Optimization methods for developing electric vehicle charging strategies

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Zongfei Wang

Abstract

Electric vehicles (EVs) are considered to be a crucial and proactive player in the future for transport electrification, energy transition, and emission reduction, as promoted by policy-makers, relevant industries, and the academia. EV charging would account for a non-negligible share in the future electricity demand. The integration of EV brings both challenges and opportunities to the electricity system, mainly from their charging profiles. When EV charging behaviors are uncontrolled, their potentially high charging rate and synchronous charging patterns may result in the bottleneck of the grid capacity and the shortage of generation ramping capacity. However, the promising load shifting potential of EVs can alleviate these problems and even bring additional flexibilities to the demand side for further applications, such as peak shaving and the integration of renewable energy.

To grasp these opportunities, novel controlled charging strategies should be developed to help integrate electric vehicles into energy systems. However, corresponding methods in current literature often have customized assumptions or settings so that they might not be practically or widely applied. Furthermore, the attention of literature is more paid to explaining the results of the methods or making consequent policy recommendations, but not sufficiently paid to demonstrating the methods themselves. The lack of the latter might undermine the credibility of the work and hinder readers' understanding. Therefore, this thesis serves as a methodological framework in response to the fundamental and universal challenges in developing charging strategies for integrating EV into energy systems. The discussions aim to raise readers' awareness of the essential but often unnoticed concerns in model development and hopefully would enlighten future researchers into this topic.

Specifically, this cumulative thesis comprises four papers and analyzes the research topic from two perspectives. With Paper A and Paper B, the micro perspective of the thesis is more applied and focuses on the successful implementation of charging scheduling solutions for each EV individually. Paper A proposes a two-stage scenario-based stochastic linear programming model to schedule EV charging behaviors and considers the uncertainties from future EVs. The model is calculated in a rolling window fashion with updated parameters. Scenario generation for future EVs is simulated by inhomogeneous Markov chains, and scenario reduction is achieved by a fast forward selection method to reduce the computational burden. The objective function is formulated as variance minimization so that the model can be flexibly implemented for various applications. Paper B applies the model proposed in Paper A to investigate how the generation of a wind turbine could be correlated with the EV controlled charging demand. An empirical controlled charging strategy is designed for comparison where EVs would charge as much as possible when wind

generation is sufficient or would postpone charging otherwise. Although these two controlled charging strategies perform similarly in terms of wind energy utilization, the solutions from the proposed model could additionally alleviate the volatility of wind energy generation by matching the EV charging curve to the electricity generation profile.

With Paper C and Paper D, the macro perspective of the thesis is more explorative and investigates how EVs as a whole would contribute to energy transition or emission reduction. Paper C investigates the greenhouse gas emissions of EVs under different charging strategies in Europe in 2050. Methodologically, the paper proposes an EV module that enables different EV controlled charging strategies to be endogenously determined by energy system models. The paper concludes that EVs would contribute to a 36% emission reduction on the European level even under an uncontrolled charging strategy. Unidirectional and bidirectional controlled charging strategies could further reduce emissions by 4% and 11%, respectively, compared with the original level. As a follow-up study of Paper C, Paper D develops, demonstrates, improves, and compares three different types of EV aggregation methods for integrating an EV module into energy system models. The analysis and demonstration of these methods are achieved by having a simplified energy system model as a testbed and the results from the individual EV modeling method as the benchmark. As different EV aggregation methods share the same data set as for the individual EV modeling method, the disturbance from parameters is minimized, and the influence from mathematical formulations is highlighted. These EV aggregation methods are compared from multiple aspects.

List of appended papers

Paper A

Wang, Z., Jochem, P., Fichtner, W., (2020). A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand. Journal of Cleaner Production 254, 119886.

https://doi.org/10.1016/j.jclepro.2019.119886

Paper B

Wang, Z., Jochem, P., (2019). How many electric vehicles can one wind turbine charge? A study on wind energy generation and electric vehicle demand correlation, 32nd International Electric Vehicle Symposium & Exhibition. Lyon, France

Paper C

Xu, L., Yilmaz, H.Ü., Wang, Z., Poganietz, W.-R., Jochem, P., (2020). Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. Transportation Research Part D: Transport and Environment 87, 102534.

https://doi.org/10.1016/j.trd.2020.102534

Paper D

Wang, Z., Jochem, P., Yilmaz, H.Ü., Xu, L., (2021). Integrating vehicle-to-grid technology into energy system models: Novel methods and their impact on greenhouse gas emissions. Journal of Industrial Ecology (early view)

https://doi.org/10.1111/JIEC.13200

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Part I: Overview

1 Introduction

1.1 Motivation

Under the Paris Agreement, ambitious policies have been proposed worldwide to reach the target of "*holding the increase in the global average temperature to well below 2 °C above pre-industrial level and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels*" (United Nations, 2018) and to design roadmaps to reach carbon-neutral towards the mid of the century (IEA, 2021a; IRENA, 2021). For example, the European Union (EU) has set a target to reduce greenhouse gas (GHG) emissions by at least 55% by 2030 and to become climate-neutral by 2050 (European Commission, 2021). The United States plans to reduce its emissions by half of 2005 levels in 2030 and reach net zero emissions no later than 2050 (Whitehouse, 2021). China aims to reach peak carbon emission by 2030 and to become carbon neutral by 2060 (C. Xu et al., 2020).

To reach these targets, the road transport sector would be an inevitable contributor to GHG emission reduction. According to the European Commission (2020), passenger cars have accounted for around 12% of total EU carbon dioxide (CO_2) emissions. Therefore, a major technical pathway to decarbonize the road transport sector is to power vehicles with *low-carbon* fuels, such as biofuels (Ternel et al., 2021), synthetic fuels (Hänggi et al., 2019; Trost et al., 2017), and electricity (Gan et al., 2021). Systematically, the overall energy efficiency of the road transport sector could also be improved by new artificial intelligence technologies like autonomous driving (C. Zhang et al., 2019) or new business modes like car-sharing (Amatuni et al., 2020; Jochem et al., 2020).

As an alternative to internal combustion engine vehicles (ICEV), electric vehicles[1] (EVs) are taken as a promising solution to decrease the GHG emissions from road transport sector (Krause et al., 2020; Märtz et al., 2021) and air pollution in urban areas (Gai et al., 2020). According to the International Energy Agency (IEA), there has been a constant increase in EV stock worldwide. Figure 1 shows an annual increase of 60% in EV stock on average from 2014 to 2019 (IEA, 2020). This significant uplift in EV stock is promoted by the progressively tightened CO_2 emission performance standards for passenger cars (European Commission,

[1] Electric vehicles in the thesis refer to battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). Hybrid electric vehicles are not considered.

2020) and the subsidies and policies for encouraging EV purchase (BMWi, 2020; Y. Li et al., 2020). However, in spite of the rapid development of EV until now, the passenger EV market shares in most EU countries are still around 5% by 2020 (Statista, 2021).

A further increase of EV market is also expected in the future. For instance, the EV30@30 campaign has been launched under Electric Vehicles Initiative (2016) to reach 30% of EV sales by 2030 among its participating countries worldwide. Some countries also set their timetables for the phase-out of petrol and diesel vehicles, e.g., the United Kingdom by 2030 (United Kingdom Department for Transport, 2020). Reiter et al. (2017) project that the market share of passenger EVs will be around 80% for most EU countries in 2050.

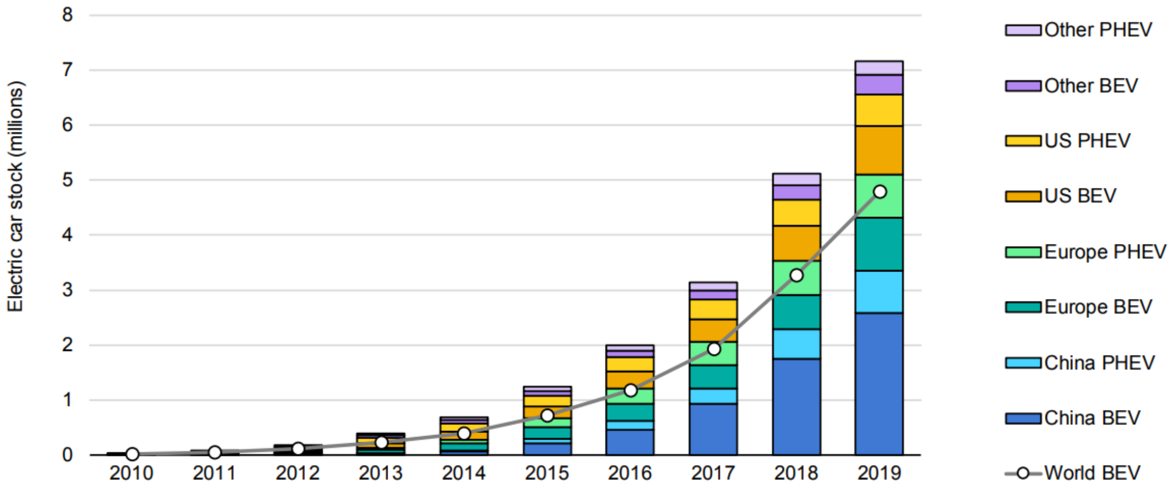

Figure 1. Global EV stock from 2010 to 2019 (IEA, 2020)

In terms of energy consumption, such ambitious projection of EV market penetration would result in a significant increase in electricity demand. The additional electricity consumption, especially during demand peak hours, may lead to the grid bottleneck and may influence the system operation (Schill and Gerbaulet, 2015). However, if EVs are charged in a controlled or coordinated manner, they could provide huge flexibilities on the demand side and benefit the energy system via peak shaving, renewable energy integration or emission reduction (Babrowski et al., 2014).

1.2 Research question

The promising potential in load shifting and the high proportion in total electricity demand provide EV with numerous possibilities in the future energy system and inspire an increasing number of studies in academia (Juan et al., 2016). Some explorative studies would investigate how EVs can contribute to the reduction of GHG emissions or the integration of renewable energy, assuming charging scheduling can be somehow controlled (Dixon et al., 2020; Seddig et al., 2017; Zhou et al., 2021). In addition, some studies focus on how EVs could participate in the electricity market as a virtual power plant or by providing ancillary services (X. Duan et al., 2021; Sarker et al., 2016; Vagropoulos and Bakirtzis, 2013; Yang et al., 2020). The optimization model for the total cost of ownership has also received increasing attention to clarify the economic foundation of EV adoption (Ouyang et al., 2021; Parker et al., 2021; Schücking and Jochem, 2021; van Velzen et al., 2019). EV-related studies cover a wide range of topics and fields, including various forms of technical, economic, societal, and environmental analysis not only within the energy system but also in coupling with other sectors like transport.

For EV-related studies, the EV's uncontrolled charging demand can be taken as an exogenously given parameter. However, the modeling of EV load shifting potential and the development of charging scheduling algorithms would naturally be the prerequisite to endogenously determine the EV charging profile if one study not only focuses on analyzing the impact of uncontrolled charging but also aims to further provide alternative solutions with controlled charging strategies. Unfortunately, it seems that the methodological challenges in developing controlled charging strategies for EV integration have not been sufficiently realized or analyzed.

In this regard, the research aim of the thesis is to make methodological suggestions to the fundamental and universal challenges in developing charging strategies for integrating EV into energy systems. This research topic can be further analyzed from two perspectives as each may have its own focuses and concerns, i.e., the micro perspective (Paper A, B) and the macro perspective (Paper C, D). The former considers EVs individually and focuses on the *operational* stage of EV integration; the latter analyzes EVs as a whole and focuses on the *planning* stage. Specifically, the following research questions are addressed by the thesis.

1) Paper A: How can the uncertainties of future EVs be considered in an EV charging scheduling model and how can the practicability, and the extensibility of the model be considered? (Wang et al., 2020)
2) Paper B: How is the correlation between the generation of a wind turbine and the demand of an EV fleet? (Wang and Jochem, 2019)
3) Paper C: How would different EV charging strategies influence the greenhouse gas emissions in Europe in the long term? (L. Xu et al., 2020b)
4) Paper D: What are the potential biases of different methods which integrate EV into energy system models, and how can these methods be further improved to reduce the biases? (Wang et al., 2021)

1.3 Structure of the thesis

The thesis includes two parts. Part I provides a methodological framework to the fundamental and universal challenges in developing charging strategies for integrating electric vehicles into energy systems and summarizes the main contributions of the appended papers as an overview. Section 1 sketches the motivation of the research question. Section 2 provides the background information on the research topic. Section 3 and Section 4 serve as the literature reviews for the research topic from the micro and the macro perspectives, respectively. Specifically, Section 3 outlines and discusses the methodological challenges, technological options in designing an EV charging scheduling model, and the respective practices of current literature. Section 4 first highlights the importance of having EV charging patterns endogenously determined by energy system models in research and then introduces the common methodological ideas shared by literature to achieve this target. Section 5 discusses the research gaps in current literature. Section 6 summarizes the main contributions of the appended papers. Section 7 concludes the overview. Part II includes the four appended papers of the thesis.

2 Background

2.1 EV charging strategies

2.1.1 The uncontrolled charging strategy

The energy consumption of EV charging will significantly increase the electricity demand. Jochem et al. (2015a) assume a 15% market share for the German EV market in 2030, implying an increase of the total electricity demand by 3%. Assuming an 80% market share of EV, Kasten et al. (2016) conclude that the EV energy demand in 2050 may be around 9.5% of total electricity demand for EU countries on average, and varied by the member countries (European Environment Agency, 2016). Other than the impact on total quantity, the fast development of EV will also reshape the original electricity demand profiles. The simulation or generation of EV demand profiles is usually based on surveys or statistics of mobility behaviors (Pareschi et al., 2020). For instance, Babrowski et al. (2014) generate EV load profiles based on nationwide mobility studies of six EU countries separately. Schäuble et al. (2017) derive and simulate realistic EV load profiles from three regional projects in southwestern Germany. Studies often assume that users charge EVs immediately when they arrive at charging facilities with the maximum charging power and stop charging when EVs are fully charged or need to leave. Therefore, such a charging strategy is often referred to as instant, uncoordinated, or uncontrolled charging.

Although EV charging profiles under the uncontrolled charging strategy are subject to users' behaviors, they still share some features in common. Figure 2 shows that, on both a working day and a weekend day, EV uncontrolled charging profiles typically start in the morning (around 6 a.m.) and end around midnight and that the profiles remain at a relatively low level after midnight. Specifically, the uncontrolled charging profiles may reach peak demand when people go to work in the morning or return home in the evening on a working day. The profiles may reach the demand peak anytime of the daytime on a weekend day, which varies by country.

This thesis mainly focuses on two challenges from EV uncontrolled charging[2]. The first one is the drastic increase in the existing peak load. For example, a 30% market share of EV in The Netherlands may increase the national and household peak load by 7% and 34%, respectively (Van Vliet et al., 2011). The increase may challenge the grid bottleneck at both the transmission and distribution levels (Crozier et al., 2020; Hu et al., 2019), resulting in

[2] EV integration also impacts the electricity grid from a more technical and engineering view, such as phase and voltage unbalance, harmonics injection, and grid stability (Das et al., 2020). Such impacts are of great importance as well but beyond the scope of the thesis.

additional investment in the network (González et al., 2019). In a case study of New Zealand, the system might even suffer from a shortage on installed generation capacity (Su et al., 2019).

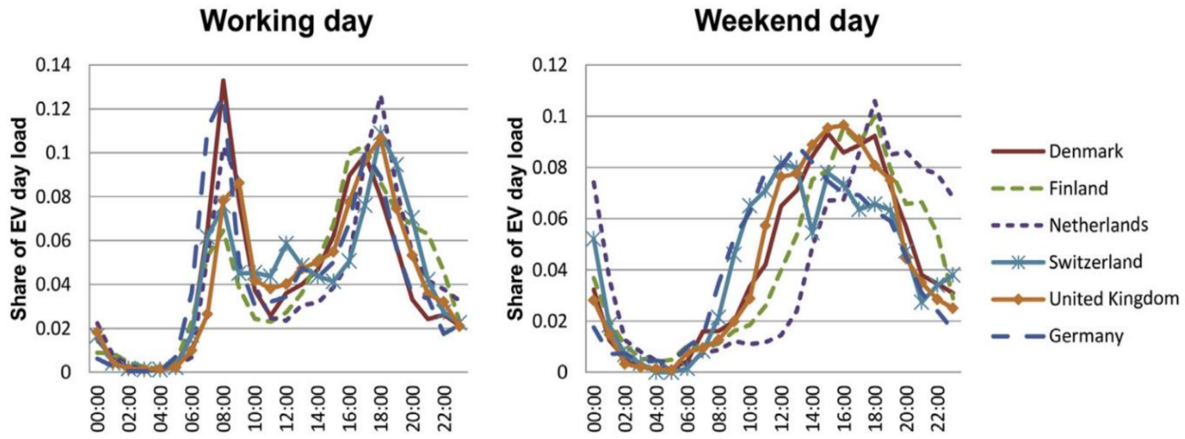

Figure 2. Country-specific EV uncontrolled charging profiles on a working day and a weekend day (Babrowski et al., 2014)

The second challenge stems from the electricity mix for EV uncontrolled charging (Xue et al., 2021). The EV-specific GHG emissions depend on the energy source of electricity of the region, i.e., whether EVs are charged with fossil fuels or renewable energies in essence (Schill and Gerbaulet, 2015). The peak demand growth may require additional dispatch or even further investment in peaking power plants (generally gas or oil-fired), which would cause more GHG emissions and would contradict the original intention of EV adoption (Krieger et al., 2016; Martinez-Bolanos et al., 2020).

2.1.2 The controlled charging strategy

Based on real EV usage patterns, it becomes evident that parking time generally lasts much longer than the actual charging time needed, although most EVs charge in the uncontrolled manner (Babrowski et al., 2014; Schäuble et al., 2017). The long idling time enables EVs to reschedule the charging behaviors, including the charging time and the time-variant charging power. Such possibility is referred to as the load shifting potential of EVs (Babrowski et al., 2014; Gnann et al., 2018). The corresponding charging strategy is often called smart, coordinated, or controlled charging.

The two challenges of uncontrolled charging mentioned above can both be tackled by controlled charging. In response to the peak demand increase, EV charging demand can be shifted to off-peak hours in case studies on different scales, such as a city (X. Li et al., 2020), a local distribution grid (Geng et al., 2019), and a single structure such as one parking lot (Wu and Sioshansi, 2017), one household (Khemakhem et al., 2019) or one university building (Ioakimidis et al., 2018).

The controlled charging strategy can also contribute to integrating renewable energy sources (RES) and influencing the electricity mix for EV charging. In Germany, 35% of the electricity generation in 2018 is from RES, and this proportion is projected to reach 40-45% in 2025 (BMWi, 2018). In 2020, RES has already accounted for 50.5% of German electricity generation (Fraunhofer ISE, 2020). The long-term target at the EU level is to raise the proportion to 80% in 2050 (European Commission, 2019). Furthermore, since RES such as wind and photovoltaic (PV) are non-dispatchable, the controlled charging strategy can also shift EV demand to hours with abundant RES availability and reduce GHG emissions from EV charging – or might even help accelerate the energy transition in the electricity system by replacing cost-intensive storage technologies.

2.2 Research perspectives of the thesis

To develop smart charging strategies for the integration of EV in energy systems, the research topic of the thesis can be analyzed from the micro and the macro perspectives separately, as each may have its own focus and is selected to serve the research topics of the applied fields. This classification is mainly characterized by the modeling resolution of EVs. Table 1 shows the typical features of the micro and the macro perspectives in EV modeling. Please note that the description only presents the stereotype of each perspective and should not be interpreted as a strict dichotomy.

	Micro perspective	**Macro perspective**
EV modeling resolution	Individually modeled	Aggregately modeled
Research topic examples	Grid stress alleviation, charging cost minimization, participation in power market	GHG emission reduction, RES integration, energy system expansion
Research object	Real grid structures, test system	City, country, global
Conclusion type	Method demonstration	Policy recommendations
Optimization horizon	Rather short (one hour to one day)	Rather long (mostly decades)

Table 1. Stylized description of micro and macro perspectives in modeling EV charging scheduling

In general, the micro perspective means that EVs are modeled separately with their individual information, such as battery state of charge (SOC), battery capacity, charging power, and usage patterns. Relevant studies more focus on how to utilize EV's load shifting potential in reality for a specific purpose, such as peaking shaving (Anastasiadis et al., 2017), congestion management (Carli and Dotoli, 2018), charging cost minimization (Seddig et al., 2019) and arbitrage in power market (Vagropoulos and Bakirtzis, 2013). The proposed models are often applied in a relatively local and realistic object, e.g., a household (Khemakhem et al., 2019), a parking garage (Lee et al., 2019) or a distribution network (Z. Liu et al., 2018). Since the micro perspective focuses more on demonstrating whether the proposed method can fulfill the promised functions, the applied scene can also be hypothetical but appropriately designed, such as the IEEE bus test system (Boonraksa et al., 2019). The time span or the optimization horizon of the models usually ranges from one hour (Wu and Sioshansi, 2017) to one day (Soares et al., 2017).

