charge amounts to 8.73 €/month.

Here, too, there are additional costs for the smart meter of 5.44 €/month plus the annual investment costs for the HEMS.

6.4.1.2 Analysis and comparison

For a better classification of the results described below, it is necessary to analyze the electricity tariffs considered. Table 6.3 shows the minimum and maximum unit rates that occur in the year for all three tariffs considered, as well as the arithmetic mean and the median. The lowest unit rate occurs in the case of the DA tariff. The minimum value for the ToU tariff is higher by 13.49 €ct/kWh. The annual mean values of the occurring prices of the dynamic tariffs are lower than the value of the static tariff, with the DA tariff being the cheapest (1.01 €ct/kWh cheaper than ToU). Consequently, the static electricity tariff – without considering the investment in the HEMS – is presumably the most expensive for all households. Furthermore, considering only the electricity procurement costs, it is reasonable to assume that the DA tariff is the cheapest for most households.

6.4.2 Effects on household load profiles

At this point, the impact on household load profiles is only considered for the High 2035 scenario. All households with a flexibility option are included in the analysis. The relevant variables identified are the maximum feed-in power, the maximum power drawn from the grid, and the standard deviation of the load. Fig. 6.7 shows the changes to these three variables for the dynamic tariffs considered compared to the static tariff without HEMS. In each case, all flexible consumers are depicted and households are additionally grouped by technologies (EV, HP, BSS).

There are no significant changes in the maximum feed-in power. For households with BSS, the maximum feed-in power can be reduced by 1.5%. The analysis of the maximum power drawn from the grid shows larger changes. On average across all flexible consumers, there is an increase of 11% for the ToU tariff, and around 15% for the DA tariff. For households with an EV or a BSS, the changes are also in the range of 11% (ToU) and 14-15% (DA). For households with a heat pump, there are significantly higher changes

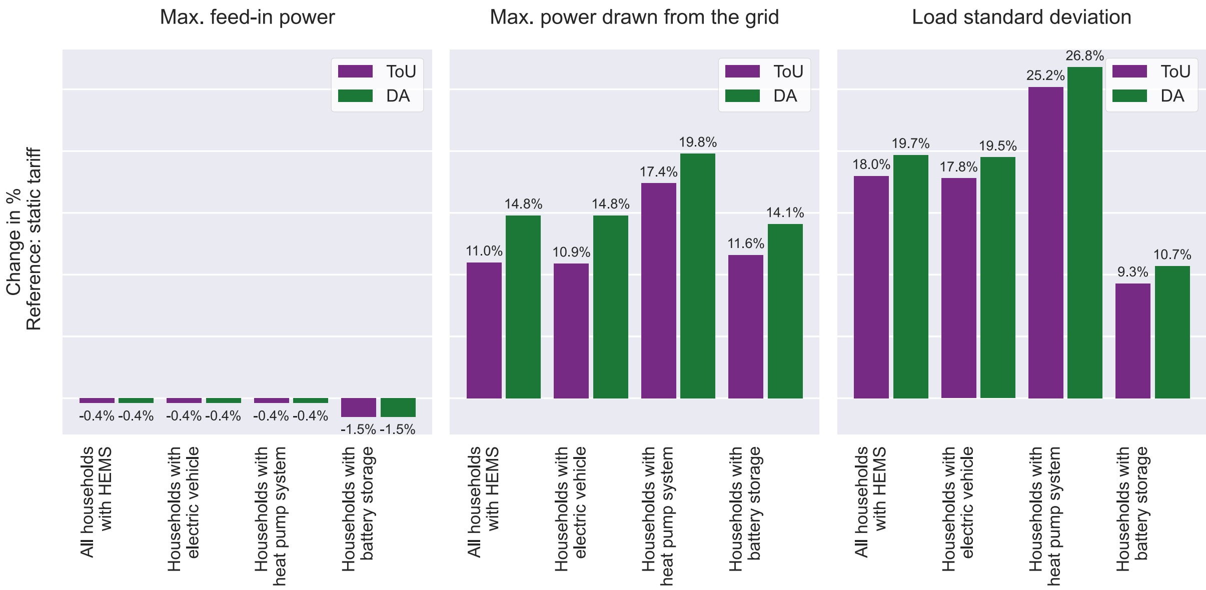


Figure 6.7: Changes in maximum feed-in, maximum grid draw, and standard deviation of load for households with HEMS installed in conjunction with a dynamic tariff in the High 2035 scenario. Reference case: static electricity tariff without HEMS. (ToU – Time-of-Use tariff; DA – hourly day-ahead tariff).

of about 17% (ToU) and about 20% (DA). This is mainly due to the installed capacity of heat pumps, which run at full capacity during flexible operation when electricity prices are favorable and fill the heat storage tank. In addition, many households that own a heat pump also have an EV, further increasing the maximum power drawn from the grid when the EV and HP respond to favorable electricity prices.

This higher change in maximum power drawn from the grid for households with heat pumps is also reflected in the change in the standard deviation of load (up to 27%). Notable in terms of the standard deviation of load are households with BSS, where the change compared to the static tariff is lower than in the other household groups (by around 9% for ToU and around 11% for DA). This difference is due to the fact that the BSS enables a time-delayed use of the cheaper electricity generated by the PV system and thus reduces the energy drawn from the grid in hours with high electricity demand (especially in the evening).

6.4.3 Impact on household electricity costs/decision-making behavior

An analysis of the electricity costs (incl. the annualized investment in HEMS) of households with flexibility shows that cost savings are possible with both the ToU and DA tariffs. However, these savings are on average 8.3% higher for the DA tariff than for the ToU tariff, which is why the discussion below focuses on the cost savings under the DA tariff compared to the static tariff. Fig. 6.8 gives an overview of the cost savings normalized to household electricity consumption for all flexible consumers by scenario and technology group. Maximum, minimum, and average values are shown in each case.

It can be seen that there are cost savings for all flexible consumers in the Status Quo and Low 2035 scenarios compared to the static tariff. For the Medium 2035 and High 2035 scenarios, there are individual households for which the DA tariff would involve additional costs. However, on average, there are cost savings in all scenarios. These range between 3.5 and 4.9 €ct/kWh. The largest average cost savings are for households with heat pumps (4.7-4.9 €ct/kWh). This is partly due to their availability; as stationary

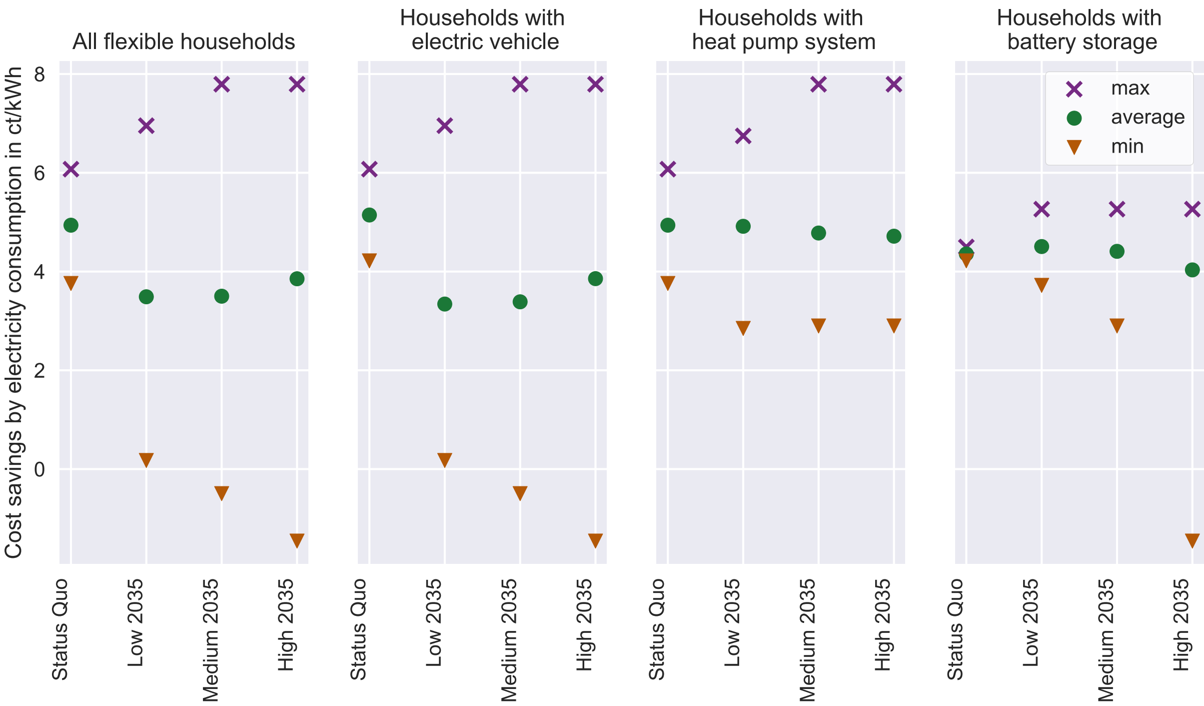


Figure 6.8: Cost savings when using the DA tariff; average, minimum, and maximum values across all households with flexibility for the scenarios considered; investments for HEMS are included.

heat storage units, their flexibility can be used at any hour of the day, making optimal use of low-price phases.

If these cost savings – viewed purely in economic terms – are combined with the WTPM described in Section 2.2. the result is the decision-making behavior regarding the electricity tariff shown in Fig. 6.9. It can be seen that the ToU tariff is not chosen by any of the flexible consumers, as the cost savings here are lower than with the DA tariff. In the Status Quo and Low 2035 scenarios, all households with flexibility choose the dynamic DA tariff. In both the Medium 2035 and High 2035 scenarios (higher shares of flexible households), a few flexible consumers opt for the static tariff. Due to the higher penetration rates of the flexibility options, households assigned to the Late Majority adopter group are also flexible in these scenarios. Households from the Late Majority group have a lower yearly energy consumption than more innovative adopter groups. At the same time, in order to opt for the dynamic tariff, for these households, the cost savings must again be higher than for the more innovative adopter groups due to their lower WTPM. This leads to some of these households choosing not to use the HEMS and a dynamic tariff.

6.4.4 Grid impacts

This section compares two cases for all technology scenarios outlined in Section 6.3.4: in the first case all households use the static tariff, in the second case we consider free choice of tariff. For each case and each scenario – as already mentioned in Section 6.2.3 – 50 iterations with random assignment of households to the grid connection points are performed. Fig. 6.10 shows the maximum voltage deviation occurring in the grid in both negative and positive directions across all iterations. Negative voltage deviations arise from electrical loads, while positive voltage deviations can arise from feed-in from PV systems. When analyzing the impact of the DA tariff on the maximum feed-in power of households (cf. Section 6.4.2), it was shown that the use of dynamic tariffs has hardly any effect. Analogously, the maximum

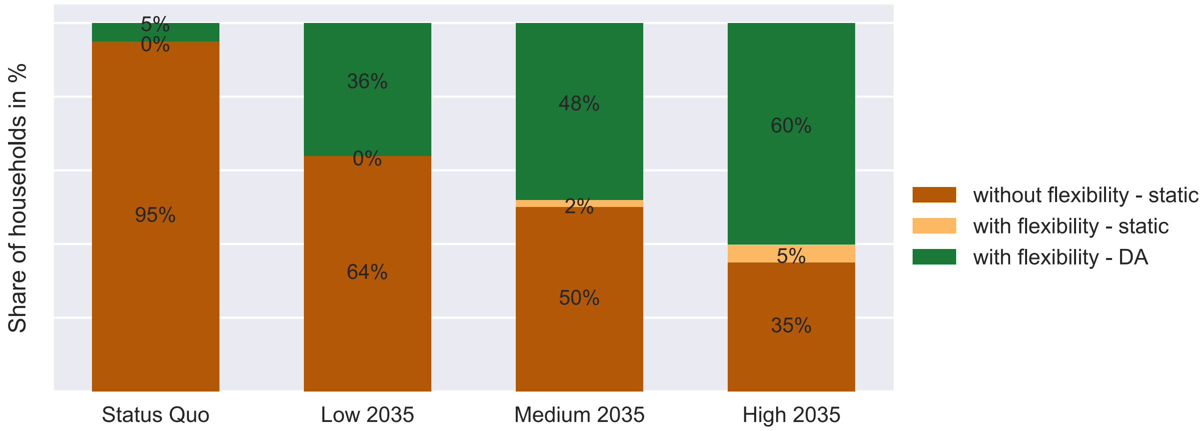


Figure 6.9: Shares of households without flexibility with static electricity tariff (brown), with flexibility choosing the static electricity tariff (ochre), and with flexibility choosing the dynamic electricity tariff (hourly day-ahead tariff, DA) (green).

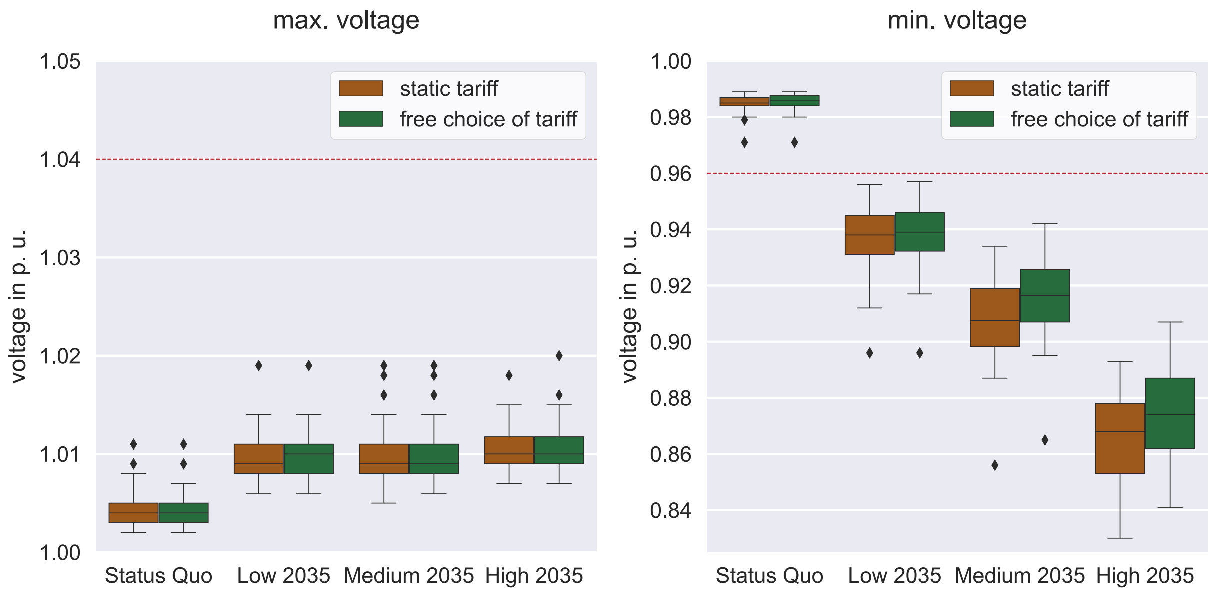


Figure 6.10: Maximum negative and positive voltage deviation for the cases static tariff and free choice of tariff over all four technology scenarios (values for all iterations).

positive voltage deviation also changes only minimally. The comparison of the maximum negative voltage deviation occurring in the grid shows improvements with a free choice of tariff, especially in the future scenarios. There are hardly any changes in the status quo scenario. If a permissible voltage band of ±4% is assumed in the low voltage grid (based on [28]; red dashed line in Fig. 6.10), the number of hours in which this grid restriction is violated can be determined (see Table 6.4). It can be seen that, for the future scenarios, there are significantly more hours with voltage band violations in the case of a free choice of tariff than in the case of using the static tariff. This suggests a higher utilization of electric equipment if the grid is expanded.

Table 6.4: Number of hours per year with voltage band violation for the cases static tariff and free choice of tariff in the considered scenarios (mean values over all iterations).

	Status Quo	Low 2035	Medium 2035	High 2035
Static	0 h/yr.	11.4 h/yr.	90.8 h/yr.	426.6 h/yr.
Free choice of tariff	0 h/yr.	86.5 h/yr.	229.0 h/yr.	649.1 h/yr.

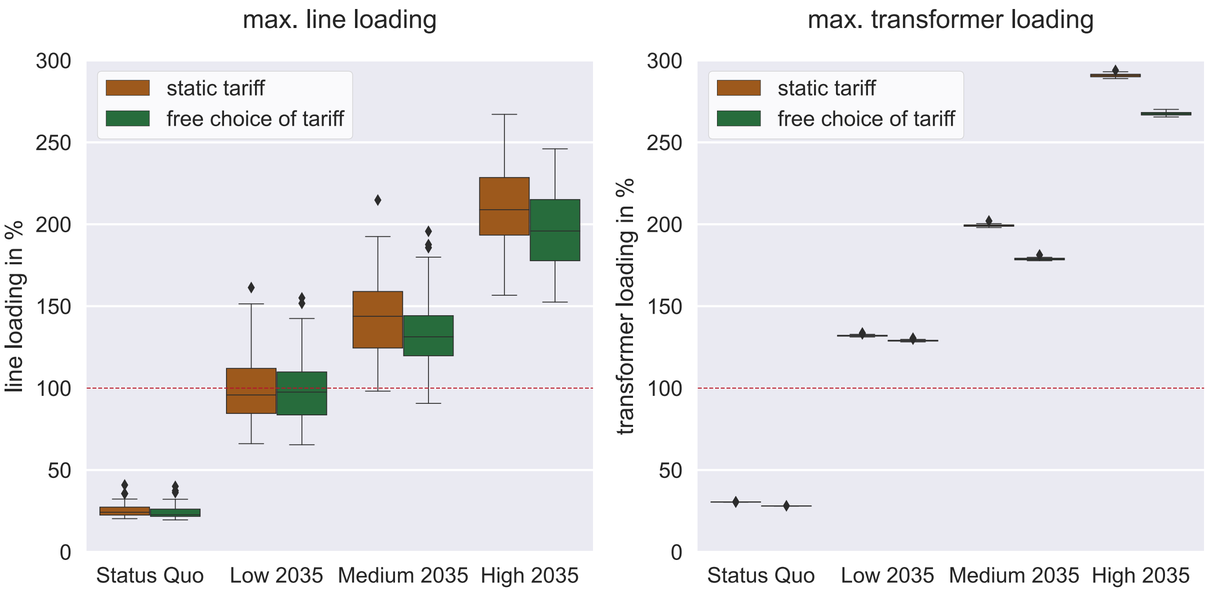


Figure 6.11: Maximum thermal load for lines and transformer for the cases static tariff and free choice of tariff over all four technology scenarios (values for all iterations).

Table 6.5: Number of hours per year with thermal overload of the lines for the cases static tariff and free choice of tariff in the considered scenarios (mean value over all iterations).

	Status Quo	Low 2035	Medium 2035	High 2035
Static	0 h/yr.	1.3 h/yr.	2.4 h/yr.	18.2 h/yr.
Free choice of tariff	0 h/yr.	23.7 h/yr.	50.8 h/yr.	146.7 h/yr.

With regard to the thermal load of lines and the transformer, notable differences can be observed between the two cases investigated (Fig. 6.11). For the lines, an improvement of the maximum thermal load can be shown for all scenarios with a free choice of tariff. Here, this improvement in the thermal load of the lines increases with the number of flexible households in the grid area. The maximum thermal load limit assumed here is 100% [45] (red dashed line in Fig. 6.11). Again, the Medium 2035 and High 2035 scenarios show that the number of hours per year in which the thermal load limit is exceeded is significantly higher in the free choice of tariff case than in the static tariff case (Table 6.5). There are also improvements in transformer thermal loading with free choice of tariff in all scenarios. However, the number of hours with thermal overload of the transformer is also higher with free choice of tariff than in the static case (Table 6.6). As for lines, the load limit is 100% [16]. These figures also indicate that, assuming the grid is expanded, there is a higher utilization in the free choice of tariff case than in the static tariff case.

Fig. 6.12 shows the change in the maximum active power drawn from the higher grid level when comparing the free choice of tariff case with the static tariff case. A reduction of the active power consumption by up to 11% is shown (Medium 2035 scenario). This reduction in active power consumption may have

Table 6.6: Number of hours per year with thermal overload of the transformer for the cases static tariff and free choice of tariff in the scenarios considered (mean value over all iterations).

	Status Quo	Low 2035	Medium 2035	High 2035
Static	0 h/yr.	2.0 h/yr.	2.0 h/yr.	337.4 h/yr.
Free choice of tariff	0 h/yr.	39.2 h/yr.	110.9 h/yr.	535.3 h/yr.

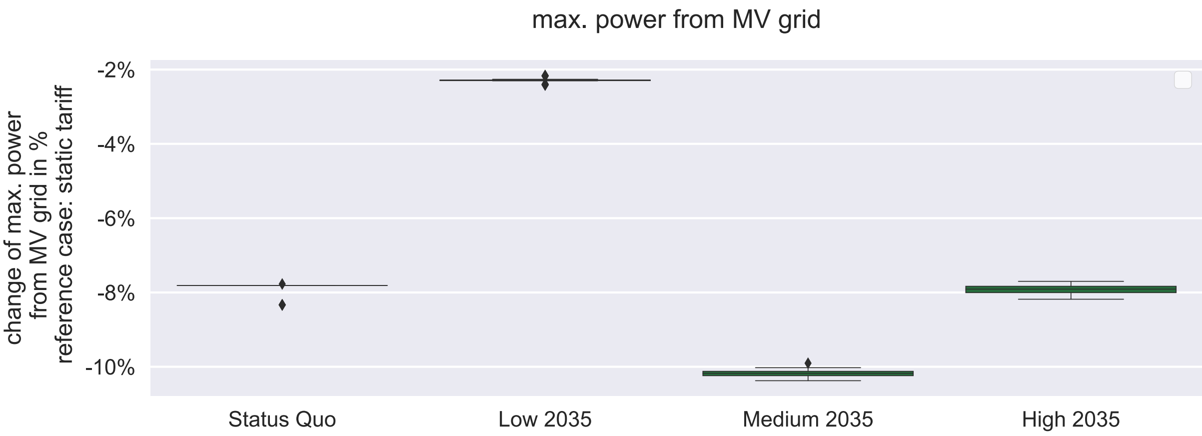


Figure 6.12: Changes in the maximum active power drawn from the higher-level grid for the free choice of tariff case over all considered scenarios (values for all iterations).

positive effects on the higher grid level, as the grid load at this level then decreases. Furthermore, a lower annual maximum power has the effect of reducing the grid charges within the low-voltage grid.

6.5 Discussion and outlook

The methodology presented and the analysis of the influence of free choice of tariff for flexible consumers results in a more realistic assessment of the influence of dynamic tariffs on a LV distribution grid and therefore adds value to the ongoing discussion in this research field. In the following, the results will be discussed regarding the important contribution of this study, the comparison to previous research in this field, as well as the limitations of this study.

Under the conditions outlined in this study, the dynamic electricity tariffs lead to substantial cost savings for most of the flexible consumers (on average between 3.5 and 4.9 €ct/kWh, which corresponds to a reduction in the electricity bill of 11,7-16,4%). This result was obtained under the assumption of perfect foresight in terms of the load and generation for the home energy management system. In reality, of course, the results of using a home energy management system are less optimal due to forecasting uncertainties and – as a consequence – cost savings are lower. Nevertheless, that dynamic electricity tariffs are financially profitable for household customers has also been demonstrated in other scientific studies [13, 14, 15, 16, 17], where the foreseen possible cost savings reach as high as 85% [15]. On an individual household level, our study shows, that dynamic tariffs can lead to an average increase of the maximum power drawn from the grid of 11.0% (ToU) and 14.8% (DA). An increased peak load when applying dynamic tariffs can also be found in Ref. [15]. Our approach considers the free choice of electricity tariffs of household customers by integrating this aspect explicitly in the model. It thus goes one step further than the state of the art by modeling the effects of dynamic tariffs on distribution grids in a more realistic manner. Our results indicate that peak loads within a LV distribution grid can be reduced due to the heterogeneous choice of tariff and the resulting mixing effects in households' peak loads. This contradicts the results of studies with scenarios with only one electricity tariff for all household customers within a grid area, where an increase in peak loads is predicted (as seen e.g., in Refs. [17, 18, 20, 21]). Including the more realistic point of the free choice of tariff for flexible consumers does give new insights into the topic. Furthermore, it should be noted that the tariff options used are based on research from the beginning of 2021. Since then, the average price level on the spot market has risen sharply and there are now larger price spreads over the course of a day. This will increase the attractiveness and have an influence on the design of dynamic electricity tariffs in the future. Our approach also represents the heterogeneity of households by using measured load profiles of different adopter groups and considering a great range of technologies such as PV systems, electric vehicles, heat pumps with heat storage and battery storage systems. As a consequence, the results in terms of household load profiles and cost savings represent a good range of households and adopter groups in the single- and two-family household sector.

The household customers were divided into adopter categories according to Rogers and each group was assigned an individual willingness to pay more. Due to a lack of data availability, values taken from another study on the willingness to pay more for a PV battery storage system were applied to a home energy management system. The willingness to pay more for a home energy management system could show other values than the one for a PV battery storage system. Therefore, a survey of the willingness to pay more for home energy management systems and dynamic tariffs could improve the quality of our findings and could be integrated into the existing model. In addition, it would be possible to map the decision-making behavior of households not only using their willingness to pay more, but also including a threshold for the minimum electricity cost savings that would have to be possible for customers to even consider switching tariffs.

Comparing the mean values of the energy price of the two existing dynamic tariffs considered in the paper shows that the DA tariff is lower than the time-of-use tariff. This results in a shift towards the DA tariff, regardless of the tariff structure. Since the focus of this paper was on the analysis of existing dynamic tariffs, the use of the two mentioned tariffs is nevertheless considered appropriate and legitimate. In further research – where the focus is not on actually available tariffs – the price level (annual average) of the tariffs should be aligned to ensure better comparability.

Since the study of household decision-making behavior was conducted under current conditions, it was assumed that the active management of flexibility options does not entail implications for the higher-level power system. Therefore, households within this study can be considered „first movers“. However, based on the attractiveness of dynamic tariffs shown within the paper, it can be assumed that a growing number of flexible consumers will opt for such tariffs in the future. As a consequence, effects on electricity markets are likely and thus also on the attractiveness of dynamic tariffs (e.g., through so-called cannibalization effects). In future studies, the free choice of tariffs implemented in this paper and the associated mapping of consumers' decision-making behavior should be complemented by considering potential repercussions between flexible households and the electricity markets.

New technologies such as electric vehicles, battery storage systems and heat pumps are expected to be adopted most rapidly in suburban areas, which is why a suburban low-voltage grid was chosen for this case study. As low-voltage grids in Germany exhibit a high degree of heterogeneity and electrification will advance in all areas, further analyses with more and different grid types (rural, urban) could lead to a better assessment of the observed mixing effects.

Furthermore, hourly resolved time series were used due to data availability. Especially in low-voltage grids, the voltage quality is evaluated in 10-min averages according to DIN EN 50160 [46]. An adjustment of the time resolution would therefore make the results even more precise.

6.6 Summary and conclusions

End-users in Germany can choose freely between multiple electricity tariffs, both dynamic and static. However, the current literature on dynamic tariffs only examines the impact of single, isolated tariffs on grids and end-users and does not reflect reality. Our study contributes to closing this research gap: We defined a more realistic scenario with several tariffs available within a grid area and investigated the resulting decision-making of flexible consumers concerning the choice of tariff. To account for the heterogeneity of household customers, we applied the „diffusion of innovations“ theory by Rogers and combined this with a willingness to pay more in the individual adopter categories. To go one step further, we analyzed the effects on the grid from flexible consumers optimizing their energy consumption behavior based on heterogeneous price signals.

Our results show that the dynamic electricity tariffs already available today can be financially attractive for household customers with flexibility: Considering the willingness to pay more of all adopter groups, more than 90% of all flexible consumers would select the tariff based on the day-ahead spot market price. This tariff offers greater benefits to all households than a 3-tier ToU tariff, even though the latter still has economic advantages when compared to a static tariff.