On the other hand, the macro perspective denotes that multiple EVs are typically considered as a whole in modeling, and their individual information will be summed up. The reason for the aggregation is that research topics from the macro perspective often require observation and analysis on a large scale, both geographically and temporally. For example, Xue et al. (2021) analyze EV emission in Japan from 2000 to 2030 under the transition of energy structure and the uncertainty of EV market penetration. Keller et al. (2019) examine the impacts of EV in the province of British Columbia in Canada in 2050 under the policy of targeting 93% of RES integration. Manríquez et al. (2020) investigate how EV integration may affect the power system expansion of Chile in 2030. Temporally, as seen from the examples above, relevant studies mainly have an optimization horizon of decades with the current year or a year in the past as the starting year and a target year in the future. Geographically, the research objects would be on a city (C. Zhou et al., 2020), a country (Heuberger et al., 2020), or multiple countries like the EU (Krause et al., 2020). Focus from the macro perspective is not mainly on the demonstration of the models or methods proposed originally (although crucial) or applied from other sources, but more on the exploration or the examination of future scenarios and the following policy recommendations.

Because of these differences between the micro and macro perspectives, respective EV modeling approaches would require different emphases in modeling. Micro perspective approaches are generally proposed to solve concrete problems at hand, so they should pay more attention to its practicability, such as the assumptions in parameter setting. By contrast, aggregately modeling from the macro perspective can be taken as an approximation of individual modeling from the micro perspective so that the emphasis of macro perspective approaches is more on the modeling accuracy within the tolerance for model complexity.

3 Micro perspective: charging scheduling for individual EVs

As discussed in Section 2, many explorative studies depict how EVs may benefit the energy systems, provided that EV charging behaviors could be controlled in certain ways. How such a prerequisite could be met is the research focus from the micro perspective, i.e., to develop charging scheduling models for individual EVs.

This section mainly gives an overview of papers focusing on the development of EV charging scheduling models from the micro perspective. Such studies are application-oriented and emphasize the feasibility of model design and setting. Table 2 alphabetically gives an overview of representative EV charging scheduling studies from the micro perspective, with appended Paper A and B listed at the bottom. All included papers apply optimization methods, labeled by the key aspects in Table 2. The explanation of Table 2 is to present the different aspects which need to be considered in developing an optimization model for EV charging scheduling and to discuss their respective technical options.

Specifically, Section 3.1 first discusses the fundamental question of how a scheduling problem could be structured. Section 3.2 then shows the objective functions commonly selected and the research topics they serve. Section 3.3 analyzes how the EV uncertainties are considered. Section 3.4 highlights the necessity of further applying the rolling window approach to EV charging scheduling models and the additional challenges.

	Model structure			Objective function					Research topic				EV uncertainties							Optimization method							Rolling window approach
	Multiple EV														Usage behavior		Charging demand										
	Centralized	Decentralized	Single EV	Cost minimization	Non-RES use minimization	Variance minimization	Profit maximization	Others	Peak shaving	RES integration	Market participation	Non-specific or multiple	Global optimum	Local optimum	Arrival time	Departure time	Arrival SOC	Departure SOC	Demand	Deterministic	Robust	Stochastic	LP[1]	MILP[2]	QP[3]	DP[4]	
Ghotge et al. (2020)	X							X	X						X	X	X	X			X			X			X
Gottwalt et al. (2017)	X			X						X			X							X			X				
Guo et al. (2018)	X			X					X					X						X			X				X
He et al. (2012)	X			X					X				X	X						X					X		X
Hu et al. (2016)	X	X		X					X					X						X					X		X
Iversen et al. (2014)			X				X					X[5]			X	X			X			X				X	X
Kaschub et al. (2016)	X						X			X			X							X			X				
Mou et al. (2015)		X				X			X					X						X					X		X
Powell et al. (2020)	X			X					X				X							X			X				
Muñoz and Jabbari (2020)		X		X					X				X							X			X				
Schuller et al. (2015)	X				X					X			X							X				X[6]			
Sharifi et al. (2020)	X			X						X		X		X						X				X			X
Su et al. (2020)	X						X		X					X						X				X[6]			X
Sun et al. (2020)	X			X								X			X	X	X	X			X		X				
Sundström and Binding (2012)	X					X			X				X							X			X				
Vagropoulos et al. (2016)	X							X			X			X						X			X				
Wu and Sioshansi (2017)	X			X					X						X				X			X	X				X
Wu et al. (2016)			X	X								X[5]			X	X			X			X				X	
Zhou et al. (2020)	X							X	X				X							X				X[6]			
Wang et al. (2020) (Paper A)	X					X						X			X	X	X	X				X	X				X
Wang and Jochem (2019) (Paper B)	X					X						X			X	X	X	X		X			X				X

Table 2. Literature review of EV charging scheduling studies from micro perspective

note: [1]linear programming; [2]mixed integer linear programming; [3]quadratic programming; [4]dynamic programming; [5]same as objective function; [6]vehicle-to-grid not considered

3.1 Number of EVs considered

The structure of EV charging scheduling models can be classified by the number of EVs considered, i.e., whether the model schedules for multiple EVs or a single EV. The former means that the charging behavior of each EV within the fleet is scheduled for one common goal, while the latter means that a single EV is scheduled for its own interest. The model structure is listed as the first concern because it can (at least partially) determine the applied methodology and the following challenges. For instance, when a model schedules multiple EVs, the uncertainties from future EVs may impact the current scheduling solutions, which does not apply to a model considering a single EV.

Considering the paths to reach the common goal, charging scheduling models for multiple EVs can be further subdivided: centralized vs. decentralized. The centralized way means that charging behaviors of multiple EVs are directly scheduled by a single operator, which is often referred to as the EV aggregator or the EV charging service provider by literature (Zheng et al., 2020). The decentralized way means that multiple EVs decide their own charging schedules while incentivized by the EV aggregator indirectly, e.g., via cost signals (Ensslen, 2019). Although EVs all pursue their own interest whether under the decentralized charging scheduling scheme or the single EV charging scheduling scheme, there is no underlying common goal for the latter.

3.1.1 Multiple EVs

In a new business model, the idea of EV aggregator has been frequently proposed by literature. The EV aggregator can either be the distribution system operator (DSO) itself or a new third-party player acting as a medium between DSO and EV users (Ensslen et al., 2020). Figure 3 illustrates the operating structure of the EV aggregator. First, the DSO monitors the status of the power system. Then the EV aggregator communicates with the DSO or the electricity market and responds accordingly. The EV aggregator would either directly control the charging behaviors of multiple EVs or indirectly influence charging behaviors via price signals as economic incentives.

As shown in Table 2, the centralized way is more opted for by literature as the direct control and can better guarantee the performance expected by the EV aggregator. However, it also sets a higher demand for supporting hardware, such as smart charging infrastructure, especially with vehicle-to-grid (V2G) mode (Chung et al., 2013; IEA, 2020). Furthermore, as controlled charging will utilize EV users' flexibility, their acceptance of the controlled charging strategy is of fundamental importance (Ensslen et al., 2020). Will and Schuller (2016) conclude that, other than financial incentives, user acceptance can be improved by advertising the public benefits of smart charging, designing customized charging tariffs and increasing transparency between EV aggregators and users.

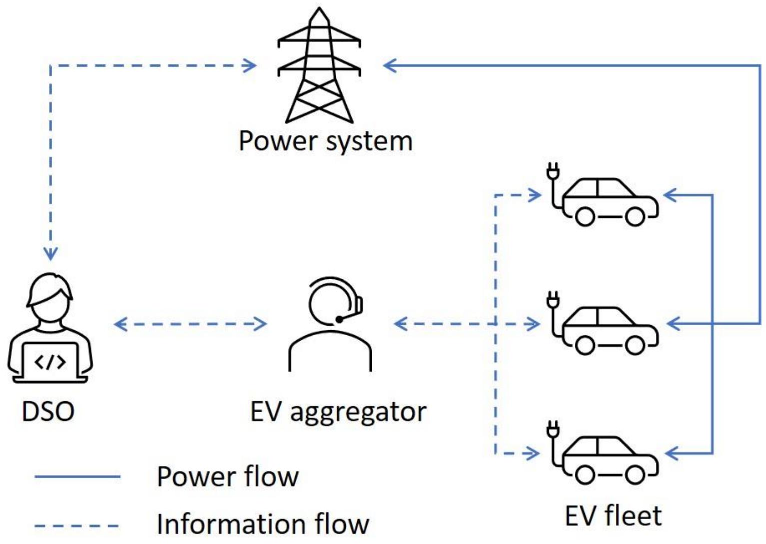

Figure 3. Operating structure of EV aggregator

By contrast, the decentralized way might be easier to implement. For example, the time-of-use (TOU) tariff, which has already been applied by utilities, is a decentralized way for demand side management (Salt River Project, 2015). However, a simple TOU tariff may not be applicable for EV charging scheduling problems. When multiple EVs receive the same incentive from the EV aggregator (mostly cost signals), it is likely that their charging schedules are similar, which may lead to tremendous load peaks (Kaschub, 2017). Such consequences are also referred to as the avalanche effect. In order to avoid such a negative effect, complex and inhomogeneous control signals should be designed for decentralized charging scheduling methods (Dallinger and Wietschel, 2012; Ensslen et al., 2018; Flath et al., 2013; Ramchurn et al., 2012).

In Table 2, both Hu et al. (2016) and Mou et al. (2015) develop time-dependent or demand-dependent charging tariffs (or control signals) to an EV fleet. When the system demand increases, their models can discourage charging behaviors to some extent so that the demand peak is limited. In Ramos Muñoz and Jabbari (2020), the proposed ordering strategy generates inhomogeneous cost signals for each EV within a fleet, depending on the arrival time or the flexibility of each EV. It might be worth analyzing how EV users would respond to the decentralized control mechanisms. For instance, if the flexibility of each EV depends on the intended driving profile and charging targets set by users, EV users in such a setting have the incentive to provide fake or distorted information in exchange for higher charging priority.

3.1.2 A single EV

Models with a single EV considered can be applied either to minimize the charging cost of the EV itself or to interact with other devices of a smart home, such as roof-top PV and stationary battery storage. Both Iversen et al. (2014) and Wu et al. (2016) in Table 2 apply the stochastic dynamic programming method to consider the uncertainty of the single EV's driving patterns. Specifically, the former schedules charging behavior according to the time-varying probabilities of starting a trip in the future. The latter presents an offline lookup table for charging scheduling that incorporates all the future scenarios. The consideration of a single EV is suitable for small-scale optimization problems such as single households or streets, but may lead to computational problems when applied in national optimization problems (Ried et al., 2020).

3.2 Objective function and research topic

Although the objective function of an optimization model has the word "objective" in it, the function itself should rather be regarded as a path to reach the destination, i.e., the fulfillment of the research topic (Vanderbei, 2014). One objective function can be applied for different research topics. Similarly, one research topic can be fulfilled via different objective functions. As can be seen from the studies in Table 2, peak shaving, the most considered research topic in EV charging scheduling, is mainly fulfilled by cost minimization and is also possible via other formulations.

Table 3 further explains how publications in Table 2 formulate the objective functions when applying EV charging scheduling for the research topic of peak shaving. Depending on specific concerns, the broader notion of peak shaving also includes valley filling, load leveling, and load flattening.

Cost minimization is the most common objective function for peak shaving, with different proposals of electricity price by literature. For instance, time-of-use tariffs and real-time pricing can encourage charging behaviors to be shifted to periods with lower cost, and the performances of the applications are also limited by the default setting of the prices (Iversen et al., 2014; Powell et al., 2020; Ramos Muñoz and Jabbari, 2020; Sun et al., 2020; Wu and Sioshansi, 2017). Therefore, some studies would propose customized electricity prices specifically for peak shaving. For example, the electricity price in Guo et al. (2018) monotonically increases over time so that EV users would prefer to charge their EVs as early as possible. The electricity price can also be a function of the current electricity demand so that the demand peak can be limited, which could also complicate the problem by introducing quadratic terms into the objective function (He et al., 2012; Hu et al., 2016; Kaschub et al., 2016).

	Formulation of objective functions	**Comments**	**Literature**
Cost minimization	$min: \sum_{t=1}^{T} c_t \times D_t$	c_t: time-of-use; linear	Iversen et al. (2014); Powell et al. (2020); Muñoz and Jabbari (2020); Sun et al. (2020)
		c_t: real-time pricing; linear	Wu and Sioshansi (2017)
		c_t: monotonically increasing; linear	Guo et al. (2018)
		c_t: a function of D_t; quadratic	Hu et al. (2016); He et al. (2012)
Variance minimization	$min: \sum_{t=1}^{T} (D_t - p)^2$	p: "ideal" demand level; quadratic	Mou et al. (2015)
	$min: \sum_{t=1}^{T} Q_t^2 + \sum_{t=2}^{T} (Q_t - Q_{t-1})^2$ where $Q_t = D_t - p_t$	p_t: "ideal" demand level at time t; quadratic	Sundström and Binding (2012); Paper A; Paper B
	$min: \sum_{t=1}^{T} \lvert Q_t \rvert + \sum_{t=2}^{T} \lvert Q_t - Q_{t-1} \rvert$ where $Q_t = D_t - p_t$	p_t: ideal demand level at time t; nonlinear, linearization possible	
Others	$min: \max_{t \in T} D_t$	linear	Ghotge et al. (2020)
	$min: (\max_{t \in T} D_t - \min_{t \in T} D_t)$	linear	Zhou et al. (2020)

Table 3. Formulations of objective functions for peak shaving in EV charging scheduling

Note: c_t is the electricity price at time t; D_t is the demand at time t

Other than cost minimization, some publications have also proposed to apply variance minimization or other forms of formulation as the objective function. These formulations are more straightforward in managing the EV demand curve and do not rely on the setting of electricity prices (cf. Table 3). Although the electricity price is not explicitly included in these objective functions, financial incentives are still implicitly considered by these studies. As a result, EV users participating under the controlled charging strategy can benefit from a cheaper charging tariff than under the uncontrolled one.

Variance minimization aims to minimize the distance between two curves. One is the actual demand curve, representing only the EV demand or the total demand (including non-EV demand). The other is the ideal or preferred demand curve. The various settings of this ideal curve provide multiple applications. For instance, the ideal curve in Mou et al. (2015) is time-independent and only achieves peak shaving, while the time-dependent setting in Sundström and Binding (2012) can further achieve the integration of renewable energy. Variance minimization can be formulated by either quadratic terms or absolute values, which are equivalent in terms of solution performance. However, the former brings more computational complexity while the latter can be linearized, as in Sundström and Binding (2012).

Although less common, there are also other forms of objective functions for peak shaving. For the ones proposed in Table 3, the performance of the demand below the peak might not be guaranteed as they only decrease the peak demand literally. In Ghotge et al. (2020), the proposed controlled charging strategy significantly decreases the peak demand compared with the uncontrolled charging strategy. However, its demand profile is rather fluctuating compared with the perfect forecasting scenario. When the concern is within a relatively small scale, such as peak shaving for a transformer, the fluctuation of the demand might not matter (Ghotge et al., 2020; Wu and Sioshansi, 2017).

3.3 The consideration of EV uncertainties in optimization models

As discussed in Section 3.1, the major model structure that this thesis focuses on for charging scheduling is a centralized model including multiple EVs[3]. For such a model structure and in terms of EV uncertainties, multiple EVs can be classified into two categories: current EVs and future EVs. Current EVs refer to EVs which are currently connected to the grid, while future EVs refer to those which may arrive in the future and join the group for charging scheduling. In principle, the departure time of the current EVs may still be uncertain to the EV aggregator. Nevertheless, a common and reasonable assumption from literature is that current EVs, with proper financial incentives, are willing to inform the EV aggregator of their expected SOC by departure and to guarantee their (earliest) departure time (He et al., 2012; Sharifi et al., 2020; Sundström and Binding, 2012; Wu and Sioshansi, 2017). Furthermore, Hahn el et al. (2013) have concluded that EV users can accurately provide such future information (although with predicting errors). Accordingly, the main concern by the literature is how to handle the uncertainties from future EVs, i.e., their usage behaviors (arrival and departure time) and their charging demand (arrival and departure SOC).

As pointed out by He et al. (2012), there are two extreme scheduling schemes on how to (indirectly) consider future EV uncertainties by deterministic optimization: global optimum and local optimum. Global optimum means that the model knows perfect information about future EVs and takes them into consideration. Perfect foresight is a strong simplification of reality and may lack practicability. It might theoretically show the best case of EV load shifting potential while the gap between reality and this prospect remains unclear. Publications

[3] The charging scheduling for a single EV with stochastic dynamic programming can better model and consider the uncertain availability of the single EV. As proposed by Iversen et al. (2014) and Wu et al. (2016), the future research of this methodological path might focus on applying the method to EV fleets.

presenting globally optimal scheduling solutions are also aware of such drawbacks and suggest that uncertainties from future EVs should be considered in future research (Gottwalt et al., 2017; Powell et al., 2020; Schuller et al., 2015; Sundström and Binding, 2012; Zhou et al., 2020).

By contrast, local optimum, although aware of the uncertainties from future EV, considers only the current EVs for charging scheduling. When the optimization horizon of a locally optimal scheduling scheme is relatively short, e.g., 8 hours (Su et al., 2020), 24 hours (Hu et al., 2016), or equal to the latest departure time of the current EVs (He et al., 2012; Sharifi et al., 2020), these publications argue that it might be acceptable to overlook the impact from future EVs. It is noteworthy that He et al. (2012) compare the solutions with global and local optimum, and the resulting differences could be narrowed by considering the uncertainties from future EVs.

Robust optimization and stochastic optimization are two optimization methods that can schedule charging behaviors of current EVs while considering the uncertainties from future EVs. The two methods have their respective focuses (Kazemzadeh et al., 2019). Robust optimization focuses more on the solution performance under the worst-case scenario and is more applied for peak reduction from the grid perspective. For instance, Ghotge et al. (2020) optimize EV charging behaviors to reduce peak demand of parking lots and consider the uncertainties from future EVs and PV arrays, while Sun et al. (2020) focus on satisfying the constraints of low voltage distribution networks. These two papers only reduce the peak demand literally without further considering load fluctuations.

Stochastic optimization calculates the solution by considering the scenarios (possible realizations) of the future information. Each scenario has weighted probabilities, which can also be simplified as a deterministic problem by considering the expectation value of the future. Specifically, the scenario-based two-stage stochastic optimization method is a good fit for the EV charging scheduling problem. The first stage refers to the current time slice depending on the temporal resolution of the model. Information of the first-stage parameters is certain, and the first stage variables concerning EVs are the current EV charging solutions only for the first (current) time slice. The second stage represents the rest of the time slices. Future EVs may join the optimization model starting from the second time slice, while information of the parameters on the second stage are all uncertain, including the arrival and departure time of future EVs and their SOC status. By comprehensively considering the uncertainties from the second stage, the two-stage stochastic optimization model makes one decision for the first stage.

However, there do not seem to be many studies applying the two-stage stochastic optimization method for EV charging scheduling and considering the uncertainties from future EVs. Bandpey and Firouzjah (2018) propose a two-stage charging scheduling framework but consider only the current EVs. Heydarian-Forushani et al. (2016) investigate the interaction between the grid and EV parking lots for wind energy integration, which is a bidding strategy problem but not for charging scheduling. Seddig et al. (2019) minimize EV charging cost at charging stations with PV while considering the uncertainties from PV generation and the demand of current EVs. Wu and Sioshansi (2017) consider the uncertainty of future EVs' arrival time. However, the parking duration of all EVs in this paper is assumed to be identical so that the uncertainty of future EVs' departure time is not considered.

Scenario generation and scenario reduction techniques are the prerequisites for applying the scenario-based stochastic optimization method (Henrion and Römisch, 2018). For scenario generation, different variants of Markov chains have been applied to simulate EV usage patterns by estimating the transition matrix of EV usage states from historical data (Iversen et al., 2017; Sun et al., 2018; Sundström et al., 2012; Wu et al., 2016). Queuing theory is also proposed to describe the EV usage behavior as a homogeneous or non-homogeneous Poisson process and to calculate the arrival and departure rates (Hafez and Bhattacharya, 2018; Kongjeen and Bhumkittipich, 2016). Huber et al. (2020) describe a quantile-base forecaster for the parking duration and next trip distance of EVs. The artificial neural network is also a promising option for forecasting future trip information, especially when coupled with machine learning and big data techniques (Akhavan-Rezai et al., 2018; Jahangir et al., 2019; Liu et al., 2021).

Forecasting or scenario generation methods for future EV availability have a significant impact on the result performance for EV charging scheduling models, regardless of specific model designs. Due to its importance, EV trip prediction has also received increasing attention in current literature (Akhavan-Rezai et al., 2018; Huber et al., 2020; Jahangir et al., 2019; Liu et al., 2021; Sundström et al., 2012). The rapid EV adoption would provide such methods with large-scale empirical data for developing, testing and application.

More scenarios can better describe and cover the future uncertainties in theory, but a large number of scenarios may also increase computational complexity in practice. Therefore, scenario reduction methods are introduced to simplify the original scenario set. The basic principle of the scenario reduction technique is to select scenarios closer to the others as representatives and then adjust the weights of these representative scenarios accordingly. Various scenario reduction techniques may differ in how to mathematically define the distance between scenarios and how to select representative scenarios. Typically, scenario reduction techniques can be classified into two groups, i.e., forward selection and backward reduction methods. Forward selection methods would iteratively select scenarios that can represent others, while backward reduction methods would iteratively delete scenarios that can be represented by others. For instance, Feng and Ryan (2013) apply a fast forward selection method for a stochastic power generation expansion planning problem. The method first calculates the Euclidean distance for every two scenarios and selects one scenario closest to the other scenarios. Iteratively, a group of representative scenarios is selected, and then all the unselected scenarios give their weights to the closest scenarios within the representative group. Sharma et al. (2013) apply a variant of backward reduction methods to reduce the number of wind generation scenarios considered. They use the Kantorovich distance matrix to measure the probability distance between different scenario sets. Scenarios are then deleted to the maximum extent under a given tolerance criterion.

3.4 Rolling window approach

The rolling window approach (or model predictive control) is a control algorithm to calculate optimization problems in an online manner, which has wide applications in many industries (Mehta and Reddy, 2015; Song et al., 2020). Its basic principle is illustrated in Figure 4. Instead of optimizing once over the whole horizon, the rolling window approach optimizes over a limited time span which can be fixed as W time slices in Figure 4 or flexible (He et al., 2012). The optimization problem is calculated iteratively (the rolling of the optimization window). Parameters are updated in every new iteration so that only the solutions for the first time slice of every iteration are carried out.

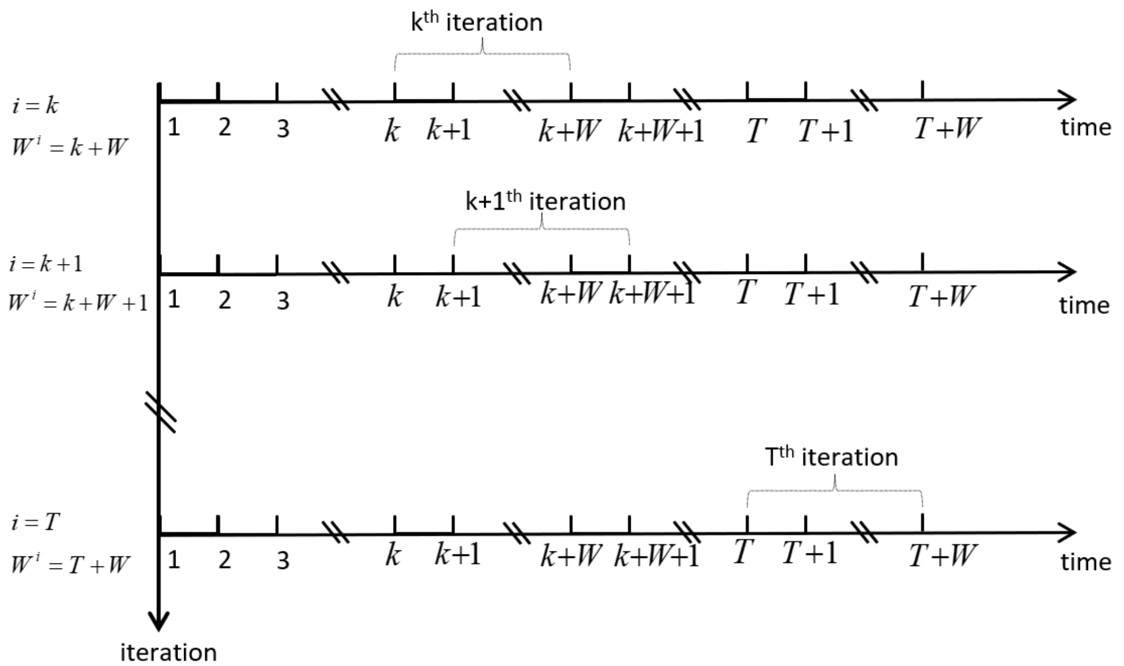

Figure 4. Illustration of the rolling window approach (from Wang et al. (2020))

As shown in Table 2, global optimum does not need the rolling window approach as it assumes perfect foresight for the future and optimizes over the entire time span. By contrast, some studies combine a locally optimal scheduling scheme with the rolling window approach, and they argue that the impact of the neglected uncertainties from future EVs can be handled by the frequent update of model information. However, Ghotge et al. (2020) and Wu and Sioshansi (2017) not only apply the rolling window approach but also consider the uncertainties from future EVs, which improves the results accordingly.

EV charging scheduling is a real-time demand side management problem and has a natural coupling with the rolling window approach. Mathematically, it can be described as follows: Let $x_{k,t}$ denote[4] the solution of an EV charging scheduling model from k^{th} iteration at time slice t. The set A_k for all the solutions from k^{th} iteration is

$\{x_{k,t}|t = k, k + 1, \dots, k + W - 1\}$,

where W is the number of time slices for a rolling window (Figure 4). As only the solution from the first time slice of each iteration ($x_{k,k}$) is carried out, the set B for these implemented solutions is

$\{x_{k,k}|k = 1,2, \dots, T\}$,

where T is the entire time span of the optimization model. Therefore, the demonstration of an EV charging scheduling model should be assessed by its performance with the rolling window approach (the set B), but not based on the solution of one iteration only (the set A_k). Since A_k is the direct solution of every iteration and B is only a collection of the first-stage solutions of all the iterations, the performance of B might not be directly guaranteed by the optimization model.

For some objective functions, the demonstration by either A_k or B may be equivalent. For instance, the objective function in Wu and Sioshansi (2017) is to minimize the total cost, and its research topic is peak demand minimization (cf. Table 2 and Table 3). The optimization in every iteration is based on the local and updated information and the assumptions for future uncertainties. For such a problem setting, the optimum of every iteration (A_k) can guarantee the optimum over the entire time span (B), although the set B is not directly optimized.

However, for the research topic of load flattening (one specific application of variance minimization), the flattened curve calculated by every iteration is A_k. Because of the information update with the rolling window approach, every element in A_k may all be flattened but on different levels (with different values) so that the set B could be fluctuated. Under such a condition, the performance of the model may not be guaranteed.

[4] Notations in the thesis only apply for their local subsections, unless otherwise specified.

Such fluctuations can be alleviated by the consideration of EV uncertainties (cf. Section 3.3) and by the proper setting of the rolling window span, i.e., the parameter W in Figure 4 especially. Table 4 shows the temporal settings in literature with the rolling window approach from Table 2. As can be seen, most studies have the same temporal resolution and update interval. When the only parameter update for local optimum is the arrival of new EVs, it may also be reasonable to update the solutions when new EVs arrive (Hu et al., 2016; Mou et al., 2015). When the uncertainties of future EVs are considered, the scenarios of the future information can also be updated, even if there is no EV arrival in the upcoming intervals. When it comes to the setting of the rolling window, the selections from literature seem rather diversified. Statistically, the EV usage behavior is, to some extent, periodic by one day, although more differentiated between weekdays and weekends (Schäuble et al., 2017). Suppose the rolling window is not (a multiple of) 24 hours, the solution A_k and A_{k+1} can both be flat but at different levels when the number of current EVs changes. This would result in unnecessary fluctuations in the actual solution B. Load flattening can be taken as a particular application of variance minimization when the ideal curve in Table 3 is set to zero. Therefore, when the objective function is variance minimization, it might be reasonable to set the rolling window to 24 hours but not shorter.

Literature	Temporal resolution (minutes)	Update interval (minutes)	Durance of Rolling window W (hour)
Ghotge et al. (2020)	15	15	24
He et al. (2012)	60	60	Dynamic, to the last EV to leave
Hu et al. (2016)	15	15[1]	24
Iversen et al. (2014)	1	1	48
Mou et al. (2015)	8.57[2]	8.57[1]	24
Sharifi et al. (2020)	60	60	Dynamic, to the last EV to leave
Su et al. (2020)	15	15	8
Wu and Sioshansi (2017)	1	1	1
Paper A	15	15	24
Paper B	15	15	24

Table 4. Parameter settings for the rolling window approach.

Note: Information from Guo et al. (2018) in Table 2 not specified. [1]or when new EV arrive and get connected; [2]the temporal resolution of the paper assumes 7 time slices per hour

4 Macro perspective: integrating EV into energy system models

In terms of modeling granularity, the macro perspective means that EVs are aggregately formulated, i.e., there is no index for individual vehicles. Content-wise, EV aggregation methods are often applied in macro-scale problems, when it may not be necessary to investigate the charging behaviors of individual vehicles, but rather their impacts on power system expansion planning (Heuberger et al., 2020), GHG emission reduction (Densing et al., 2012) or the integration of renewable energy (Chen et al., 2018). In terms of operations research, the feasible solution spaces (polytopes) by the individual EV modeling method can be exactly summed up by methods such as the Minkowski sum (Ried et al., 2020). However, Ried et al. (2020) point out that calculating the exact Minkowski sum is an NP-hard problem, so that the computational time will exponentially increase with the number of EVs included and the number of time slots considered (Tiwary, 2008). Therefore, EV aggregation methods are proposed to approximate the performance of the individual EV modeling method. These approximation methods, unfortunately, would result in a bias toward the load shifting potential of individual EVs.

Section 4.1 highlight the importance of applying EV aggregation methods with a motivational research topic. Section 4.2 presents the common EV aggregation methods in literature.

4.1 Motivational research topic: EV emission assessment

As a motivation, Section 4.1.1 introduces the fundamentals in assessing vehicles emissions (both ICEV and EV) and points out the unique methodological challenges in assessing emissions by EVs. Section 4.1.2 discusses the common practices by current literature in assessing EV emissions.

4.1.1 Methodological challenges in determining the electricity mix

GHG emission reduction has been a major motivation for the electrification of the transport sector (Leard and Mcconnell, 2020). Märtz et al. (2021) conclude that a very early EV market diffusion could significantly reduce the GHG emission in vehicle usage and meet the remaining carbon budget globally. However, this challenge is dependent on the emissions from vehicle production (which is the focus of the life cycle assessment (LCA)) and the emissions during the vehicle usage phase (which is the focus of the well-to-wheel (WTW) analysis). While LCA additionally considers the energy use and emission in building facilities and vehicles and their recycling and disposal, WTW focuses on the entire production chain of the fuels (Edwards et al., 2014) and is more related to the concern of the thesis.

In general, the WTW analysis of a vehicle (ICEV or EV) can be divided into two processes, as illustrated in Figure 5 (Woo et al., 2017). For ICEV, the first stage of WTW analysis includes mining, transporting, and storing of the energy to the vehicle, i.e., well-to-tank (WTT); the second stage includes driving the vehicle with the stored energy, i.e., tank-to-wheel (TTW). The two stages for EV are similar, i.e., well-to-plant (WTP) and plant-to-wheel (PTW), respectively.

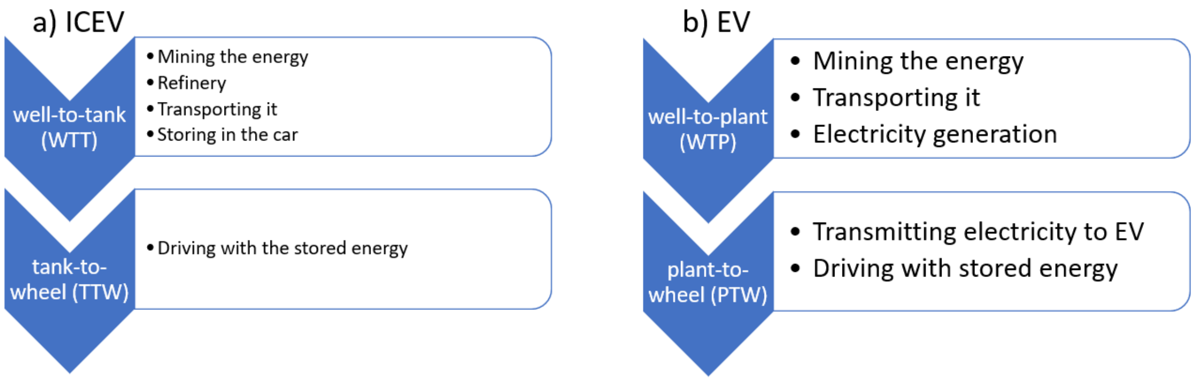

Figure 5. WTW processes of ICEV (left) and EV (right)

The WTW emissions of ICEV and EV ($Emission^{WTW\_ICEV}$ and $Emission^{WTW\_EV}$) can be calculated by Eq. (S4.1) and Eq. (S4.2), respectively. In Eq. (S4.1), $Emission^{WTT\_ICEV}$ and $Emission^{TTW\_ICEV}$ denote ICEV emission from WTT and TTW processes, respectively, and are measured in the unit of g CO_2 eq/L. η^{ICEV} represents the fuel efficiency of ICEV, measured in the unit of L/km. In Eq. (S4.2), $Emission_s^{WTP\_EV}$ and $Emission^{PTW\_EV}$ denote EV emission from WTP and PTW process, respectively, measured in the unit of g CO_2 eq/kWh. Additionally, the first terms is indexed by the source of the electricity s and is therefore multiplied by the percentage of each source of electricity (π_s), such as coal, PV and nuclear. η^{EV} is the electricity efficiency of EV, measured in the unit of kWh/km.

$$Emission^{WTW\_ICEV} = (Emission^{WTT\_ICEV} + Emission^{TTW\_ICEV}) \times \eta^{ICEV} \quad \text{(S4.1)}$$

$$Emission^{WTW\_EV} = (\sum_s \pi_s \times Emission_s^{WTP\_EV} + Emission^{PTW\_EV}) \times \eta^{EV} \quad \text{(S4.2)}$$

Compared with the conventional practice of analyzing WTW emission of ICEV, π_s, i.e., the electricity mix of EV usage, is a newly introduced factor and might bring additional challenges in analyzing WTW emission of EV. Different from conventional gasoline or diesel for ICEV, electricity, in some sense, is a rather “hybrid” fuel, as its environmental impact greatly depends on the primary source of energy[5]. Furthermore, instead of being static data from statistics, the electricity mix changes significantly over time and might be greatly determined

[5] ICEVs might also be energized by synthetic fuels or biofuels so that their environmental performances could be improved (Hänggi et al., 2019; Ternel et al., 2021). This topic is beyond the scope of the thesis.

by its assessment target, as illustrated by Figure 6. Therefore, it may be worth considering the time-specific character of the electricity mix (cf. Jochem et al., 2015a and Section 4.1.2).

As discussed in Section 2, the load shifting potential of EVs can be utilized by significantly changing the charging patterns. In the short run or instantaneously, EVs can “select” the charging periods. For instance, Miller et al. (2020) analyze the EV emission of US by regional US grid data and conclude that overnight EV charging in California and New York produce 70% more and 20% fewer emissions than daytime charging, respectively. When the flexibility of EV patterns is considered in the power system investment planning problem, the electricity system may also be influenced in the long run (Sterchele et al., 2020). This unique challenge is not faced with by conventional emission assessment for ICEV.

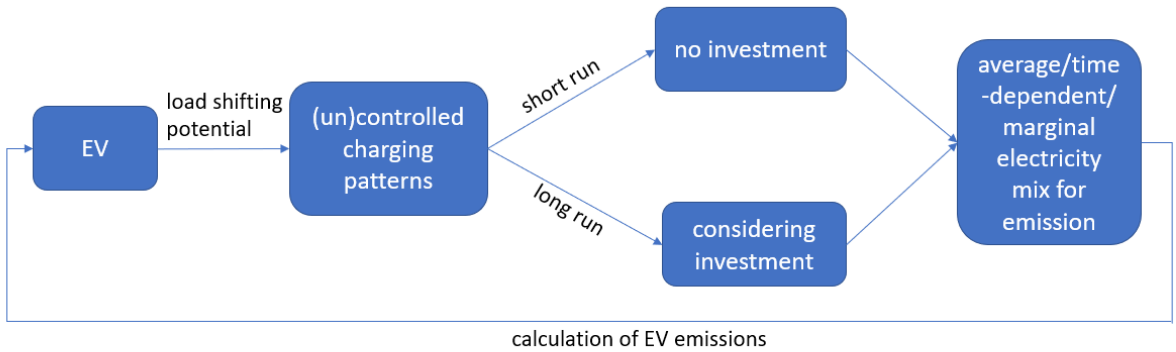

Figure 6. Decision process in EV emission assessment

4.1.2 Practices by literature

Table 5 gives an overview of literature analyzing EV emission assessment and focuses on the selection of the electricity mix for assessment, the consideration of the impact from EV charging patterns, and the flexibility of the assessment methods.

So far, there is no consensus on which electricity mix to select on assessing the GHG emission from EV, and three common options clarified by Jochem et al. (2015a) are listed as follows:

1. Annual average mix: a simple yet commonly adopted method that uses the national or regional average mix. This value will be multiplied by the total EV charging demand.
2. Time-dependent average mix: using the time-dependent (mostly hourly in literature) electricity mix when EVs are charged. This value will be multiplied separately by the EV charging demand at the same time slice. Time-specific characters are considered because the type of dispatched power plants greatly varies by time and the generation profile, and the corresponding GHG emissions from electricity may be rather time-dependent (as in Figure 7). Therefore, the use of annual average mix may result in bias.
3. Marginal mix: the additional electricity generation specifically due to the demand increase from EV charging. This value is achieved by comparing the electricity

generation profile with and without additional EV demand, which provides a more accurate assessment.

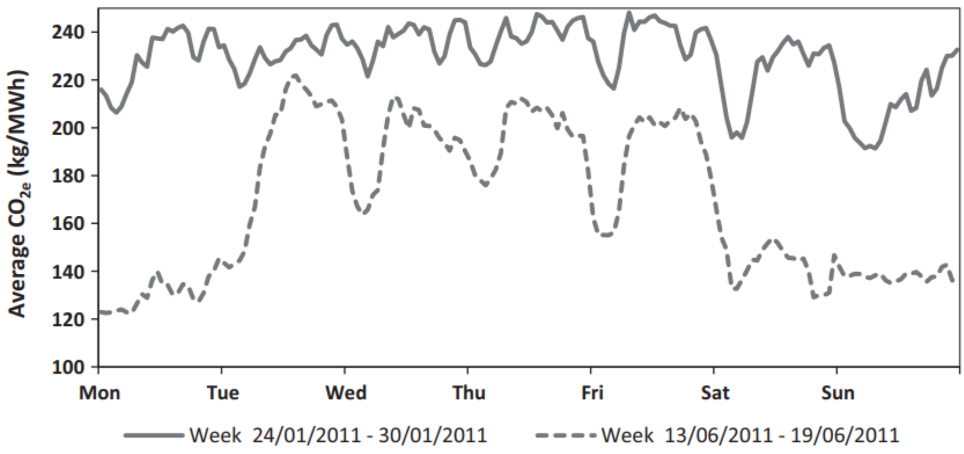

Figure 7. CO_2 equivalent emission of electricity in typical wind and summer weeks in 2011, Belgium (Rangaraju et al., 2015)

In addition, Bauer et al. (2015) highlight the importance of using electricity from "clean sources" by comparing the environmental impacts of EV operated with electricity from different sources separately, as shown in Table 5.

Studies may also differ in their approaches to consider the impacts from EV charging patterns which can be classified by the degree of control, i.e., uncontrolled, unidirectional controlled (EV discharging not considered), and bidirectional controlled (i.e., V2G). Some studies would artificially design specific charging strategies as scenarios of charging patterns, such as off-peak charging and postponed charging (Van Vliet et al., 2011). If vehicle discharging is not considered, they would all be taken as unidirectional. The flexibility in Table 5 denotes the overall flexibility of a study, i.e., whether EV charging patterns can flexibly influence or determine the electricity mix used for assessing the EV emissions.