Our results demonstrate that, if household customers with flexibility are given the choice between various static and dynamic tariffs, they will select different tariffs depending on the individual benefits they stand to gain. We further show that, even though dynamic tariffs lead to an increase of certain households' peak loads, the diversification of tariffs in an area is still favorable for the grid, since it results in lower thermal loads and lower voltage band deviations (in terms of magnitude) in the grid due to the mixing effects of different tariff schemes. Despite the fact that there are more hours with violations of grid restrictions with free choice of tariff, with respect to grid expansion, this would mean that less expansion measurements might be necessary due to the lower maximum grid load. Additionally, the utilization of the expanded grid would be higher. This finding should have implications for distribution grid planning. Our study goes beyond the current state of the art as it allows for the selection and coexistence of multiple tariffs within one distribution grid. With this novel methodological approach, we generated results that are closer to reality than previous studies.

While this work focused on the effects of heterogeneous household customers and their individual decision-making on financial attractiveness and grid load, further research is planned to also examine the required grid expansion. This could integrate the perspective of the grid operators more strongly into the economic evaluation and would also allow for a quantification of the effects on local grid charges. Even though the tariffs applied in this study were based on incentives from a centralized market, which does not necessarily reflect the local grid situation, we were still able to demonstrate that dynamic tariffs reduced the grid load due to the above-mentioned mixing effects. Comparing these results to other demand response options such as peak load shaving or dynamic grid charges, however, could improve the understanding of possible future pricing options.

Credit author statement

Judith Stute: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Funding acquisition. **Matthias Kühnbach**: Writing – Review & Editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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[End of Publication II]

7 Publication III: Assessing the conditions for economic viability of dynamic electricity retail tariffs for households

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[Start of Publication III]

Assessing the conditions for economic viability of dynamic electricity retail tariffs for households

Judith Stute[a], *, Sabine Pelka[b], Matthias Kühnbach[c], Marian Klobasa[b]

* Corresponding author.
[a] Fraunhofer Institution for Energy Infrastructures and Geothermal Systems, Breslauer Strasse 48, 76139, Karlsruhe, Germany
[b] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139, Karlsruhe, Germany
[c] Fraunhofer Institute for Solar Energy Systems ISE, Heidenhofstr. 2, Freiburg, 79910, Germany

Highlights

- We analyze cost benefits of smart operation of electric vehicles & heat pumps.
- We consider the costs for home energy management systems and smart meters.
- Dynamic prices reduce costs of flexible consumers substantially.
- Increasing self-consumption is the financially most attractive option for heat pumps.
- Results are evaluated for various price scenarios (average price & price spread).

Abstract

The success of the energy transition relies on effectively utilizing flexibility in the power system. Dynamic tariffs are a highly discussed and promising innovation for incentivizing the use of residential flexibility. However, their full potential can only be realized if households achieve significant benefits. This paper specifically addresses this topic. We examine the leverage of household flexibility and the financial benefits of using dynamic tariffs, considering household heterogeneity, the costs of home energy management systems and smart meters, the impact of higher electricity prices and price spreads and the differences between types of prosumers. To comprehensively address this topic, we use the EVaTar-building model, a simulation framework that includes embedded optimization designed to simulate household electricity consumption patterns under the influence of a home energy management system or in response to dynamic tariffs. The study's main finding is that households can achieve significant cost savings and increase flexibility utilization by using a home energy management system and dynamic electricity tariffs, provided that electricity prices and price spreads reach higher levels. When comparing price levels in a low and high electricity price scenario, with an increase of the average electricity price by 15.2 €ct/kWh (67 % higher than the average for the year 2019) and an increase of the price spread by 8.9 €ct/kWh (494 % higher), the percentage of households achieving cost savings increases from 3.9 % to 62.5 %. Households with both an electric vehicle and a heat pump observed the highest cost benefits. Sufficiently high price incentives or sufficiently low costs for home energy management systems and metering point operation are required to enable households to mitigate rising electricity costs and ensure residential flexibility for the energy system through electric vehicles and heat pumps.

Keywords

Dynamic tariffs; Electric vehicle; Heat pump; Energy management system; Smart meter; Demand response

Nomenclature

t	Time step (h)
Δt	Difference between two time steps (h)
T	Set of all time steps considered
T_{out}	Set of time steps where outliers in price time series occur
c_{2019}	Electricity price time series for the year 2019 (€ct/kWh)
$c_{\text{out,p}}$	Positive outliers of the electricity price time series (€ct/kWh)
c_{scen}	Electricity price time series for the specified scenario (€ct/kWh)
$C_{\text{sc,min}}$	Minimum price level of a given electricity price scenario (€ct/kWh)
$C_{\text{sc,max}}$	Maximum price level of a given electricity price scenario (€ct/kWh)
c_{adj}	Adjusted price time series without outliers (€ct/kWh)
$c_{\text{out,adj,pos}}$	Adjusted price values for positive outliers (€ct/kWh)
$E_{\text{grid,building}}$	Energy drawn from the grid (kWh)
$E_{\text{PV,grid}}$	Energy fed into the grid from the PV system (kWh)
E_{H}	The household's inflexible energy demand (kWh)

$E_{\text{PV,building}}$	Energy supplied to the building by the PV system (kWh)
E_{BSS}	Energy supplied to the building by the BSS (kWh)
E_{EV}	Energy demand of the EV charging process (kWh)
$E_{\text{HP,el}}$	Electrical energy demand of the heating system (kWh)
α_{PV}	Binary variable to indicate, if a PV system is available in the building
α_{BSS}	Binary variable to indicate, if a BSS is available in the building
α_{EV}	Binary variable to indicate, if an EV is available in the building
α_{HP}	Binary variable to indicate, if a HP is available in the building
$c_{\text{elec. price}}$	Electricity unit rate cost (€ct/kWh)
$c_{\text{feed-in}}$	Feed-in remuneration (€ct/kWh)
P_{H}	Power flow from the building to the household appliances (kW)
$P_{\text{PV,grid}}$	Power flow from the PV system to the grid (kW)
$P_{\text{PV,building}}$	Power flow from the PV system to the building (kW)
$P_{\text{PV,BSS}}$	Power flow from the PV system to the BSS (kW)
$P_{\text{PV,generation}}$	Power output of the PV system (kW)
E_{BSS}	Energy stored in the BSS (kWh)
P_{BSS}	Power flow from the BSS to the building (kW)
$\eta_{\text{BSS,charge}}$	Charging efficiency of the battery
$\eta_{\text{BSS,discharge}}$	Discharging efficiency of the battery
$q_{\text{losses,BSS}}$	Standby losses of the BSS (%/h)
$P_{\text{BSS,max}}$	Maximum charge/discharge power of the BSS (kW)
$E_{\text{BSS,max}}$	Usable capacity of the BSS (kWh)
E_{EV}	Energy stored in the EV battery (kWh)
P_{EV}	Charging power of the EV battery (kW)
$P_{\text{EV,max,ch}}$	Maximum charging power of the EV battery (kW)
$E_{\text{EV,demand}}$	Energy demand of the EV (kWh)
$\eta_{\text{EV,charge}}$	Charging efficiency of the EV battery
$q_{\text{losses,EV}}$	Standby losses of the EV battery (%/h)
$E_{\text{min,departure}}$	Minimum energy stored in the EV battery at time of departure (kWh)
$f_{\text{avail.}}$	Availability of the EV at the home location (binary)
$E_{\text{min,charge}}$	Minimum energy level of the EV battery, before charging process starts (kWh)
$E_{\text{EV,max}}$	Capacity of the EV battery (kWh)
$\dot{Q}_{\text{heat demand}}$	Building's thermal heat demand (kW_{th})
$\dot{Q}_{\text{HP,building}}$	Thermal power flow from the heat pump to the building (kW_{th})
$\dot{Q}_{\text{HS,building}}$	Thermal power flow from the heat storage to the building (kW_{th})
COP	Coefficient of performance of the HP (p.u.)
η_{COP}	Quality grade/scale-down factor of the HP's Carnot efficiency
T_{high}	Flow temperature of the heating system (K)
$T_{\text{high,max}}$	Technically maximum possible flow temperature of the heating system (K)
$T_{\text{amb.}}$	Ambient temperature (K)
$T_{\text{amb.,norm}}$	Norm outside temperature (K)
T_{room}	Inside temperature (K)
T_{icing}	Temperature threshold below which icing occurs (°C)
f_{icing}	Factor of COP reduction due to icing (p.u.)

$\dot{Q}_{\text{max,th}}$	Maximum thermal power output of the HP (kW_{th})
COP_{nom}	Nominal coefficient of performance (p.u.)
$\dot{Q}_{\text{nom,th}}$	Nominal thermal power output of the HP (kW_{th})
$P_{\text{HP,el}}$	Power flow from the building to the HP (kW)
$\dot{Q}_{\text{HP,th}}$	Thermal power generation of the HP (kW_{th})
$\dot{Q}_{\text{HP,HS}}$	Thermal power flow from the HP to the heat storage (kW_{th})
$\dot{Q}_{\text{amb,norm}}$	Heat demand at norm outside temperature (kW_{th})
$\dot{Q}_{\text{th,20°C}}$	Heat demand at ambient temperature of 20°C (kW_{th})
$\dot{Q}_{\text{th,min}}$	Heat demand at minimal ambient temperature (kW_{th})
$f_{\text{HP,flexibility}}$	Flexibility factor for HP sizing (p.u.)
E_{HS}	Energy stored in the heat storage (kW_{th})
$E_{\text{HS,max}}$	Storage capacity of the heat storage (kW_{th})
$q_{\text{losses,HS}}$	Standby losses of the heat storage (%/h)

7.1 Introduction

The recent energy crisis in Europe and in Germany in particular, has had significant impacts on various sectors. Amidst rising electricity prices[1] and the increasing volatility observed on day-ahead spot market prices in Germany in recent months (see Fig. 7.1), this crisis has not only meant a greater financial burden for households, but has also highlighted the urgent need for sustainable energy solutions. As a result, households are becoming increasingly aware of their energy expenditures.

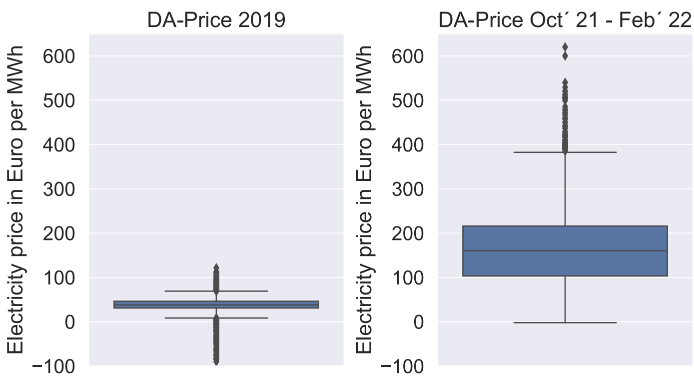

Figure 7.1: Historical day-ahead spot market electricity prices for the year 2019 and from October 2021 to February 2022.

This crisis has also accelerated the adoption of sector-coupling technologies, such as electric vehicles (EVs) and heat pumps (HPs), but also of PV battery storage systems (PV-BSSs). While these technologies represent a shift towards a more sustainable future, they also lead to an increase in electricity consumption. This surge in electricity demand prompts households to find ways to reduce their overall energy expenditure. Additionally, higher electricity consumption and peak loads due to these technologies and the increasing share of wind and solar power plants in power systems worldwide can pose challenges to local energy infrastructure in the future and requires power systems to become more flexible. In this context, managing

[1] Average price on the day-ahead spot market for Germany: 96.85 €/MWh in the year 2021 and 235.45 €/MWh in 2022 [1]

high electricity costs and alleviating grid stress become crucial and a key strategy in this regard is the flexible operation of EVs, HPs and PV-BSSs. Assessing the conditions for incentivizing this residential flexibility in an efficient and system friendly manner is relevant in many power systems worldwide with an increasing share of renewable energy sources and sector coupling technologies. Core conditions encompass instruments and enabling technologies for utilizing residential flexibility.

7.1.1 Instruments to utilize residential flexibility

A wide range of instruments, so called demand response (DR) mechanisms, are being discussed to incentivize residential flexibility. DR mechanisms are strategies that involve shifting or shedding of electricity demand, providing flexibility to assist in balancing the grid. DR mechanisms can be beneficial for both end-users and utilities as they can increase overall system security and maximize social welfare [2]. DR mechanisms can generally be divided into incentive- or event-driven mechanisms, and price-driven mechanisms [3] with the social context considered critical for successful implementation. Incentive- or event-driven mechanisms include direct load control, emergency demand response programs, capacity market programs, interruptible/curtailable services, demand bidding/buyback programs, and ancillary service market programs [3]. Price-driven DR mechanisms comprise dynamic electricity retail tariffs. These mostly time-variable tariffs incentivize consumers to shift their load from times with higher electricity prices to times with lower ones, thus offering a solution to the challenges posed by the current energy crisis and ongoing energy transition. One advantage of price-driven DR mechanisms is that they are implemented „behind the meter“, on the customer side [4], and, in combination with smart meters, enable end-consumers to make informed decisions about their electricity consumption.

7.1.2 Role of enabling technologies for flexibility utilization in households

Next to DR mechanisms such as dynamic electricity tariffs, enabling technologies play an important role for utilizing flexibility. These enabling technologies, which allow for an automated response to price incentives, are generally classified into three categories: control devices, monitoring systems, and communication systems [5]. Control devices and monitoring systems are combined in home energy management systems (HEMS). A HEMS within this study is considered to actively manage the household's energy use by implementing control strategies and utilizing optimizing controllers to efficiently operate energy-using equipment including EVs, HPs and PV-BSSs. Together with smart meters acting as communication devices and dynamic electricity prices, these constitute the basic requirements for household customers to be able to operate their flexible assets in an intelligent, cost-optimized manner. A survey described by Buryk et al. [6] indicates that automated load shifting may play a critical role in encouraging customers to transition from a fixed to a dynamic pricing model. According to Parrish et al. [7], automation can simplify the process for households, reducing the complexity and effort required to respond to dynamic tariffs, thus preventing response fatigue and increasing participation. This was shown in a field study in the Flemish region, where after 18 months, no indication of user fatigue was observed [8]. In a field study in the US for households with plug-in hybrid EVs, households with a dynamic electricity tariff preferred managed charging via a programmable smart plug [9]. Another field study in the Netherlands concluded that automatic and smart control of appliances was the most popular strategy amongst the participating households [10].

7.1.3 Effects of the smart operation of flexible technologies on the economic viability of dynamic electricity retail tariffs for households

If a PV system and a battery storage system (BSS) are combined with a new ToU tariff that varies for different types of day and shows a more extended dependence on energy drawn from the grid, Bignucolo et al. [11] find that applying the enhanced ToU tariff to both the power drawn from and fed into the grid can reduce the daily electricity costs for households in Italy by up to 72 %.

EVs have been discussed as a very promising technology to increase the utilization and financial benefits of dynamic tariffs. Applying the principle of smart charging, Martinenas et al. [12] find that a reduction in charging costs between 48 % and 61 % can be achieved when using a dynamic tariff in Denmark. von Bonin et al. [13] study households with an EV, a PV system, and a day-ahead real time pricing (DA-RTP) tariff in Germany and define four charging strategies: direct charging, PV optimized charging, and optimizing electricity costs with the DA-RTP tariff with and without a PV system. The best result in terms of reducing electricity costs is obtained for the PV optimized charging case (35 % cheaper than direct charging), followed by the optimizing electricity costs with the DA-RTP tariff with a PV system case (34.0 % cheaper). A more comprehensive analysis of the change in electricity costs is presented by Kühnbach et al. [14]. Their study shows electricity costs decrease for all residential consumers by up to -3.7 % when EVs in Germany apply controlled charging responding to a price signal derived from the national residual load. The analysis includes the change in electricity procurement costs due to controlled charging and the change in grid charges from the grid expansion needed due to the uptake of EVs. Aguilar-Dominguez et al. [15] investigate different dynamic tariff schemes (time-of-use (ToU), time-of-day, real time pricing (RTP)) for UK households with an EV, a PV system, and a BSS. Their results show a reduction in electricity costs of up to 85 %. Huang et al. [16] find that electricity purchase costs can be reduced by 22.5 % for households with renewable generation, EVs, and air conditioning in Anhui, China, when a HEMS is used. A further reduction of 26.6 % can be achieved if a BSS is included in the system. Lu et al. [17] show similar results. In their setup of a household in Shanghai with an EV, air conditioning and different sizes of PV-BSSs, they obtain a possible cost reduction of up to 71.4 % when using a HEMS and a ToU tariff. Ren et al. [18] find that in households with an EV and a PV-BSS in China, household electricity costs can be reduced by 18 % with an RTP tariff, taking into account uncertainties in forecasting electricity prices and PV output.

According to Pena-Bello et al. [19], households with a HP and a PV system in Switzerland can increase their self-consumption rate and reduce the levelized costs of meeting electricity demand by between 13 % and 26 % if a heat storage is added to the system. Ali et al. [20] show that energy cost savings of up to 40 % are possible from using a DA-RTP with electric space heating and partial thermal storage in Finland. Klaassen et al. [21] assume a DA-RTP tariff for a household in the Netherlands with a HP for floor heating and domestic hot water demand and apply a control algorithm to minimize heating costs. The results show an 8 % reduction in energy heating costs. For a setting in Switzerland applying a DA-RTP tariff, Wilczynski et al. [22] find that households that only have a HP can still achieve cost savings of approximately 1 % attributable to using the HP flexibly.

Looking at households that have both an EV and a HP, and an additional PV system, Yousefi et al. [23] analyze buildings with various energy labels and two different heat emission systems in Denmark. They show possible home energy cost savings between 26 % and 41 %, when a HEMS and a ToU tariff are combined. Yang et al. [24] consider households with an EV, a HP, and a PV-BSS and possible electricity cost savings when a ToU tariff is applied for a household in different climate zones in the US. Results indicate that cost savings ranging from 12 % to 38 % are possible.

A summary of the above presented articles on cost savings through flexibility utilization can be found in Table 7.1.

7.1.4 Research gap and contribution

The literature consistently illustrates the positive general impact of dynamic pricing. It effectively reduces procurement costs, particularly when combined with a smart and automated HEMS. However, as a growing proportion of households adopt flexible technologies, our review uncovers significant knowledge gaps that must be bridged in order to evaluate the benefits of dynamic electricity tariffs more comprehensively:

1. **Narrow focus on single technologies:** Predominantly, the existing research concentrates on isolated flexible technologies – such as EVs or HPs, frequently in combination with PV systems or PV-BSSs. These investigations seldom explore the interaction among multiple technologies within a household responding to dynamic electricity prices.
2. **Neglect of household heterogeneity:** The limited variety of load curves considered in these studies overlooks the critical dimension of household heterogeneity, thus limiting the comprehensive understanding and applicability of insights regarding the impact of dynamic electricity prices on households with flexible appliances.
3. **Presumption of HEMS and smart meters:** A common assumption across studies is the pre-existence of HEMS and smart meters. However, the widespread acceptance and implementation of dynamic electricity pricing models and HEMS crucially depend on ensuring that the initial investment costs of such systems are not higher than the financial savings achieved through DR strategies. Therefore, it is essential to incorporate the costs associated with HEMS and smart meters into the analysis.
4. **Need for comprehensive comparisons:** It is vital to benchmark the performance of flexible technologies under dynamic electricity pricing not merely against scenarios with no explicit flexibility utilization, but also against setups aimed at optimized self-consumption.

The main research question stems from these identified gaps and the recent developments on electricity markets and digital advancements:

- **Under what conditions are dynamic electricity retail tariffs the most economically viable option for households?**

To systematically address this question, we pose several subquestions related to the identified research gaps:

- How does flexibility utilization[2] via a HEMS in households under dynamic electricity tariffs compare with self-consumption in households equipped with a PV system?

[2] Utilization of flexibility in the context of this study means the implementation of a HEMS facilitating the load shifting of flexible technologies such as EVs, HPs or PV-BSSs.

- How are the economic benefits of dynamic electricity tariffs for households influenced by the interaction of multiple flexible technologies, different average electricity prices and different price spreads[3]?
- Do the potential cost savings offset the additional costs of metering point operation and the HEMS?

To address these questions, we introduce the *EVaTar-building* model – a simulation framework featuring embedded optimization designed to simulate household electricity consumption patterns under a HEMS or in response to dynamic tariffs. We explore three cases: households not explicitly utilizing their flexibility, households employing a HEMS to enhance self-consumption via a PV system or a PV-BSS, and households utilizing a HEMS alongside a smart meter, adopting a dynamic electricity tariff based on the day-ahead spot market price. The model's outputs enable a thorough economic analysis considering the investments in a HEMS and metering point operation costs. Furthermore, an analysis on changes in annual electricity consumption per household, and the resulting changes to the load curves is carried out, thereby providing a comprehensive picture of the scenarios.

The study is organized as follows: Section 7.2 describes the methodological approach, the data used, the electricity price scenarios, and the underlying assumptions of the case study. Section 7.3 provides an overview of the study results. Section 7.4 discusses the results, and the study closes with the summary and conclusion (Section 7.5).

[3] A price spread is defined as the difference between the minimum and maximum value of a price time series over a predefined period of time.

Ref.	Available technologies				Profile Heterogeneity	Tariff Scheme	Operating Strategies	Included Costs	Cost Savings
	PV	EV	HP	BSS					
Bignucolo et al. [11]	x		x		2 households load profiles, 1 PV generation profile, 24h	ToU, E-ToU	Electricity cost minimization, no flexibility utilization as benchmark	Electricity costs and PV-BSS amortization, no VAT	37% with ToU, up to 72% with E-ToU
Martinenas et al. [12]		x			2 load profiles, less than 24h	Dynamic Tariff based on Nord Pool spot, including signals for immediate and predicted grid state	Smart charging (cost optimized), direct charging as benchmark	Unit rate costs without taxes	48-61%
von Bonin et al. [13]	x	x			74 household load profiles, 100 EV profiles, 27 PV generation profiles, 1 year	Static, DA-RTP	PV optimized charging, price optimized charging, price and PV optimized charging, direct charging as benchmark	Total costs of electricity for EV charging	PV optimized charging: 35%, price optimized charging: 11%, PV + price optimized charging: 34%
Kühnbach et al. [14]	x	x			1 household load profile, 1 PV generation profile, different starting points for EV charging, 1 year	Tariff based on residual load of the system	price optimized charging, direct charging as benchmark	Unit rate costs with all fiscal charges; focus: grid charges & retail & acquisition	Up to 4% lower electricity unit rate costs for all households
Aguilar-Dominguez et al. [15]	x	x		x	1 household load profile, 1 PV generation profiles, 2 BSS sizes, 2 EV types, 2 weeks	Flat, ToU, ToD, RTP based on energy trade market in the UK	BSS or V2H for electricity bill minimization, no flexibility utilization as benchmark	Total cost of electricity (unit rate costs with taxes)	Up to 85%
Huang et al. [16]	x	x		x	1 household load profile, 1 PV generation profile, 24 h in summer and transition season	RTP of the power grid	Price optimized scheduling of loads, no flexibility utilization as benchmark	Electricity purchase costs	23% without BSS compared to no flexibility utilization, 27% with BSS compared to flexibility utilization without BSS
Lu et al. [17]	x	x		x	1 household load profile, different combinations of PV and BSS sizes, 24h	ToU	Combined price & peak load optimized scheduling of loads, no flexibility utilization as benchmark	Electricity purchase costs	Up to 71%
Ren et al. [18]	x	x		x	1 household load profile, 1 PV generation profile, 24h	RTP	Electricity cost minimization while ensuring user's demand, no flexibility utilization as benchmark	Electricity purchase costs	18%
Pena-Bello et al. [19]	x		x	x	549 household load profiles, 3 different heat demands, 1 PV profile, 1 year	ToU, + capacity based grid charge	Electricity cost minimization, no flexibility utilization as benchmark	Levelized cost of meeting electricity demand	13-26% for households with PV + HP + heat storage
Ali et al. [20]			x		1 household load profile, 1 heat demand, different heat storage sizes, 1 day in winter	DA-RTP	Electricity cost minimization, no flexibility utilization as benchmark	Wholesale energy costs	Up to 40%
Klaassen et al. [21]			x		1 household load profile including heat demand, 1 year	DA-RTP	Electricity cost minimization, no flexibility utilization as benchmark	Energy heating costs	8%
Wilczynski et al. [22]			x		2 building archetypes, 1 year	Flat, ToU, DA-RTP, DA-RTP for a system with full HP penetration	Electricity cost minimization, no flexibility utilization as benchmark	Cost savings attributable to HP flexibility	Approximately 1%
Yousefi et al. [23]	x	x	x		7 buildings with different energy labels, 2 heat emission systems, 1 household load profile, 1 EV profile, 1 PV generation profile, heat demand depending on building type, 1 week in winter	ToU	Electricity cost minimization, no flexibility utilization as benchmark	Home energy costs	26-41%
Yang et al. [24]	x	x	x	x	1 household load profile, 1 EV profile, 3 climate zones for PV generation & heat demand, 1 year	ToU	Electricity cost minimization, conventional control strategy as benchmark	Electricity costs	12-38%

Table 7.1: Key aspects of the analyzed literature regarding the identified research gaps.

7.2 Material and methods

Our methodology is divided into two parts: the generation of external price signals and the description of consumer flexibility utilization in response to these signals. First, we discuss the methodology developed to generate electricity price signals relevant to the purchase of electricity. In addition, we explain the calculation of the market value that serves as a proxy for the PV feed-in tariff. These price signals are central to our analysis, as they allow for seamless comparison between different scenarios. We then describe the *EVaTar-building* model, which illustrates three different operational strategies for different household types and their flexible technologies, such as EVs, HPs, and PV-BSSs. Finally, we outline the characteristics of the flexible technologies and time series data used in our study.

7.2.1 Preparation of price signals

For households using a HEMS, two price signals are important: the price per kilowatt-hour of electricity purchased from the grid, and the feed-in tariff paid for each kilowatt-hour generated by their PV system and fed back into the grid.[4]

7.2.1.1 Manipulating electricity price time series to create dynamic electricity retail tariffs

To ensure broad applicability of our findings, we examine dynamic electricity tariffs across diverse price scenarios. For ease of comparison, we have selected the year 2019[5] and modify the price time series to create price scenarios while retaining its intrinsic structure.

In a first step, given the presence of hours within the year characterized by relatively high and low prices, we define the 1 % percentile of all electricity prices in the time series as outliers (ct). This identification yields a set of time steps, Tout, during which these outliers are observed. We then recalibrate the mean value and standard deviation of the remaining data set to match the intended scenarios in accordance with Eq. (7.1).

$$c^t_{\text{adj}} = \frac{c^t_{2019} - \overline{c^t_{2019}}}{\sigma(c^t_{2019})} \cdot \sigma_{\text{scen}} + \varnothing_{\text{scen}}, \qquad \forall t \in T_{\text{out}} \tag{7.1}$$

In this context, c^t_{2019} represents the electricity price at each time step t, excluding instances identified as outliers within this time series. σ_{scen} denotes the standard deviation, and $\varnothing_{\text{scen}}$ signifies the mean value of the electricity price for the specified scenario. c^t_{adj} stands for the adjusted time series, which omits the outliers.

[4] This assumes the current regulatory framework in Germany, where electricity is paid in €ct/kWh without any costs for the capacity used.

[5] The choice of 2019 as the base year allows for the creation of a consistent scenario, particularly in combination with available data for weather, temperature etc., for the flexible consumers. This decision was driven by the lack of comprehensive data for more recent years accessible to the authors.