	Case study (location/timeframe[1])	Selection of electricity mix				Consideration of charging patterns				Flexibility	
						No	Yes				
		By single energy source	Annual average	Time-dependent average	Marginal		Uncontrolled	Unidirectional controlled	Bidirectional controlled	No	Yes
Alimujiang and Jiang (2020)	Shanghai, China/-		X			X				X	
Arvesen et al. (2021)	EU/2050			X	X			X[2]			X
Bauer et al. (2015)	EU/2030	X				X					X
Burchart-Korol et al. (2020)	EU/2050		X			X				X	
Casals et al. (2016)	EU/-		X			X				X	
Chen et al. (2018)	Beijing, China/2020				X				X		X
Cox et al. (2018)	Globe/2040		X[2]			X				X	
Donateo et al. (2015)	Rome, Italy/-			X			X			X	
Ensslen et al. (2017)	EV Fleet/-			X[3]			X			X	
Falcão et al. (2017)	Single vehicle/-		X			X				X	
Gai et al. (2019)	Toronto, Canada/-				X		X[2]	X		X	X
García Sánchez et al. (2013)	Spain/2030		X[2]			X				X	
Held and Schücking (2019)	EV fleet/-		X[3]			X				X	
Hoehne and Chester (2016)	US/-				X[3]		X		X	X	
Huo et al. (2015)	China; US/-		X[3]			X				X	
Jochem et al. (2015a)	Germany/2030		X	X	X		X	X			X
Kamiya et al. (2019)	Canada/2050			X	X		X[2]			X	X
Krause et al. (2020)	EU/2050		X			X				X	
McLaren et al. (2016)	US/-			X[3]			X[2]			X	
Miller et al. (2020)	US/-			X[3]			X[3]			X	
Naranjo et al. (2021)	Spain/2050		X			X				X	
Plötz et al. (2018)	EV fleet/-		X			X				X	
Rangaraju et al. (2015)	Belgium/-			X			X[3]			X	
Schill and Gerbaulet (2015)	Germany/2030				X		X	X			X[4]
Van Vliet et al. (2011)	Netherlands/-				X		X	X		X	
Weis et al. (2016)	PJM[5], US/2018			X			X	X			X
Wolfram and Wiedmann (2017)	Australia/2050		X[2]			X				X	
Wu et al. (2018)	China/2020		X[2]			X				X	
Xiong et al. (2019)	China/2030		X			X				X	
Xue et al. (2021)	Japan/2030		X[2]			X				X	
Yang et al. (2021)	China/-		X[2]			X				X	
Zhang and Hanaoka (2021)	China/2060		X			X				X	
L. Xu et al. (2020b) (Paper C)	EU/2050				X		X	X	X		X

Table 5. Literature review on determining electricity mix for EV emission assessment

[1]projected year of the case study specified; [2]multiple scenarios; [3]multiple statistical profiles considered; [4]future installed capacity of renewable energy determined by scenarios; [5]PJM: an independent system operator for multiple US states

Logically, there are some fixed combinations in the selections of the three methodological options in Table 5, i.e., the selection of electricity mix, the consideration of the charging patterns, and the overall flexibility of the methodology:

1. When the annual average electricity mix is selected, considering the total EV demand might suffice. As a simple estimation, this is most seen in literature (Alimujiang and Jiang, 2020; Burchart-Korol et al., 2020; Canals Casals et al., 2016; Cox et al., 2018; Falcão et al., 2017; García Sánchez et al., 2013; Held and Schücking, 2019; Huo et al., 2015; Krause et al., 2020; Plötz et al., 2018; Naranjo et al., 2021; Wolfram and Wiedmann, 2017; Wu et al., 2018; Xiong et al., 2019; Xue et al., 2021; Yang et al., 2021; Zhang and Hanaoka, 2021). Additionally, Jochem et al. (2015a) analyze the EV emission under different charging patterns with different assessment methods so that multiple options of electricity mix are checked.
2. When a study would further consider the time difference of the electricity mix (whether time-dependent average or marginal), the EV charging patterns shall be considered. A majority of literature would consider uncontrolled or unidirectional control charging patterns and may consider multiple profiles from statistics, simulations, assumptions or scenarios (Arvesen et al., 2021; Gai et al., 2019; Jochem et al., 2015a; Kamiya et al., 2019; McLaren et al., 2016; Miller et al., 2020; Rangaraju et al., 2015; Schill and Gerbaulet, 2015; Van Vliet et al., 2011; Weis et al., 2016). However, the EV emission assessment under bidirectional controlled charging patterns is so far less discussed (Chen et al., 2018; Hoehne and Chester, 2016).
3. Concerning the overall flexibility of the methodology, literature focusing on the emission assessment for the present primarily determine the electricity mix passively (i.e., the EV charging patterns have no impact on this electricity mix) so that they would take the historical data from statistics (Alimujiang and Jiang, 2020; Canals Casals et al., 2016; Donateo et al., 2015; Ensslen et al., 2017; Falcão et al., 2017; Held and Schücking, 2019; Hoehne and Chester, 2016; Huo et al., 2015; McLaren et al., 2016; Miller et al., 2020; Plötz et al., 2018; Rangaraju et al., 2015; Van Vliet et al., 2011; Yang et al., 2021). Additionally, one of the EV charging scenarios in Gai et al. (2019) is that EVs are charged when the emission factor of the marginal electricity mix is lowest (if possible) so that the electricity mix of this charging pattern is considered to be actively determined.
4. Literature focusing on the emission assessment in the long term can passively design scenarios for the future electricity mix (Burchart-Korol et al., 2020; Cox et al., 2018; García Sánchez et al., 2013; Geng et al., 2019; Puig-Samper Naranjo et al., 2021; Wolfram and Wiedmann, 2017; Wu et al., 2018; Xiong et al., 2019; Xue et al., 2021; Zhang and Hanaoka, 2021). By contrast, the emerging trend is to integrate EV into

energy system models so that EV will have an impact on the future electricity structure and the future electricity mix for EV use can be actively determined (Arvesen et al., 2021; Chen et al., 2018; Jochem et al., 2015a; Schill and Gerbaulet, 2015; Weis et al., 2016). Kamiya et al. (2019) assess the EV emission from both a short-term and a long-term perspective, which uses historical data (passive) and solutions of an energy-economy model (active) for the respective electricity mix.

Table 5 shows that an improved assessment of EV emission requires a further investigation of the charging patterns and a flexible and synergistic determination of the electricity mix, which can be achieved by coupling EV module with energy system models.

4.2 Current methodologies in literature

The motivational research topic of Section 4.1 has shown that EV charging patterns would proactively influence the electricity mix for assessing EV emissions. Therefore, to generalize the methodological challenge in the previous section, Section 4.2 investigates how charging patterns of an EV fleet are considered in energy system models from the macro perspective. Different from the micro perspective, which aims to calculate specific charging scheduling solutions for individual EVs, the macro perspective would instead take the overall charging patterns as “auxiliaries” in order to calculate the consequential or targeted outcomes, such as electricity mix, system cost or expansion plan. Moreover, it might not be computationally possible to model EVs individually in a large-scale optimization problem.

Table 6 lists studies that aggregately consider EV charging patterns in optimization models from the macro perspective. Content-wise, EV aggregation methods have been applied in a wide range of topics, although many research topics are rather interrelated. For example, most optimization models minimize the total system cost; controlled charging belongs to the topic of demand side management by definition; system expansion planning is a common research topic for the energy system analysis in the long term. If loosely selected, most literature would incorporate multiple research topics, which might not be informative. Therefore, Table 6 would only select the most relevant topics (two at most). Even so, it can be seen that renewable energy integration is the most considered research topic for applying EV aggregation methods, followed by emission assessment or reduction.

	Research topic (focus)									Exogenous			Endogenous						
															Aggregation methods				
	Emission assessment/reduction	RES integration	System cost reduction	Infrastructure needs	EV deployment	Demand side management	Market participation	System expansion planning	Sector coupling	Uncontrolled	Unidirectional controlled	Bidirectional controlled	Unidirectional controlled	Bidirectional controlled	Dynamic EV fleet	Aggregated boundary	Rescheduled daily demand	Postponed charging	Representation (scale of original problem/ number of representative EVs)
Arvesen et al. (2021)	X	X									X[2,3]								
Beltramo et al. (2017)		X	X							X[1,4]				X					Netherlands / 2215
Chen et al. (2018)	X	X												X		X			
Colbertaldo et al. (2020)				X						X[1,4]									
Densing et al. (2012)					X					X[1,3]									
Fattori et al. (2014)		X								X[1,4]			X	X	X				
Gunkel et al. (2020)		X						X		X[1,4]			X	X	X				
Heinisch et al. (2021)									X	X[1,4]			X	X	X				
Heuberger et al. (2020)		X			X						X[2,3]								
Jochem et al. (2015a)	X									X[1,4]			X				X		
Jovanovic et al. (2021)						X							X						3 million EVs / 200
Luca de Tena and Pregger (2018)		X								X[1,4]			X	X	X				
Lund and Kempton (2008)		X									X[1,3]		X	X	X				
Manríquez et al. (2020)							X			X[2,4]			X	X			X		
Masuta et al. (2014)		X				X					X[1,3]		X				X		
Pavić et al. (2015)							X			X[1,4]				X					3 million EVs / 1
Schill and Gerbaulet (2015)	X	X								X[1,4]			X		X				
Soares et al. (2017)							X							X					1300 EVs / 100
Sterchele et al. (2020)									X	X[1,4]				X	X				
Szinai et al. (2020)	X	X								X[1,4]	X[1,4]		X			X			
Taljegard et al. (2019)								X					X	X					Scandinavia, Germany / 200
Weis et al. (2015)	X		X							X[1,4]			X						PJM / 20
Wulff et al. (2020)		X							X	X[1,4]				X	X				
L. Xu et al. (2020b) (Paper C)	X	X								X[1,4]			X	X				X	
Wang et al. (2021) (Paper D)	Method development, demonstration and comparison													X	X	X		X	

Table 6. Literature review for methods to integrate EVs into energy system models from the macro perspective

Note: [1]Single profile considered; [2]multiple profiles considered; [3]based on simple assumptions; [4]based on statistical data or simulation results

Methodologically, the consideration of charging patterns for EV fleet can be classified from two aspects:

1. Which charging strategies are considered, i.e., uncontrolled charging, unidirectional controlled charging, or bidirectional controlled charging.
2. How EV charging patterns are determined, i.e., exogenously from references or by assumptions, or endogenously by the optimization model where EV aggregation methods would be applied (cf. Section 4.2.1 and 4.2.2 respectively).

4.2.1 EV demand exogenously determined by energy system models

For uncontrolled charging strategy, charging patterns can only be determined exogenously by data from statistics, field tests, or simulation results and are taken as parameters for the optimization model (marked with X^4 in Table 6). In Manríquez et al. (2020), the multiple profiles of uncontrolled charging patterns refer to different scenarios of EV penetration (marked with X^2 in Table 6). Some literature would end here without further considering any controlled charging strategies (Colbertaldo et al., 2020; Densing et al., 2012).

For studies that further consider controlled charging strategies, only a few still have unidirectional controlled patterns exogenously determined. The majority of these studies would simply assume unidirectional charging patterns (Arvesen et al., 2021; Heuberger et al., 2020; Lund and Kempton, 2008; Masuta et al., 2014), while Szinai et al. (2020) generate a unidirectional controlled charging pattern under time-of-use tariff with a transportation simulation model. So far, no research seems to have bidirectional controlled charging patterns exogenously determined.

4.2.2 EV demand endogenously determined by energy system models

When charging patterns are endogenously determined, Table 6 separately shows which controlled strategies are considered and which EV aggregation method is applied. For controlled charging strategies, the unidirectional one can be taken as a simplified version of the bidirectional one. Therefore, aggregation methods for bidirectional charging strategy are "backward-compatible" (by setting EV discharging energy to zero), although respective studies may not consider the unidirectional charging strategy (Beltramo et al., 2017; Chen et al., 2018; Pavić et al., 2015; Soares et al., 2017; Sterchele et al., 2020; Wulff et al., 2020). By contrast, if an EV aggregation method is only developed for the unidirectional charging strategy, this method may require further improvement for additional applications under bidirectional charging strategies (Jochem et al., 2015a; Jovanovic et al., 2021; Masuta et al., 2014; Schill and Gerbaulet, 2015; Weis et al., 2015). Although Szinai et al. (2020) only consider the unidirectional charging strategy, their adopted method is developed for bidirectional charging strategies.

Since considering EVs as a whole can be taken as a simplification of reality (individual EV modeling), multiple EV aggregation methods have been proposed by literature with various forms of formulations. Please note that the classification of Table 6 is only by the basic ideas that these papers may share on how an EV aggregation method should be formulated in general. Even within the same category, different papers may still vary by the specific formulations, certain parameter settings, and assumptions. So far, five EV aggregation methods are summarized from the literature. By referring to their fundamental ideas respectively, these five methods can be named as "dynamic EV fleet", "aggregated boundary", "rescheduled daily demand", "postponed charging", and "representation".

4.2.2.1 Dynamic EV fleet method

The "dynamic EV fleet" method aims to model all individual EVs as an aggregated one. This is a rather natural idea on how EV aggregation methods should be developed and is widely shared by literature (Fattori et al., 2014; Gunkel et al., 2020; Heinisch et al., 2021; Luca de Tena and Pregger, 2018; Lund and Kempton, 2008; Schill and Gerbaulet, 2015; Sterchele et al., 2020; Wulff et al., 2020).

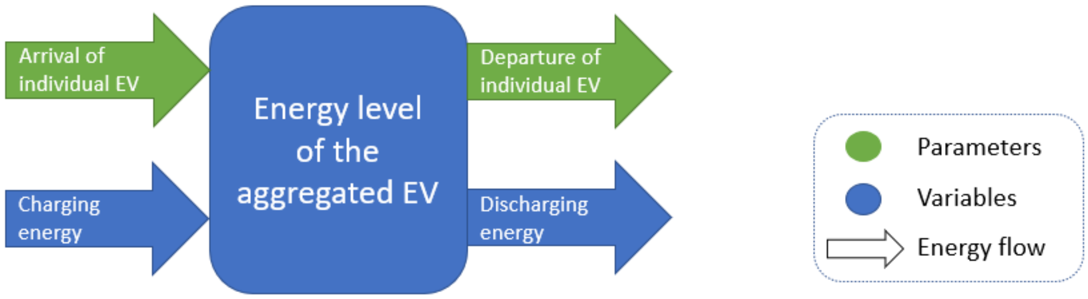

Figure 8. Illustration for the "dynamic EV fleet" method

Formulations for this aggregated EV can be partially inspired by the experience of modeling a single EV, while this aggregated EV still has its unique features if compared with a single one. On the one hand, the energy level of the aggregated EV is increased by the arrival of individual EVs with their initial SOC status and the decision to charge this aggregated EV, as illustrated in Figure 8. On the other hand, its energy level will be reduced by the departure of individual EVs with their final (targeted) SOC status and the decision to feed back into the grid. The dynamic of the aggregated EV results from the number of individual EVs constituting it, including the maximum capacity of the aggregated EV and its maximum charging and discharging power. The upper bounds of these constraints would all be time-dependent. Additionally, the aggregated EV can also decide to charge and discharge simultaneously, which is different from a single EV.

Based on these ideas in common, the "dynamic EV fleet" method may further customize details, such as the ratio of individual EVs with access to charging infrastructure over all parking EVs, the ratio of individual EVs participating in the controlled charging strategy over all grid-connected EVs, or the ratio of individual EVs allowing for discharging over all individual EVs under the bidirectional charging strategy.

4.2.2.2 Aggregated boundary method

The basic idea of the "aggregated boundary" method is to aggregate individual EVs by their arrival time and to sum up the boundaries of individual EVs as the boundaries of the aggregated EV. This idea is separately proposed by Hahn et al. (2013) and Zhang et al. (2017) and applied in Chen et al. (2018) and Szinai et al. (2020).

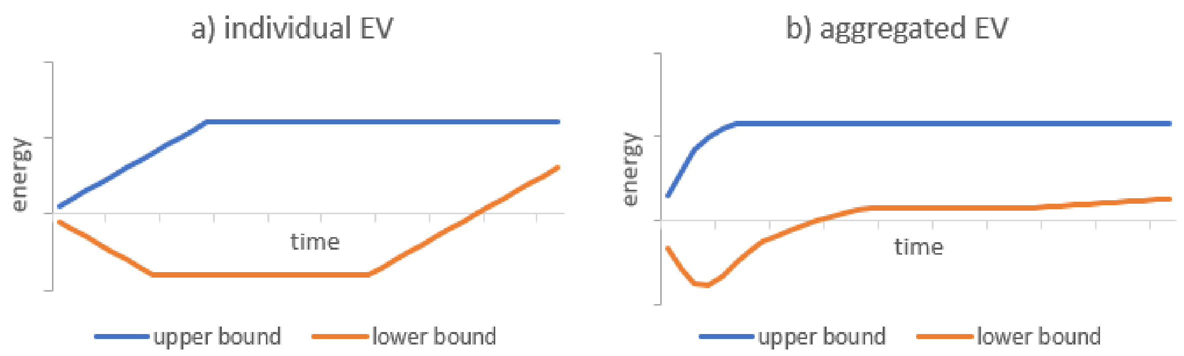

Figure 9. Exemplary boundary of the charging trajectory

Note: The y-axis donotes the cumulative energy change of the EV, with the unit of energy (such as kWh)

Let the charging trajectory denote the cumulative energy change of one individual or aggregated EV and both charging and discharging energy since the beginning are considered. For an individual EV, its upper bound is achieved by charging as much as possible upon arrival until the vehicle is fully charged. As in Figure 9 (a), the upper bound of the individual EV charging trajectory would first increase with the steepest slope and then would remain flat until the vehicle departs. A typical lower bound is achieved by first discharging as much as possible upon arrival, then postponing charging as much as possible and charging only to the necessary energy level but not until fully charged. The possibility of discharging depends on the parking duration. Boundaries of individual EVs are then summed up by their arrival time, and the resulting boundaries are respectively taken as the upper and lower bound of the aggregated EV, as illustrated in Figure 9 (b). The charging and discharging power of this aggregated EV depends on the number of individual EVs, while these individual EVs will continuously leave this aggregation according to their own departure time.

4.2.2.3 Rescheduled daily demand method

The "rescheduled daily demand" method proposes to redistribute the daily EV demand profiles within the same day as a realization of the controlled charging pattern (Jochem et al., 2015a; Manríquez et al., 2020; Masuta et al., 2014). As illustrated by Figure 10[6], the original daily EV demand profile is, in general, an uncontrolled charging profile from statistical data or simulation results. The controlled charging pattern can be rescheduled within the same day, as long as the total daily demand remains the same. In Figure 10, it means that the area between the blue curve and the x-axis and the area between the orange curve and the x-axis are the same. Furthermore, the time-dependent peak of the controlled demand might be limited by the maximum hourly demand, which may depend on the number of individual EVs available. A certain ratio of non-shiftable uncontrolled demand can also be considered. As an illustration, Figure 10 shows that the controlled demand is limited by the maximum hourly demand at hour 6.

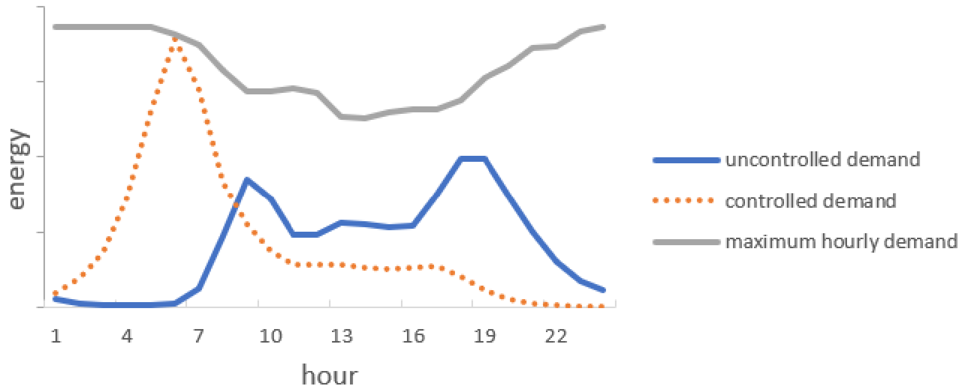

Figure 10. Illustration for the "rescheduled daily demand" method

Note: The y-axis denotes the cumulative energy change of the EV, with the unit of energy (such as kWh)

4.2.2.4 Postponed charging method

The "postponed charging" method, proposed in Paper C, can be taken as an improvement of the "rescheduled daily demand" method. Since uncontrolled demand is, in general, derived from instant charging behavior, i.e., charging as early as possible, it might not be appropriate to shift the uncontrolled demand to an earlier time slice. Therefore, the "postponed charging" method assumes the uncontrolled demand can be completed in the following time slots by both charging and discharging decisions. This time span can stretch to the next day if necessary.

An illustration is given by Figure 11, assuming that the uncontrolled demand can be postponed by 5 hours at most. A 10-kWh uncontrolled demand is assumed at hour 1. A part of this uncontrolled demand can remain at the original time slice, either by setting or by calculation (2 kWh in the example). Charging and discharging solutions can be determined within these 5 hours, and the summation is equal to 10 kWh. It is also feasible for charging

[6] Uncontrolled and controlled demand data are from Jochem et al. (2015a). Maximum hourly demand data is further processed based on Paper A. Figure 10 reconstructs these data for illustration purpose.

and discharging solutions for hour 1 to coexist in any of these 5 hours, although they might not be the optimal solutions. For every hour, there will be 5 "pieces" of charging decisions separately for each of the previous 5 hours. The total of these 5 pieces would be the controlled charging demand at this hour. So is the case for the controlled discharging demand.

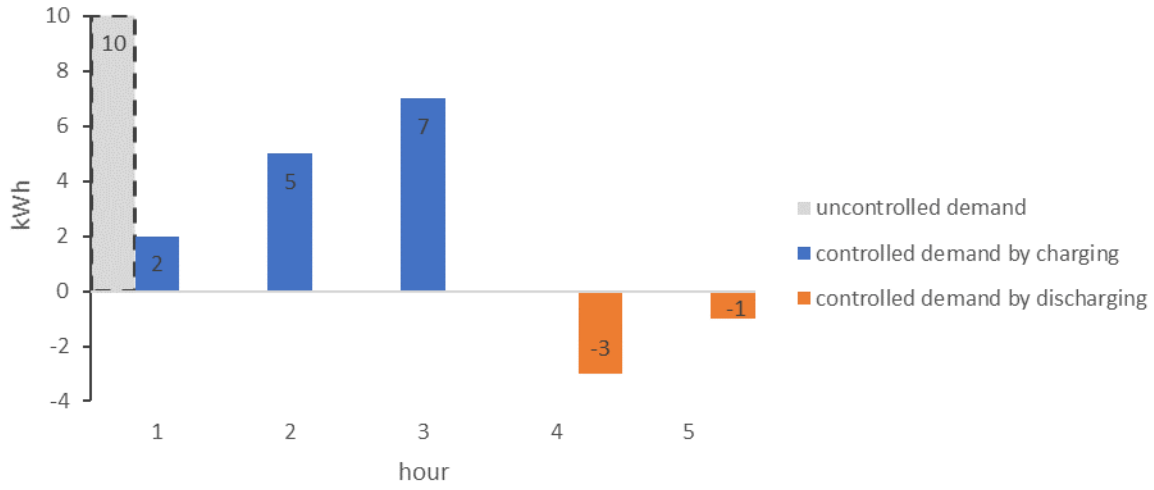

Figure 11. Illustration for the "postponed charging" method

4.2.2.5 Representation method

The "representation" method aims to cluster individual EVs as one or multiple scaled-up EVs as representatives (Beltramo et al., 2017; Jovanovic et al., 2021; Pavić et al., 2015; Soares et al., 2017; Taljegard et al., 2019; Weis et al., 2015). In the "aggregated boundary" method, one aggregated EV would consider additional features which may be derived from the concept of aggregation, such as the dynamic EV capacity, and simultaneous charging and discharging behavior. By contrast, constraints for a representative EV would be the same as those for a single EV, with only scaled-up numerical values depending on the size of the individual EVs represented.

For the "representation" method, Table 6 also lists the geographical scope of the case studies or the original size of the EV fleets, compared with the number of representative EVs considered. The idea of representation may be feasible for determining the uncontrolled EV charging pattern. For example, an uncontrolled pattern of a city could be scaled up as a representation of a country. Although empirically feasible, the application of the "representation" method for endogenous determination might require further demonstration for the accuracy of such a high level of simplification, which is rarely seen in current literature.

In short, the "dynamic EV fleet" method and the "aggregated boundary" method try to construct a hypothetical EV by aggregation while developing constraints inspired by those in individual EV modeling. The "rescheduled daily demand" method and the "postponed charging” method originate from the uncontrolled EV charging pattern and consider how this “business-as-usual” pattern could be reallocated. The “representation” method takes scalded-up individual EVs as representatives, without additionally developing constraints for an EV fleet.

5 Research gaps and discussions

5.1 The micro perspective

In light of the globally increasing EV uptake and the corresponding potential grid bottlenecks, the development of adequate EV charging scheduling approaches in energy systems has not received sufficient attention yet. Specifically, the following three points are still lagging in current research: the extensibility in model development, the feasibility of problem setting, and the transparency in result presentation.

First, chosen methods may limit the number of EVs considered. For instance, Iversen et al. (2014) and Wu et al. (2016) apply dynamic programming methods to optimize the charging behaviors of a single EV. They both suggest that future research may focus on how to extend the method to consider multiple EVs. Furthermore, some studies focus on solving specific problems with specially designed objective functions or price signals. As EV's load shifting potential can be utilized by many applications, it may be worthwhile to consider in advance the model extensibility in the development stage.

Second, EV charging scheduling models are to be applied in real-time and in practice. Therefore, model assumptions should not be oversimplified or cause inconvenience to EV users. Regarding how future EV uncertainties should be considered, two common options are proposed in literature, i.e., a globally optimal scheduling scheme and a locally optimal scheduling scheme. In a global optimum scheme, models would either assume EV behavior known in advance or ask EV users to guarantee future travel plans. In a local optimum scheme, models do not consider the future EV uncertainties but only the current EVs. Future EV uncertainties can be considered by stochastic optimization or robust optimization methods, which have not been adequately discussed in literature.

Third, the latest charging scheduling solutions are iteratively sent to EV users so that the corresponding models should be calculated in a rolling window fashion. The implementation of the rolling window approach may result in extra challenges in solution performance, but the importance of parameter setting in the rolling window approach has not received enough attention in literature. Furthermore, it might be encouraged to present solutions over a time span of several days in a row, or one entire day at least, as the EV usage patterns greatly vary within a day but are periodic in one day cycle (though not strictly). For instance, it might not be convincing that an EV charging scheduling model claims that the EV uncertainties have been considered while presenting solutions only during the hours around midnight, because there are in general very few EV arrivals during this period and the challenges from future uncertainties might in fact be diminished by the characteristics of EV usage patterns, but not by model design.

5.2 The macro perspective

Emission assessment is a common research topic of applying EV modeling methods from the macro perspective. With the methodological concern, a major challenge is how the electricity mix should be determined for the EV usage stage. A review by Hamels et al. (2021) summarizes how current studies assess the energy use of CO_2 emissions of different technologies (including EV), and it is found that 85% of 110 studies select average conversion factors[7] instead of marginal ones. Although being a common practice, the use of the average electricity mix in EV emission reduction ignores its time-dependent feature. Further compared with the time-dependent average electricity mix, the marginal one could consider the impact of additional EV demand on the generation portfolio. Moreover, the marginal electricity mix will be dependent on different EV charging strategies, including uncontrolled charging, unidirectional controlled charging, and bidirectional controlled charging. So far, only a few studies consider the impact of various charging strategies on the marginal electricity mix when assessing EV emission, as presented in Table 5.

In addition to its importance in EV emission assessment, the calculation of the EV charging patterns is also crucial to many macro research topics, which highlights the necessity of further developing modeling approaches to integrate EV into energy system models. The most considered EV charging pattern is the uncontrolled one, which is in general exogenously determined by statistics or simulation results as a representation of reality. To exogenously determine the unidirectional controlled patterns, the majority of studies use assumptions as representatives for specific charging strategies (e.g., off-peak or night charging). However, there is no demonstration of how well these simple assumptions can represent these charging strategies respectively. As a result, the conclusions for these strategies might be ungrounded. At the moment, there seems to be no literature exogenously determining bidirectional charging patterns by simple assumptions, which indirectly undermines the validity of simple assumptions for controlled charging patterns.

To endogenously determine the control charging patterns (whether unidirectional or bidirectional), multiple EV aggregation methods have been proposed and are rather diversified in terms of their formulation details. The reason for such diversity is that the notion of the aggregated EV is, to some extent, *imaginary*. It is not as concrete and descriptive as in modeling individual EVs. The task of aggregately modeling an EV fleet is to find a simplified

[7] The notion of conversion factor in this literature includes the CO_2 intensity of electricity used, which obviously depends on the electricity mix.

and approximated way of separately modeling every individual EV. Therefore, literature may propose different EV aggregation methods to determine the charging patterns endogenously. Unfortunately, current literature could only indirectly demonstrate their proposal by empirical judgments or by the resemblance of their formulations to those in individual EV modeling. Logically, even if the feasibility of all the proposed formulations could be assured, it is still unclear whether these constraints would suffice or whether introducing extra constraints might further improve the method. The lack of method demonstration may weaken the theoretical foundation of their applications and conclusions, while the demonstration is limited by the computational challenge of modeling EVs individually in a large-scale energy system model.

6 Contribution of the appended papers

Section 6 summarizes the four appended papers of this thesis. Figure 12 provides an overview of the appended papers, including the contribution of each paper to the overall topic and their connections.

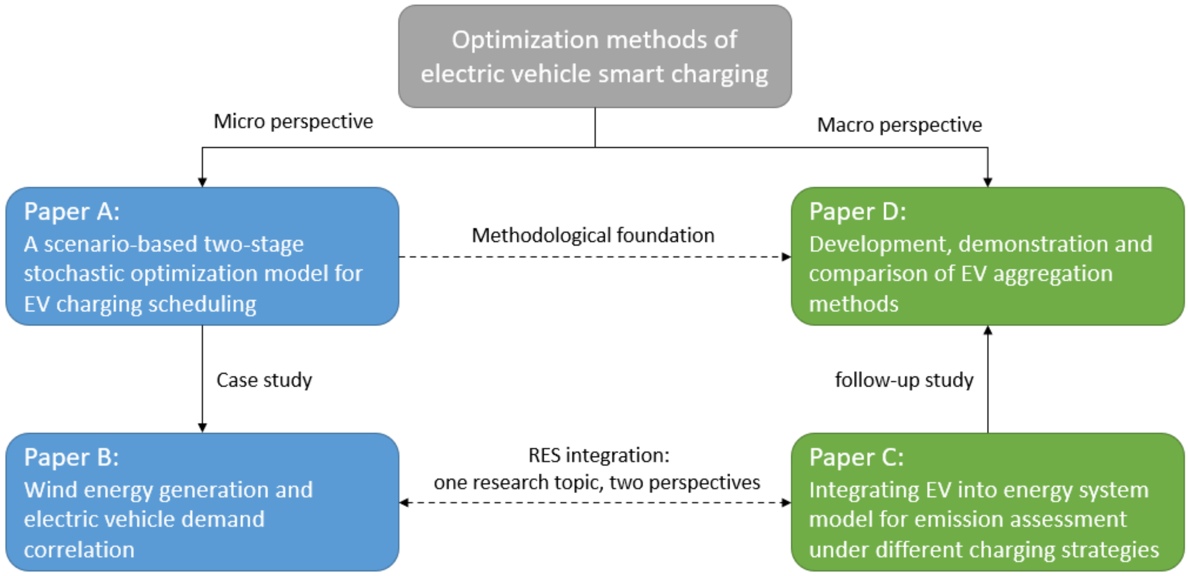

Figure 12. Overview structure of appended papers

The development of optimization methods for integrating EV into energy systems can be classified according to the research focus. From the micro perspective, EV charging scheduling methods should be application-oriented and focus on the feasibility of the assumptions and the settings. From the macro perspective, EV aggregation methods are the approximations of the individual EV modeling method, and they should focus on providing an outlook of the successful realization of EV's load shifting potential in energy system models. Paper A and Paper B are from the micro perspective; Paper C and Paper D are from the macro perspective.

Paper A proposes a scenario-based two-stage stochastic optimization model for EV charging scheduling. Paper B provides an extensive case study with the versatile model proposed by Paper A, which couples the output of a wind turbine with an EV fleet. Paper C proposes an EV aggregation method for energy system models to assess the GHG emission of EV under different charging strategies in Europe in 2050. The results show that a more flexible charging strategy (V2G) could support more renewable energy usage in the future. By comparing the focuses and modeling details in respective optimization methods, Paper B and Paper C together illustrate how one research topic (RES integration) related to EV smart charging is considered differently from the micro or macro perspectives. Methodologically, the focus of Paper C is how the electricity mix is dependent on various EV charging patterns. As a follow-up study of Paper C, Paper D focuses on how these various EV charging patterns can be endogenously determined by energy system models, by different EV aggregation methods. Including the one from Paper C, three types of EV aggregation methods are presented, improved (if possible), demonstrated, and compared. This is achieved by introducing all three types separately into a simplified energy system model with an individual EV modeling approach as the benchmark.

6.1 Paper A: A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand

Paper A schedules individual EV charging loads with a scenario-based two-stage stochastic optimization model in a centralized manner for multiple EVs. A key contribution of the paper is the consideration of future EV by scenarios. The original EV data used by scenario generation is from the iZEUS project (Schäuble et al., 2017) where multiple commercial EV usage profiles (driving, parking only, and charging) are recorded with a one-minute time resolution for over six months. Time-dependent usage probabilities of each EV are summarized and presented in the form of a transition matrix. The original scenarios for future EVs are generated by the inhomogeneous Markov chains method (Iversen et al., 2017; Widén et al., 2009). Although a large set of scenarios can well describe the future, it may also bring a computational burden to the model. Therefore, the fast forward selection method (a scenario reduction technique) is further applied so that only a limited number of scenarios are selected as representatives for the original set, each with adjusted weights (Feng and Ryan, 2013; Heitsch and Römisch, 2003). The value of the stochastic model is demonstrated by comparing it with a deterministic one and by taking the perfect foresight model as a benchmark. The results show that the stochastic model can better handle extreme cases in the future.

The formulation of the objective function is variance minimization, which enables the model to serve various applications. Specifically, three potential applications are presented: EV demand flattening (Figure 13), load leveling, and demand response. The proposed model is applied with 112 EVs and a temporal resolution of 15 minutes. While a simple peak shaving strategy may only lower the maximum demand and might have EV demand curve fluctuated below the peak (Ghotge et al., 2020; Wu and Sioshansi, 2017; Zhou et al., 2020), the demand flattening application in Figure 13 further alleviates such fluctuations. With the rolling window approach, the two-day result here is a combination of 192 iterations of calculation (24-hour optimization horizon and 15-minute temporal resolution). In general, some EV-related parameters are highly time-dependent within a day, such as the number of EVs available for controlled charging and the number of EV arrivals in every time slice, as is the case in this paper. Therefore, it is highly recommended to present EV charging scheduling results for at least 24 hours, but not a selected period of a day.

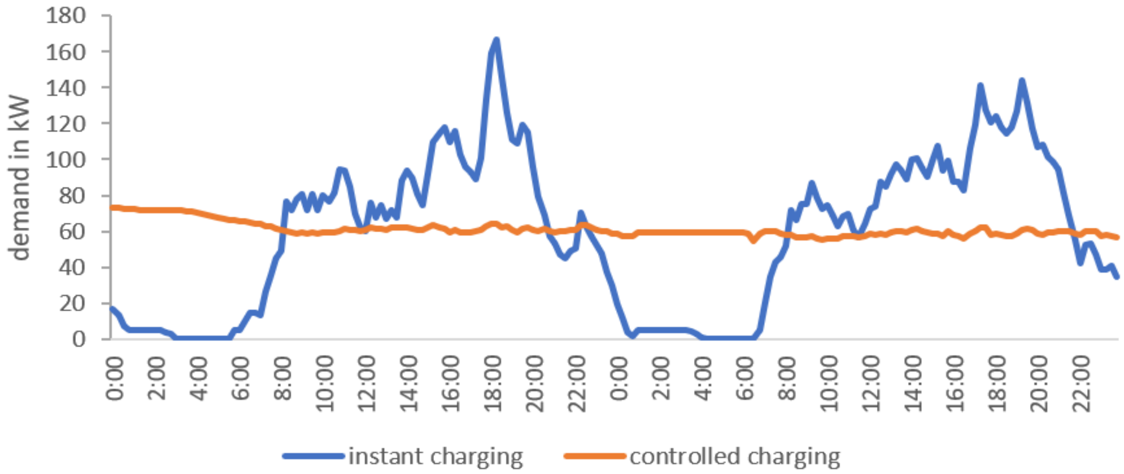

Figure 13. EV charging demand under instant and controlled charging strategy (adjusted from Wang et al. (2020))

6.2 Paper B: How many electric vehicles can one wind turbine charge? A study on wind energy generation and electric vehicle demand correlation

Paper B focuses on applying EV charging scheduling for wind energy integration. The energy use of an uncontrolled (instant) charging strategy is taken as the benchmark. Two controlled charging strategies are considered here:

1. *Myopic* charging strategy: This empirical strategy maximizes the use of wind energy. EV would charge instantly upon arrival when there is sufficient wind energy generation. Otherwise, EV would postpone charging behaviors as much as possible to limit the use of electricity from the grid. This strategy only considers EVs which are currently plugged in.
2. *Following* charging strategy: This strategy tries to follow the wind generation profile with the EV charging demand. This is derived from the model proposed in Paper A by simply taking the wind generation profile as the “ideal” curve in the variance minimization objective function (cf. Table 3). The model in Paper A is simplified as a deterministic one by using the expected number of future EV arrivals instead of scenarios.

A wind turbine with 3 MW capacity is considered, and its yearly generation profile is simulated in a 15-minute time resolution. 2000 EVs are considered, and their parameter setting method is the same as in Paper A. The two controlled charging models iteratively optimize for a 24-hour horizon with the rolling window approach for four selected months of the yearly wind turbine generation profile (January, April, July and October). The total EV charging demand which could be covered by the wind under the myopic and following charging strategy are 1133 MWh and 1130 MWh, respectively, while the one under the instant charging strategy equals 907 MWh only. Both controlled charging strategies significantly improve the usage of wind energy and have similar results. Nevertheless, the unutilized wind energy would be either curtailed or exported. When there is insufficient wind generation, EV charging would also need support from the grid. Overall, the share of electricity for EV from wind equals about 45% of the overall wind generation in both controlled charging strategies. Therefore, it may also be beneficial if an EV charging strategy could additionally alleviate the volatility of wind generation. Figure 14 shows how wind generation volatility is alleviated by these two controlled charging strategies. The perfect foresight assumes complete information about future EV arrival and can be regarded as the best case. The positive value means that there is excess wind energy after EV charging, and the negative value means that there is insufficient wind energy for EV charging and that grid support is needed. The result illustrates that the following charging strategy could additionally alleviate wind energy generation, which is not considered by the empirical myopic charging strategy.

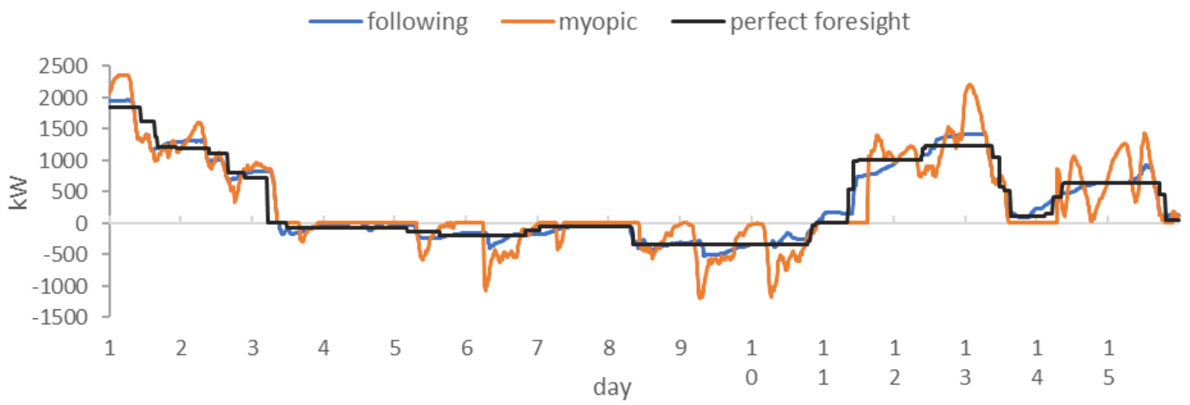

Figure 14. Alleviation of wind generation volatility under two controlled charging strategies (adjusted from Wang and Jochem (2019))

6.3 Paper C: Greenhouse gas emission of electric vehicles in Europe considering different charging strategies

Paper C investigates how GHG emissions by EVs in Europe in 2050 may be potentially reduced under different charging strategies, including uncontrolled charging, unidirectional controlled charging, and bidirectional controlled charging (V2G). Marginal electricity mix is selected for GHG emission assessment because the additional EV demand under various charging strategies may significantly influence the structure of the future electricity system. Methodologically, this is achieved by developing an EV module for the European energy system model, PERSEUS (Keles and Yilmaz, 2020), which optimizes the generation expansion decision for the future. A brief introduction of the method for developing the EV module can be found in Section 4.2.2.4. A list of methodological alternatives by current literature on the topic of EV emission assessment is presented in Table 5 and discussed in Section 4.1, where the majority assumes the electricity mix is independent of EV charging strategies and V2G charging strategy is rarely considered. Paper C calculates both the direct and life cycle emission from the electricity generation for EV usage because RES-based generation technologies have no direct GHG emissions, and the life cycle emission, as a supplement, could provide a comprehensive assessment. The coupling of the LCA and the energy system model is guided by L. Xu et al. (2020a) to mitigate the differences between the two sides, including system boundaries, database, and assumptions.

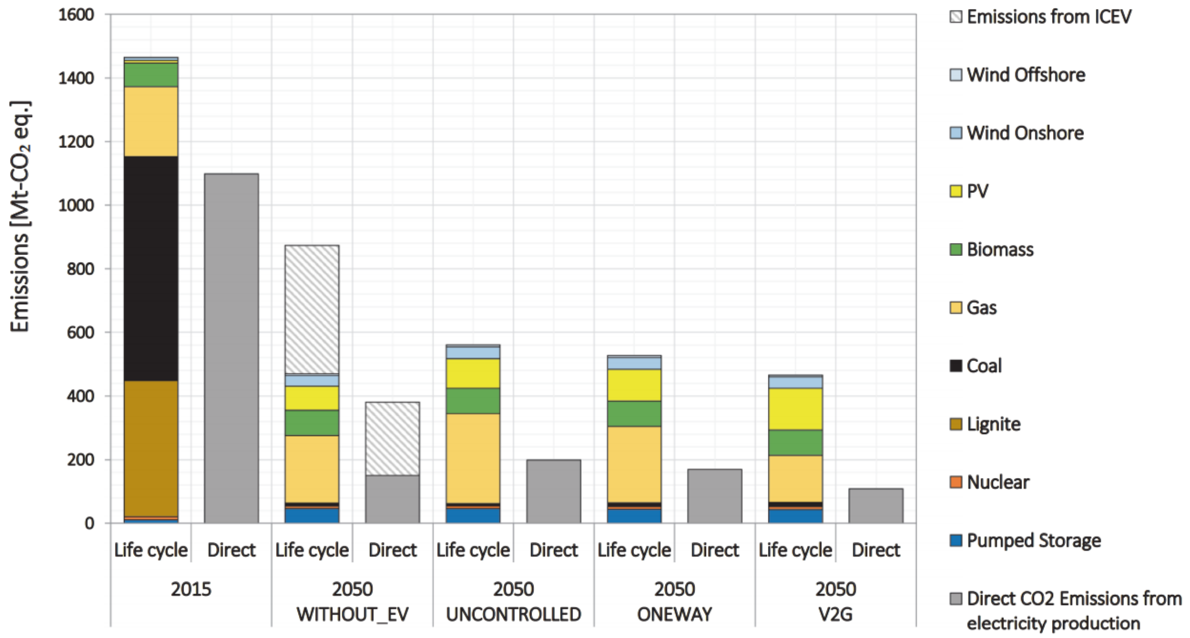

Figure 15. The direct and life cycle GHG emissions associated with the production of electricity in the UNCONTROLLED, ONEWAY (unidirectional controlled), and V2G (bidirectional controlled) charging strategies compared to WITHOUT_EV in 2050 and the base year 2015 (adjusted from L. Xu et al. (2020b))

Note:
WITHOUT_EV: A hypothetical reference scenario where ICEVs are not replaced by EVs.
UNCONTROLLED: The EV charging process is not controlled and EVs charge instantly when they are connected to the grid.
ONEWAY: This controlled charging strategy can postpone the uncontrolled EV charging demand maximally by 12 hours.
V2G: This controlled charging strategy is based on the ONEWAY scenario and additionally allows for discharging within the next 12 hours.