In the subsequent step, we modify the outliers so that they fall within the bounds defined by the minimum and maximum values of the chosen price scenario ($C_{\text{sc,min}}$ and $C_{\text{sc,max}}$) as well as the minimum and maximum values of the adjusted time series ($\min c^t_{\text{adj}}$ and $\max c^t_{\text{adj}}$). This adjustment is carried out separately for positive and negative outliers. Eq. (7.2) provides an example for handling positive outliers ($c^t_{\text{out, p}}$).

$$c^t_{\text{out,adj,pos}} = \begin{cases} \frac{c^t_{\text{out,p}} - \min c^t_{\text{out,p}}}{\max c^t_{\text{out,p}} - \min c^t_{\text{out,p}}} \cdot (C_{\text{sc,max}} - \max c^t_{\text{adj}}) + \max c^t_{\text{adj}}, & \forall c^t_{\text{out,p}} \geq c^t_{\text{adj}}, \forall t \in T_{\text{out}} \\ \max c^t_{\text{adj}}, & \forall c^t_{\text{out,p}} < c^t_{\text{adj}}, \forall t \in T_{\text{out}} \end{cases} \tag{7.2}$$

Upon finalizing the manipulation of the distinct datasets c^t_{adj}, $c^t_{\text{out,adj,pos}}$, and $c^t_{\text{out,adj,neg}}$, they are consolidated into a single time series, c^t_{scen}, which represents the electricity price scenario.

7.2.1.2 Calculating PV market values for the feed-in tariff

As prices in the day-ahead spot market are different for each price scenario, so are the market values of electricity generated from PV systems. To account for this variability in the different price scenarios, we assume a constant feed-in tariff for electricity generated by rooftop PV systems. For easy comparison between scenarios, we derive a PV market value, MV_{solar}, based on the day-ahead spot market prices. The electricity price $c^t_{\text{electricity}}$ is weighted by the amount of electricity generated by PV systems E^t_{PV} for each hour t, as shown in Eq. (7.3).

$$\text{MV}_{\text{solar}} = \frac{\sum_{t=0}^{8760} E^t_{\text{PV}} \cdot c^t_{\text{electricity}}}{\sum_{t=0}^{8760} E^t_{\text{PV}}}, \quad \forall t \in T \tag{7.3}$$

7.2.2 Modeling flexible consumers: EVaTar-building model

Our computational framework integrates various elements, including inflexible household demand, battery storage operations, and the demand response capabilities of EVs and heating systems. This model allows the representation of three different operating strategies for households:

- **No-flex case:** This serves as the baseline case, representing the status quo where households have flexible technologies but do **not explicitly** utilize their flexibility. Households are further subjected to a static tariff.
- **SC-flex case:** In this case, households aim to increase their **self-consumption** through the use of a HEMS, thereby minimizing their electricity purchase costs under a static tariff.
- **DT-flex case:** This case introduces a **dynamic electricity tariff** and a smart meter into the household, allowing a more strategic use of flexibility to take advantage of periods with low electricity prices.

For the no-flex case, a simulation model illustrates the absence of explicit flexibility utilization. For the SC-flex and DT-flex cases, a mixed integer linear programming (MILP) optimization represents operation of the HEMS, providing detailed and efficient strategy for managing household energy consumption.

The following sections outline the general implementation approach for each technology, followed by specific implementations for both inflexible (no-flex case) and flexible (SC-flex and DT-flex cases) behaviors of households.

7.2.2.1 Building representation and household appliances

Building representation. The model represents each building as a household, which may have additional technologies such as EVs, PV systems, BSSs, and heating systems that include both a HP and a heat storage tank. Connected to a low-voltage grid, each building can either withdraw electricity from or feed electricity generated by the PV system back into the grid. Fig. 7.2 shows the basic structure and energy flows of a flexible consumer in the *EVaTar-building* model.

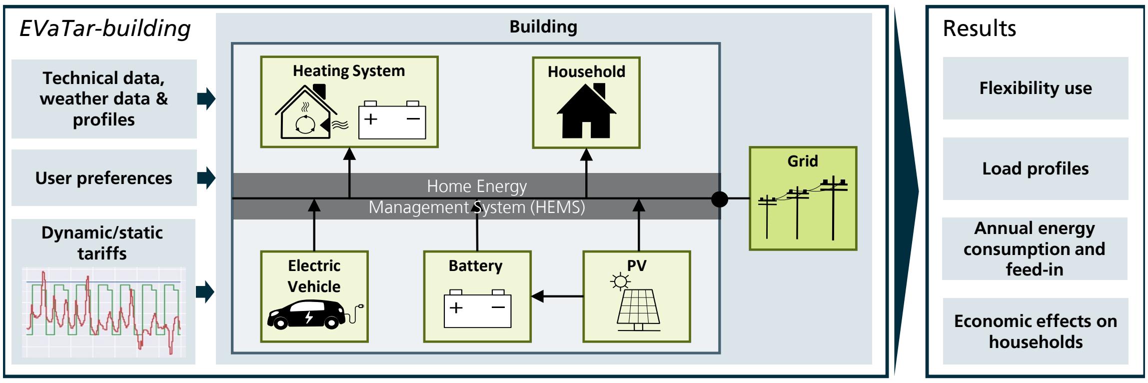

Figure 7.2: Schematic overview of the flexible consumer model *EVaTar-building*. The figure details the input data, the modeled energy flows within the building and to and from the grid, and the derived results.

For the SC-flex and DT-flex cases, it is assumed that each household can be equipped with a HEMS that operates with perfect foresight. To address uncertainties in load and generation forecasts, the model uses a rolling horizon scheme. This scheme considers a 3-day planning horizon with a control horizon of 24 h. The HEMS is responsible for actively optimizing building operations to minimize electricity purchase costs, as stated in Eq. (7.4):

$$\text{minimize} \sum_{t=0}^{t_{\text{max}}} E^t_{\text{grid,building}} \cdot c^t_{\text{elec. price}} - E^t_{\text{PV,grid}} \cdot c_{\text{feed-in}}, \quad \forall t \in T \tag{7.4}$$

Here, $E^t_{\text{grid,building}}$ represents the amount of energy drawn from the grid during time step t, while $c^t_{\text{elec. price}}$ denotes the applicable electricity price during this time unit. $E^t_{\text{PV,grid}}$ signifies the energy fed back into the grid from the PV system during time step t, and $c_{\text{feed-in}}$ is the time-independent feed-in remuneration. The energy drawn from the grid $E^t_{\text{grid,building}}$ is specified as follows:

$$E^t_{\text{grid,building}} = E^t_{\text{H}} - \alpha_{\text{PV}} \cdot E^t_{\text{PV,building}} - \alpha_{\text{BSS}} \cdot E^t_{\text{BSS}} + \alpha_{\text{EV}} \cdot E^t_{\text{EV}} + \alpha_{\text{HP}} \cdot E^t_{\text{HP,el}}, \quad \forall t \in T \tag{7.5}$$

In this context, the variable α is binary and indicates the presence of a particular technology in a household. E^t_{H} refers to the household's inflexible electricity demand during time step t. $E^t_{\text{PV,building}}$ signifies the amount of energy supplied to the building from the PV system during time step t. E^t_{BSS} denotes the energy provided to the building by the battery storage system in time step t. E^t_{EV} represents the energy requirements of the EV charging process during time step t. Finally, $E^t_{\text{HP,el}}$ specifies the electrical energy demand of the heating system during time step t.

Household appliances. This study considers the electricity demand of household appliances as inflexible and defines it exogenously through household load profiles.

7.2.2.2 PV systems

The PV system can supply power to various applications in the building, charge a BSS, and feed electricity into the grid. To represent this, the power output from the PV system $P^t_{\text{PV,generation}}$ for a given time step t is divided into three different power flows (as shown in Eq. (7.6)).

$$P^t_{\text{PV,grid}} + P^t_{\text{PV,building}} + P^t_{\text{PV,BSS}} = P^t_{\text{PV,generation}}, \quad \forall t \in T \tag{7.6}$$

The power flow from the PV system to the grid is represented by $P^t_{\text{PV,grid}}$, while $P^t_{\text{PV,building}}$ represents the power flow from the PV system to the building, and $P^t_{\text{PV,BSS}}$ is the power flow from the PV system to the BSS. Buildings that consist solely of a household and a PV system, without any of the flexibility options presented below, are considered inflexible.

7.2.2.3 Battery storage systems

The building's BSS can be charged with electricity generated by the PV system and it can provide power to the various technologies available in the building. The energy stored in the battery, E^t_{BSS}, at a given time step t is defined as follows:

$$E^t_{\text{BSS}} = (1 - q_{\text{losses,BSS}}) \cdot E^{t-1}_{\text{BSS}} + P^t_{\text{PV,BSS}} \cdot \eta_{\text{BSS,charge}} \cdot \Delta t - P^t_{\text{BSS}} \cdot \frac{1}{\eta_{\text{BSS,discharge}}} \cdot \Delta t, \quad \forall t \in T \tag{7.7}$$

With:

$$0 \leq P^t_{\text{PV,BSS}} \leq P_{\text{BSS,max}}, \quad \forall t \in T \tag{7.8}$$

$$0 \leq P^t_{\text{BSS}} \leq P_{\text{BSS,max}}, \quad \forall t \in T \tag{7.9}$$

$$0 \leq E^t_{\text{BSS}} \leq E_{\text{BSS,max}}, \quad \forall t \in T \tag{7.10}$$

$P^t_{\text{PV,BSS}}$ represents the power flow from the PV system to the BSS. P^t_{BSS} denotes the power flow from the battery to the building. $P_{\text{BSS,max}}$ is the maximum charge/discharge power of the BSS, and $E_{\text{BSS,max}}$ is its maximum usable capacity. The charging and discharging efficiency factors are represented by $\eta_{\text{BSS,charge}}$ and $\eta_{\text{BSS,discharge}}$, respectively. $q_{\text{losses,BSS}}$ depicts the standby losses.

BSS operation strategy in the no-flex case. The operating strategy for inflexible behavior represents the prevalent mode of operation for residential PV-BSS, functioning independently of the tariff system and typical for households without a HEMS. This strategy prioritizes the use of PV generated electricity to meet the building's demand, including EV and HP demands. Any excess generation charges the battery, and any further surplus is fed into the grid. Conversely, when the building's electricity demand exceeds the PV output, the system draws electricity from the battery to supply the household's energy demand.

BSS operating strategy in the SC-flex and DT-flex cases. With the introduction of a smart operating strategy, BSSs undergo a transformation to support flexible and predictive functioning, especially under dynamic tariffs. This advanced strategy integrates the BSS within the building's HEMS, aiming to minimize the overall energy procurement costs (as detailed in Eq. (7.4)).[6] A key constraint of this strategy is the requirement for the state of charge (SOC) of the BSS at the beginning of the planning horizon to match the SOC at the end, ensuring energy continuity and system integrity. Moreover, it is specified that the battery cannot be simultaneously charged and discharged, reflecting the physical limitations of battery technology.

7.2.2.4 Electric vehicles

EVs are implemented as mobile battery storage units within the model, implying that the EV battery's availability as a flexibility resource is not constant but varies over time. Driving profiles with the corresponding energy demand, $E^t_{\text{EV,demand}}$, are allocated to the households under study. The allocation is based on the socio-demographic metadata of the households and the driving profiles. This method ensures a realistic representation of EV usage and its impact on household electricity demand. Furthermore, the hourly availability of a vehicle at the home location, represented by $f^t_{\text{avail.}}$ is exogenously specified.

The energy currently stored in the EV battery E^t_{EV} is defined as follows (Eq. (7.11)):

$$E^t_{\text{EV}} = (1 - q_{\text{losses,EV}}) \cdot E^{t-1}_{\text{EV}} + P^t_{\text{EV}} \cdot \eta_{\text{EV,charge}} \cdot \Delta t - E^t_{\text{EV,demand}}, \quad \forall t \in T \tag{7.11}$$

Here $\eta_{\text{EV,charge}}$ represents the efficiency of the charging process and P^t_{EV} depicts the charging power at a time step t, and $q_{\text{losses,EV}}$ stands for the standby losses of the EV battery.

The maximum charging power for the EV battery is limited to $P_{\text{EV,max,ch}}$ (Eq. (7.12). Similarly, the total amount of energy that the EV battery can store is constrained by its maximum usable capacity $E_{\text{EV,max}}$ (Eq. (7.13).

$$0 \leq P^t_{\text{EV}} \leq P_{\text{EV,max,ch}}, \quad \forall t \in T \tag{7.12}$$

$$0 \leq E^t_{\text{EV}} \leq E_{\text{EV,max}}, \quad \forall t \in T \tag{7.13}$$

Uncontrolled charging of EVs in the no-flex case. The operating strategy involves continuous charging of the EV upon arrival until a state of charge of 100 % is reached or the EV starts driving again.

[6] Battery-to-grid power supply is not included in our analysis. This exclusion is based on the fact that the battery can only be charged via the PV system, and given the constant feed-in remuneration, employing the battery would merely result in additional energy losses.

Controlled charging of EVs in the SC-flex and DT-flex cases. The smart operating strategy for EVs involves controlled charging, where the EV is integrated into the building's HEMS. EV owners can input their preferences into the HEMS. This includes the minimum range and minimum energy stored in the battery at the time of departure $E_{\text{min,departure}}$ (Eq. (7.14)), as well as the latest minimum energy level $E_{\text{min,charge}}$ at which they want to start charging their vehicle, (Eq. (7.15)).

$$E^t_{\text{EV}} \geq E_{\text{min,departure}}, \quad \forall t \in T \quad \text{where } f^{t-1}_{\text{avail.}} = 1 \wedge f^t_{\text{avail.}} = 0 \tag{7.14}$$

$$E_{\text{min,charge}} \leq E^t_{\text{EV}} \leq E_{\text{EV,max}}, \quad \forall t \in T \tag{7.15}$$

Where $E_{\text{EV,max}}$ represents the maximum capacity of the EV battery.

7.2.2.5 Heating systems

The heating system of a building consists of an air-to-water HP and a heat storage tank (HS). The HP can supply energy to both the building ($\dot{Q}^t_{\text{HP,building}}$) and the heat storage tank ($\dot{Q}^t_{\text{HP,HS}}$). The heat storage tank can only supply the building ($\dot{Q}^t_{\text{HS,building}}$). The building's heat demand $\dot{Q}^t_{\text{heat demand}}$ must be met for each time step t (Eq. (7.16).

$$\dot{Q}^t_{\text{heat demand}} = \dot{Q}^t_{\text{HP,building}} + \dot{Q}^t_{\text{HS,building}}, \quad \forall t \in T \tag{7.16}$$

The flow temperature of the heating system T_{high} follows a heating curve and is, therefore, dependent on the ambient temperature. It is calculated as follows (Eq. (7.17)):

$$T^t_{\text{high}} = T_{\text{room}} + (T_{\text{high,max}} - T_{\text{room}}) \cdot \left(\frac{T_{\text{room}} - T^t_{\text{amb.}}}{T_{\text{room}} - T_{\text{amb.,norm}}} \right)^{1/n} \tag{7.17}$$

where T_{room} is the inside temperature, which is considered to be held constant by the HP system, $T_{\text{high,max}}$ represents the technically maximum possible flow temperature of the HP, T depicts the ambient temperature at a given time step t, $T_{\text{amb.,norm}}$ is the norm outside temperature for the given location and n is the radiator exponent which is set to $n = 1.33$ for wall mounted radiators.

Furthermore, a temperature-dependent coefficient of performance COP^t is assumed for the air/water HP. In addition, we account for efficiency losses due to icing at ambient temperatures below 2°C (T_{icing}) by reducing the COP for low temperatures by a factor of $f_{\text{icing}} = 0.2$. With a typical quality grade for air-to-water HPs of $\eta_{\text{COP}} = 0.4$ [25], the COP at time step t is calculated as follows (Eq. (7.18)):

$$\text{COP}^t = \begin{cases} \eta_{\text{COP}} \cdot \frac{T^t_{\text{high}}}{T^t_{\text{high}} - T^t_{\text{amb.}}} & T^t_{\text{amb}} > T_{\text{icing}} \\ \eta_{\text{COP}} \cdot \frac{T^t_{\text{high}}}{T^t_{\text{high}} - T^t_{\text{amb.}}} \cdot (1 - f_{\text{icing}}) & T^t_{\text{amb.}} \leq T_{\text{icing}} \end{cases}, \quad \forall t \in T \tag{7.18}$$

where T_{high} represents the flow temperature of the heating system.

With the time-dependent COP^t, the nominal COP$_{\text{nom}}$ and the nominal power output $\dot{Q}_{\text{nom,th}}$ of the HP, the maximum possible power output $\dot{Q}^t_{\text{max,th}}$ at time step t can be calculated for each time step:

$$\dot{Q}^t_{\text{max,th}} = \frac{\text{COP}^t}{\text{COP}_{\text{nom}}} \cdot \dot{Q}_{\text{nom,th}}, \quad \forall t \in T \tag{7.19}$$

The necessary electric power consumption from the building to the HP $P^t_{\text{HP,el}}$ is defined as the ratio of the thermal power generation $\dot{Q}^t_{\text{HP,th}}$ of the HP and the COP:

$$P^t_{\text{HP,el}} = \frac{\dot{Q}^t_{\text{HP,th}}}{\text{COP}^t} = \frac{\dot{Q}1t_{\text{HP,building}} + \dot{Q}^t_{\text{HP,HS}}}{\text{COP}^t}, \quad \forall t \in T \tag{7.20}$$

The sizing of the HP is endogenously calculated using data on the building's annual heating demand per square meter, its living space, and the norm outside temperature. Initially, the heat demand at norm outside temperature, denoted as $\dot{Q}_{\text{amb,norm}}$, is established using the derived heat demand curve and the time series of the ambient temperature (Eq. (7.21)).

$$\dot{Q}_{\text{amb,norm}} = (T_{\text{amb,norm}} - T_{20°\text{C}}) \cdot \frac{\dot{Q}_{\text{th,20°C}} - \dot{Q}_{\text{th,T}_{\text{min}}}}{T_{20°\text{C}} - T_{\text{min}}} \tag{7.21}$$

Where $\dot{Q}_{\text{th,20°C}}$ depicts the heat demand at an ambient temperature of 20°C and $\dot{Q}_{\text{th,T}_{\text{min}}}$ stands for the heat demand at the minimal ambient temperature of the underlying time series.

The HP's maximum thermal power output is then set using a flexibility factor $f_{\text{HP,flexibility}}$. This factor enables more flexible use of the HP, even during periods of low ambient temperatures.

The heat storage tank is used to make the heating system more flexible. Its storage capacity$E^t_{\text{HS,max}}$ is defined so that it can store the energy of two hours of the maximum power output of the HP.[7]

The energy currently stored E^t_{HS} in the heat storage is defined as (Eq. (7.22)):

$$E^t_{\text{HS}} = (1 - q_{\text{losses,HS}}) \cdot E^{t-1}_{\text{HS}} + \dot{Q}^t_{\text{HP,HS}} \cdot \Delta t - \dot{Q}^t_{\text{HS,building}} \cdot \Delta t, \quad \forall t \in T \tag{7.22}$$

Here $q_{\text{losses,HS}}$ represents the factor of the standby losses of the heat storage tank.

Inflexible operation of the heating system in the no-flex case. The heating system follows the heat demand. To guarantee heating availability even in the event of a blackout or technical problems, the heat storage tank is maintained at full charge during the entire heating period.

Flexible operation of the heating system in the SC- and DT-flex cases. When the flexibility of the HP is utilized, the heating system is integrated into the HEMS. This implies that the heat storage tank plays a crucial role in managing the household's heat supply. By utilizing the tank, we can strategically shift when the HP is operated while still meeting the household's heat demand.

[7] This corresponds to a typical design parameter for heat storage tanks in Germany. Heat storage tanks of this size are compact enough to be retrofitted into most single-family homes. At the same time, they allow for the bridging of restricted periods as per §14a of the German Energy Act (EnWG).

7.2.3 Input data

In this section, we present the data and assumptions for our analysis, starting with the characteristics of the two price signals relevant to the approach: the electricity price scenarios used for the assessment of dynamic electricity retail tariffs and the PV feed-in tariffs used for these scenarios. We then present a comprehensive overview of data used to represent the households and their flexible and inflexible technologies.

7.2.3.1 Electricity price scenarios of the dynamic electricity retail tariffs

We define three scenarios:

- a **low price scenario** that corresponds to the 2019 day-ahead spot market price time series for Germany,
- a **high price scenario** that uses statistical values of the day-ahead spot market price time series from October 2021 to February 2022[8] (see Fig. 7.1),
- and a **medium price scenario** that lies between these two.

Statistical values for the resulting time series after the electricity price time series manipulation are listed in Table 7.2.

Fig. 7.3(a) shows average prices for each hour of the day seen by a household (including taxes, levies, and surcharges), broken down by season and the range from minimum to maximum value for all three price scenarios. The prices are seasonally dependent, particularly in the range between the minimum and maximum values. For all seasons the lowest prices can be seen in the early morning hours and – to some extent – in the early afternoon. Fig. 7.3(b) shows the intraday and intraweek price spreads, which exhibit a clear seasonal difference in the intraweek spreads, with smaller differences in the intraday spreads.

To provide a basis for comparison, a static tariff for each price scenario is defined, which corresponds to the level of the mean value of the dynamic tariff (see Table 7.2). In the context of electricity pricing structures in Germany, static tariffs exhibit a higher average value compared to dynamic tariffs. However, utilizing the mean value of dynamic tariffs as proxy for static tariffs serves as a worst-case scenario from the standpoint of flexibility utilization.

Table 7.2: Mean values, standard deviation, and minimal and maximal values of the electricity price scenarios used.

	Mean in €ct/kWh	Standard deviation in €ct/kWh	Minimal value in €ct/kWh	Maximal value in €ct/kWh
Low price scenario	22.6	1.8	7.4	32.6
Medium price scenario	30.2	6.2	4.4	48.3
High price scenario	37.8	10.7	1.5	91.9

[8] Values from October 2021 to February 2022 are used, as data for a time period beyond February 2022 was not available at the point of the creation of this study and the sharp increase in spot market prices was seen approx. from October 2021.

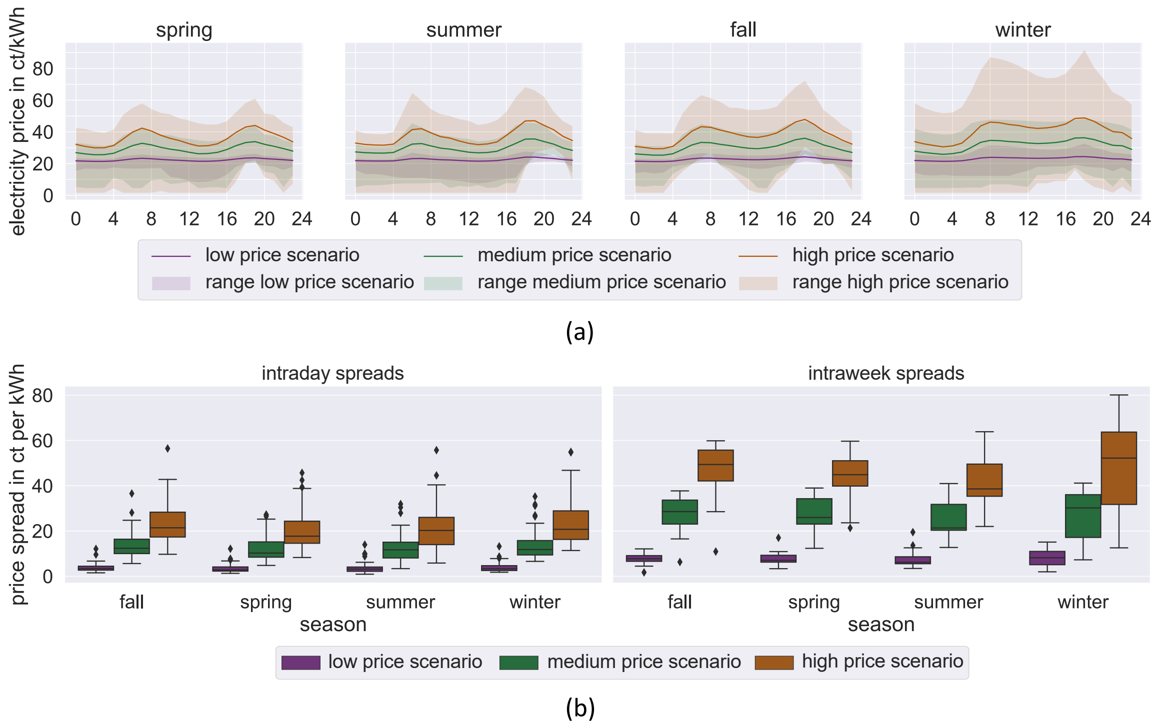

Figure 7.3: (a) Average prices and range for each hour of the day broken down by season for the three price scenarios; (b) Intraday and intraweek spreads for the three price scenarios.

7.2.3.2 Resulting PV feed-in tariff for each electricity price scenario

The feed-in from PV systems will be remunerated with the market value of the underlying price scenario (see Table 7.3).[9] The market value is obtained as described in Section 7.2.1.2.

Table 7.3: PV market values for the three electricity price scenarios.

Electricity price scenario	PV market value MV_{solar}
Low price scenario	3.62 €ct/kWh
Medium price scenario	9.71 €ct/kWh
High price scenario	15.81 €ct/kWh

7.2.3.3 Load and generation data, and technology specific parameters of buildings

Building data includes load and generation profiles, temperature profiles, and further technology specific parameters. General information on data sources is given below. Technology specific parameters are shown in Table 7.4.

Household load profiles. To cover the heterogeneity of household load profiles, we use residential load profiles of 316 households from a smart meter field study carried out in Austria and Germany [26]. An overview of the households' annual electricity consumption can be found in Fig. 7.9(a).

[9] A constant value is selected because time-varying remuneration is generally not observed for smaller photovoltaic systems installed in single-family homes in Germany.

Table 7.4: Technology specific parameters for the underlying case study.

Technology	Parameter	Value
Battery storage system	C-Rate	1
	Round-trip efficiency	0.95
	Standby losses	0.01 %/h
Electric vehicle	Energy consumption while driving	0.15 to 0.20 kWh/km
	Usable battery capacity	34.2 to 90.0 kWh
	$E_{\text{min,departure}}$	80 % of maximum range
	$E_{\text{min,charge}}$	20 % of maximum range
	Charging power	11 kW
	Standby losses	0.01 %/h
Heating system	$T_{\text{high,max}}$	50°C
	η_{COP}	0.4
	Standby losses	0.2 %/h

PV generation profile and design. For buildings with a PV system, we adjust the installed capacity to the annual electricity consumption of each household. We do this by using information from [27]. For an overview of the installed capacity for all PV systems considered, see Fig. 7.11(a). The PV generation profile is taken from renewables.ninja[10] for the year 2019 and the city of Karlsruhe.

Battery storage system design. To determine the usable battery capacity of the BSS for each household with a PV system, we consider two factors: the household's annual electricity consumption and the installed capacity of their PV system. The correlation between these factors and the usable battery capacity is obtained from [27]. The resulting distribution of usable battery capacity for the households considered can be found in Fig. 7.11(b).

Electric vehicle's driving and availability profiles. The availability at the home location and the power output while driving EVs are taken from Ref. [31]. The data is computed with the vehicle diffusion model ALADIN,[11] which uses vehicle usage data from Ref. [35]. Fig. 7.10(c) gives an overview of the yearly mileage of all EVs considered. The EV profiles are mapped to the households using socio-demographic data.

Heating system design and temperature profile. To determine the appropriate size of the HP for each building, we use the living space of the building, which was obtained from the aforementioned smart meter field study [26].[12] The HP is sized according to the heating demand of the building, which is assumed to be 100 kWh/m^2/a. The heat demand profile is obtained from HotMaps [36] for the city of Karlsruhe (DE12). For consistency, the ambient temperature for the same year (2019) and location is obtained from the Climate Data Center of the German Weather Service (Deutscher Wetterdienst) for Station ID 4177 [37].

The heat storage is designed to meet the maximum heat demand for two consecutive hours.

[10] Renewables.ninja is an open-source tool that considers historical weather characteristics and technical parameters to calculate supply profiles. For PV, we use an azimuth angle of 180° and a tilt of 35°. Provided by [28] and described in [29] and [30].

[11] For more information on the ALADIN model, we refer to [32, 33], and [34]

[12] An overview on the living space of all households considered is given in Fig. 7.9(b).

7.2.4 Case study

We consider different technology combinations, operational strategies, and electricity price scenarios. By this, we address the research gap of possible interactions between multiple flexible technologies within one household. We examine three different cases regarding the utilization of flexibility in households, which are described in detail in Section 7.2.2: the no-flex case, the SC-flex case, and the DT-flex case. Each case is simulated for each electricity price scenario described in Section 7.2.3.1, resulting in nine observations (see Table 7.5). For each observation, results are analyzed for the 316 households and nine technology combinations to account for heterogeneity in households, which sums up to 2,844 profiles for each observation. The technology combinations considered are shown in Fig. 7.4.

Table 7.5: Overview of the nine combinations of operational strategy cases for flexibility utilization and electricity price scenarios considered within the study.

Operational strategy case	Electricity price scenario
No-flex	Low
	Medium
	High
SC-flex	Low
	Medium
	High
DT-flex	Low
	Medium
	High

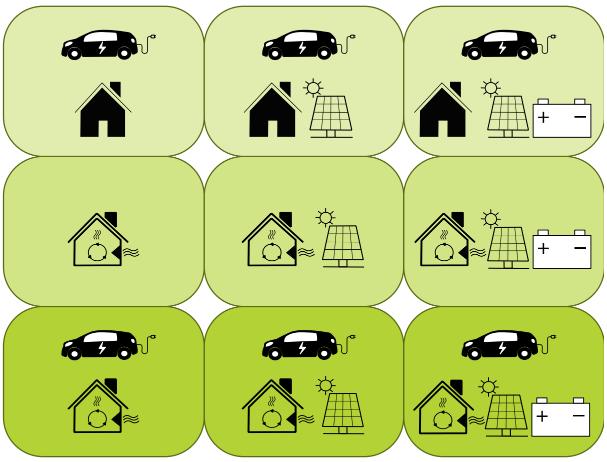

Figure 7.4: Technology combinations of EVs, HPs, PV systems, and PV-BSS considered within the study.

To thoroughly investigate the research questions introduced in Section 7.1, we have structured our analysis in a logical sequence:

- **Load curve analysis and analysis of electricity draw and self-consumption:** We analyze the difference in flexibility utilization via HEMS in households under dynamic electricity tariffs and households which increase self-consumption. We first examine the impact of HEMS utilization on household load curves, focusing on how and when the load is shifted. Subsequently, we investigate the variations in electricity drawn from the grid and self-consumption rates.

- **Economic benefits of dynamic electricity tariffs:** The financial implications of dynamic electricity pricing for households are evaluated. The effects on annual variable electricity costs (unit rate costs minus feed-in remuneration) are examined. The focus lies on the interaction of multiple flexible technologies and the impact of varying average electricity prices and price spreads.

- **Cost-benefit analysis:** We evaluate whether the potential cost savings outweigh the additional costs of HEMS in the SC-flex case and HEMS and metering point operation in the DT-flex case. We also assess the maximum tolerable costs for enabling technologies (HEMS, smart meter), that would allow at least 75 % of the households considered to still realize financial benefits from flexibility utilization, in either the SC-flex or the DT-flex case.

7.3 Results

7.3.1 Comparing flexibility utilization: dynamic electricity tariffs vs. self-consumption optimization

7.3.1.1 Impact assessment: flexibility utilization and its influence on load curve dynamics

When analyzing the introduction of a HEMS in the SC-flex and DT-flex cases, significant shifts in the households' electricity consumption patterns can be observed, as shown in Fig. 7.5.

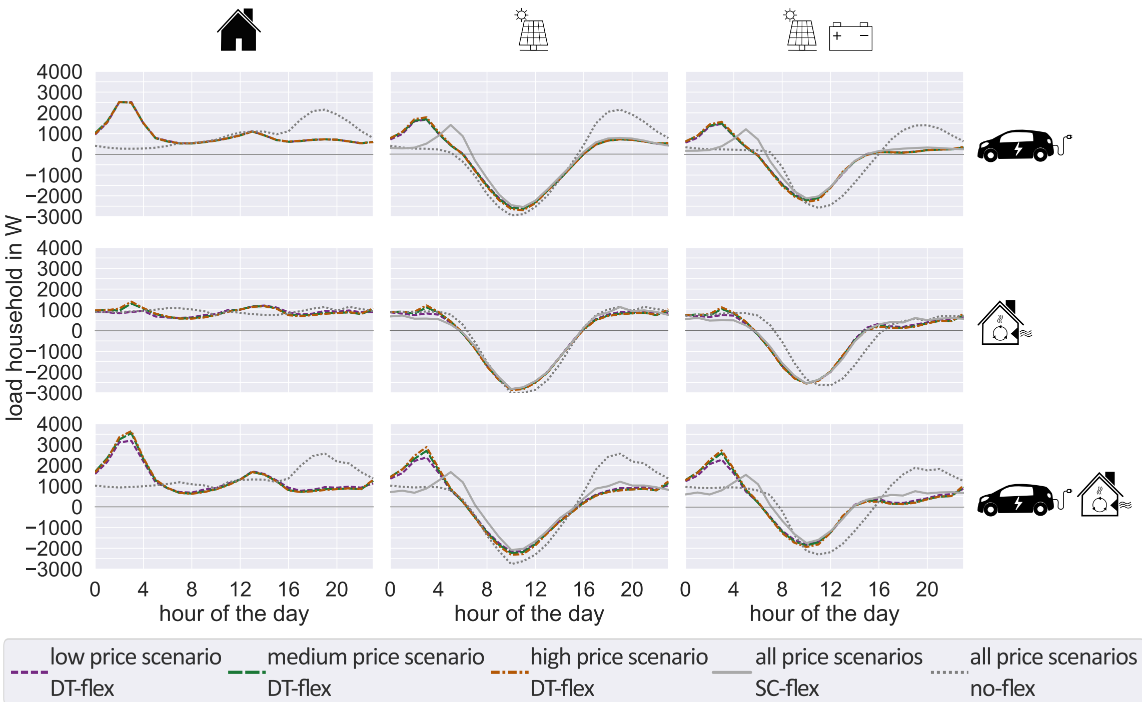

Figure 7.5: Yearly average household load for each hour of the day including all households considered for the defined cases and scenarios.

For households with an EV, the DT-flex case shows a notable change in the average hourly load curves, with the peak load shifting from evening hours to early morning hours, which is a result of the strategic use of lower electricity prices available during these times. The presence of a PV system or a PV-BSS reduces this effect, as households can leverage self-generated electricity for EV charging, reducing their dependency on electricity from the grid during high-cost periods. The load curves remain relatively consistent across the three electricity price scenarios.

The SC-flex case shows a distinct shift in load from evening to morning hours, with EV charging taking place later than in the no-flex and DT-flex cases, close to the daily departure time of the EVs. This is due to the HEMS's operation considering the self-discharge rates of EV batteries, optimizing charging times for energy efficiency.

For households with a HP, the DT-flex case shows a clear shift in load to the early morning hours, when electricity prices are at their lowest, and the afternoon. This shift is significantly influenced by the interplay between electricity prices and the temperature-dependent COP alongside the heating curve. During the day, when outside temperatures are higher, the HP operates more efficiently due to a higher COP. The load shift to the afternoon due to this efficiency gain is more noticeable in the low price scenario as price spreads are lower. This means that if the price spreads are higher, it is more likely that a lower COP can be compensated for and the load is shifted to times with the lowest electricity prices.

The incorporation of a PV system or a PV-BSS into households with a HP enables the use of self-generated electricity to power the heating system, which can be observed in the SC-flex case. However, in the DT-flex case, there is still an observed increase in load during the early morning hours, indicating a responsive behavior to dynamic electricity prices. The use of a HP has a more significant impact during winter months when the demand for heating is higher due to lower outside temperatures.

For households that have both an EV and a HP, the effects described above are combined. However, we observe a stronger impact from the EV effects.

For a comprehensive analysis, please refer to Fig. 7.9, which provides a seasonal evaluation of the effect for each technology combination. Table 7.6 presents a summary of the time of day when load peaks most likely occur across the technology combinations and operational strategy cases.

Table 7.6: Time of day of the occurring load peaks for the technology combinations broken down by cases considered.

Available technologies	Load peaks no-flex case	Load peaks SC-flex case	Load peaks DT-flex case
EV	Evening	–	Early morning
EV + PV or PV-BSS	Evening	Morning	Early morning
HP	Morning/evening	–	Early morning/afternoon
HP + PV or PV-BSS	Morning/evening	Evening	Early morning
EV + HP	Evening	–	Early morning/afternoon
EV + HP + PV or PV-BSS	Evening	Morning	Early morning

7.3.1.2 Analyzing the impact on electricity draw and self-consumption rates

The analysis of load curves showed the effective use of flexibility provided by the HEMS in managing HP operations. This is further demonstrated by the reduction in annual electricity draw from the grid. In the DT-flex scenario, a significant decrease in annual electricity draw ranging from 2.4 % to 10.9 % across all households is observed, highlighting the HEMS's ability to optimize energy efficiency by leveraging hours with higher COP values to operate the heating system.

When comparing households with a PV system or a PV-BSS to the no-flex case, both the SC-flex and DT-flex cases show improvements in self-consumption rates in all price scenarios, with rates reaching up to 62.1 % (as shown in Fig. 7.6). This maximum improvement is observed for households with an EV, a HP, and a PV-BSS. In the low price scenario, self-consumption rates are similar across the SC-flex and DT-flex cases for all technology combinations. However, in scenarios with higher electricity prices, the DT-flex case exhibits lower self-consumption rates because the HEMS shifts the load towards hours with lower electricity prices, rather than solely focusing on increasing self-consumption.

Figure 7.6: Average self-consumption rate for the SC-flex and DT-flex case for all three price scenarios.

7.3.2 Evaluating economic benefits of dynamic electricity tariffs: analysis of multiple flexible technology combinations and price scenarios

The households' annual variable electricity costs (unit rate costs minus feed-in remuneration) are impacted by the changes in self-consumption, annual electricity drawn from the grid, and the use of dynamic tariffs. Fig. 7.7 shows that the annual variable electricity costs averaged across all households differ significantly across the three price scenarios and the three operational strategy cases considered. Table 7.7 presents the average cost savings for all households between the SC-flex and no-flex cases, as well as between the DT-flex and no-flex cases.

The SC-flex case demonstrates a reduction in annual variable electricity costs across all price scenarios when compared to the no-flex case, ranging from 25 % to 404 % depending on the available technologies and price scenario. In the low and medium price scenarios, households with an EV benefit more than

Figure 7.7: Annual variable electricity costs (unit rate costs minus feed-in remuneration) for the no-flex, SC-flex, and DT-flex cases for all three price scenarios (average over all households).

Table 7.7: Relative change in annual variable electricity costs averaged over all households for the SC-flex and DT-flex cases, reference case: no-flex case.

Available technologies	SC-flex case			DT-flex case		
	Low price scenario	Medium price scenario	High price scenario	Low price scenario	Medium price scenario	High price scenario
EV	–	–	–	-4 %	-11 %	-15 %
EV + PV	-29 %	-44 %	-72 %	-33 %	-61 %	-112 %
EV + PV-BSS	-43 %	-175 %	-404 %	-51 %	-272 %	-821 %
HP	–	–	–	-6 %	-5 %	-5 %
HP + PV	-15 %	-38 %	-103 %	-23 %	-35 %	-97 %
HP + PV-BSS	-30 %	-116 %	-400 %	-30 %	-126 %	-485 %
EV + HP	–	–	–	-7 %	-12 %	-14 %
EV + HP + PV	-26 %	-29 %	-52 %	-28 %	-37 %	-72 %
EV + HP + PV-BSS	-27 %	-44 %	-70 %	-30 %	-60 %	-114 %

those with a HP. However, in the high price scenario, households with a HP and a PV system benefit more.

The introduction of a dynamic tariff in the DT-flex case results in further cost reductions in almost all cases. Households with an EV benefit the most, with potential savings of up to 821 %[13] (for households with an EV and a PV-BSS). However, households with a HP and a PV system experience lower cost savings on average in the DT-flex case compared to the SC-flex case in terms of annual variable electricity

[13] For households equipped with a PV-BSS or a PV system, the percentage change in costs can be significantly high, particularly since overall electricity expenses are relatively low in the no-flex scenario.

costs, as the HEMS is not able to shift the load of HPs as freely as the load of EVs. This is because HPs must follow a relatively steady heat demand of the household with a comparably small storage capacity. As a result, electricity consumption cannot be completely shifted away from hours with high prices, especially in the evening hours. This results in higher overall costs as the unit rate for the dynamic tariff during peak hours can exceed the rate offered by the static tariff.

7.3.3 Assessing the cost-effectiveness of HEMS and smart meters: do savings outweigh additional expenses?

7.3.3.1 Evaluating the financial attractiveness of HEMS and smart meter integration

Assuming an investment of €1500 in the HEMS, the estimated annualized costs are 167 €/yr.[14] Additionally, the metering point operation costs of 7.5 €/month result in annual costs of €90. Fig. 7.8 shows the distribution of the most financially attractive option for households in each price scenario, considering these additional costs.

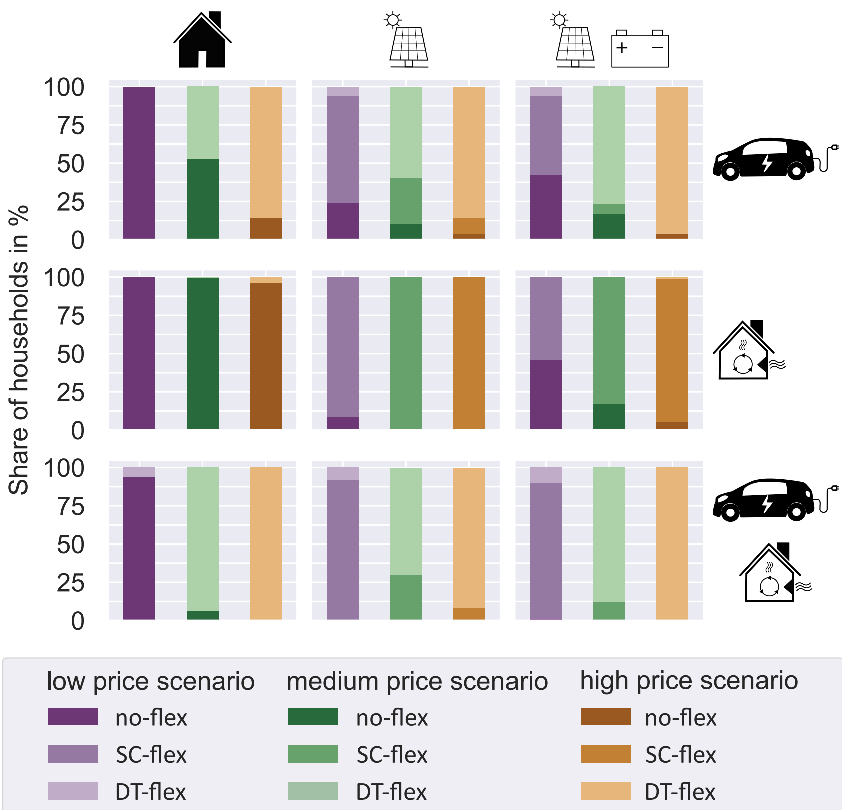

Figure 7.8: Distribution of the most financially attractive option across all households for all electricity price scenarios and technology combinations.

The analysis shows that higher price scenarios make it more financially attractive to adopt a HEMS and a dynamic tariff. It is important to note that households with an EV benefit more from dynamic tariffs than those with a HP, due to annual variable electricity cost savings being lower for households with

[14] With an assumed lifetime of 10 years and an interest rate of 2 %

a HP, and therefore the additional metering point operation costs for the DT-flex case not being easily offset. Therefore, the SC-flex case is more financially attractive for households with a HP. In the high price scenario, 85.4 % of households that own an EV choose the DT-flex case, while only one household with a HP would choose this option. When a PV system is incorporated, the SC-flex case becomes the most financially attractive option for all households equipped with a HP in the medium and high price scenarios. For households that have both an EV and a HP, the dynamic tariffs under the DT-flex case offer even greater financial benefits. In the medium price scenario, 93.7 % of these households consider the DT-flex case to be the financially most attractive option, increasing to 99.4 % in the high price scenario. Finally, the financial attractiveness of the DT-flex and the SC-flex cases for households with an EV, a HP or both can be further increased by adding a PV system or a PV-BSS.

7.3.3.2 Threshold analysis: determining the maximum tolerable costs of HEMS and smart meter for incentivizing flexibility

Our analysis highlights the importance of considering the investment costs in a HEMS and metering point operation costs when determining the financial attractiveness of using a HEMS, as well as dynamic tariffs. Therefore, we determine the maximum tolerable costs while still promoting the adoption of HEMS or dynamic tariffs. To do this, we assume that households will invest in a HEMS or a HEMS in combination with dynamic tariffs in the SC-flex and DT-flex case only if they can cover the costs of HEMS and metering point operation through savings in their annual variable electricity costs compared to the no-flex case. We define the maximum tolerable costs of the HEMS and metering point operation as the annual variable electricity cost savings.

Determining the maximum tolerable costs for all technology combinations and all three price scenarios shows a significant variation across households (refer to Fig. 7.12), with less variance for households with a HP than for households with an EV. In reality, it is unlikely that all households will be incentivized to utilize their flexibility. Therefore, this analysis focuses on the 75th percentile of all households (refer to Table 7.8).

Table 7.8: Maximum annual tolerable costs for the investment costs for HEMS or both, the investment costs for HEMS and metering point operation costs for smart meters for the SC-flex and DT-flex case, and all electricity price scenarios.

Price scenario	SC-flex case			DT-flex case		
	Low	Medium	High	Low	Medium	High
EV	–	–	–	€50	€188	€316
EV + PV	€171	€183	€196	€211	€310	€413
EV + PV-BSS	€126	€136	€145	€171	€291	€420
HP	–	–	–	€84	€97	€111
HP + PV	€200	€241	€282	€186	€209	€237
HP + PV-BSS	€146	€183	€220	€144	€197	€255
EV + HP	–	-	–	€153	€330	€501
EV + HP + PV	€354	€410	€466	€390	€545	€695
EV + HP + PV-BSS	€281	€331	€383	€324	€500	€694

In the SC-flex case, households equipped with an EV and a PV system can tolerate maximum annual costs for the HEMS ranging from €171 in the low price scenario to €196 in the high price scenario. The addition of a BSS reduces these tolerable costs to between €126 and €145. For households equipped with a HP, a PV system or PV-BSS, the range of maximum tolerable costs for the HEMS is wider, ranging from €146 in the low price scenario (HP and PV-BSS) to €282 in the high price scenario (HP and PV system). Households that have both an EV and a HP can tolerate even higher costs for the HEMS.

In the DT-flex case, which additionally considers metering point operation costs, there is potential for higher maximum tolerable costs. For households with an EV and a PV system, the maximum tolerable costs range from €211 in the low price scenario to €413 in the high price scenario. For households with only an EV, the maximum tolerable costs range from €50 in the low price scenario to €316 in the high price scenario. For households with a HP, which tend to see lower cost savings in the DT-flex case, leading to correspondingly lower maximum tolerable costs, ranging from €84 in the low price scenario to €111 in the high price scenario. Introducing a PV system increases the maximum tolerable costs for HEMS and metering point operation to €186 in the low price scenario and €237 in the high price scenario. In the low and medium price scenarios, an additional BSS decreases the maximum tolerable costs.[15] However, in the high price scenario, the maximum tolerable costs increase slightly.

The analysis of the DT-flex and SC-flex cases shows clear patterns in the maximum tolerable costs for the considered technology combinations and electricity price scenarios:

- In the DT-flex case, households that solely own an EV have the lowest maximum tolerable costs in the low price scenario, at €50. In the medium and high price scenarios, households that solely own a HP have the lowest maximum tolerable costs, at €97 and €111, respectively.
- In the SC-flex case, households with an EV and a PV-BSS determine the lowest maximum tolerable costs in all price scenarios. The costs range from €126 in the low price scenario to €145 in the high price scenario.

7.4 Discussion

We present a synthesis of our findings to address the research questions posed, while also acknowledging the limitations of our study.

7.4.1 Synthesis of findings

Comparing the utilization of flexibility via HEMS in households under dynamic electricity tariffs with self-consumption in households equipped with a PV system, a difference can be observed in when peak loads occur at the grid connection point. In the SC-flex case, there is a peak in the morning hours for households with an EV, while the load is comparatively steady for households with a HP. The analysis of the DT-flex case shows a shift in households' load to the early morning hours and an increase in peak load when electricity prices are the lowest for households with an EV or a HP. The study finds that air/water HPs need a larger spread between high and low prices to respond effectively to dynamic electricity tariffs. Otherwise, households with only a HP experience a load shift mainly towards midday. The midday

[15] The reason for this is that households with a BSS already experience lower overall electricity costs even without making use of flexibility. Hence, the additional cost savings gained through flexibility utilization in such households are relatively modest.

load shift is caused by the interaction between the ambient temperature-dependent COP and dynamic prices. Additionally, the results show that households with an EV or a HP in combination with a PV system or PV-BSS have an increase in self-consumption rates for both the DT-flex and the SC-flex cases. Self-consumption rates in the DT-flex case are slightly lower and decrease with higher price scenarios.

Regarding the interaction of multiple flexible technologies and varying price spreads on the economic benefits of dynamic electricity tariffs, our analysis indicates that higher electricity prices and wider price spreads increase the financial incentives for households to use the flexibility of their HPs and EVs, both independently and in combination with PV systems and PV-BSSs. Cost savings can be achieved for both the DT-flex and SC-flex cases when using appropriate enabling technologies such as HEMS and smart meters. The highest benefits are observed in households with both an EV and a HP, emphasizing the importance of accounting for the interaction between both. In case a dynamic tariff is used, the largest benefits can be seen for households with an EV. Our findings align with those in Refs. [12, 15]. However, Ref. [13] suggests that households with both an EV and a PV system could achieve higher cost savings by optimizing self-sufficiency rather than using a DA-RTP tariff. This contradicts our findings, but is likely due to the higher price spreads assumed in our calculations. According to our findings, households with a HP can achieve cost savings by using a dynamic tariff. These results are consistent with those found in Refs. [19, 20, 21]. However, our results indicate that the financially best choice for households with a HP is using a HEMS to increase self-consumption with a static tariff (SC-flex case). This highlights the importance of comparing the use of dynamic tariffs not only with the case of no flexibility use at all but also with the case of smart operation of flexible technologies for self-consumption.

Considering the associated costs of HEMS and smart meters and the question if possible cost savings from utilizing flexibility compensate for them, we analyzed the highest tolerable costs for both technologies that would still make the utilization of flexibility financially appealing for 75 % of the households considered. Households equipped with both an EV and a HP can tolerate the highest costs while benefiting the most from their flexibility utilization. Our results show that households with both an EV and a PV-BSS have the highest tolerable costs for the HEMS across all electricity price scenarios in the SC-flex case. For the DT-flex case, households with only an EV present the lowest tolerable costs in the low price scenario. However, in the medium and high price scenarios, this shifts towards households equipped with a HP.

7.4.2 Limitations of the study

To address the issue of data uncertainty in our modeling, we implemented strategies to ensure the reliability of our findings despite the limitations of our input data. Our model incorporates a comprehensive set of household load profiles to accurately reflect the heterogeneity of household behaviors and energy consumption. This approach aims to reduce the influence of the peculiarities of a single data set on our overall results. Lastly, the dataset we used in this paper has been used and validated by previous studies by various researchers [38, 39].

To cover a wide range of potential future electricity market prices, our analysis examines three different price scenarios. These scenarios are based on recent trends observed in 2021 and 2022 to project higher price levels and larger price spreads, which are also anticipated with the growing share of renewable energies. Our scenarios aim to capture this, considering that actual electricity prices are subject to a multitude of factors, including the increase in renewable energies, the decommissioning of fossil fuel plants, and the electricity market design. While forecasting future electricity prices is beyond the scope of this paper, we can derive from our results that the future electricity mix with even higher shares of renewables and thus increased price spreads will make dynamic tariffs even more attractive.

Additionally, our analysis accounts for seasonal variations by using whole-year profiles to model energy consumption and generation. This ensures that fluctuations in household electricity demand and PV generation across different seasons are captured, which makes the study more comprehensive and provides a more accurate reflection of the year-round dynamics of household energy management under a dynamic pricing scheme.

However, our study acknowledges specific limitations, particularly regarding the representation of ambient temperature and PV generation profiles. The decision to model based on a single weather year introduces a simplification that may not fully encapsulate year-to-year variations in weather conditions, which could directly affect self-consumption levels and the operational efficiency of PV systems and PV-BSS. Expanding the analysis to include multiple weather scenarios would enhance the understanding of dynamic electricity tariffs' potential impacts.

Furthermore, although our model assumes perfect foresight in energy management decisions, we acknowledge the practical challenges of forecasting errors in real-world scenarios. To address this issue, we have included a rolling horizon scheme within the *EVaTar-building* model. This scheme attempts to approximate the impact of such forecasting errors, thereby providing a more nuanced and realistic assessment of the benefits and limitations of dynamic electricity tariffs and HEMS. Future iterations of our model could benefit from additionally integrating stochastic modeling techniques, as suggested by [40], to further refine our analysis by accounting for the probabilistic nature of many input variables. This would enhance the model's predictive accuracy and reliability.

The findings of our study demonstrate that the strategies analyzed can effectively be used for a variety of households, despite their heterogeneity. For EV charging, we considered heterogeneous driving and availability profiles, but did not account for differences in individual household preferences or control affinity (as for example in [41]), which could influence the adoption of dynamic tariffs.

Our case study specifically focuses on air/water HPs. It is important to note that other types of HPs, such as brine/water, may offer different benefits due to their more stable COP, which may enhance their responsiveness to price signals. Our model assumes a constant indoor temperature, which simplifies real-world complexities. For example, households may adjust their thermostatic settings during high energy costs, which could further optimize energy flexibility.

Our study, which is centered on Germany, utilizes different price scenarios, and can therefore provide insights for other regions with comparable market dynamics and end-user costs. Our research contributes significantly to a better understanding of the value of flexibility in energy systems, aiding in the more effective integration of renewable energies and laying the groundwork for smart readiness. These aspects are crucial not just within the German context but also hold significant importance internationally, demonstrating the broader applicability of our study's insights. Our findings are particularly pertinent to regions that have already implemented dynamic tariffs, such as Norway, which also has a more advanced distribution of electric heating and EVs. For southern countries, where air conditioning plays a significant role in households' energy consumption, additional analyses including the flexibility of this technology could enrich the understanding of the effects on dynamic tariffs.

Within the study, we consider the additional costs for households incurred by the investment in a HEMS and metering point operation costs. In the context of developing new business models that pair dynamic electricity tariffs with HEMS, it is important to recognize the ancillary costs for suppliers. These include transactional expenses, data sharing, and the costs associated with forecasting weather, load, generation capacity, and pricing.

The upfront costs of EVs, HPs, or BSSs are not discussed in this study, as it assumes these technologies are acquired with expectations of static tariffs, and potential cost savings through dynamic tariffs are considered post-purchase. Including the investments would broaden the results but is outside the scope of this analysis.

Lastly, our analysis suggests broader implications for energy systems, indicating areas for future investigation, such as the potential of conflicting price signals with the introduction of dynamic grid charges and the retroactive effects of flexibility utilization on market dynamics. A holistic approach to modeling energy market responses is important due to the significant influence that factors can have on load shifting incentives and outcomes.

7.5 Summary and conclusions

Although dynamic electricity tariffs are already widely examined in the literature, we identified four important research gaps: (1) considering multiple flexible technologies and also the interaction between them, (2) explicitly comparing the benefits of dynamic tariffs with flexibility utilization to enhance self-consumption, (3) accounting for load variability and household heterogeneity and (4) adding the costs for intelligent metering and control infrastructure when evaluating dynamic tariffs. We addressed these gaps in the literature by analyzing the effects of higher electricity prices and larger price spreads on the financial attractiveness of the smart operation of electric vehicles and heat pumps.