The main results of the four scenarios are shown in Figure 15. Taking the WITHOUT_EV scenario in 2050 as the benchmark, the life cycle emission of the energy system under the UNCONTROLLED scenario increases by 19%, as EV integration in 2050 would result in a 15% increase in electricity generation according to Paper C’s setting. When charging strategies are progressively applied, the life cycle GHG emissions in ONEWAY and V2G are lower by 6% and 17%, respectively. Furthermore, when the life cycle emission from ICEV is considered and the overall life cycle emissions from the transport and energy sector under the WITHOUT_EV scenario serves as the updated benchmark, EV could reduce life cycle GHG emission by 36% even under the UNCONTROLLED scenario, and an additional 4% or 11% more under the ONEWAY or V2G scenario, respectively.

Another contribution of Paper C is to take the extra emissions from EV battery degradation under the V2G scenario into account. Even when the life cycle emission of additional EV battery production is included, Paper C concludes that the whole system could still benefit from the V2G scenario for emission reduction. The paper also discusses the uncertainties from battery technology development, including energy density and cycle life.

6.4 Paper D: Integrating vehicle-to-grid technology into energy system models: novel methods and their impact on greenhouse gas emissions

Paper D investigates the potential bias and impacts of three EV aggregation methods that enable EV controlled charging patterns to be endogenously determined by energy system models: a “dynamic EV fleet” method uniquely proposed by Paper D, the “aggregated boundary” method applied in literature, and the “postponed charging” method by Paper C (cf. Section 4.2 for the basic ideas of each method). These three EV aggregation methods are benchmarked against the “individual” EV modeling method which models 2000 EVs individually.

The testbed designed for these methods is a simple energy system model which optimizes its generation portfolio (including gas, PV, and wind) and considers the demand side flexibility from V2G. Some characteristics of the model refer to the settings for Germany in 2050 by Paper C. Relevant parameters (e.g., electricity demand and generation technology investment cost) are scaled down to match the scope of the test model (2000 EVs and four representative weeks for a whole year). Since the three EV aggregation methods share the same original parameters from these 2000 EVs, the paper filters the impact of parameter settings on result performance and focuses on the impacts only from modeling methods.

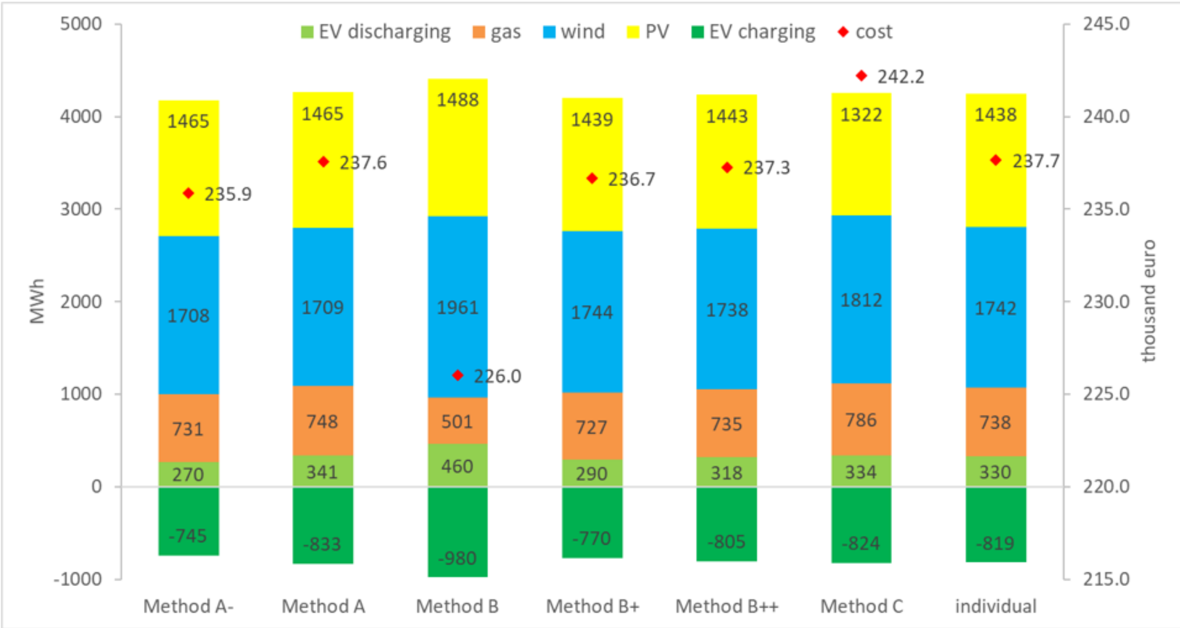

Figure 16. Electricity mix, EV charging demand and total cost for different EV aggregation methods (from Wang et al. (2021))

Note: The electricity mix is presented in stacked columns as positive values on the primary y-axis, the EV charging demand as negative values on the primary y-axis and the total costs in scatter plot on the secondary y-axis. The difference between EV charging and EV discharging from the EV side is the EV charging tasks, which is a constant value proportional to EV annual mileage and same for all methods. Here, EV charging and discharging values are shown from the grid side considering efficiency so that their differences under different methods vary slightly. (Method A-/A: "dynamic EV fleet" method; Method B/B+/B++: "aggregated boundary" method; Method C: "postponed charging" method)

Figure 16 shows the main results of the paper, with the results from the individual EV modeling method as the benchmark. Method A- is the paper's reproduction based on the general idea of the "dynamic EV fleet" method. Method A is one contribution of the paper, which additionally formulates constraints for the charging tasks of individual EVs by their departure time. Method B is the paper's reproduction based on the general idea of the "aggregated boundary" method. Method B+ corrects the upper bound of the charging trajectory so that the aggregated EV would depart with only the necessary level, but not with the maximum. Method B++ further adds constraints for the charging task, which is inspired by the contribution of Method A. By comparison, Method A, Method B+, and Method B++, following the general idea of respective methods, significantly improve the result accuracy, which is the core contribution of Paper D. The performance of the EV aggregation method proposed by Paper C (the "postponed charging" method) is also demonstrated. Paper D further analyzes, in terms of formulation, the reasons why Method A, Method B+ and Method B++ could improve the performance, which may inspire further studies into developing EV aggregation methods. In addition, the paper compares the difference of these methods in the assessment of emission reduction, the fitting for the actual EV charging pattern, computational complexity, and parameter requirement. So far, no literature seems to demonstrate their EV aggregation methods or compare them with alternative methods in order to reveal the mechanisms behind result differences.

7 Conclusions

This section concludes the overview of the thesis. Section 7.1 summarizes the main contributions of the thesis. Section 7.2 discusses the limitations of the thesis and the possible improvements in future work. Section 7.3 outlines possible directions for further research in relevant fields.

7.1 Summary

This cumulative thesis serves as a methodological framework in response to the fundamental and universal challenges in developing charging strategies for integrating electric vehicles into energy systems. The discussions aim to raise readers' awareness of the crucial but often unnoticed concerns in model development and hopefully would inspire future researchers into this topic.

This research topic is analyzed from two research perspectives, as each may have its unique emphasis or mindset. The micro perspective focuses on developing EV charging scheduling models, while the macro perspective focuses on integrating EVs into energy system models. The two perspectives are not separated but mutually dependent. The macro perspective points out "where to go" for the *planning* stage, and the micro perspective answers "how to get there" for the *operational* stage.

From the micro perspective, this thesis proposes a stochastic optimization model for EV charging scheduling and emphasizes the feasibility of assumptions and parameter settings (Paper A). The model considers the uncertainties of future EVs, including their availability and charging demand. The objective function is formulated to minimize the variance between the actual EV charging curve and the preferred one. The flexible settings of the latter enable the models to be easily implemented for various applications, including peak shaving and demand response. One further case study investigates the correlation between the generation of a wind turbine and the demand of an EV fleet (Paper B). Compared with the uncontrolled charging strategy, the controlled charging strategy of the model could utilize 24.5% more wind energy. Additionally, the model could significantly alleviate the volatility of the unutilized wind generation by matching the EV charging curve to the electricity generation profile.

From the macro perspective, the thesis first extends an energy system model with a vehicle-to-grid option (Paper C). One case study of the extended model is to investigate the impact of different EV charging strategies on the greenhouse gas emissions in Europe in 2050. Results show that, by simply replacing conventional vehicles, EVs could reduce emissions by 36%. In addition, unidirectional and bidirectional controlled charging strategies could further reduce emissions by 4% and 11%, respectively, compared with the original level. A follow-up study of the thesis is to analyze the potential bias of EV aggregation methods in energy system modeling (Paper D). Three types of methods are investigated, and their biases are analyzed. Two of these methods are also significantly improved with modified parameters or additional constraints. To the best knowledge of the authors, such validation of EV aggregation methods is mostly overlooked in literature.

7.2 Critical review and future work

The appended papers are subject to several limitations. From the micro perspective, Paper A and Paper B first assume that all EV users would be willing to participate in controlled charging programs and that these participants would not leave earlier than their guaranteed departure time. User acceptance could be further investigated and promoted for the convenience of the EV controlled charging strategies and with economic or societal incentives (Ensslen et al., 2013). Moreover, the vehicle-to-grid option has not been considered by the model proposed, which may not result in a challenge in modeling, but an increase in computational complexity from the introduction of binary variables. Therefore, heuristic algorithms, such as genetic algorithms or particle swarm optimization, might be further applied in problem-solving (Amin et al., 2020; Mukherjee and Gupta, 2015; Tan et al., 2016). For EV battery characteristics, the decrease of maximum charging power by the state of charge of the battery is modeled in a linearized way (Kaschub et al., 2013). However, the impact of charging scheduling on battery degradation has not been considered (Wei et al., 2018). Future work may also focus on the interaction of EV charging with other components at the residential level, such as PV-battery systems (Langenmayr et al., 2020), stationary battery storage and heating device (Dengiz et al., 2021; Dengiz and Jochem, 2020), micro combined heat and power units (Jochem et al., 2015b) or the impact of EV on electricity grid at transmission or distribution level with network models (Crozier et al., 2020; Held et al., 2019).

From the macro perspective, the application of EV aggregation methods in case studies is first limited by the abstraction of macro-scope energy system models. The potential network restrictions by EV charging are also not considered, which should be analyzed in detail by a network model. The degradation of EV battery is assumed to be linearly dependent on the cumulative usage for charging, which may technologically be affected by multiple factors, such as charging temperature, battery state of charge, and charging power (Hoke et al., 2011). Long-term studies are also subject to the projections for technology development, as is the case in Paper C concerning EV battery, including its lifetime, capacity, energy density, and material. For charging strategies, Paper C assumes that 50% of EVs would be available for controlled charging and that uncontrolled charging demand can be postponed by maximally

12 hours. Fuel cell powered EV is not considered in the paper, which might further contribute to greenhouse gas emission reduction and could be a topic for further work.

Although Paper D aims to highlight the impact from different EV modeling methods, the disturbance from parameter setting is not perfectly eliminated. The EV aggregation methods assume that the charging window for controlled charging is 12 hours, which is in fact dependent on the time of the charging task within a day. However, further improvement for the charging window might be marginal. For applications in energy system models, parameters required by some EV aggregation methods might not be currently available from statistics or simulation results, which could be a topic for future work. Novel EV aggregation methods proposed and demonstrated by Paper D could then be applied by case studies in future research.

7.3 Outlook

In addition to the responses to the specific limitations discussed above, the following technological pathways or relevant research topics might also be of interest for research within a broader scope.

From the micro perspective, a premise for the majority of EV charging scheduling models is that EV users cannot swap their batteries for daily usage. Therefore, charging decisions for one battery are greatly influenced by the availability of the EV. However, this premise may not exist under the business model of "battery swapping", which has been commercialized by EV manufacturers (Electrive, 2021) and encouraged by national policies (IEA, 2021b). Such a business model is relatively a minor concern in current literature (X. Liu et al., 2018; Tan et al., 2019). However, it is noteworthy that the fundamental logic in developing a battery-swapping-based EV charging scheduling model would greatly differ from the common ones discussed in the thesis, as EVs and the batteries they use are separately considered in the former. Another technical option is fast charging, as it would significantly decrease EVs' charging time and promote the market diffusion of EVs (X. Duan et al., 2021). However, fast charging would also reduce EV's load shifting potential within one charging window. Therefore, the development of EV charging scheduling models under the fast-charging scenario would also be of interest for future research.

With cost minimization as the objective function, the performance of price-based EV charging scheduling models depends on not only the model design but also the electricity price for charging. Future studies in this path might focus more on designing pricing mechanisms for EV charging (Hu et al., 2016), in addition to taking electricity prices from external sources.

Methodologies in addition to operations research are also worth considering, such as queueing theory (Said and Mouftah, 2020; Y. Zhang et al., 2019).

From the macro perspective, the demonstration has always been a challenge for energy system models, as their results may not be directly validated by comparison with real-world observations. As a compromise, inter-model or multi-model comparison could be conducted for weak validation (DeCarolis et al., 2012; Duan et al., 2019; Ruhnau et al., 2021). For instance, H. Duan et al. (2021) investigate China's decarbonization pathway in 2050 and provide a strand of results from different models for multi-model comparison. Such result differences are inevitably sensitive to the *value-laden* assumptions or scenarios and may also be affected by modeling approaches (Bistline et al., 2021; Myers, 1995; Schneider, 1997). Furthermore, an encouraging trend is to make model documentations and the code publicly available (DeCarolis et al., 2017). Although these practices can increase the model transparency, the documentation and the code are in essence descriptions, but not demonstrations. Other than the promotion in public accessibility and the interoperability among models, DeCarolis et al. (2012) recommend the development of test systems for verification exercises. In addition to the validation for EV modules in energy system models by the thesis, a test system for other modules or even the whole energy system might be a topic of interest or necessity. Before computing capabilities significantly improve, there might not be a silver bullet that can eliminate the errors by approximations in energy system modeling. Still, developers may understand and present the performance of the models.

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Part II: Papers A to D

Paper A

Wang, Z., Jochem, P., Fichtner, W., (2020). A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand. Journal of Cleaner Production 254, 119886.

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Paper B

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Paper C

Xu, L., Yilmaz, H.Ü., Wang, Z., Poganietz, W.-R., Jochem, P., (2020). Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. Transportation Research Part D: Transport and Environment 87, 102534.

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Paper D

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A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand

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ABSTRACT

The integration of electric vehicles (EVs) into the electricity systems comprises both threats and chances. A successful control strategy of EV charging processes is beneficial for both EVs and electricity grid. This paper proposes a scenario-based two-stage stochastic linear programming model for scheduling EV charging processes for different grid requirements in real time using a rolling window approach. The model considers the uncertainties in EV availability (i.e. arrival time and departure time) and electricity demand upon arrival (i.e. initial and target state of charge of the battery). Monte Carlo simulation shows how different input parameters may affect the results. Inhomogeneous Markov Chains are used for EV usage pattern simulation and for scenario generation. For reducing computing time, the amount of scenarios is again reduced by scenario reduction technique. The proposed model is applicable for various grid purposes. We demonstrate the applicability of our model by three example cases: Load flattening (only EV charging load), load leveling (together with conventional household load) and demand response (for wind energy integration or ancillary service).

1. Introduction

With an increasing market share of electric vehicles (EVs), large integration of EVs may bring both challenges and opportunities to the power system (Fischer et al., 2019; Wellers et al., 2016). When EV customers charge EVs without external incentives, they prefer to charge EVs to their desired level as quickly as possible, which is often referred to as uncontrolled charging, or instant charging. By contrast, controlled charging means either EV's charging power is regulated within the given limits or the charging time is scheduled. We do not consider bidirectional charging (so called vehicle-to-grid or V2G) here. With instant charging, EVs will immediately start charging upon arrival with their maximum charging power until their charging targets are completed (Perez et al., 2017; Taljegard et al., 2019; Zhang et al., 2018). This leads to high peak loads, mainly during evening hours, which challenges the electricity grid and may influence the operation of power plants (Schill and Gerbaulet, 2015).

However, due to long idle time, the load shifting potential of EVs is significant and might accordingly be used to alleviate the challenge to the electricity system (Babrowski et al., 2014). The topic of integrating EVs synergistically into the electricity system has gained increasing attention in the literature. Moreover, the promising load shift potential of EVs provides not only the possibility of peak shaving but also the prospect for other applications (J. Hu et al., 2016; Yang et al., 2015). Many literatures focus on the integration of renewable energy with EVs (Goonewardena and Le, 2012; Mehrjerdi and Rakhshani, 2019; Seddig et al., 2017; Yang et al., 2015). Another interesting topic is to maximize the profit of an EV aggregator by participating in the electricity market (Baringo and Sánchez Amaro, 2017; Sarker et al., 2016).

As a foundation of all the promising EV applications above, EV charging behaviors should be scheduled when they are connected to the grid and these behaviors depend on the uncertainties of EV availabilities (i.e. arrival and departure time and the charging demand upon arrival). These uncertainties would deteriorate the practicability of an EV charging scheduling model. Most current literature either assume perfect information about these uncertainties or only consider one of them. Therefore, this paper aims to develop a real-time EV charging scheduling model with a focus

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Nomenclature

$m(EV^i)$	Electric vehicles (EVs) that are available for charging at period i
t	Time intervals
s	Time intervals (for estimation of future EV arrivals)
ω	Scenarios
λ	Penalty factor
Cap	Capacity of an EV, [kWh]
e	EV charging efficiency, [%]
Δt	Length of a time interval, [hour]
P^{max}	Maximum EV charging power of an EV, [kW]
i	Starting period of a rolling window
$A_{m,t}$	Availability of EV m in period t, [binary]
SOC_m^{ini}	Initial state of charge (SOC) of EV m before charging, [%]
$SOC_0^{'}$	Initial SOC for EVs that are estimated to arrive in future periods, [%]
SOC^{max}	Maximum SOC of EV, [%]
SOC_m^{target}	SOC target of EV m when charging ends, [%]
SOC_s^{target}	SOC target of EV from future period s when charging ends, [%]
$\alpha_{s,\omega}$	Number of EVs that are estimated to arrive in future period s in scenario ω
W^i	Ending period of the rolling window that starts in period i
AA_m	Availability of EV m after the rolling window that starts in period i, [binary]
D_t^{pref}	Preferred total EV charging demand in period t, [kW]
π_ω	Probability of scenario ω
D_{i-1}	Total EV charging power in the period before the rolling window which starts in period i, [kW]
Gap_m	Gap between SOC_m^{target} and SOC of EV m when the rolling windows ends, [%]
$Gap_{s,\omega}^{'}$	Gap between SOC_s^{target} and SOC of EVs from future period s in scenario ω, [%]
$D_{t,(\omega)}$	EV charging demand assumed in period t (in scenario ω), [kW]
$SOC_{m,t}$	SOC of EV m in period t, [%]
$SOC_{s,t,\omega}^{'}$	SOC of EVs in period t in scenario ω, [%]
$P_{m,t}$	Charging power of EV m in period t, [kW]
$P_{s,t,\omega}^{'}$	Charging power in period t of EVs from period s in scenario ω, [kW]
$D_{t,(\omega)}^{I}$	Difference between $D_{t,(\omega)}^{total}$ and D_t^{pref} in period t (in scenario ω), [kW]
$D_{t,\omega}^{II}$	Change of $D_{t,\omega}^{I}$ in two consecutive periods in period t in scenario ω, [kW]
$\min(\cdot,\ \cdot)$	Minimum of the two numbers
$\max\{\cdots\}$	Maximum value in the set

on the inevitable uncertainties from EV availability. Moreover, as current studies mostly apply EV's load shifting potential for one specific objective (e.g. load flattening), we structure the model in a flexible way so that it can be easily extensible for different specific applications.

In terms of optimization methods, Sundström and Binding (2012) develop both quadratic and linear programming models which satisfy EV owners' requirements while avoiding distribution grid constraints, and point out the computational challenge of quadratic programming. Both Iversen et al. (2014) and Wu et al. (2016) apply stochastic dynamic programming to minimize the operational cost of a single EV but not an EV fleet. Multi-objective optimization is also applied to balance the tradeoff between conflicting objectives (Ju et al., 2016; Lu et al., 2018), such as demand response and renewable energy integration. When V2G is considered, mixed integer linear programming is often applied because of the binary nature of decision variables for charging or discharging state (Sabillon Antunez et al., 2016).

In this paper, we propose a scenario-based two-stage stochastic linear programming (SLP) model for EV charging scheduling in real time. EV usage patterns are generated by inhomogeneous Markov chains. With regards to real-time scheduling, this myopic (online or local) optimizing environment is considered by a rolling window approach. In the model formulation, future EVs are aggregated by their arrival time so that their uncertainties (i.e. the availabilities and charging demand) are considered by scenario-based stochastic optimization. Representative scenarios are selected by a scenario reduction technique. With Monte Carlo simulation, we further demonstrate the performance of the model with different input parameters (EV usage profiles and their electricity demand). The aggregation of future EVs also keeps the computing time compatible for empirical applications, since we capture their uncertainties in the model but limit the consequential complexities.