Based on 316 measured household load profiles including various technologies such as electric vehicles, heat pumps, PV systems and battery storage systems, we used a MILP model to maximize the electricity cost savings for households.

Our findings show that dynamic electricity tariffs based on the day-ahead spot market price in Germany can offer significant economic benefits to a wide variety of households and therefore incentivize them to use the flexibility provided by electric vehicles and heat pumps. The key to realizing these benefits is to ensure that the financial gains from dynamic electricity tariffs and increased self-consumption outweigh the additional costs for buying and installing a home energy management system and metering point operation costs. Specifically, we found that the recent trend on the day-ahead spot market in Germany during the energy crisis 2021/2022, which saw the average electricity price increase by 15.2 €ct/kWh (+67 % of the average for the year 2019) and the average price spread increase by 8.9 €ct/kWh (+494 %), greatly enhances the attractiveness of dynamic tariffs, with the proportion of households achieving cost savings increasing from 3.9 % to 62.5 %.

Our findings suggest that dynamic tariffs can effectively enhance flexibility utilization and help to combat rising electricity costs for households. However, depending on the available technologies, these tariffs are not necessarily the best choice financially. Notably, for households with a heat pump, optimizing self-consumption, especially when combined with a photovoltaic (PV) system or a PV battery storage system, can lead to greater savings than dynamic tariffs. At the same time, however, flexibility from these households could be critical to alleviate grid congestion in winter due to the anticipated simultaneous heating demands and to facilitate wind energy integration. If this flexibility is to be utilized, price incentives must be sufficiently attractive, or the costs for home energy management systems and metering point operation need to be low enough to ensure households with a heat pump respond to dynamic pricing signals rather than only using their flexibility to maximize their own self-consumption.

From a market perspective, it can be advantageous for the providers of home energy management systems to offer their systems to households that have both electric vehicles and heat pumps, as this is where the most significant savings potential lies, although this also means additional challenges in terms of the interoperability of components.

The cost savings associated with a home energy management system and/or dynamic tariffs can make technologies such as heat pumps and electric vehicles financially more attractive and help promote a faster energy transition.[16] To further promote greater flexibility provision in residential electricity demand, efforts should focus on expanding rooftop PV systems, as the potential cost savings increase for households with electric vehicles and heat pumps when a PV rooftop system is added. At the same time, reducing the costs associated with smart meter operation and accelerating the smart meter rollout could further incentivize dynamic tariff adoption.

In conclusion, making use of the flexibility of electric vehicles, heat pumps and PV battery storage systems can mitigate rising electricity costs for a large number of households provided that business models and pricing schemes create sufficient incentives for all parties involved.

CRediT authorship contribution statement

Judith Stute: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sabine Pelka:** Writing – review & editing. **Matthias Kühnbach:** Writing – review & editing, Conceptualization. **Marian Klobasa:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[16] If we assume an investment of €25,000, an interest rate of 2 % and a lifetime of 15 years for electric vehicles, the annual annuity is €1,375. In comparison yearly savings of €420 (so roughly 30 % of the annual annuity) were achieved in the high price scenario for a household with an electric vehicle and a PV battery storage system; If we make the same assumptions for the annual annuity of heat pumps, we can compare this to yearly savings of €255 (around 18 % of the annual annuity) for households with an additional PV battery storage system.

Data availability

The authors do not have permission to share data.

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Annex

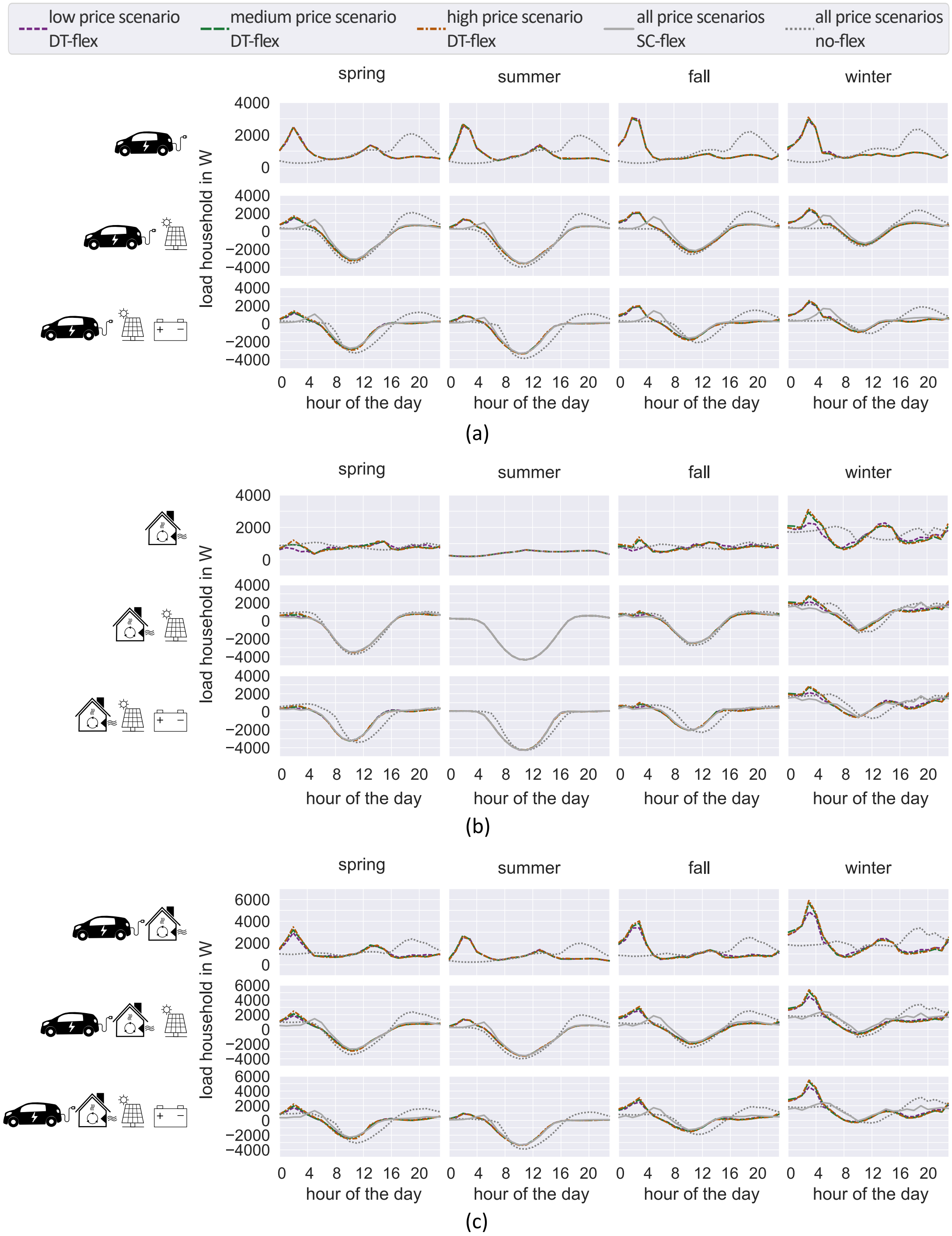

Figure 7.9: Average household load per season for each hour of the day including all households considered for the defined cases and scenarios.

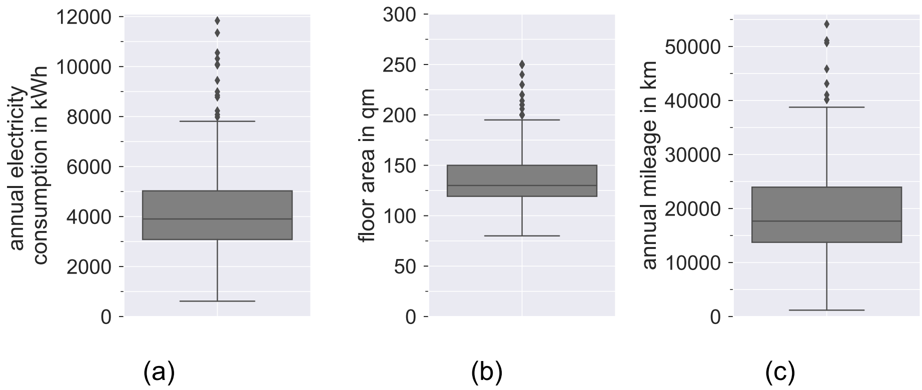

Figure 7.10: (a) Boxplot of annual electricity consumption for all households considered; (b) Boxplot of the heated floor area of all households considered; (c) Boxplot of the annual mileage of all EVs considered.

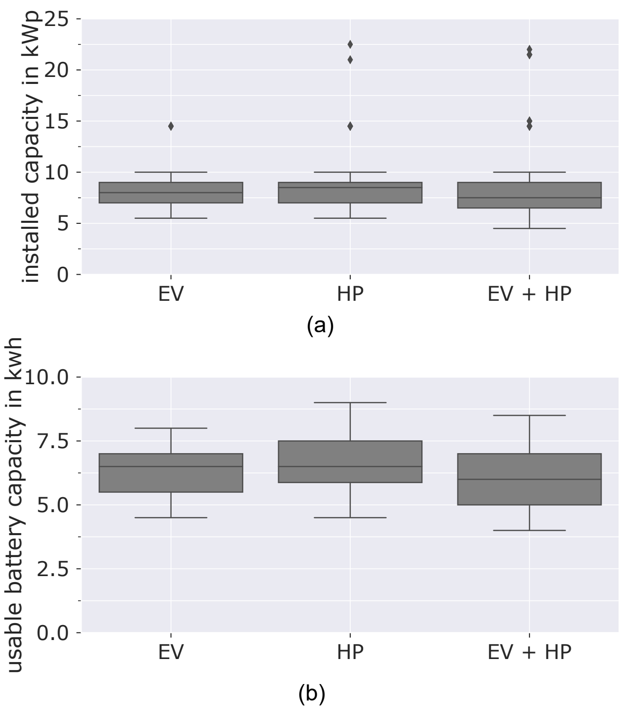

Figure 7.11: (a) Boxplot of the installed PV capacity for all households with an EV, a HP, or an EV and a HP; (b) Boxplot of the usable battery capacity for all households with an EV, a HP, or an EV and a HP

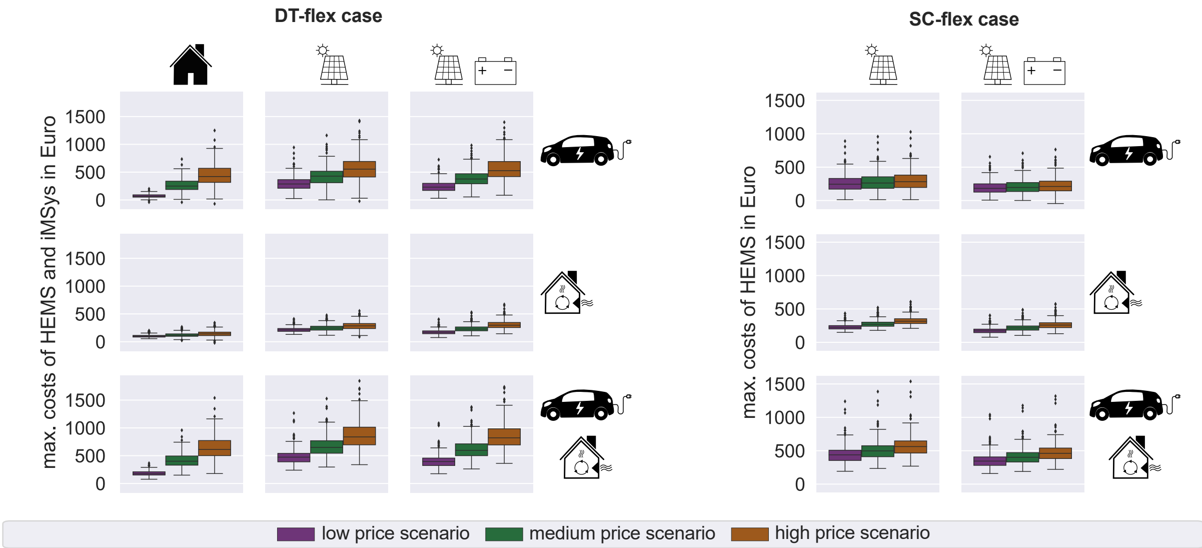

Figure 7.12: Max. tolerable costs of HEMS and metering point operation to make the utilization of flexibility financially attractive for households. Results are shown for the DT-flex (left) and the SC-flex (right) cases for all three price scenarios.

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[End of Publication III]

8 Publication IV: How do dynamic electricity tariffs and different grid charge designs interact? – Implications for residential consumers and grid reinforcement requirements

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[Start of Publication IV]

How do dynamic electricity tariffs and different grid charge designs interact? – Implications for residential consumers and grid reinforcement requirements

Judith Stute[a,*], Marian Klobasa[b]

[*] Corresponding author.
[a] Fraunhofer Institution for Energy Infrastructures and Geothermal Systems, Breslauer Strasse 48, 76139, Karlsruhe, Germany
[b] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139, Karlsruhe, Germany

Highlights

- We model the interaction of dynamic retail tariffs and grid charge designs (GCDs).
- Effect on decision for energy management system and choice of tariff are analyzed.
- Load flow analyses to assess grid expansion requirements and costs.
- Capacity subscription GCD supports the diffusion of dynamic tariffs in households.
- GCDs with capacity subscription boost flexibility use & reduce grid expansion needs.

Abstract

Dynamic electricity retail tariffs and different grid charge designs are discussed as key measures to support renewable energy integration. This article investigates the interplay between both, examining their impact on residential consumers regarding their economic savings and choice of retail tariff and on grid reinforcement requirements in low-voltage grids. We use a model-based approach for determining grid reinforcement requirements combined with an optimization model to assess residential consumer behavior towards different combinations of dynamic electricity retail tariffs and grid charge designs. We explore how these options influence the choice of households in Germany to invest in a home energy management system and to opt for a dynamic electricity retail tariff. Our findings show that with a grid charge design with capacity subscription, the share of households utilizing their flexibility and opting for a dynamic electricity retail tariff can be increased up to 74% (vs. 67% for a volumetric grid charge design). Furthermore, grid reinforcement costs can be reduced with a capacity subscription based grid charge design by 37% in rural low-voltage grids compared to the current grid charge design in Germany. This study offers novel perspectives on the interplay of dynamic electricity retail tariffs and grid charge designs, emphasizing the need for integrated policy approaches that allow residential consumers to benefit from reduced electricity costs while limiting grid reinforcement costs for distribution system operators.

Keywords

Dynamic electricity tariffs; Retail tariffs; Grid charges; Demand response; Grid reinforcement;

Abbreviations

BSS, Battery Storage System; CPP, Critical Peak Pricing; DA, Day-Ahead; DET, Dynamic Electricity Tariff; DSO, Distribution System Operator; EV, Electric Vehicle; GCD, Grid Charge Design; HEMS, Home Energy Management System; HP, Heat Pump; LV, Low-Voltage; PV-BSS, PV Battery Storage System; RTP, Real Time Pricing; SFH, Single- and Two-Family House; ToU, Time-of-Use; WTPM, Willingness to Pay More.

Nomenclature

t	Subscript for sim step/hour considered
$c_{\text{electricity price}}$	Price of energy drawn from the grid (€ct/kWh)
$c_{\text{feed-in}}$	Feed-in remuneration (€ct/kWh)
$E_{\text{grid, building}}$	Energy drawn from the grid (kWh)
$E_{\text{PV, grid}}$	Energy fed into the grid from the PV system (kWh)
E_{H}	Inflexible electricity demand of the household (kWh)
$E_{\text{PV, building}}$	Energy supplied to the building by the PV system (kWh)
E_{BSS}	Energy supplied to the building by the battery storage system (kWh)
E_{EV}	Energy demand of the charging process of the EV (kWh)
$E_{\text{HP, el}}$	Electrical energy demand of the heat pump (kWh)
α	Binary variable defining whether a specific technology is available in the household
n	Subscript for the different electricity retail tariffs
N	Quantity of all tariffs considered
$C_{\text{electricity costs}}$	Overall annual electricity costs of a household (€)

8.1 Introduction

The landscape of home energy management is evolving rapidly, with the introduction of tools like smart meters and home energy management systems (HEMSs) offering new ways to optimize our electricity consumption. For consumers equipped with flexible technologies such as Electric Vehicles (EVs), Heat Pumps (HPs), or PV Battery Storage Systems (PV-BSSs), there is a clear opportunity to utilize their flexibility for cost-efficiency. As power companies offer dynamic pricing schemes, consumers have the opportunity to adjust their energy consumption patterns to benefit from lower electricity costs. Concurrently, there is a broader discussion happening about how best to manage the increasing grid load, especially in distribution grids through grid charge design [1, 2]. A central theme through all these changes is the responsiveness of residential consumers with flexible technologies to financial incentives.

Financial incentives in form of dynamic or variable electricity price components are part of price-driven demand response (DR) mechanisms [3]. DR mechanisms encompass strategies that facilitate the shifting or shedding of electricity demand, thereby providing flexibility for balancing the electrical grid. These mechanisms serve two purposes: they have the potential to lower electricity costs for end-users whilst also aiding utilities in reducing peak loads and enhancing overall system stability [4].

Electricity retail tariffs for residential consumers consist of various components through which price incentives from DR mechanisms can be given. They are composed of costs for electricity procurement and retail plus fiscal and non-fiscal charges like grid charges. In Germany in 2022 the price component for electricity procurement and retail made up around 38.9% of the electricity price for residential consumers, while grid charges accounted for 21.8%.[1] The average share of grid charges on the residential electricity bill in the EU is even higher with around 28.3% in 2021 [5]. These two electricity price components are mainly discussed as possibilities for financial incentives for the use of flexibility by residential

1 https://strom-report.com/strompreise/strompreis-zusammensetzung/ (last accessed: 24.08.2023).

consumers. The resulting load determines the financial savings for households but also impacts on peak load development of power grids.

So far, studies have often focused on only one electricity price component at a time – mainly either electricity procurement and retail or grid charges. Therefore, the focus of this study lies in investigating the interplay of both dynamic electricity tariffs (DETs) and different grid charge designs (GCDs).

8.1.1 Electricity procurement and retail – dynamic electricity retail tariffs

For the electricity price component electricity procurement and retail, according to European Parliament and European Council [6], residential consumers in the EU have a free choice of supplier and are entitled to dynamic electricity price contracts if they have a smart meter installed. Therefore, electricity suppliers offer Dynamic Electricity Retail Tariffs (DETs). There are several options of DETs discussed in literature and already available on the market, with the most relevant to this study being elaborated upon in the following. The simplest form of time-varying electricity tariffs is the Time of Use (ToU) tariff, where each time period of a day is assigned to a certain price level [7]. Within one day, mostly two or three price levels are defined (2- and 3-tier ToU). Price levels are set in advance and usually valid for at least 12 months. Another option is a Real Time Pricing (RTP) tariff, where there is a different price level for each hour of the day based on the wholesale electricity market (either the Day-Ahead (DA) or the intraday market) [8]. In case of a RTP tariff based on the Day-Ahead (DA) spot market, the spot market price can be passed on directly to the consumer, but certain min/max limits can also be set. Price levels and time periods are set the day before after market clearing. Another option is the Critical Peak Pricing (CPP), where a peak price is set for specific time periods [7]. The aim of CPP is to alleviate grid congestion during specific periods of the year. As a result, CPP is a subject that is discussed more frequently in countries where there is no unbundling between energy supply and grid operation, or when it is seen as a means of designing grid charges.

8.1.1.1 DET adoption

Various factors contribute to the adoption of DETs among residential consumers. Yunusov and Torriti [9] illustrate that in the absence of flexibility utilization, the efficacy of ToU tariffs on residential consumers diverges, depending on their time availability at home – a factor that is additionally influenced by geographical variances. Therefore, with additional flexible technologies, such as EVs, HPs, and PV-BSSs, automation of flexibility utilization is key to reduce the necessity for home-based intervention, broaden consumer inclusion, and mitigate fatigue effects associated with manual shifts in consumption [10, 11, 12]. Alongside the advancement of automation and smart meters, data privacy concerns emerge as potential obstacles to DET adoption. A survey conducted by von Loessl [13] reveals that data privacy concerns are rated as intermediate or high by 76.4% of German households. However, these concerns can be mitigated by enhancing information transparency regarding the data sharing practices. Similarly, Belton and Lunn [14] assert that greater transparency and information provision are critical factors for consumers when evaluating DETs. Lang et al. [15] further suggest that offering a variety of DETs for comparison significantly increases the likelihood of residential consumers opting for such pricing schemes.

8.1.1.2 Impacts on households' electricity expenses and peak load

Considering both the potential for reduced electricity expenses for residential consumers and alterations in peak load patterns within individual households, DETs have been examined through both empirical field studies and computational modeling techniques.

Faruqui and Sergici [7] explore numerous field studies focusing on households without EVs, HPs and PV-BSSs. The authors reveal that the use of enabling technologies, like programmable communication thermostats for air-conditioning, in-home displays or energy orbs for visual feedback, can lead to significant peak load reductions ranging from 21%-30% for ToU tariffs and 27%-44% for CPP tariffs. Without such enabling technologies, the peak load reduction was notably smaller, falling within the range of 3%-6% for ToU and 13%-20% for CPP.

Wilczynski et al. [16] examine cost savings for buildings with a HP across various tariff types (static, ToU, DA-RTP based on the DA spot market and DA-RTP based on a price time series of a system with higher HP penetration rates). They make distinctions between inefficient and efficient buildings, showing that efficient buildings could achieve cost savings attributable to flexibility utilization between 1%(DA-RTP) and 4.65% (ToU) compared to inefficient buildings with a static tariff. However, when only looking at efficient buildings, peak load increases under all DETs between 5.2% (ToU) and 9.8% (both DA-RTP options). Klaassen et al. [17] demonstrate cost savings of 8% for heating costs for the period October 2013 to March 2014 for households equipped with a ground-source HP and a DA-RTP tariff. Similarly, Ali et al. [18] report modest cost saving potentials of 5.51% for households with a HPs under a DA-RTP tariff, but reveal that the use of heat storage can substantially increase cost savings (cost reduction of 46% is possible with a heat storage that can cover 40% of the full day heat demand).

The influence of electrical storage such as PV-BSSs and EVs is discussed in Aguilar-Dominguez et al. [19]. The authors compare different battery sizes and show that larger battery capacities contribute to greater cost savings, with potential savings of up to 82% for a 2-tier ToU tariff, 90% for a 3-tier ToU tariff and 80% for a RTP tariff for households with a PV-BSS. For households equipped with an EVs, savings were comparable (79% 2-tier ToU, 89% 3-tier ToU, 78% RTP). Here too, the study showed an increase in the individual households' peak loads for all dynamic tariff cases.

8.1.1.3 Impact of DETs on LV grids

Stute and Kühnbach [20] argue that the increase in peak load for individual households does not necessarily have a negative impact on the overall grid load in Low-Voltage (LV) grids. They show that in a realistic setting where residential consumers are free to choose from a variety of electricity tariffs (static, ToU, DA-RTP), DETs can actually have a positive effect due to the variety of tariff choices made by residential consumers with different types of technologies and the resulting mixing effects in peak loads. Nevertheless, DETs are not explicitly designed to alleviate grid congestion and keep grid reinforcement needs to a minimum. That goal can be achieved more effectively through the electricity price component grid charges.

8.1.2 Grid charges

Competing objectives exist when setting the Grid Charge Design (GCD) [21]: sufficiency, cost reflectivity, economic efficiency, non-discriminatory cost allocation, transparency, stability and predictability, and intelligibility. Each GCD presents a trade-off of these objectives.

The current GCD in Germany for residential consumers consists of a base charge which is independent of the amount of energy used (€/year) and a fixed volumetric tariff, where consumers pay per kWh of energy they used (€ct/kWh). With the electrification of mobility and heat in the residential sector and the increase in self-consumption, the fixed volumetric GCD has been under discussion, as cost-reflectivity is low with this design as it incentivizes a reduction in energy consumption but does not reflect grid costs, which are mostly driven by peak demand [21, 22].

Another option for a GCD is a capacity-based tariff (€/kW), where residential customers are billed by their maximum power draw within a certain period of time. For both extremes, different design options exist [21]: for the volumetric tariff, there can be a fixed price for a predefined amount of energy (flat), a fixed price per unit of energy (fixed), a price per amount of energy that depends on the time of consumption (ToU), an event-driven price (for example CPP, with higher prices in times of load peaks or grid congestion), and a dynamic price. For the case of capacity-based tariffs, the options are a fixed price for a fixed capacity (flat), different price levels for different capacity levels (variable, with pricing conducted via capacity subscription or pricing structured around a post-consumption evaluation of peak demand, so called demand charges), or a price that depends on the time of consumption (ToU). Capacity-based grid charges refer to different interpretations of peak demand, such as the peak demand at the time of a system-wide peak, the peak demand in designated peak time periods (peak coincidental demand) or the individual consumers maximum demand (non-peak coincidental demand) [23]. Combinations of volumetric and capacity-based tariffs are possible as well.

Throughout Europe, a shift towards capacity-based GCDs can be observed [24, 25]. For example a capacity-based grid tariff with a yearly fee based on the grid connection capacity in the Netherlands, a combination of a 3-tier ToU volumetric charge and a 2-tier ToU capacity charge in Spain, or a combination of a ToU volumetric charge and a monthly capacity subscription based on the average of the three hours of a month with the highest mean load of a household in Norway [22].

8.1.2.1 DSO cost recovery

Various forms of GCDs are discussed in literature, including the issue of Distribution System Operator (DSO) sunk cost recovery associated with increased adoption of PV-BSSs. Schittekatte et al. [26] investigate several GCDs and categorize consumers as either passive or active – the latter having the ability to invest in PV-BSSs. The study finds that poorly designed capacity-based grid charges can over-encourage investments in PV-BSSs, exacerbating the DSOs sunk cost recovery dilemma. Hoarau and Perez [27] explore the balancing effects of EVs and PV-BSSs in terms of DSO cost recovery. They demonstrate that while households with an EV increase energy uptake from the grid, those with PV-BSSs reduce it. The paper shows that capacity-based grid charges create stronger incentives for Battery Storage Systems (BSSs) compared to volumetric GCDs for both households with and without an EV. Pena-Bello et al. [28] also highlight the promotional effect of including a capacity component in the GCD on the adoption of both PV systems and PV-BSSs. Additionally, they evaluate the impact of daily versus monthly billing cycles for capacity-based GCDs, revealing that monthly billing leads to a reduction in both imports and exports within the LV grids.

8.1.2.2 Cost-reflectivity and predictability

Examining both cost-reflectivity and predictability of revenues, Nijhuis et al. [29] find that a GCD based on costs determined by annual peak load is the most effective for households equipped with an EV or a PV-BSS. This is followed by a GCD reliant on peak load contribution (peak coincidental), and then by a capacity-based GCD with predefined power levels (non-peak coincidental). The study notes that with higher shares of EVs or PV systems, the cost-reflectivity for the capacity-based GCD will increase.

8.1.2.3 GCDs and DA-RTP – potential cost savings

Numerous studies investigate the possible cost savings for households under a DA-RTP tariff, considering various GCDs. Bjarghov et al. [30] evaluate different GCDs such as volumetric, power based, 3-tier ToU and subscription-based tariffs, focusing on households with either a PV system and an EV, or a PV-BSS. They find that households with a PV system and an EV can achieve annual savings ranging from 12 to 19.2%, with the power based tariff emerging as the most favorable option. On the other hand, households with a PV-BSS observe lower savings (as the battery capacity is smaller) ranging from 8.9 to 14.4% with the best option being the ToU tariff. Backe et al. [31] examine capacity subscription GCDs, comparing those that allow for either annual or weekly adjustments, and considering either individual households' non-peak coincidental load or a collective peak coincidental load across multiple households in a given grid area. Their findings suggest that more frequent adjustments in subscription levels and the incorporation of scarcity pricing based on the peak coincidental load of multiple consumers yield both higher grid efficiency and greater household savings. Another study by Bjarghov and Doorman [32] contrasts a capacity subscription tariff based on the individual peak load of households with an excess fee, against one based on periods of grid congestion (coincident load of a grid area). For the latter option, each household's electricity demand is physically capped at the subscribed level only during instances of grid congestion. This scenario proves to be financially most advantageous for households with electrical heating systems, both with and without a PV-BSS, offering savings ranging from 2.6% to 6.8%.

8.1.2.4 Total system energy costs

Avau et al. [33] introduce an additional layer of complexity to the discussion on GCDs. They argue that evaluations should extend beyond grid-level impacts and economic effects of individual households to encompass effects on total system energy costs as well. They propose a „relative flexibility value", which is calculated as the ratio between the actual cost reduction attained through the use of flexibility under various GCDs and the theoretical maximum cost reduction achievable if there were no grid charges and all flexibility were dedicated to the wholesale market. Based on their findings, they conclude that a fixed tariff performs best when considering total system energy costs, primarily because it does not disrupt price signals emanating from the wholesale market.

8.1.2.5 Impact of GCDs on LV grids

Steen et al. [34] focus on the grid implications of various GCDs. They demonstrate that when flexible loads, such as laundry, dryer, dishwasher, domestic hot water, space heating and plug-in hybrid electric vehicles, respond to both spot market prices and the respective GCD, a volumetric tariff can exacerbate peak demand – a phenomenon not observed in the case of capacity-based GCDs with daily or monthly billing cycles. Although they notice an increase in active power loss, transformer overloading, and voltage variation for all three types of GCDs, their results indicate that these adverse effects are most pronounced under a volumetric tariff.

8.1.2.6 Price signal conflict DET and GCD

The previously described studies included different GCDs with DA-RTP prices. Bjarghov and Hofmann [35] examine the intersection of different GCDs with DA-RTP prices, aiming to identify a possible price signal conflict between both. The study narrows its focus to residential and commercial consumers and considers only load reduction via discomfort costs, excluding load shifting. The authors find that when DA-RTP pricing is introduced, the effectiveness of peak load reduction diminishes for both volumetric ToU and subscribed capacity GCDs, compared to a static retail pricing model. Interestingly, this effect is not observed in the case of demand charges.

8.1.3 Research gap and research questions

Even though comprehensive studies on DETs and different GCDs, as well as their effects on residential consumers and LV grids, have been conducted, we identify a gap in the literature. No comprehensive studies have been found that explore the interplay between DETs and different GCDs and its effects on the residential consumers choice of tariff and on grid reinforcement requirements. This paper thus goes beyond earlier research by combining different DETs and GCDs for a great variety of household consumers and available flexible technologies, and depicting the choice of tariff of residential consumers in Germany and the effects of these choices and the different GCDs on LV grids. With this, we address three main research questions:

- What are the economic effects on residential consumers when faced with various combinations of DETs and GCDs?
- How do different GCDs affect residential consumers' choices regarding DETs and investments in a HEMS?
- What are the implications for the grid, particularly in terms of potential grid reinforcement requirements?

A simulation-based approach is chosen to analyze the dynamics related to these research questions. The model used has been previously described in Stute and Kühnbach [20] and Stute et al. [36] and has been extended for this study. It incorporates households, factoring in both their static and flexible electricity consumption and generation units, within a HEMS, aiming to reduce electricity purchase costs for these households. The model takes into account various DETs and different GCDs and incorporates the decision-making behavior regarding the choice of retail tariffs and the decision whether to invest in a HEMS of residential customers. To assess and understand the impact on a specific grid area, load flow analyses and a grid reinforcement algorithm are employed.

The remainder of this article is organized as follows: Section 8.2 outlines the employed methods including the model described above. The data and case study are presented in Section 8.3. The findings are presented and dissected in Section 8.4. Section 8.5 discusses the limitations of the study and gives an outlook on further research options. Section 8.6 summarizes our key findings, highlights their importance for policy makers, and provides practical recommendations.

8.2 Methodology

The model *EVaTar* („Efficient Variable Tariffs", devised by the first author), is employed to address the research questions specified. It is divided into four modules (Fig. 8.1).

1. *EVaTar-building*[2] This initial module maps the load and generation patterns of residential consumers. Within the module, two methodologies are available:
   - A simulation tailored to depict inelastic behavior
   - An optimization engineered to map the response of residential consumers to DETs and different GCDs using a HEMS, detailed further in Section 8.2.1.
2. *EVaTar-decisions*[3] Once the households' load and generation profiles are determined for different dynamic and static tariff designs, the decision-making behavior of residential consumers regarding the choice of electricity tariff and the decision whether to invest in a HEMS is determined (see Section 8.2.2).
3. *EVaTar-grid*: The third module is equipped to perform load flow calculations for LV power grids.
4. *EVaTar-gridex*: In the concluding module, necessary grid reinforcement measures can be determined by a heuristic grid reinforcement algorithm (see Section 8.2.3).

Collectively, the integration of these modules within the model allows for an comprehensive study on the effects of DETs and different GCDs on the household level but also on the LV grid level.

A more detailed description of the individual modules is given below.

8.2.1 Flexible and non-flexible behavior of households (*EVaTar-building*)

In the model, a household – or building – can be equipped with various flexible technologies such as an EV, a heating system (HP and additional heat storage tank), a PV-system, or a PV-BSS.

[2] A detailed description of this module can be found in Stute et al. [36].
[3] A detailed description of this module can be found in Stute and Kühnbach [20].

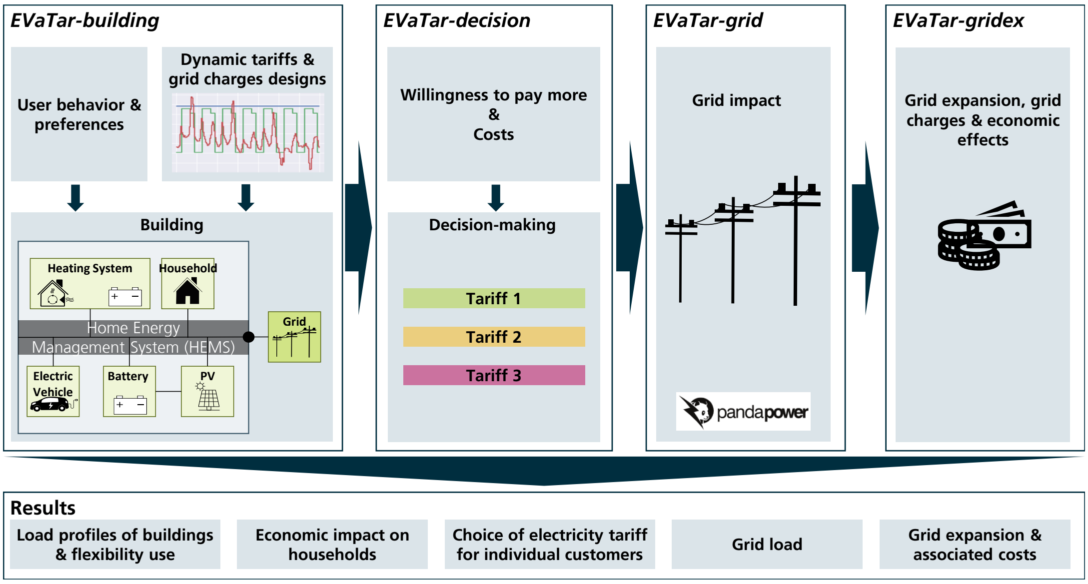

Figure 8.1: Schematic illustration of the simulation model *EVaTar* and its modules (Further development of the model already described in [20] and [36].)

A household can have an entirely inflexible demand, which is depicted by a simulation model. Inflexible demand implies continuous charging of the EV upon arrival, operation of the HP to meet the heat demand at any given time, and straightforward operation of the PV-BSS (charging the battery in case of a generation surplus, discharging in case of electricity demand exceeding PV generation).

Additionally, each building has the option to utilize a HEMS to minimize its electricity purchase costs. This can be done either by increasing self-consumption or by using DETs. The HEMS coordinates the operation of flexible technologies and thus depicts the flexible demand of a household. The related objective function is presented in Eq. (8.1).

$$\min \sum_{t=0}^{t_{\max}} E^t_{\text{grid, building}} \cdot c^t_{\text{electricity price}} - E^t_{\text{PV, grid}} \cdot c_{\text{feed-in}} \tag{8.1}$$

Here, $c^t_{\text{electricity price}}$ (€ct/kWh) stands for the price of energy drawn from the grid in an hour t. The energy fed into the grid from the PV system in an hour t is represented by $E^t_{\text{PV, grid}}$ (kWh) and $c_{\text{feed-in}}$ (€ct/kWh) is the according feed-in remuneration. The energy drawn from the grid in an hour t is depicted by $E^t_{\text{grid, building}}$ (kWh) and defined as follows (Eq. (8.2)):

$$\begin{aligned} E^t_{\text{grid, building}} &= E^t_{\text{H}} - \alpha_{\text{PV}} \cdot E^t_{\text{PV, building}} \\ -\alpha_{\text{BSS}} \cdot E^t_{\text{BSS}} &+ \alpha_{\text{EV}} \cdot E^t_{\text{EV}} + \alpha_{\text{HP}} \cdot E^t_{\text{HP, el}} \end{aligned} \tag{8.2}$$

where α is a binary variable defining whether a specific technology is available in a household or not. E^t_{H} (kWh) depicts the inflexible electricity demand of the household in an hour t. The energy supplied to the building by the PV system in an hour t is represented by $E^t_{\text{PV, building}}$ (kWh) and the energy supplied by the BSS in an hour t is represented by E^t_{BSS} (kWh). E^t_{EV} (kWh) stands for the energy demand of the charging process of the EV in an hour t and the electrical energy demand of the heating system in an hour t is given by $E^t_{\text{HP, el}}$ (kWh).

A more detailed description of the underlying optimization model and its constraints is available in Stute et al. [36].

For this study, the possibility of different GCDs was added to the model, including an additional constraint, specifying a maximum allowed grid connection capacity. The financially most attractive choice for the subscription to a specific power level in case of a GCD with capacity subscription is modeled in an iterative process for each specified period of time, starting with the lowest power level. In case no solution is found for this power level, the next higher level is chosen, until a solution is found. From there, the overall electricity costs are compared to the costs of the next higher power level until no further profit can be achieved by subscribing to the next higher power level.

8.2.2 Decision-making behavior regarding electricity retail tariffs and the use of a HEMS (*EVaTar-decisions*)

The decision-making process for flexible residential consumers regarding an electricity retail tariff is not exclusively a financial one. Other behavioral drivers, such as the desire for self-sufficiency, interest in innovative technologies, pursuit of status and prestige, and the perception of environmental values, can have a great influence on the decision-making behavior. Taking this into account, we use the „diffusion of innovations“ theory of Rogers [37] to depict the decision-making behavior of households regarding the adoption of a HEMS and DETs. Here, each household is assigned to one of the five adopter categories according to Rogers (innovators, early adopters, early majority, late majority, laggards). For each adopter category, a certain Willingness to Pay More (WTPM) for non-financial values can be specified.[4] Taking the WTPM into account, we compare the overall annual electricity costs for each electricity retail tariff and the underlying GCD. The overall electricity costs $C^n_{\text{electricity costs}}$ (€) of a tariff n are composed of the annual unit rate costs, the annual feed-in remuneration, the standing charge, the metering point operation costs, and the investment for a HEMS, if one is used. In the next step, we find the option n_{min} with the lowest costs for the household, taking into account the WTPM (see Eq. (8.3)).

$$n_{\text{min}} = \underset{n \in N}{\arg\min} \left(C^n_{\text{electricity costs}} \cdot (1 - \text{WTPM}) \right) \tag{8.3}$$

The methodology is described in more detail in Stute and Kühnbach [20].

8.2.3 Grid impact and grid reinforcement (*EVaTar-grid* and *EVaTar-gridex*)

To assess the impact of DETs and different GCDs on an LV grid, households and their respective electricity tariff choices are randomly allocated to the grid connection points within the LV grid. This random-based assignment is conducted 50 times for each scenario to yield more robust results. For each resulting grid configuration, load flow calculations are performed using the open-source model pandapower [38] and a heuristic grid reinforcement algorithm is applied to determine the required grid reinforcement measures

[4] The WTPM is given in percent. A positive WTPM depicts the case, that a household is willing to accept a cost increase, a negative WTPM shows that a household needs higher savings in order chose a specific option.

and their associated costs. The algorithm is adapted from prior work [39, 40] and has been discussed with representatives of a DSO. It is described in the following.

First, a load flow calculation is performed for the LV grid under consideration. It is then checked whether there are thermal overloads of equipment or voltage band violations. If such issues are found, the grid reinforcement algorithm takes effect. Transformer overloads are addressed first. Secondly, voltage band violations are resolved. Finally, overloads of cables and overhead lines are addressed.

8.2.3.1 Transformer overload

A transformer overload is defined as the transformer loading exceeding 100%. If such a transformer overload occurs, the current transformer is initially replaced with one that has higher apparent power. This replacement process is performed until the overload is resolved. If the maximum size of the transformer is reached without resolving the overload, an identical transformer is installed in parallel (see Fig. 8.2a).

8.2.3.2 Voltage band violation

The permissible voltage band for the LV grid is set at ±5% of the nominal voltage. To address voltage band violations, a feeder separation is carried out at approximately two-thirds of the distance from the transformer to the grid node where the voltage band violation occurs (see Fig. 8.2b). Feeder separation means dividing the affected grid feeder into two separate ones.

8.2.3.3 Line overload

In LV grids, lines (both overhead lines and cables) may be loaded up to 100%. If a line overload occurs, a line of the same type is initially built in parallel. If this measure is not sufficient to resolve the line overload, then the two parallel lines are replaced with a stronger line (see Fig. 8.2c). The standard NAYY-J 4 x 150 mm^2 (or NAYY-J 4 x 240 mm^2) is used for this purpose.

8.2.4 Tariffs and grid charge designs

Within the study, various types of electricity retail tariffs and different GCDs are examined. Details on these aspects are provided below.

8.2.4.1 Electricity retail tariffs

We consider several electricity retail tariffs: a static tariff representing the status quo, and two DETs: namely a 3-tier ToU tariff and a RTP tariff based on the DA spot market price, hereafter referred to as DA tariff. To use the different tariffs efficiently, certain enabling technologies are necessary. For households that do not use their flexibility, no additional technology is required. However, if self-consumption optimization is considered, or flexibility is to be used in conjunction with a DET, a HEMS must be installed, which represents an investment. The investment is annualized and added to the annual electricity

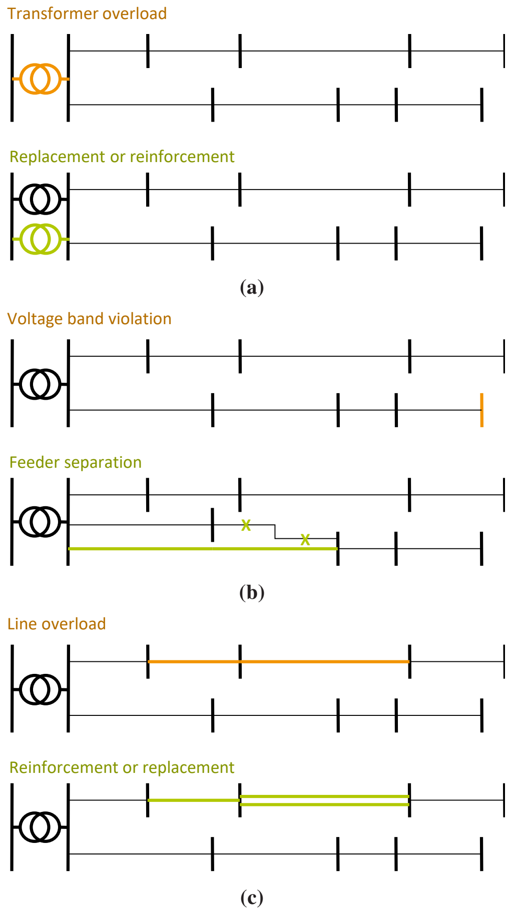

Figure 8.2: Schematic illustration of the grid reinforcement algorithm; (a) grid reinforcement measures in case of transformer overload, (b) grid reinforcement measures in case of voltage band violation, (c) grid reinforcement measures in case of line overload (adapted from [39, 40], own illustration)

costs. If flexibility is used in combination with a DET, a smart meter must be installed. Since a 2035 scenario is chosen for this study, we assume that every household will have a smart meter installed. Therefore, all households will have to pay costs for metering point operation.

8.2.4.2 Grid charge designs

The most commonly discussed approaches to GCDs were selected for the study:

- Volumetric grid charges (VOL):
  As a reference case to the status quo in Germany, volumetric grid charges are considered. This means, that a price in €ct/kWh is set, which residential consumers have to pay for each kWh drawn from the grid.

- Capacity subscription charge (CAP):
  In contrast to volumetric grid charges, the residential customer does not pay for the energy drawn from the grid but for its maximum power consumption or feed-in. Therefore, a price in €/kW is defined for different power levels. The power levels are shown in Fig. 8.4. The allocation to a power level is done on a monthly basis.

- Capacity subscription and volumetric grid charges (CAP-VOL):
  This option is a combination of the capacity subscription and the volumetric grid charges.
- Critical peak pricing grid charges (CPP):
  Critical peak pricing can be counted as part of volumetric pricing. There is a base price for each kWh drawn from the grid. For hours with the highest peak coincidental load in a grid area a critical peak price is defined, which is considerably higher than the base price.

For all grid charge designs examined, we specify that the annual revenues from grid charges for the DSO must remain largely the same. Under the assumption that the distribution costs are fully sunk, we therefore define a DSO with approximately 190,000 metering points in its LV grids.[5] For this purpose, the grid charge components are adjusted in an iterative process until the revenues from the grid charges reach ±10% of the revenues from the reference case, considering the households' tariff decisions and decisions of investing in a HEMS in this iterative process as well (see Table 8.9).[6]

8.3 Data

The study requires a wide range of input data. These include the data for the individual consideration of households and information on the penetration rates of the flexible technologies for the considered scenario year 2035. Furthermore, the electricity retail tariffs and the parameters of the GCDs have to be determined. Finally, the LV grids and the assumptions on the cost of grid reinforcement are required. Information on these input data is given below.

8.3.1 Households and flexible consumers

8.3.1.1 Household appliances

In this study, we treat the electricity consumption of household appliances as fixed and use predefined household load profiles. To account for the heterogeneity of household load profiles, we incorporate load profiles obtained from 312 households that participated in a smart meter field study in Austria and Germany [42]. A range of socio-demographic data is available for each household, and each household was assigned to one of the adopter categories according to Rogers in Klingler [43].

5 This corresponds to a DSO such as Stadtwerke Karlsruhe Netzservice GmbH, Karlsruhe being a city in Germany with a population of about 300,000 [41].

6 This simplified approach is due to the high computation times per iteration of about 14 h.

8.3.1.2 PV systems

The capacity of the PV systems is defined by the respective annual electricity consumption of each household. This adjustment is based on data from Figgener et al. [44]. The PV generation profile used is consistent with data from renewables.ninja[7] for the city of Karlsruhe in 2019.

8.3.1.3 Battery storage systems

When calculating the feasible battery capacity for households equipped with PV systems, we consider two main elements: the household's annual electricity consumption and the installed capacity of its PV system. The correlation between these factors and battery capacity is taken from Figgener et al. [44]. We assume a C-rate of 1, standby losses of 0.01% per hour, and a round-trip efficiency of 0.95.

8.3.1.4 Electric vehicles

Data on EV availability at home and energy consumption during EV operation are extracted from Gnann and Speth [48]. These data are generated using the „ALADIN" model,[8] a vehicle diffusion model using vehicle usage information from für Verkehrswesen der Universität Karlsruhe [52]. Energy consumption during driving ranges from 0.15 to 0.20 kWh/km, while battery capacity ranges from 34.2 to 90.0 kWh. The minimum energy stored in the battery at the time of departure is set at 50% of the maximum storage capacity (and thus maximum range), while the minimum energy level at which EV owners want to start recharging their vehicle at the latest is set at 20% of the maximum storage capacity.[9] The charging capacity is set at 11 kW and the standby losses are assumed to be 0.01% per hour.

8.3.1.5 Heating systems

To determine the appropriate HP capacity for each building, we use the total floor area of the building as determined by the according smart meter field study [42]. The HP sizing is based on the building's heat demand, which is assumed to be 100 kWh/m^2 per year. The heat demand profile is taken from HotMaps [53] for the city of Karlsruhe (DE12). To maintain consistency, meteorological data for the corresponding year (2019) and geographical location are obtained from the Climate Data Center of the German Weather Service (Deutscher Wetterdienst) for station ID 4177 [54]. The technically maximum possible flow temperature is set to 50°C and the quality grade is assumed to be 0.4.

The thermal storage system is designed to store enough energy to meet the peak heat demand of the building for a continuous period of two hours. The standby losses of the thermal storage are considered at a rate of 0.2% per hour.

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[7] Renewables.ninja is an open source tool that uses historical weather data and technical specifications to determine generation profiles. It is available at https://www.renewables.ninja/ [45] and described in Pfenninger and Staffell [46] and Staffell and Pfenninger [47].

[8] Additional information on the model can be found in Fraunhofer Institute for Systems and Innovation Research ISI [49], Gnann [50], and Plötz et al. [51].

[9] These assumptions are based on the results of a survey of EV owners, in the development of which the author of this paper was actively involved.

8.3.2 Framework scenario

Assumptions regarding EV, HP, PV system, and BSS penetration rates for the framework scenario are shown in Table 8.1. To obtain these numbers, we use figures from the TN45 electricity scenario from for Systems and ISI [55] (long-term scenarios for green house gas neutrality in Germany by 2045) and break them down to a Single- and Two-Family House (SFH) level.

Number of SFH in Germany	16.758.485
Share of SFH with electric vehicle	93.2%
Share of SFH with heat pump	60.2%
Share of SFH with PV system	55.1%
Share of SFH with battery storage system	42.2%

Table 8.1: Assumptions regarding penetration rates of flexible technologies in single-family houses (SFH) in Germany for the year 2035.

In addition to the penetration rates of the technologies, the distribution of adopter categories according to Rogers needs to be determined. The share of each category as well as the WTPM are taken from Klingler [43] and presented in Table 8.2.[10]

Adopter categories	Share	WTPM
Innovators	2.1%	60%
Early Adopters	9.1%	10%
Early Majority	35.1%	0%
Late Majority	21.8%	-5%
Laggards	31.9%	-10%

Table 8.2: Share and willingness to pay more (WTPM) of adopter categories according to Rogers [37] taken from [43].

8.3.3 Retail tariffs, metering point operation costs, and HEMS investment

As described in Section 8.2.4, three different retail tariffs are defined:

- a static tariff,
- a 3-tier ToU tariff,
- and a DA tariff.

The annual average of the electricity price component for electricity procurement and retail is set at 10 €ct/kWh for all three tariffs. The DA tariff profile is based on the German DA spot market prices for 2019 [56] and is adjusted to an average of 10 €ct/kWh, a standard deviation of 5.5 €ct/kWh, a minimum values of -8.7 €ct/kWh and a maximum value of 33.2 €ct/kWh. The standard deviation and the minimum and maximum values are based on for Systems and ISI [55]. The average profile of the electricity procurement and retail price component of the three retail tariffs for each hour of the day is

[10] Note that the WTPM from the given study refers to PV-BSSs and was used here in lack of available data for HEMSs and DETs, but is assumed to be comparable.

shown in Fig. 8.3. A standing charge of 58 € per year is considered, which corresponds to the average value in Germany for 2022 [57]. The cost of metering point operation is assumed to be 60 € per year.

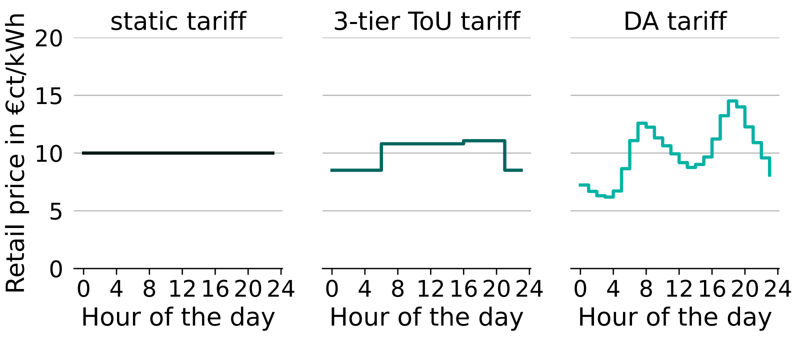


Figure 8.3: Electricity retail tariffs analyzed in the study: static, 3-tier time-of-use (ToU) and day-ahead spot market based (DA) tariffs.

The additional taxes, fees and surcharges are based on the situation in Germany in 2022 and are shown in Table 8.3. Grid charges are described in the next section. The investment for a HEMS is assumed to be 1,500 €, which – annualized[11] – corresponds to an annual payment of 167 €.

Green levy (EEG)	3.723 €ct/kWh
Electricity tax	2.050 €ct/kWh
Concession fee	1.990 €ct/kWh
CHP surcharge (KWKG)	0.378 €ct/kWh
Other surcharges	0.859 €ct/kWh
Value-added tax	19%

Table 8.3: Assumptions for taxes, fees and surcharges on residential costumers' electricity prices (based on the situation in Germany for the year 2022).

8.3.4 Grid charge designs

For the reference case, namely the volumetric GCD (VOL), we set the grid charge at 8.12 €ct/kWh, corresponding to the level of the average grid charge for residential consumers in Germany for 2022 [57]. The prices for the different power levels for the capacity subscription charge (CAP) and the combination of capacity subscription and volumetric charge (CAP-VOL) are shown in Fig. 8.4. For the Critical Peak Pricing GCD (CPP), the coincident load from the load profiles of the defined grid area (see Section 8.2.4.2) is calculated. From there, the hours with a coincident load above the 97th percentile are defined as critical hours, which corresponds to 263 hours of the year. This number exceeds the range of typical peak hours given in Faruqui and Palmer [58] and is designed in a way, that the highest coincident load outside of the critical hours would equal to a load of 3.7 kW for each household. This value falls below the typical planning figures for SFHs in Germany equipped with a HP or an EV, which range between 4 kW and 12.52 kW in Germany [59]. This is the basis for our assumption that the use of flexibility is incentivized by the given CPP design. The volumetric charges for all GCDs are shown in Table 8.4.

[11] Interest rate: 2%, lifetime: 10 years

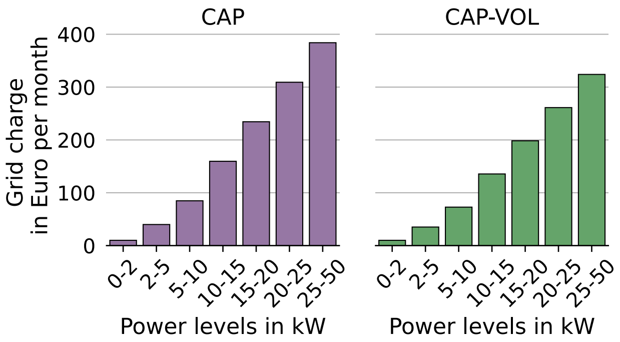


Figure 8.4: Grid charges for different power levels for the capacity subscription case (CAP) and the combination of capacity subscription and volumetric grid charge case (CAP-VOL).

Grid charges design	Price in €ct/kWh
Volumetric	8.12
Capacity subscription	-
Volumetric & capacity subscription	2.00
CPP – base price	7.28
CPP – peak price for critical hours	21.11

Table 8.4: Volumetric grid charges for the grid charges designs under consideration.

8.3.5 Grid

For the grid analysis, we selected the SimBench LV grids [60]. These grids exhibit a radial structure and have a nominal voltage of 0.4 kV. Line types used are NAYY 4 x 150SE 0.6/1 kV for the LV rural 1-3 and the LV semiurb 4 grid, and NAYY 4 x 240SE 0.6/1 kV for the LV semiurb 5 and the LV urban 6 grid. A summary of relevant grid descriptors is provided in Table 8.5. The households considered in this study substitute the predefined loads and generation units.