The formulation of the model objective is kept slim and as general as possible in order to guarantee its flexible and straightforward application. The model objective is to minimize the distance between the EV charging demand and a pre-defined curve. By simply adjusting this pre-defined curve, we demonstrate the performance of our model using three potential applications. The first application is for load flattening of the charging demand of EV fleets. With the conventional load from households, the second application is for load leveling (peak shaving and valley filling). The last application is related to demand response for wind energy integration and ancillary services in the reserve market.

Our main contributions to the current literature are summarized as follows:

(1) We develop a stochastic optimization model for EV charging scheduling in real time which especially considers the uncertainties from EV availabilities and their demand upon arrival. We also demonstrate the value of using a stochastic model by comparing with a deterministic one.
(2) The objective of the proposed model is formulated in a flexible way and is ready to be implemented for specific applications by only setting different values to one parameter. We extensively present three examples to elaborate the method.
(3) Our problem is applied on empirical field test data represented by usage patterns of dozens of EVs for over six months.

The remainder of the paper is organized as follows. Section 2 gives a short overview of current literature on the EV charging scheduling problem and the current research gap is discussed. Section 3 outlines the formulation of the model. Section 4 explains the setting of the parameters in the model. Section 5 presents three potential applications of the model. Section 6 concludes the paper.

2. Related work

This section gives an overview of current literature focusing on EV charging scheduling problem. The consequential uncertainties are clarified and the research gap is discussed.

2.1. Objectives for EV charging scheduling

There are two typical ways to schedule EV charging behaviors: the decentralized and the centralized way (Richardson et al., 2012; Sundström and Binding, 2011). The decentralized way means that EVs schedule their own charging behaviors based on information they can receive from outside. Wu et al. (2016) develop a stochastic dynamic programming model to minimize the energy cost of a smart home with EV, battery storage, and photovoltaic array. Iversen et al. (2014) also apply stochastic dynamic programming for charging scheduling of a single EV to minimize the operating cost. A potential drawback of this way is that if multiple EVs receive the same external information (e.g. electricity price) and schedule their charging behaviors under the same strategy, it is likely that their schedules are similar, and this may lead to peak shifting but not peak shaving (Ramchurn, 2012). However, Hu et al. (2016) propose a dynamic pricing mechanism which offers different charging tariffs for EV users depending on their arrival times and the current demand.

The centralized approach means that an entity would schedule charging behaviors for a group of EVs by controlling the charging processes directly or indirectly, e.g. by giving price incentives. This new entity is often referred to as charging service provider, EV aggregator or fleet operator (J. Hu et al., 2016; Sundström and Binding, 2011). Such charging service provider can be the grid operator or a new third-party player that makes a profit by providing demand-side management service. State of charge (SOC), the level of battery charge in percentage, is a key indicator for EV charging scheduling. Together with initial SOC and target SOC, charging service providers need collect EV information (e.g. battery capacity and maximum charging power) and communicate with EVs to schedule optimal charging behaviors. In order to provide a certain kind of service (e.g. reserve) to the grid, an EV charging scheduling model should have a relatively large amount of EVs to schedule.

Charging service providers can schedule charging behavior for EVs. Literally, the charging service is a service provided to an EV to control its charging behavior and to charge the EV in a certain way. In fact, it is a service primarily to the grid or utility because the initial motivation of controlled charging originates from the potential challenge that the grid might face, as discussed in Section 1. Potential cost savings for EV owners guarantee this possibility. With the discussions above, this paper schedules EV charging behaviors in a centralized way. A centralized model may include EVs connected to one location, e.g. one charging infrastructure or one charging station.

2.2. How uncertainties of EV are considered in modelling

In this paper, we clarify and analyze two kinds of uncertainties in EV charging scheduling. One uncertainty is EV's availability for charging, which means EV's arrival time to the grid and its departure time. We categorize EVs into two groups: EVs that are currently connected to the grid and EVs that may arrive in the future. For currently connected EVs, the arrival times are apparently known. Regarding the departure time, it is assumed in this paper that with proper financial incentive EV owners will guarantee their departure times upon arrival and send this information to the charging service provider. Please note that this guaranteed departure time can be earlier than the actual departure time but not later. For future EVs, their availabilities remain unknown in this paper. The other uncertainty is the charging demand upon arrival or the SOC of the EV battery, i.e., the initial SOC upon arrival and target SOC at departure. For currently connected EVs, the initial SOC is known and user's target SOC can also be communicated to the charging service provider. For future EVs, their SOC is not known to the system.

Therefore, the uncertainties of EV charging scheduling we consider are not from EVs that are currently connected to the grid, but from EVs that may arrive in future periods, i.e. from their availability and SOC statuses. Although EV charging scheduling models only optimize solutions for currently connected EVs, the arrival of future EVs should also be taken into account. From a systematic aspect, when we schedule the charging behaviors of currently connected EV over a time span, the arrival of future EVs would also have an impact on the total charging demand of the system and the solutions of currently connected EVs in future periods are accordingly affected. The above discussions on EV charging scheduling and its uncertainties provide a framework and contribute to categorizing and analyzing current studies concerning EV charging scheduling.

One way to handle this future EV availability is to only consider the currently-connected EVs into the model and to recalculate the model with updated information whenever new EV arrives. Guo et al. (2018) propose an online linear programming model to decrease the peak of EV charging demand. He et al. (2012) minimize the total charging cost with a quadratic programming model for real-time charging scheduling problem of EVs. Both Guo et al. (2018) and He et al. (2012) compare their optimal solutions between a global (offline) optimum which has perfect information about future EVs and a local (online) optimum which considers only the currently connected EVs. The resulting differences indicate the necessity of considering uncertainty of future EV arrivals for more empirically-related modelling.

The uncertainties from future EV have also received increasing attention by literature. Lu et al. (2018) propose a multi-objective load dispatch model for a microgrid including distributed generations and electric vehicles. The uncertainties from EV usage behavior and charging load are tackled with Monte Carlo simulation which would not apply in real-time EV charging scheduling problem. Heydarian-Forushani et al. (2016) develop a scenario-based stochastic programming model and study the interaction between EV parking lots and wind energy. In this paper, EVs are both aggregated by their arrival time and departure time. Therefore, there is no individual EV in the model and individual charging target is not considered. Instead of using scenarios, Akhavan-Rezai et al. (2018) build and train an artificial neural network to hourly forecast future EV arrivals. However, the uncertainty in future EVs' departure time is not considered. Wu and Sioshansi (2017) develop a two-stage stochastic optimization model for EV charging scheduling at a fast charging station which minimizes the operating cost and avoids overloading the transformer. Their paper models uncertainties in EV arrival time and charging demands upon arrival. However, this paper assumes the same charging duration for all flexible EVs, so the uncertainty in EV departure time is not considered, and the currently connected EVs are in fact modeled in an aggregated way.

In addition to EVs, an energy scheduling model may also incorporate other components (e.g., electricity price, household loads, photovoltaic and wind energy production and stationary battery storage) e.g. Refs. (Le Goff Latimier et al., 2015; Wu et al., 2016; Zhang et al., 2014). In this paper, the parameters of such components will not be considered uncertain.

2.3. Rolling window approach

As EV charging is persistently scheduled for EVs that arrive, the rolling window approach, or model predictive control, seems to be highly suitable for real-world charging scheduling models. A charging scheduling model optimizes for a fixed time span (W periods in Fig. 1). Every time the model iterates, this time span moves forward by one period. The starting period i and the ending period W^i are updated accordingly, as shown in Fig. 1. The set of EVs that are currently available EV^i is also updated, and so are all parameters indexed by m. Although the optimal solutions are calculated for W periods, only the solution for the first period (period i) will be implemented.

However, few current literatures take rolling window approach into account. Wu and Sioshansi (2017) further apply it to their model with a fixed optimization horizon of 60 min while they assume that all EV charging windows are 40 min. He et al. (2012) do not fix their optimization horizon (rolling window) when updating charging schedule but only until the last departure time of the currently-connected EVs. Lee et al. (2019) use model predictive control to reschedule EV charging rates when a new EV arrives or the last computed solution exceeds a certain period. Z. Hu et al. (2016) also suggest that the rolling window approach be further applied upon their proposed model for load valley filling by EV charging.

In spite of its necessity, the rolling window approach may bring further challenges to the performance of an EV charging scheduling model, which is rarely mentioned in the current literature. In reality, it is possible that some currently-connected or future EVs might have their charging windows (availabilities) beyond the defined optimization horizon. The first challenge is how to set charging targets for these EVs by the end of the current optimization horizon. For instance in k^{th} iteration of Fig. 1, a future EV may arrive in period $k+W-1$ but the optimization horizon ends in period $k+W$. It is highly likely that this future EV is still available for charging after period $k+W$. Therefore, a feasible charging targets should be assigned for such EVs. Second, a proposed model may only guarantee the performance of the solution of the current iteration while the true result is a combination of a series of iterations, which might fluctuate (cf. Fig. 6 below). For example, if the objective of a certain EV charging scheduling model is to flatten the total EV charging demand, the optimization solution for k^{th} iteration would be a flat curve. However, if no EV departs at period $k+1$ and more EVs arrive at period $k+1$, the optimization solution for $(k+1)^{th}$ iteration would also be a flat curve, but operating at a higher level. As only the first-period result of every iteration will be implemented, the actual charging demand might fluctuate.

2.4. Research gap

With the discussions and the literature review above, the current research gap in EV charging scheduling, where this paper aims to contribute, is mainly on how to consider each EV's uncertainty in the formulation and how to make assumptions in EV parameter settings without oversimplifying them, especially when a model is applied under rolling window approach.

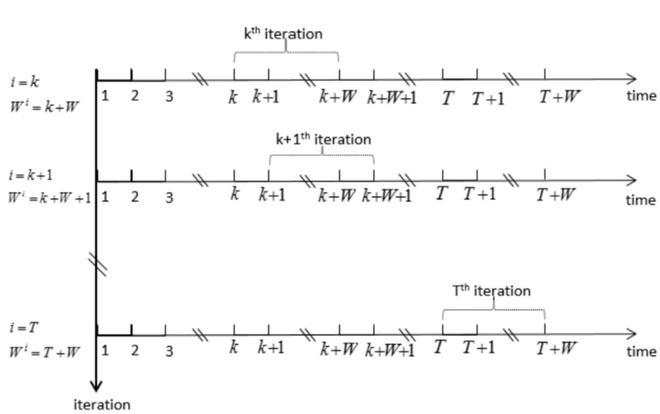


Fig. 1. Illustration of the rolling window approach.

3. EV charging scheduling model

We formulate the EV charging scheduling problem as a scenario-based two-stage SLP problem and minimize the distance between the actual EV charging demand and a pre-defined preferred charging demand over a time span. The first stage is only for the current period and determines the charging demand of the EVs that are currently connected to the grid. The second stage is for the rest of the time span and determines the estimated charging demand of the currently connected EVs as well as possible future EVs. For random parameters in the second stage, we use scenarios to represent the possible realizations of the parameters in the second stage.

The model uses the rolling window approach and, hence, only the known EV charging demand in the first stage ($t=i$) for the first 15 min are set ultimately (but considering also the estimated future demand). As time moves forward by one period, the optimization horizon also rolls forward by one period and the model recalculates solutions for all following periods ($t>i$) with updated data.

3.1. Model formulation

The formulation of the model is as follows:

$$\text{Min: } D_i^I+\sum_{\omega}\sum_{t=i+1}^{t=W^i}\pi_\omega\times\left(\left|D_{t,\omega}^I\right|+\left|D_{t,\omega}^{II}\right|\right)\qquad+\sum_m Gap_m\times\lambda+\sum_{s,\omega}\pi_\omega\times Gap'_{s,\omega}\times\lambda \tag{1}$$

Subject to:

$$D_t=\sum_{m\in EV^i}P_{m,t}\quad t=i \tag{2}$$

$$D_{t,\omega}=\sum_{m\in EV^i}P_{m,t}+\sum_{s=i+1}^{t}P'_{s,t,\omega}\quad i+1\le t\le W^i\ \forall\omega \tag{3}$$

$$D_t^I=D_t-D_t^{pref}\quad t=i \tag{4}$$

$$D_{t,\omega}^I=D_{t,\omega}-D_t^{pref}\quad i+1\le t\le W^i\ \forall\omega \tag{5}$$

$$D_{t,\omega}^{II}=D_{t,\omega}^I-D_{t-1,\omega}^I\quad i+1\le t\le W^i\ \forall\omega \tag{6}$$

$$SOC_{m,t}\times Cap=SOC_{m,t-1}\times Cap+P_{m,t}\times e\times\Delta t\quad m\in EV^i\quad i+1\le t\le W^i \tag{7}$$

$$SOC_{m,t}\times Cap=SOC_m^{ini}\times Cap+P_{m,t}\times e\times\Delta t\quad m\in EV^i\quad t=i \tag{8}$$

$$SOC_{m,t}\le SOC^{max}\quad m\in EV^i\quad i+1\le t\le W^i \tag{9}$$

$$SOC_{m,t}+Gap_m\ge SOC_m^{target}\times(1-AA_m)\quad m\in EV^i\quad t=W^i \tag{10}$$

$$P_{m,t}\le P^{max}\times A_{m,t}\quad m\in EV^i\quad i+1\le t\le W^i \tag{11}$$

$$P_{m,t}\le P^{max}\times(4-4\times SOC_{m,t-1})\quad m\in EV^i\quad i+1\le t\le W^i \tag{12}$$

$$P_{m,t} \le P^{max} \times \left(4 - 4 \times SOC_m^{ini}\right) \; m \in EV^i \; t = i \tag{13}$$

$$SOC'_{s,t,\omega} \times Cap \times \alpha_{s,\omega} = SOC'_{s,t-1,\omega} \times Cap \times \alpha_{s,\omega} + P'_{s,t,\omega} \times e \times \Delta t i + 1 \le t \le W^i i + 1 \le s < t \forall \omega \tag{14}$$

$$SOC'_{s,t,\omega} \times Cap \times \alpha_{s,\omega} = SOC'_0 \times Cap \times \alpha_{s,\omega} + P'_{s,t,\omega} \times e \times \Delta t \; i + 1 \le t \le W^i s = t \forall \omega \tag{15}$$

$$SOC'_{s,t,\omega} \le SOC^{max} i + 1 \le t \le W^i \; i + 1 \le s \le t \; \forall \omega \tag{16}$$

$$SOC'_{s,t,\omega} + Gap'_{s,\omega} \ge SOC_s^{target} t = W^i \; s \ge i + 1 \; \forall \omega \tag{17}$$

$$P'_{s,t,\omega} \le P^{max} \times \alpha_{s,\omega} i + 1 \le t \le W^i \; i + 1 \le s \le t \; \forall \omega \tag{18}$$

As the potential challenge of EV charging is the increase of peak demand within a day, the basic application of our optimization model is peak shaving or load leveling Both Z. Hu et al. (2016) and He et al. (2012) design pricing mechanisms for peak shaving and develop a quadratic programming model to EV charging scheduling. Instead of using electricity price signals as a guidance, this paper proposes to use a preferred total charging demand curve. Objective (1) minimizes the distance between the EV charging curve and this preferred curve and makes sure the distance over a time span could be equally distributed if possible. With Objective (1), the actual total charging demand would try to follow this pre-defined preferred curve. The curve makes the model extensible since the true model task depends on the value of this preferred curve. In (1), D_i^I is the objective function of the first stage, namely the distance between the EV charging demand and the preferred demand only for the current period ($t = i$). $\sum_{\omega} \sum_{t=i+1}^{t=W^i} \pi_\omega \times \left(\left|D_{t,\omega}^I\right| + \left|D_{t,\omega}^{II}\right|\right)$ is the objective function of the second stage, namely the distance for the rest of the time span ($t \in \{i+1, \ldots, W^i\}$). As we use scenarios to represent the uncertain parameters in the future, variables in the second stage are scenario-dependent (indexed by ω) and the objective function of the second stage is a weight average of different scenarios. $\sum_{m} Gap_m \times \lambda$ and $\sum_{s,\omega} \pi_\omega \times Gap'_{s,\omega} \times \lambda$ are relaxation terms to guarantee that the model will not be infeasible in case EV users' charging target cannot be satisfied. The penalty factor λ here is set to be a very high positive value (10^6 in our case). As a result, to meet users' request is prior to following the preferred curve so that the high penalty could be avoided.

Constraints (2)–(6) define the variables in Objective (1). The total EV charging demand D_i and $D_{t,\omega}$ are defined in (2) and (3). Unlike D_i, second-stage variable $D_{t,\omega}$ also considers demand from EVs that might arrive in future periods. There are three indices for the charging power of future-connected EVs $P'_{s,t,\omega}$. The first index s points out the future periods when these EVs are estimated to arrive. The second index t stands for the period of a charging behavior. The third index ω indicates scenarios, as estimations for the number of EV arrivals in the future may vary among scenarios. According to the definition of $P'_{s,t,\omega}$, its charging time t cannot be earlier than the arrival time s (one EV can only be charged upon arrival). For instance, $P'_{2,4,8}$ means that the charging power in period 4 for the EVs that are estimated to arrive in period 2 by scenario 8. By comparison, $P'_{4,2,8}$ means one EV is charged before its arrival time, which is not feasible. In (4), D_t^I and $D_{t,\omega}^I$ are the difference between total charging demand D_t and preferred charging demand D_t^{pref} for the starting period i. Similar to D_t^I, $D_{t,\omega}^I$ in (5) is the difference between total charging demand $D_{t,\omega}$ and preferred charging demand D_t^{pref} for the following periods. In (6), $D_{t,\omega}^{II}$ is the change of this difference. Gap_m and $Gap'_{s,\omega}$ in (1) serve as a relaxation for the model in case it fails to meet the charging target set by a certain user when the charging service ends.

(7)–(13) are for EVs that are currently connected to the grid. (7)–(10) are constraints for EV SOC. (7) and (8) are for SOC in two consecutive periods. (9) guarantees that the SOC will not exceed the maximum value. (10) is to make sure that the SOC target set by the user can be satisfied at the end of the current rolling horizon. Two exceptions are considered in (10). First, Gap_m guarantees that if the final SOC of an EV is still lower than the SOC target set by the user, the model will not be infeasible. The penalty λ is set to be a very high value so that meeting users' request has priority over following preferred charging demands. Second, AA_m^i in (10) is a binary parameter and is equal to 1 when the availability of an EV is beyond the current rolling window horizon. By giving more charging flexibility to EVs that have longer available periods, AA_m^i avoids long periods with high SOC and protects battery lifetime (Lunz et al., 2012). (11) limits the charging power of the EVs. $A_{m,t}$ is the availability of EVs that are currently connected to the grid. The departure times of these EVs are assumed to be known in advance, as explained in Section 2.2. As assumed in Kaschub et al. (2013), EV's maximum charging power will decrease as SOC increases. We also model this maximum charging power decrease in a linearized way. (12) and (13) assume that the maximum charging power will start to decrease linearly when SOC is over 75% and will drop to zero at full SOC.

Constraints (14)–(18) are for EVs that are estimated to arrive in future periods, and are similar to constraints (7)–(11). However, EVs that are estimated to arrive in the same future period are taken as one "aggregated" EV in the model. The number of EVs that arrive in one same future period is a random parameter and we formulate the stochastic problem in a scenario-based way, which means this random parameter is replaced by its weighted scenarios (possible realizations). Such replacement turns a stochastic model into a deterministic one (Seddig et al., 2019; Wu and Sioshansi, 2017). Parameter $\alpha_{s,\omega}$ estimates the number of EVs that may arrive in future periods in different scenarios. The capacity and maximum charging power of these aggregated EV depend on the number of EVs aggregated. With this aggregation, the model does not need to individually consider the uncertainties in departure time and SOC of future EVs. Constraint (14) and (15) are for the SOC of this aggregated EV in two consecutive periods. (16) guarantees that SOC of the aggregated EV will not exceed maximum value. Similar to (10), (17) also sets a charging target for future EVs and considers the uncertainty of future EV departure time. For these aggregated EVs, the charging target SOC_s^{target} by the end of the optimization horizon will be set to be proper values, which will be further discussed in Section 4.2. Linearization of maximum charging power is not applied to these aggregated EVs. (18) limits the charging power of the aggregated EV.

4. Parameter setting

4.1. Temporal setting

With the rolling window approach, newly-arrived EVs can be integrated into the model and the set of connected EVs is always updated. The model optimizes charging scheduling for the next 24 h and the time resolution is 15 min. The setting of 24-h rolling horizon is because the total charging demand within 24 h is similar between different rolling windows, although the EV charging demand can be shifted to some extent. The model runs every 15 min with updated parameters, hence only the here-and-now solution for the first stage will be actually implemented.

4.2. EV setting

4.2.1. EV usage pattern

The original EV usage data employed in this paper is from iZEUS (2012), the intelligent Zero Emission Urban System project which aims to enhance research, development, and practical demonstration in the fields of smart traffic and smart grid. From this project, usage patterns of 28 EVs are recorded for six months by minute. The usage data are recorded in three states: driving, parking only and charging. With this data set and inhomogeneous Markov chains (Iversen et al., 2017; Widén et al., 2009), this paper generates EV availability patterns and scenarios for future EV arrivals.