Parameter	LV rural 1	LV rural 2	LV rural 3	LV semiurb 4	LV semiurb 5	LV urban 6
Rated power transformer	160 kVA	250 kVA	400 kVA	400 kVA	630 kVA	630 kVA
Number of feeders	4	4	9	3	6	7
Number of nodes	13	96	128	43	110	58
Total line length	0.560 km	1.470 km	2.350 km	0.746 km	1.790 km	1.078 km
Average line length	43.05 m	15.44 m	18.52 m	17.76 m	16.42 m	18.90 m
Number of consumers	13	99	118	41	104	111

Table 8.5: Relevant grid descriptive parameters for the considered SimBench LV grids [61].

8.3.6 Grid reinforcement costs

The grid reinforcement costs result from the individual grid reinforcement measures after successful completion of the grid reinforcement algorithm. The cost estimates for transformer reinforcement are based on standard estimates from DSOs and presented in Table 8.6. The costs are divided between investments in the transformer and investments in the MV/LV local substation. Grid reinforcement costs are also incurred to repair voltage band violations and line overloads caused by the construction of the line from the transformer to the feeder separation point, the construction of parallel lines or replacement of existing lines. When assessing the cost of cables and overhead lines, several cost components are included in the analysis: Cost of materials, labor expenses, cost of external services, and overhead surcharges. Depending on the DSO, the depth of in-house labor may differ, so an assumed average total cost of construction for cable/overhead line extension is used. This applies to a major city, encompassing outlying areas (central, suburban, rural), and totals to 160,000–180,000 € per km for the LV grid.

Transformer apparent power	Investment transformer	Investment MV/LV substation
250 kVA	19,000 €	45,000 €
400 kVA	21,000 €	45,000 €
630 kVA	24,000 €	45,000 €
800 kVA	30,000 €	45,000 €

Table 8.6: Grid reinforcement costs for transformers (10/0.4 kV or 20/0.4 kV) and MV/LV substations.

8.3.7 Case study

The case study is divided into two parts: First, we analyze the impact at the household level and then at the LV grid level. To start, we combine the 312 household load profiles and generate all conceivable technology combinations for each household (12 in total). We analyze each case to determine the inflexible and flexible behavior for every combination of the three electricity retail tariffs and four GCDs. The resulting 82,368 load profiles are then analyzed.

In the second part, we perform a grid analysis using the results obtained from analyzing individual households. To do this, we assign households with their respective choice of electricity retail tariff to the grid connection points as described in Section 8.2.3. This is done individually for each LV grid and each GCD. The households within a LV grid are the same for each GCD scenario, but the households' tariff choices are based on the tariff choice for each GCD.

8.4 Results and discussion

In the following sections, we first focus on the individual household level in Section 8.4.1. Subsequently, in Section 8.4.2, we present the results of the grid reinforcement analysis.

8.4.1 Household level

At the household level, we examine various points of interest: We investigate the changes in electricity expenses when a DET is selected, compare annual grid charges paid in the GCD scenarios, evaluate the impact on annual variable electricity costs (unit rate costs minus feed-in remuneration), and examine households' tariff preferences under the different GCDs. Additionally, we discuss the incentive effect of the different GCDs on individual households' maximum power draw or feed-in.

8.4.1.1 Total electricity costs

In order to comprehend the interaction between DETs and the different GCDs, we initially examine the difference in total electricity costs (including all costs mentioned in Section 8.3.3) amongst the retail tariffs. Fig. 8.5 displays the difference (median across all households) for the evaluated DETs compared to the static tariff without a HEMS for the VOL GCD for all technology combinations with and without a HEMS. Without flexibility utilization, an increase in costs can be observed for most technology combinations with the DA tariff. However, with the implementation of a HEMS, this increase can be turned into a decrease for all households, except for those with only a HP or a PV-BSS. The cost change for households with only a PV-BSS is comparably high, as those households initially have low electricity costs with the static tariff and without a HEMS and the additional investment in a HEMS would eliminate cost savings that can be achieved through smart operation of the PV-BSS. The highest cost savings can be achieved for households that have an EV and a PV-BSS. Looking at the ToU tariff and the case without a HEMS, a comparably lower increase in costs can be seen for households with none of the technology options, with an EV or an EV and a PV-system and households with an EV and a HP. The incorporation of a HEMS leads to a reduction in costs for most technology combinations with the ToU tariff in comparison to the static tariff. However, cost savings are generally lower than with the DA tariff, with the exception of households with a HP with or without an additional PV system or PV-BSS. Further details on the median annual electricity cost variation for the other GCDs examined are provided in Figs. 8.10–8.12. From these figures, it is evident that the savings from utilizing flexibility and opting for a DET are generally greater under the CAP and CAP-VOL GCDs. However, this trend does not hold for households equipped with a HP or those with a combination of an HP and a PV system.

8.4.1.2 Effects on annual grid charges

The median annual grid charges paid for the different household technology combinations and GCDs are shown in Fig. 8.6. For a deeper insight into the effects of the different GCDs, the median of annual grid charges paid over the annual electricity drawn from the grid and over the maximum power draw/feed-in can be found in Figs. 8.13 and 8.14, respectively. We did not differentiate between the three retail tariffs since the variations across the tariffs were negligible. In the following, we compare the three GCDs CAP, CAP-VOL and CPP to the base case VOL (gray bars in the graph). All numerical values refer to the median of the change from VOL to one of the other GCDs.

Minor changes are evident when considering the CPP. Nevertheless, households that possess both a HP and an EV, as well as a HP on its own, may experience a decrease in annual grid charges in case of the use of a HEMS by up to -10%. On the other hand, the absence of a HEMS can lead to an increase in annual grid charges of up to 9%. Examining the results for the GCDs CAP and CAP-VOL (with capacity subscription), there is a considerable increase in annual grid charges for most cases without a HEMS, particularly for households equipped with a PV-BSS (up to 565%) or an EV (up to 479%). However, these high charges for households with an EV can be offset by the use of a HEMS. For households which possess only a HP, reduced annual grid charges can be observed across all GCDs. Generally, for households with a HP with or without a PV system or PV-BSS, the rise in annual grid charges is lower than that for households with an EV. Yet, the potential for further reductions via a HEMS is restricted by the fundamental characteristics of HP loads. The greatest benefits of utilizing a HEMS are apparent

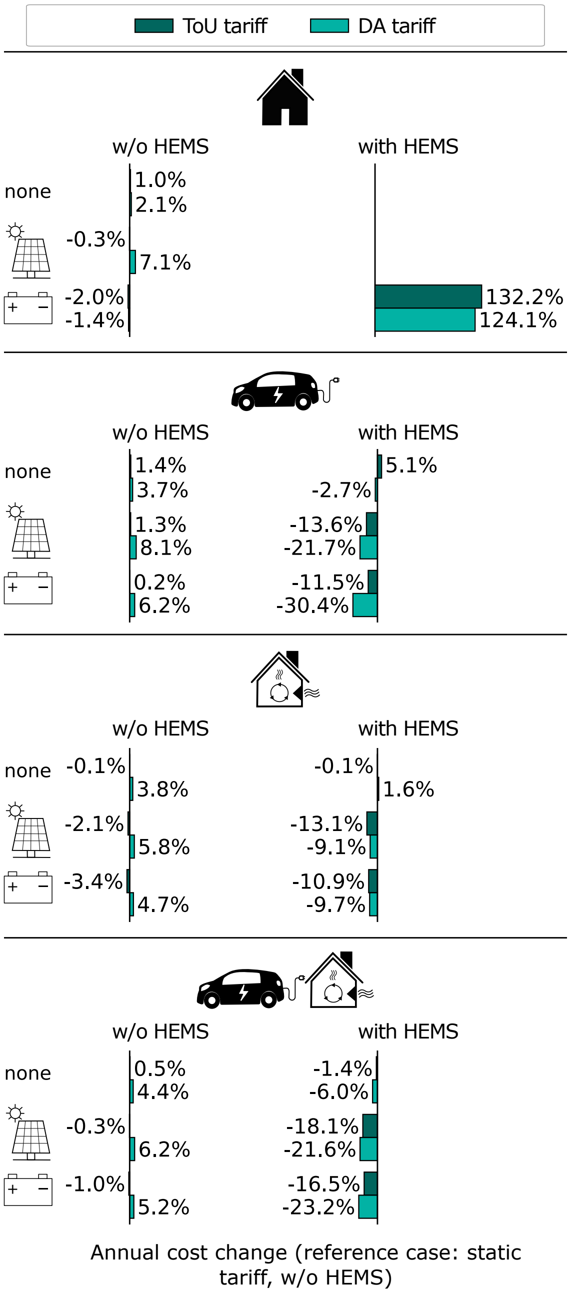


Figure 8.5: Median change of annual electricity costs incl. additional costs for the two DETs and the VOL GCD (reference case: static tariff without a HEMS).

when households possess both an EV and a HP, where (also for the case with a PV system or PV-BSS) changes in annual grid charges are less than 20%. Comparing the CAP and CAP-VOL GCDs, lower annual grid charges can be seen for most cases in the CAP-VOL design for households without a HEMS. When a HEMS is installed, this changes for the cases of households without a PV system or PV-BSS and households equipped with all flexible technologies considered.

In general, the results demonstrate that the implementation of the CAP or CAP-VOL GCD leads to an increase in annual grid charges for most technology combinations, when flexibility is not utilized (no HEMS). However, equipping households with a HEMS can offset this effect and significantly reduce the annual grid charges. Therefore, CAP and CAP-VOL would enhance the incentive for utilizing the flexibility of EVs, HPs and PV-BSSs.

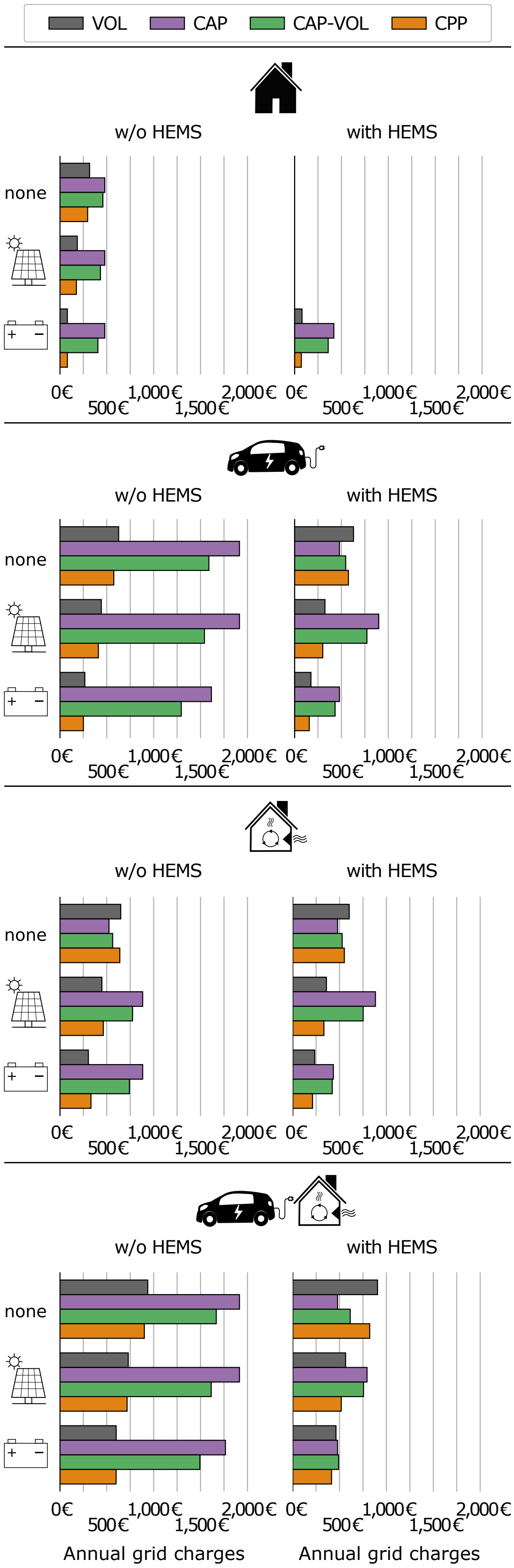


Figure 8.6: Median of annual grid charges for all technology combinations and GCDs.

8.4.1.3 Effects on annual variable electricity costs

One noteworthy aspect to consider when examining the interplay between DETs and various GCDs is the impact of GCDs on annual variable electricity costs (unit rate costs minus feed-in remuneration) for households.[12] With regards to the static and ToU tariff, minimal changes of less than 1 € (median for all households, grouped by available technologies) are observable. These changes can be attributed to standby losses of the heat storage and the BSS. For the DA tariff, greater changes are apparent as households are unable to take advantage of periods with lower electricity prices to the same degree as with the VOL GCD. This is due to the limited amount of power that can be drawn from or fed into the grid under the CAP and CAP-VOL GCDs, while the grid charges may be increased during certain low-priced periods under the CPP GCD. One could expect an increase in annual variable electricity costs for these three GCDs because of greater limitations on the energy consumption compared to the VOL case.

Table 8.7 displays the median annual variable electricity cost changes for the CAP, CAP-VOL and CPP cases in comparison to the VOL case for the DA tariff. In this instance, the unit rate costs encompass only the expenses for electricity procurement and retail and other applicable taxes, levies, and surcharges, excluding any grid charges. It is clear that the earlier assumption of rising annual variable electricity costs is invalid. On the contrary, there is a decrease in annual variable electricity costs for all cases with a PV system or a PV-BSS, and the case with only a HP. In case of an available PV system or PV-BSS, the HEMS adopts a different strategy. Specifically, in the VOL case, self-generated electricity is preferably used for EV charging or using the flexibility of the HP, thereby increasing the self-sufficiency rate of the household. As the volumetric electricity price seen by the HEMS or household is lower in the CAP and CAP-VOL case, with the volumetric grid charges being significantly lower or non-existent, there are some hours in the year where the electricity price falls below the feed-in remuneration. Therefore, the HEMS shifts the charging process of the EV or the flexibility of the HP to hours with lower electricity prices and feeds the self-generated electricity from the PV system into the grid. This results in a decrease in annual variable electricity costs of up to -10.7% (households with an EV and a PV-BSS) for the CAP and CAP-VOL cases compared to the VOL case. For the CPP case, the expected increase in annual variable electricity costs is seen, reaching up to 17.3% (households with a HP and a PV-BSS).

Even though cost reduction can be observed for the DA tariff for all households with a PV system or a PV-BSS and households with solely a HP, they do not compensate for the cost increase incurred by the CAP and CAP-VOL GCDs with capacity subscription. In summary, when faced with different combinations of DETs and GCDs, the changes in the electricity bill are mainly driven by the GCD.

[12] Unit rate costs are the electricity costs in €ct/kWh that a household has to pay for each kWh drawn from the grid. They include costs for energy procurement and retail and taxes, levies and surcharges.

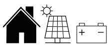
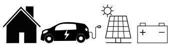
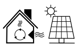
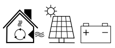
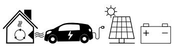
	Change in annual variable electricity costs					
Available technology	CAP		CAP-VOL		CPP	
	− 2.0 €	(−1.3%)	− 1.9 €	(−1.3%)	+ 3.9 €	(+2.8%)
	+ 3.9 €	(+0.3%)	+ 3.9 €	(+0.3%)	+ 22.7 €	(+1.6%)
	− 12.5 €	(−6.2%)	− 11.7 €	(−5.8%)	+ 16.7 €	(+7.5%)
	− 17.1 €	(−10.7%)	− 16.0 €	(−10.1%)	+ 20.7 €	(+10.0%)
	− 1.8 €	(−0.1%)	− 1.7 €	(−0.1%)	+ 21.0 €	(+1.3%)
	− 3.6 €	(−1.1%)	− 3.3 €	(−1.0%)	+ 18.6 €	(+5.8%)
	− 5.3 €	(−4.1%)	− 4.8 €	(−3.8%)	+ 24.0 €	(+17.3%)
	+ 7.1 €	(+0.3%)	+ 7.1 €	(+0.3%)	+ 44.7 €	(+2.0%)
	− 10.4 €	(−1.0%)	− 9.3 €	(−0.9%)	+ 39.5 €	(+4.1%)
	− 8.7 €	(−1.1%)	− 7.7 €	(−0.9%)	+ 46.8 €	(+5.8%)

Table 8.7: Median change in annual variable electricity costs (exclusive volumetric grid charges) for the considered grid charge designs compared to the volumetric grid tariff. Results are shown for households with various technology combinations using a HEMS and the DA tariff and all grid charge designs (base case: VOL, positive values in yellow, negative values in blue).

8.4.1.4 Decisions regarding the choice of electricity retail tariff and the investment in a HEMS

By combining all costs (including unit rate costs, grid charges, additional taxes, fees and surcharges, standing charges, metering point operation costs, and HEMS investment outlined in Section 8.3.3) and the revenues from the feed-in remuneration with the WTPM for the different adopter categories (refer to Section 8.3.2), one can determine the decisions of the households regarding the choice of electricity retail tariff and the usage of a HEMS, as described in Section 8.2.2. Subsequently, the choices made by all households of the grid area described in Section 8.2.4.2 for each GCD can be aggregated and shares can be determined as shown in Fig. 8.7.

The first noticeable aspect is that the lowest percentage of households choosing to use a HEMS to utilize their flexibility is found with the VOL GCD, at 67.2%. In contrast, the percentages for the other GCDs – CAP, CAP-VOL, and CPP – are higher, with 74.1%, 73.9%, and 74.9%, respectively. The potential for annual savings on grid charges by utilizing a HEMS is particularly high in the CAP and CAP-VOL GCD, especially for households with an EV. Under the CPP GCD, households with a HP stand to gain notably from investing in a HEMS (see Fig. 8.6). Even with the VOL GCD, savings are achievable through DETs for a high share of households, which accounts for the moderate rise in HEMS adoption when moving from VOL to the other GCDs. Variations are also seen in the choice of electricity retail tariffs. The adoption of the DA tariff in conjunction with a HEMS is most prevalent under the CAP and CAP-VOL GCDs (64.2% and 62.3%, respectively). Households on a static tariff with a HEMS use their flexibility to maximize self-consumption, particularly those with a HP. This pattern is less evident across the various GCDs, except for the CPP GCD, which sees a higher share in households opting for both the ToU (19.5%) and static (3.5%) tariffs when paired with a HEMS.

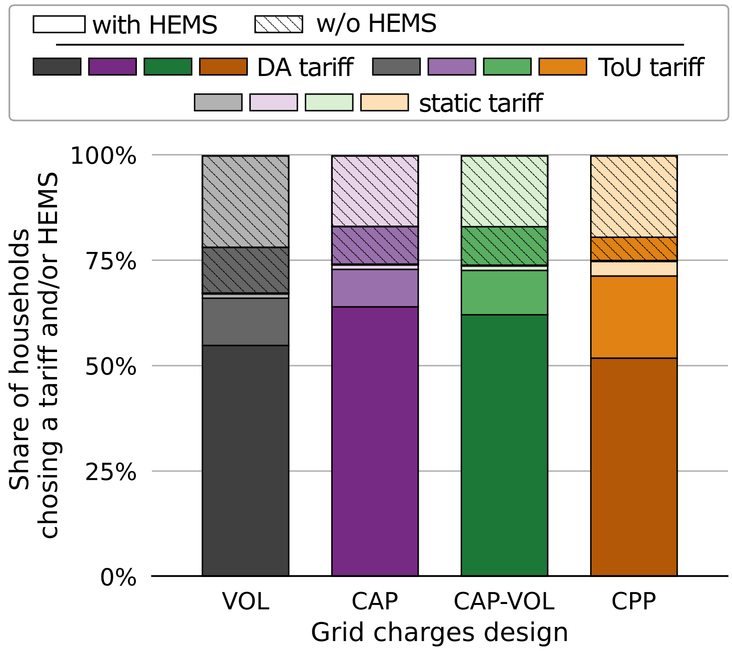


Figure 8.7: Share of households' decisions regarding the choice of tariff and the use of a HEMS for all four grid charge designs.

In summary, the design of the grid charges impacts households' decisions about utilizing their flexibility with a HEMS and the choice of an electricity retail tariff for that case. The CAP GCD offers the most significant incentives for utilizing flexibility and opting for the DA tariff, closely followed by the CAP-VOL GCD. The CPP GCD encourages the use of flexibility, albeit with a greater emphasis on optimizing self-consumption.

8.4.1.5 Annual grid charges and maximum power draw/feed-in

By investigating the relationship between annual grid charges paid by residential consumers and the maximum power draw or feed-in, we can gain insights into the cost-reflectivity of GCDs and the incentive effect on households to utilize their flexibility.

Fig. 8.8 illustrates this relationship among all considered GCDs and for each household and electricity retail tariff, both with and without a HEMS. The most significant load on the grid from each household is represented by the highest absolute value of either the maximum power draw or the maximum power feed-in. The GCDs CAP and CAP-VOL show a steeper slope without a HEMS. This is expected, as grid charges depend on the maximum power draw or feed-in in these cases. However, while comparing VOL and CPP, VOL exhibits a slightly steeper slope.

Most households are keeping their maximum power draw or feed-in below 20 kW when a HEMS is utilized, demonstrating the impact of the incentive introduced through these GCDs. This can also be seen when looking at the annual mean subscribed capacity level (Table 8.10). Moreover, the more pronounced slope for the CAP and CAP-VOL GCDs decreases with the use of HEMSs. This can largely be attributed to households subscribing to a capacity level on a monthly basis. While this approach maintains a high annual maximum power draw or feed-in, it decreases the average power draw or feed-in. Monthly subscription proves advantageous to households. They can, for example, increase power levels during high-demand winter months (when a HP is used), consequently saving money in the summer when demand is lower. Nonetheless, the monthly subscription model may inadvertently promote inefficiencies from the grid's perspective. This is because reinforcement measures are predicated on grid load. The difference between the average and the peak loads for individual households is increasing, indicating that an annual subscription may be a more sensible option from a grid perspective. With regards to the other GCDs, VOL and CPP, the introduction of a HEMS results in minimal alterations, implying a lack of incentivization.

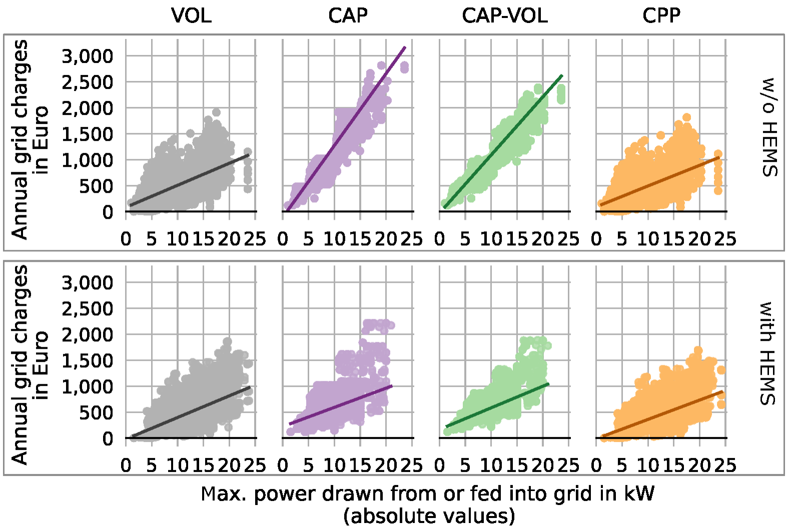


Figure 8.8: Annual grid charges over max. power drawn from or fed into the grid (dots) with linear regression (lines) for each grid charge design with and without a HEMS.

8.4.2 Grid level

On the LV grid level, we focus on evaluations of the grid load and violations of grid restrictions in the LV rural 3 grid depicted in Section 8.3.5. Additionally, we perform an examination of the grid reinforcement requirements and associated costs under the different GCD scenarios for all six LV grids.

8.4.2.1 Violations of grid restrictions

Table 8.8 presents the annual hours with violations of grid restrictions for all four GCDs in the LV rural 3 grid. This grid was chosen as an example. The data shows the average result of the power flow iterations. The table differentiates between transformer thermal overloads, positive and negative voltage band violations (load and generation driven), and line thermal overloads.

As for thermal overloads of the transformer, the CAP GCD has the highest average number of hours with overload, followed closely by the CAP-VOL scenario. However, these two GCDs exhibit a lower maximum transformer loading than the VOL and CPP designs. This can be interpreted as a positive aspect as it indicates a higher grid utilization, making grid reinforcement more efficient. The CPP scenario displays the highest maximum transformer loading with a value of 339%.

For instances of positive voltage band violations, more hours per year with overload are observed for the CAP and CAP-VOL scenarios, but there are no variations in the maximum positive voltage deviation. Conversely, just a few hours per year are seen across all GCDs for negative voltage band violations, with the CPP scenario leading to the greatest number of hours. As regards the maximum negative voltage deviation, the highest values are observed for the CPP and VOL scenarios, demonstrating the efficacy of the CAP and CAP-VOL designs in reducing the maximum power draw of households.

The thermal overload results for lines are similar to those for the negative voltage band violations. CAP and CAP-VOL exhibit the least number of annual hours with overload and the lowest maximum line loading during an overload.

The results suggest that implementation of the CAP and CAP-VOL design leads to higher grid utilization compared to the VOL and CPP design and – at the same time – the overall grid load (in terms of violations of grid restrictions) is lower.

Thermal overload transformer				
Grid charge design	Hours with overload (average)	Percentage of total annual hours	Mean transformer loading in HOL	Max. transformer loading in HOL
VOL	239	2.7%	150%	335%
CAP	303	3.5%	137%	217%
CAP-VOL	294	3.4%	137%	217%
CPP	259	3.0%	151%	339%

Voltage band violation – positive				
Grid charge design	Hours with overload (average)	Percentage of total annual hours	Mean pos. voltage deviation in HOL	Max. pos. voltage deviation in HOL
VOL	191	2.2%	5.3%	6.7%
CAP	225	2.6%	5.3%	6.7%
CAP-VOL	217	2.5%	5.3%	6.7%
CPP	192	2.2%	5.3%	6.7%

Voltage band violation – negative				
Grid charge design	Hours with overload (average)	Percentage of total annual hours	Mean neg. voltage deviation in HOL	Max. neg. voltage deviation in HOL
VOL	71	0.8%	-7.7%	-18.0%
CAP	65	0.7%	-5.9%	-10.0%
CAP-VOL	62	0.7%	-5.9%	-10.0%
CPP	80	0.9%	-7.0%	-17.9%

Thermal overload line				
Grid charge design	Hours with overload (average)	Percentage of total annual hours	Mean transformer line in HOL	Max. line loading in HOL
VOL	50	0.6%	118%	200%
CAP	17	0.2%	107%	134%
CAP-VOL	17	0.2%	107%	134%
CPP	56	0.6%	118%	199%

Table 8.8: Summary of grid restriction violations under different grid charge designs for the LV rural 3 grid. The table presents average hours with overload (HOL), the percentage of total annual hours for these events, and the mean and maximum loading during these hours.

8.4.2.2 Grid reinforcement measures and associated costs

The necessary grid reinforcement measures for all LV grids under consideration (refer to Fig. 8.15) result in the grid reinforcement costs illustrated in Fig. 8.9. There is no grid reinforcement required for the LV rural 1 grid. On average over all other considered LV grids and iterations, the CPP scenario exhibits the highest grid reinforcement costs, followed closely by the VOL scenario. Conversely, the CAP and CAP-VOL scenarios demonstrate significantly lower grid reinforcement costs in all LV grids (average reduction between 14% and 88%, depending on the grid). The relative difference in grid reinforcement costs between the GCDs are lowest for the LV urban 6 grid and highest for both suburban grids. The higher grid reinforcement costs for the CPP scenario in conjunction with the high transformer loading mentioned above indicate that the design of the critical peak hours described in Section 8.2.4.2 is not sufficiently specific for individual LV grids.

Overall, the CAP and CAP-VOL GCDs seem to be most advantageous for the LV grids under consideration and are also effective in incentivizing flexibility use in households. Nevertheless, they result in higher annual grid charges for households not utilizing their flexibility or lacking flexibility options. Furthermore, a higher grid reinforcement need (also when broken down per residential customer) is observed for the LV rural 2 and rural 3 grids, which is in line with results from other studies that see the highest need for grid reinforcement in rural areas [39].[13]

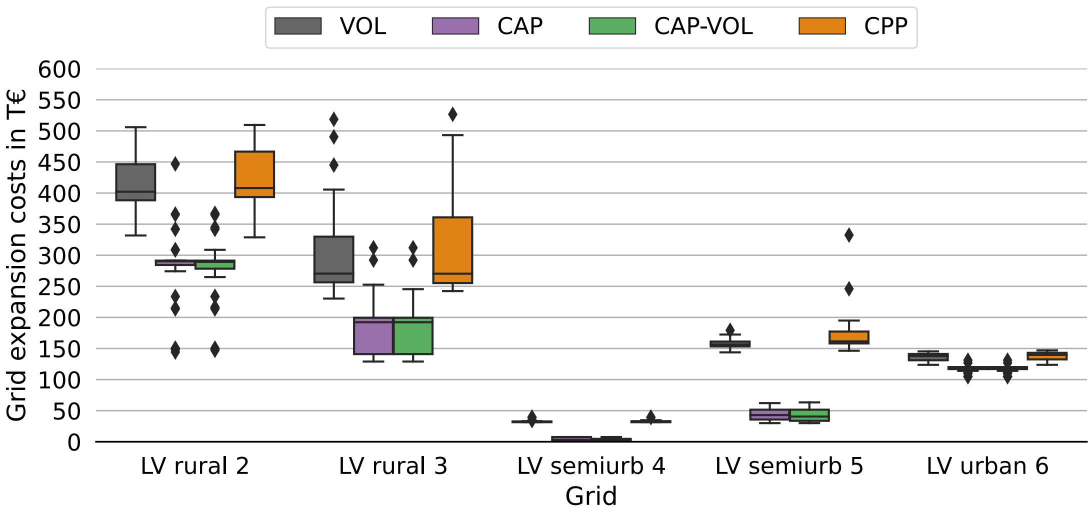


Figure 8.9: Grid reinforcement costs for all considered LV grids differentiated by the four grid charge scenarios. The box plots include all 50 iterations per scenario and grid. LV rural 1 grid is not presented, as no need for grid reinforcement occurred.

8.5 Limitations and further research

While the present study provides important insights for understanding the interactions between DETs and GCDs, it is important to consider some limitations of the study design and further research options. These limitations also provide opportunities for future research that could provide an even more comprehensive

[13] It is important to note that we did not differentiate in the framework scenarios for different settlement categories.

picture of the issues addressed.

Although the study encompasses a wide array of individual household load profiles complemented by socio-demographic data, the sample does not represent the average of the German population. The household sample is characterized as comprising „households with higher electricity consumption, most likely due to a larger number of household members, more children and larger dwellings“ [62].

The model considers the flexibility of households either fully through the use of a HEMS or not at all. This considers automated flexibility and neglects manually activated flexibility. Studies show that the willingness to deploy flexibility manually and to shift load decreases over time [11]. Therefore the chosen approach could overestimate flexibility deployment, but further research on the topic seems necessary.

Further, the flexibility potential is limited due to the study's focus on SFHs. Multi-family homes and the tertiary sector were not considered, as SFHs have the highest flexibility potentials (in relation to the technologies considered). However, these excluded sectors also offer flexibility and should be considered in future analyses.

The reaction to price incentives only includes load shifting, but no load curtailment, as curtailment is expected to have much higher discomfort costs for the households. Nevertheless, as shown in 2022, energy savings by households due to high unit rate costs (€ct/kWh) can be observed and play a role in households' reactions to price incentives and would increase the flexibility provided. Further analyses should include energy savings as well.

Predicting the development of electricity prices, but also penetration rates of EVs, HPs and PV-BSSs is subject to larger uncertainties. Future analyses can evaluate these uncertainties with sensitivity analyses to investigate effects also at other ratios of infrastructure and generation costs.

Concerning the WTPM model employed, the values were sourced from a household survey focused on the WTPM for PV-BSSs. While the authors anticipate comparable WTPM figures for households considering HEMSs and DETs, conducting a dedicated household survey could provide more accurate data.

At grid level, the heterogeneity of LV grids was included via six different benchmark grids. However, in reality there are of course many more different LV grids, which is why more precise grid analyses may be necessary if the results are to be transferred to specific grids.

Only grid reinforcement measures and no grid optimization measures were considered. With this approach the upper limit of grid reinforcement costs are considered as in some case optimization measures with lower costs could be sufficient.

The reported grid reinforcement costs are based on current costs and were used in this study for a comparison between the LV grids and GCDs, which means that the difference between both are relevant. The cost assumptions are subject to uncertainties e.g. the increase of material or labor costs due to inflation or a shortage of skilled workers.

In the parameterization of the CPP GCD, the results show that the goal of preventing critical grid conditions and to some extent grid reinforcement requirements, is not achieved. Incorporating additional critical peak hours into the GCD could enhance the likelihood of alignment between peak pricing hours and the peak load periods of individual households. This alignment may improve outcomes related to preventing grid reinforcement requirements. However, it could also result in diminished cost savings for households since peak prices may conflict with the savings offered by DETs (see also Table 8.7). Moreover, if peak prices coincide with low retail prices, it is possible that peak loads may not be effectively mitigated. Here, a parameterization with a higher temporal and local resolution would be expedient, but this is considered out of scope for this study.

Concerning the allowed $\pm 10\%$ difference in DSO revenues for the different GCDs, we have to distinguish the two scenarios of higher and lower revenues. Concerning the CAP and CAP-VOL GCDs, revenues are higher compared to the VOL GCD, which could suggest a potential decrease in grid charges. This decrease might lead to slightly lower incentives for peak demand reduction. When this difference is distributed among all grid users within the described grid area, it translates to approximately a 48 € difference per user per year, or about 4 €/month. Given that the price steps between the power levels are around 15 times higher, the implications of this difference are expected to be minimal.

For the CPP GCD, revenues are lower than those for the VOL GCD, indicating a need to increase grid charges, which implies a stronger price incentive. Distributing the difference among all grid users within the grid area translates to approximately 39 €/year. As indicated in Table 8.7, the price signal in the scenario we described is already sufficient to incentivize load shifting. It is plausible that the heightened incentives for flexibility utilization could increase the number of residential consumers opting to leverage their flexibility. As the CPP GCD in our results does not lower grid reinforcement needs but increases it, we do not expect this to change with a higher number of households utilizing their flexibility.

In the context of grid reinforcement measures, we observe differences between the GCDs ranging from 14% to 88%. Therefore, the $\pm 10\%$ revenue variance should not qualitatively affect our results.

More broadly, it should be noted that grid charges are determined through an ex-ante setting process, and as such, revenues are never precisely as expected by a DSO. The accuracy depends strongly on historical data and forecasts, which may not be readily available, especially at the outset of introducing new GCDs. Given these considerations, our approach is justified as a reasonable representation of the expected revenues under different GCDs.

8.6 Conclusions and policy implications

In this study, we address a gap in literature regarding the interplay between Dynamic Retail Electricity Tariffs (DETs) and different Grid Charge Designs (GCDs). We shed light on its economic effects on residential consumers and the impacts on their choices regarding dynamic electricity retail tariffs. We further analyze the implications for the grid and potential grid reinforcement requirements in Germany.

We utilized an advanced simulation model with embedded optimization that in a first step integrates both static and flexible electricity consumption and generation within a Home Energy Management System (HEMS). The objective of the model is to optimize household electricity expenses, accounting for different combinations of DETs and GCDs. In the next step the model depicts the decision-making process of residential consumers when selecting their electricity retail tariffs and deciding whether to invest in a HEMS. To evaluate the impact on the grid and potential grid reinforcement costs, load flow analyses were performed for various low-voltage grids. Finally a grid reinforcement algorithm was utilized to model the grid development.

From the results, we derive several conclusions and implications for policy and residential consumers, which are outlined below.

8.6.1 Dynamic electricity retail tariffs significantly lower electricity costs for households with electric vehicles and heat pumps when flexibility is utilized

DETs and different GCDs aim to improve the integration of renewable energies and limit the extension of grid infrastructure to an efficient level. The key technology solutions to achieve this are smart meters and HEMS, which enable adaptation to electricity price and grid tariff incentives. The results indicate that a great share of residential consumers can realize cost savings for electricity purchase costs if they use electric vehicles or heat pumps flexibly. The median potential savings across all evaluated households can reach up to 30.4% for those equipped with an electric vehicle and a PV battery storage system with the current GCD in Germany. Higher savings can be achieved with the use of a HEMS, when DETs and GCDs with capacity subscription are combined. Here we see up to 62.3% cost savings for households with an electric vehicle and a PV battery storage system. However, reduced savings can be observed for households with a heat pump or with a heat pump and a PV system.

Results show that electricity costs for residential consumers may increase if time-of-use tariffs or tariffs based on the day-ahead spot market price are used compared to a static electricity tariff, unless residential consumers respond by utilizing the flexibility available to them.

Depending on the GCD, between 66% and 73% of the residential consumers could benefit from and would opt for DETs and a HEMS. From a pure economic perspective, a higher share of residential consumers would achieve cost savings through DETs and a HEMS. As, in our analysis, we consider other behavioral drivers of households than solely financial ones when considering the choice to use a HEMS and opt for a DET (willingness to pay more), we see that for the adopter categories late majority and laggards, an adoption of DETs and a HEMS is only assumed with larger economic benefits. Thus, enhancing user acceptance among these groups, and therefore also increasing the willingness to pay more, could lead to a greater proportion of residential consumers choosing DETs and investing in a HEMS.

8.6.2 Strategic grid charge design is key to minimizing grid reinforcements requirements

Next to improved integration of renewable energy generation, there is a more equitable distribution of grid costs among residential consumers for GCDs with a capacity subscription component. Additionally, the use of capacity subscriptions in GCDs can reduce grid load and grid reinforcement requirements. On average, associated grid costs are decreased ranging from 14% to 88%, depending on the specific low-voltage grid in question.

The analysis also suggests that implementing Critical Peak Pricing GCDs may not have the intended effect if critical peak prices are applied uniformly to all residential consumers. If a Critical Peak Pricing GCD is applied, residential consumers benefit less from DETs and are encouraged to increase self-consumption, while at the same time better utilization and more efficient grid use is not achieved. To reach the overarching goal of better integration of renewable energy generation and reduced grid reinforcement requirements with a Critical Peak Pricing GCD, the GCD parameterization must be adapted to local and temporal grid congestion, which requires a higher data availability.

8.6.3 Integrated view on dynamic electricity retail tariffs and grid charge designs is essential for enhancing renewable energy utilization and flexibility

The main policy implications arising from the results highlight the necessity of simultaneously considering the implications between DET design, GCDs, and incentives for renewable generation and flexibility. Adapting to a more capacity-oriented GCD could enable a flexible use of the available renewable generation and reduce grid reinforcement requirements. In contrary, under the current regime, electricity costs for residential consumers are rising more sharply because cheap electricity generated from renewable sources is being underutilized and grid reinforcement requirements are higher. Distribution system operators can limit additional costs for grid reinforcement due to a high share of PV systems, if residential consumers invest in electric vehicles, heat pumps, and HEMS simultaneously. DETs will enhance the profitability for many households and provide the right incentive to utilize their flexibility. Flexible operation and the choice for a dynamic tariff as well as a HEMS is further increased if a GCD with capacity subscription is implemented. Therefore the results highlight that a combination is needed of both, DETs for residential consumers and a more cost-reflective GCD to utilize flexibility. The GCD with only capacity subscription and a combined one with capacity subscription and a fixed volumetric charge show only small differences in terms of flexibility utilization and grid reinforcement costs. Therefore, adding a fixed volumetric charge does not reduce the effect of capacity subscription and incentivizes energy conservation, combining the benefits of both designs.

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CRediT authorship contribution statement

Judith Stute: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Marian Klobasa:** Funding acquisition, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix

A.1. Revenues from grid charges of the DSO

Table 8.9

Grid charges design	Revenues	Deviation
VOL (reference)	€95.92 million	-
CAP	€102.04 million	+6.38%
CAP-VOL	€105.06 million	+9.53%
CPP	€88.49 million	−7.74%

Table 8.9: Revenues from grid charges of the DSO with 190,000 metering points.

A.2. Change of annual electricity costs for the considered GCDs

Figs. 8.10–8.12

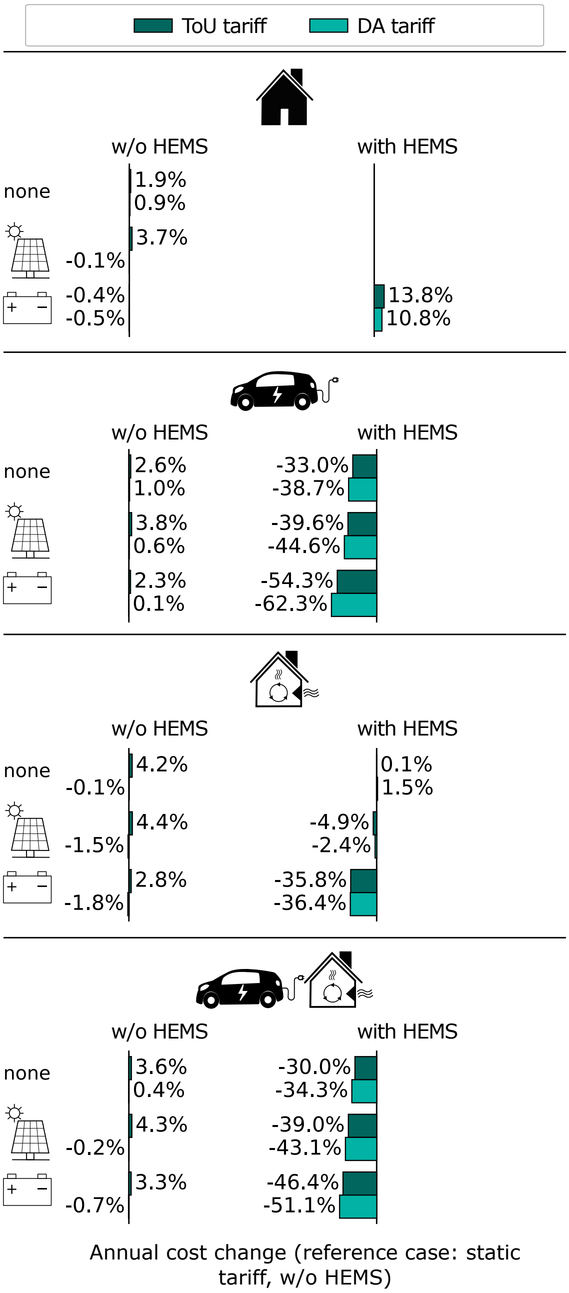


Figure 8.10: Median change of annual electricity costs incl. additional costs for the two DETs and the CAP GCD (reference case: static tariff without a HEMS).

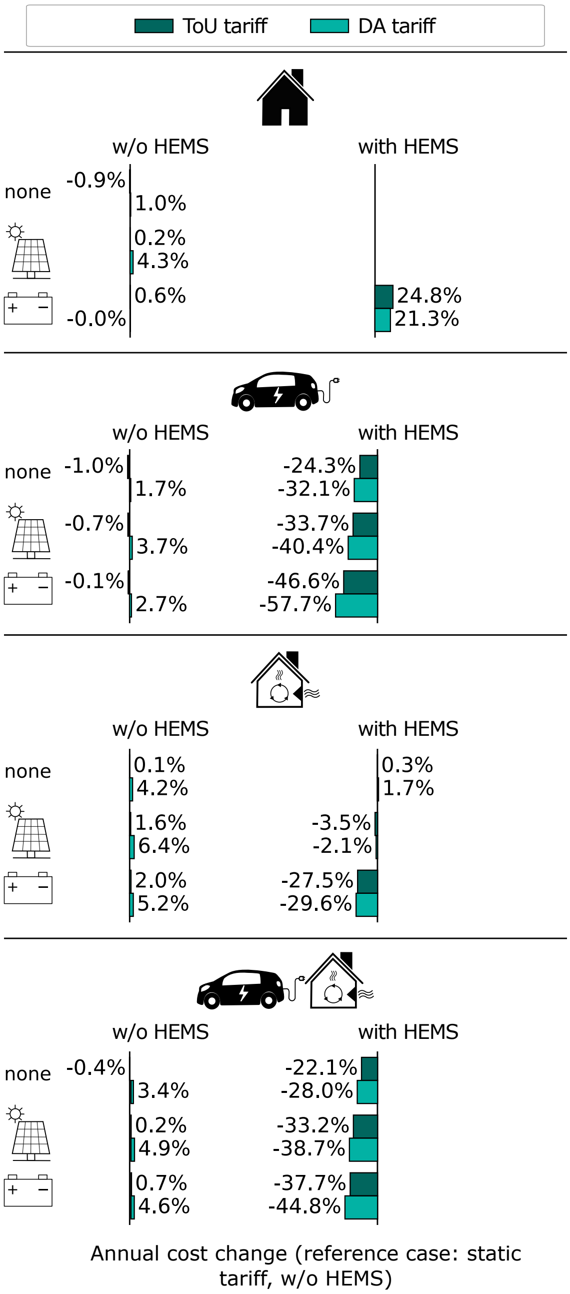


Figure 8.11: Median change of annual electricity costs incl. additional costs for the two DETs and the CAP-VOL GCD (reference case: static tariff without a HEMS).

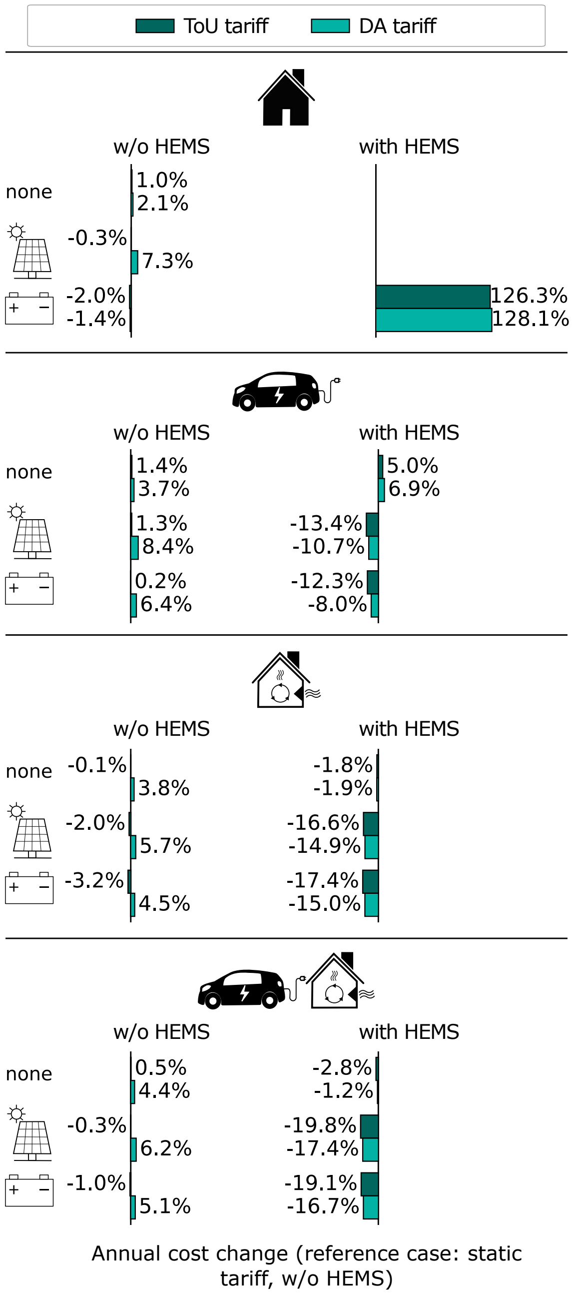


Figure 8.12: Median change of annual electricity costs incl. additional costs for the two DETs and the CPP GCD (reference case: static tariff without a HEMS).

A.3. Annual grid charges over electricity drawn from the grid and maximum power draw/feed-in

Figs. 8.13–8.15

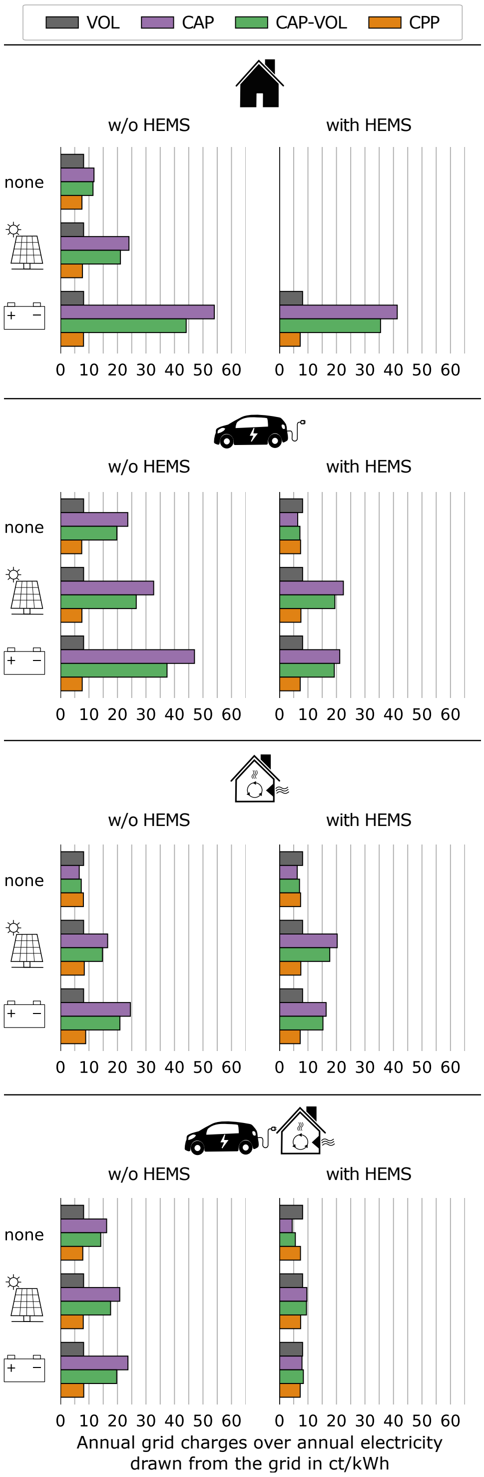


Figure 8.13: Median of annual grid charges over the annual electricity drawn from the grid.

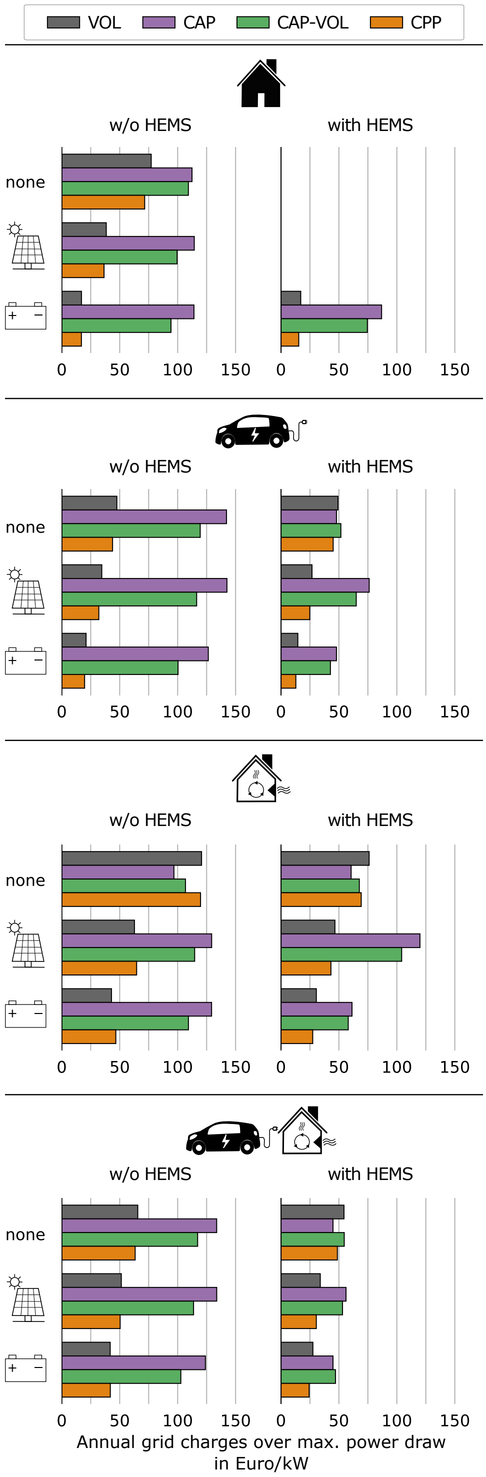


Figure 8.14: Median of annual grid charges over the maximum power draw/feed-in from the grid.

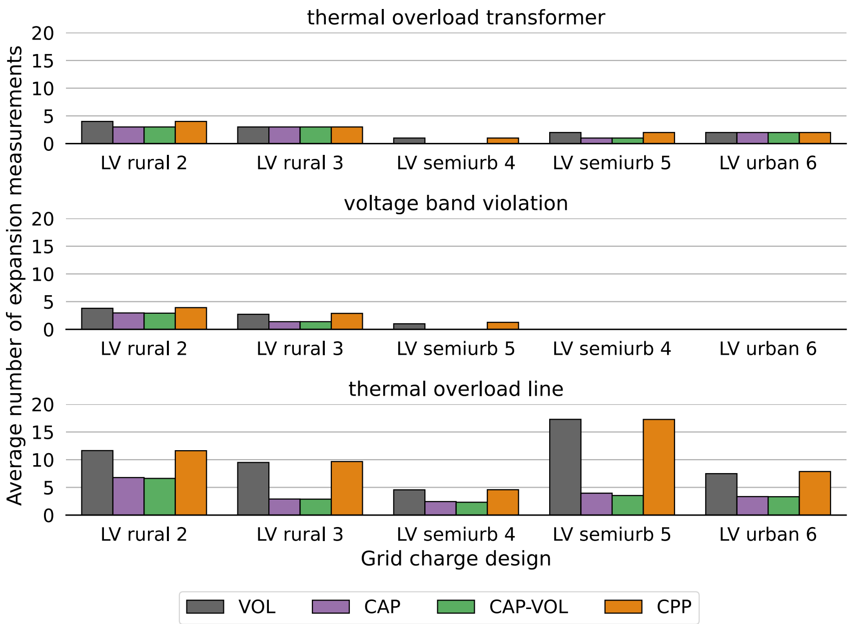


Figure 8.15: Number of grid reinforcement measurements by grid restriction type for all LV grids differentiated by grid charge design (average over all iterations).

A.4. Annual mean subscribed capacity level

Table 8.10

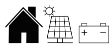
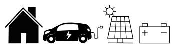
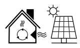
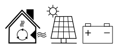
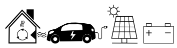
	Annual mean subscribed capacity level in kW	
Available technology	w/o HEMS	with HEMS
	5.97	4.51
	14.63	5.39
	14.50	8.40
	13.27	5.17
	5.65	5.14
	8.49	8.10
	8.44	4.99
	14.94	5.48
	14.88	7.65
	14.00	5.24

Table 8.10: Annual mean subscribed capacity level for all technology combinations. As differences between CAP and CAP-VOL are negligible, no differentiation is made.

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[End of Publication IV]

List of Publications

Peer-reviewed publications

[1] M. Haendel and **J. Stute**. Grid expansion costs considering different price control strategies of power-to-X options based on dynamic tariffs at the low-voltage level. *2019 16th International Conference on the European Energy Market (EEM)*, 2019. doi: 10.1109/EEM.2019.8916475.

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