In a nutshell, there are two steps to follow in order to generate EV usage data from inhomogeneous Markov chains. The first step is to obtain the transition matrix for each EV, as shown in (19).

$$M(t)=\begin{bmatrix} p_{11}(t) & p_{12}(t) & p_{13}(t) \\ p_{21}(t) & p_{22}(t) & p_{23}(t) \\ p_{31}(t) & p_{32}(t) & p_{33}(t) \end{bmatrix},\ p_{ab}(t)=P(X_{t+1}=b|X_t=a) \tag{19}$$

In (19), X_t denotes the state of an EV in time t. $p_{ab}(t)$ is the transition probability and it denotes the probability of EV to change from state a to state b in time t. We use inhomogeneous Markov chains because this transition probability is time-variant within a day. For example, EVs are more likely to remain parked at night than in the day-time. $p_{ab}(t)$ can be estimated from statistical data (original EV trip data in this paper). For example, an EV has two states (0 for parking and 1 for driving) and (X_t,X_{t+1}) denotes EV's state in two consecutive periods. According to original trip data, we have ten samples of (X_t,X_{t+1}), which are $(0,0)$, $(0,1)$, $(0,1)$, $(0,1)$, $(1,0)$, $(1,1)$, $(1,1)$, $(1,1)$, $(1,1)$ and $(1,1)$. Then we have

$$M(t)=\begin{bmatrix} p_{00}(t) & p_{01}(t) \\ p_{10}(t) & p_{11}(t) \end{bmatrix}=\begin{bmatrix} 1/4 & 3/4 \\ 1/6 & 5/6 \end{bmatrix}, p_{ab}(t)=P(X_{t+1}=b|X_t=a) \tag{19a}$$

The second step is to generate simulated data by using $M(t)$ and a random number, which is uniformly distributed between 0 and 1. X_1, the state at the starting period, can be assumed to be zero. To get the value of X_2, we compare $M(1)$ with a random sampling of this random number, say 0.2. If we suppose $M(1)$ is equal to $M(t)$ in (19a), this 0.2 is less than 0.25 and X_2 is equal to 0. In such a way, we could generate a time series of EV usage pattern.

We assume that when an EV is not in the driving state, it is available for charging. With this assumption, we convert X_t into each $A_{m,t}$ (a binary parameter in the proposed model). Only availability periods longer than 3 h are considered for controlled charging, because shorter availability periods are more suitable for instant charging. As a relatively large amount of EVs are necessary for centralized scheduling, this paper generates four availability patterns with each of the 28 transition matrices from inhomogeneous Markov chains so that there are 112 EVs in the model for $A_{m,t}$.

An EV has load shifting potential only when its parking duration is beyond its minimum charging time. A longer extra parking time means a greater load shifting potential, which could also have an impact on the performance of a model. With extra parking time, charging behaviors can be postponed or shifted (Babrowski et al., 2014). Otherwise, instant charging would be the only option. Therefore, we present the simulation data of $A_{m,t}$ (EV availability). In order to present the uncertainty of EV usage patterns, we compare $M(t)$ with repeated random sampling of the random number uniformly distributed between 0 and 1. With 500 runs of Monte Carlo simulation, Fig. 2 shows the proportions of EVs' parking events with different durations in the total number of parking events. Fig. 3 shows the number of parked EVs within a day. The curve presents the median and the shaded area is for data between 25% and 75% quantile.

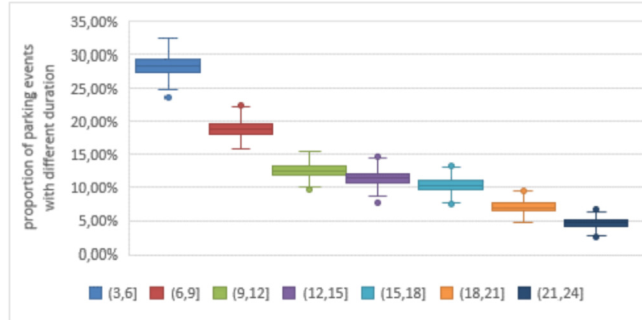


Fig. 2. Box plots of EV parking durations (in blocks of 3 h).

As shown in Fig. 2, on average, about 60% of the parking events we consider have availability durations of less than 12 h. Schäuble et al. (2017) have similar findings concerning the distribution of charging availability durations. Please note that we only consider EVs with availability periods longer than 3 h, as discussed in Section 4.2. Based on the EV settings in Section 4.2.2, it takes about 5 h to fully charge an empty EV with maximum charging power in our model. If an EV would like to have a 50% SOC increase within 3 h, this leaves almost no potential for load shifting. Even under a controlled charging strategy, its EV charging curve would still behave like one under instant charging strategy. Therefore, due to the EV settings of the paper, we only consider EVs parking more than 3 h as they have relatively sufficient potential for load shifting. In Fig. 3, most EV are parked before 6 a.m. and then this parking number decreases in the daytime, which is similar to the findings of Schäuble et al. (2016) and Brady and O'Mahony (2016).

In order to approximate the uncertainty of random parameter $\alpha_{s,\omega}$, a large set (500) of scenarios is generated with inhomogeneous Markov chains mentioned above. As such a large scenario set would also bring computational challenge to the model, scenario reduction technique is then applied to reduce the number of scenarios used in the model. The commonly used scenario reduction methods are forward selection methods, backward reduction methods and their variants. Both forward selection and backward reduction methods run in an iterative fashion. For one iteration, forward selection methods select one representative scenario out of the original set while backward reduction methods exclude one scenario which could be represented by others. As we plan to pick 10 (a small number of) scenarios out of 500, forward selection takes fewer iterations to solve and outperforms backward reduction in terms of computational time (Wang, 2010). We apply the fast forward selection method (Feng and Ryan, 2013; Heitsch and Römisch, 2003), which is briefly reviewed as follows. The Euclidean distance of each two scenarios is first calculated and one scenario which is closest to the other scenarios can be selected. Then the second scenario can be selected which is closest to the remaining scenarios. The process iterates until the method selects a subset of the original scenario set which includes 10 scenarios and has the shortest distance to the remaining scenarios. A smaller set of

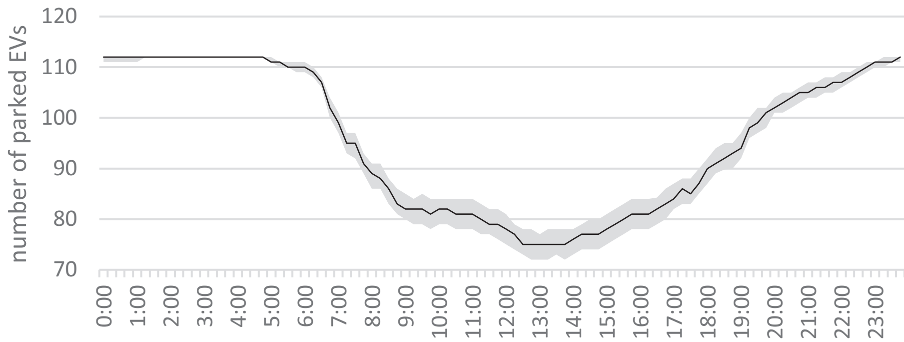


Fig. 3. Distribution of parked EV quantity in every 15 min (with median — curve; 25% & 75% quantile - shade).

scenarios are selected to represent the possible realizations and guarantee low computation time. Unselected scenarios will then add their own probabilities to one of selected ones which has the shortest distance to them.

Fig. 4 presents the distribution of EV arrival quantity and its variation throughout a day and shows the randomness of the stochastic parameter $\alpha_{s,\omega}$. The curve presents the median and the shaded area is for data between 25% and 75% quantile. It can be seen that most arrivals happen after 6 a.m. and peak in the evening hours.

4.2.2. EV model specification

In the field test of iZEUS (2012), Daimler electric Smart is used for several months generating comprehensive driving and charging patterns. In this paper, the corresponding EV specification in the parameter settings, as listed in Table 1, are considered for the following calculations.

The rationale of Table 1 is to follow the specification of Daimler electric Smart (the car model used in iZEUS). The battery capacity of Daimler electric Smart is 17.6 kWh. 90% is a reasonable assumption for EV charging efficiency. The maximum charging power P^{max} at a standard charging point is usually between 2.5 kW and 7 kW. We assume that the initial battery level SOC_m^{ini} is between 15% and 75% so that the average value is 45%. In equation (20), we set the target SOC to be 90% if possible. Therefore, this setting would meet the daily energy consumption of one EV, which is about 8 kWh.

The setting of SOC_m^{target} considers the availability parking duration T_m (in 15 min) of each EV and its initial SOC. As in (20), SOC_m^{target} is set to be an appropriate value and is below 90% so that the SOC target can be satisfied within the charging period, and the load shifting potential is also guaranteed. With maximum charging power, the SOC increase of one EV in our model in one period (15 min) is about 6%. For flexibility of charging scheduling, we assume a 3% SOC increase per period (half of maximum SOC increase). Since future arrivals of EVs are aggregated, the notion of departure time does not apply to this aggregated EV. The model only needs to assign a proper charging task SOC_s^{target} by the end of a rolling horizon, as is explained in (21). Please note that although (20) and (21) look similar in form, the meanings behind SOC_m^{target} and SOC_s^{target} are different. SOC_m^{target} is the real charging target for the currently connected EVs while SOC_s^{target} assigns charging tasks for the aggregated future EVs and is only an estimation for the future.

Table 1
EV specification settings.

Parameter	Setting	Parameter	Setting
Cap	17.6 kWh	e	90%
P^{max}	5 kW	SOC_m^{ini}	$U(15\%, 75\%)$
$SOC_0^{'}$	45%	SOC^{max}	100%

$$SOC_m^{target} = \min\left(SOC_m^{initial} + T_m \times 0.03,\ 0.9\right),\ \forall m \tag{20}$$

$$SOC_s^{target} = \min\left(SOC_0^{'} + \left(W^i - s\right) \times 0.03,\ 0.9\right),\ \forall s \tag{21}$$

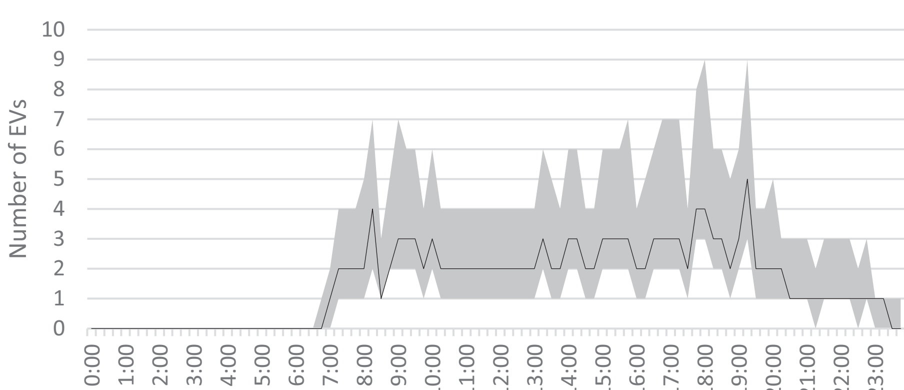


Fig. 4. Distribution of EV arrival quantity in every 15 min (with median — curve; 25% & 75% quantile - shade).

5. Results and discussions

In this section, we will illustrate the proposed model with three potential applications. ***Application I*** is to flatten the total charging demand of EVs. With ***Application I***, we compare the performance of our model with that of a deterministic one. ***Application II*** is for peak shaving and valley filling (together with conventional load from households). ***Application III*** contributes to wind energy integration and ancillary services in the reserve market. We also validate the choice of the stochastic model instead of a deterministic one. The formulated model is a two-stage SLP model and includes 260,981 variables and 549,470 constraints. The model is implemented in GAMS with CPLEX solver installed in a personal laptop with Intel Core i5-7200U processor and 8 GB RAM. As the model runs iteratively in a rolling window fashion, it takes about 15 s to solve one iteration.

5.1. Application I: flattening EV charging demand

In order to give a quantitative example of the load shifting potential of EVs, *Application I* is to flatten the EV charging demand, which decreases the peak demand of EV charging and increases the workload of the electricity grid without an additional investment in the new grid hardware, e.g. EV parking lots (Jochem et al., 2016; Lee et al., 2019). To achieve this goal, the preferred demand curve D_t^{pref} is defined in (22). With this, the charging demand curve aims to be as flat and as low as possible. For comparison, we also simulate a charging demand curve for instant charging with the same EV usage data. Our proposed model runs for a two-day time span and results are shown in Fig. 5.

$$D_t^{pref} = 0,\ \forall t \tag{22}$$

As discussed in Section 4.2, we assume that all parked EVs have charging requests and are available for charging (connected to the grid). In Fig. 5(a), the number of EVs connected to the grid decreases during daytime. In Fig. 5(b), the instant charging curve is simulated under the assumption that EVs charge upon arrival with maximum charging power until they reach their charging targets. The controlled charging curve is the optimization results of the proposed model where EVs' charging time can be scheduled within their parking time and their charging power can be regulated. The instant charging demand of these EVs peaks significantly in early evening hours and drops to a low level at night time. This simulated result of instant charging demand shows characteristics similar to those found by Schäuble et al. (2017). There is some synergy effect between the instant charging demand and the number of EV arrivals (Fig. 4), which is in line with the definition of instant charging. The instant charging demand depends more on the number of EV arrivals and less on the number of parked EVs. In controlled charging, EV charging demand is flattened and distributed throughout the entire day. The peak demand of instant charging strategy is 167 kW while the peak demand of controlled charging strategy is 73 kW. A potentially applicable situation of this example could be a parking garage or a charging station which might otherwise need to increase its capacity.

5.2. Comparison of stochastic and deterministic models

The number of future EV arrivals is the main uncertain parameter in EV scheduling. The proposed model in Section 3 is formulated as a scenario-based stochastic problem for this uncertain parameter ($\alpha_{s,\omega}$). The value of the proposed stochastic model is compared with a deterministic model in which the number of future EV arrivals is estimated with the mean value of each period (cf. Fig. 4). As a benchmark, the solution of a *perfect* model is also presented where we use the real arrival quantity of each future period as an estimation. Please note that all other parameter settings remain the same for all three models. The *perfect* model here is not a perfect foresight model.

To illustrate the performance of the three models, we present their solutions under two new EV usage profiles with ***Application I***, as shown in Fig. 6. In both Fig. 6(a) and (b), the perfect solution is not perfectly flat as other uncertainties still remain ($SOC_0^{'}$ and SOC_s^{target}) and the rolling window approach is applied. In spite of that, the perfect solution can serve as a benchmark for the other two solutions. In terms of curve fitting, we introduce two indicators to check whether the stochastic model gives a better fit (closer to the perfect model solution), namely mean absolute error (MAE) and root mean square error (RMSE). For a solution of n periods, e_j is the error for each period ($e_j,\ j = 1, 2, \dots n$). MAE and RMSE are calculated as

$$MAE = \frac{1}{n}\sum_{j=1}^{n} e_j \tag{23}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n} e_j^2} \tag{24}$$

with the definitions in (23) and (24), RMSE gives more weight to

Fig. 5(a). Number of parked EVs.

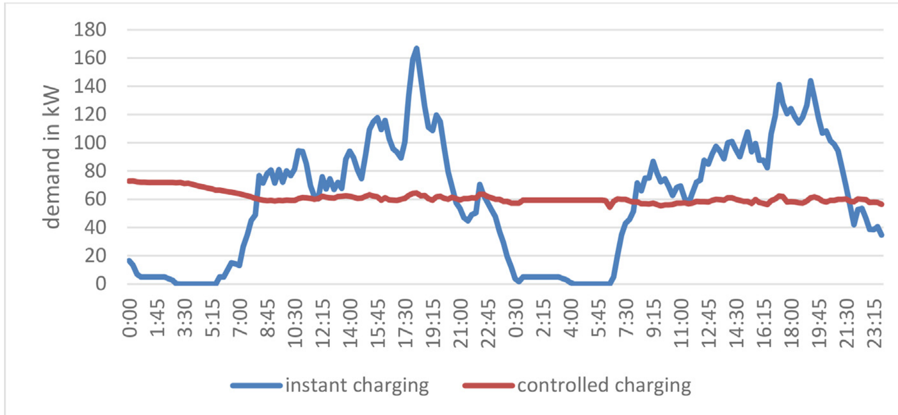


Fig. 5(b). EV charging demand of instant and controlled charging strategy.

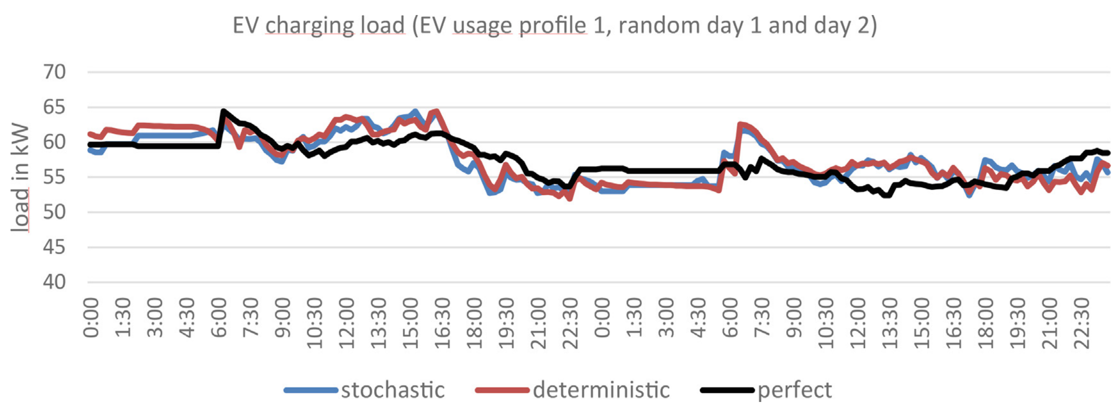


Fig. 6(a). Flattened EV charging load under EV usage profile 1.

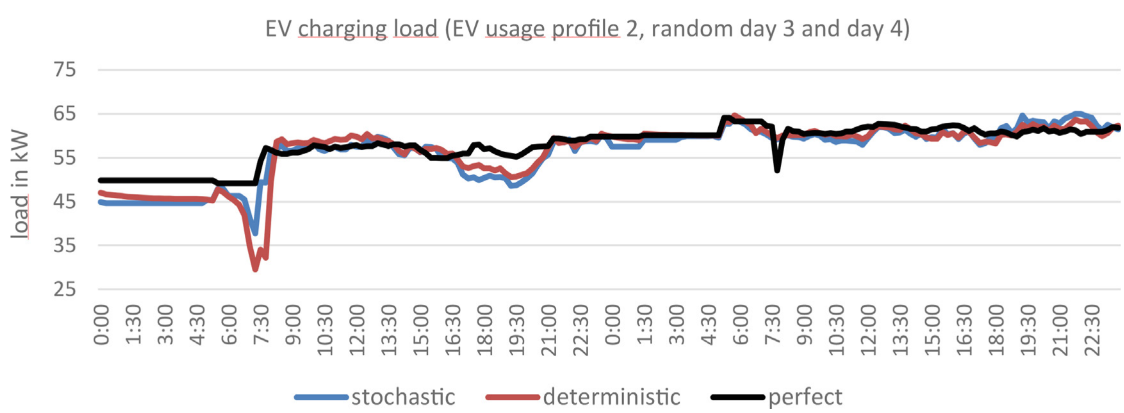


Fig. 6(b). Flattened EV charging load under EV usage profile 2.

Table 2
MAE and RMSE under two EV usage profiles of Fig. 6 (kW).

	MAE		RMSE	
	Stochastic	Deterministic	Stochastic	Deterministic
Fig. 6(a)	1.9491	2.1062	2.2968	2.4377
Fig. 6(b)	2.3448	2.1665	3.1476	3.7510

Table 3
Different criteria for stochastic and deterministic model comparison (kW).

	Stochastic	Deterministic
Average MAE	2.0731	**2.0223**
Average RMSE	**2.6001**	2.7679
Maximum deviation	**19.2003**	36.6387
Deviation of top 1‰	≥**11.3074**	≥20.2641

larger errors while MAE is unbiased. Table 2 shows the comparison results of Fig. 6. The two indicators may or may not draw the same conclusion under different EV usage profiles.

With Monte Carlo simulation, average errors are calculated for 100 random EV usage profiles. Please note that one random EV usage profile here consists of 112 EV usage behaviors for 2 day as input data. Furthermore, we present the maximum deviation of a single period and the top 1‰ deviations in Table 3. The overall performance of the two models (stochastic and deterministic) can therefore be presented by various indicators and under a large size of different input data. With the favorable results shown in bold type, the stochastic model is found to give a better curve fitting in terms of avoiding larger deviations (errors). One example of a large deviation is Fig. 6(b) which has a significant load drop around 7:30 a.m. on the first day. However, the stochastic model outperforms the deterministic one under such extreme case.

5.3. Application II: peak shaving and valley filling

More applications of EV charging scheduling are related to the interaction of the latter with other elements in the power systems, e.g., original load, renewable energy and stationary battery storage. According to Sundström and Binding (2012) and Liu (2012), instant charging demand increases significantly during evening hours. This has a negative impact on the electricity system.

Application II of the proposed model is to shift EV charging demand for peak shaving and valley filling from conventional load $Base_t$, which refers to the total household load of 112 families. Together with this conventional load, *Application II* shifts more EV charging load to off-peak hours and limits the increase in peak load. The preferred load curve is defined in (25). With Monte Carlo simulation, we present how different input parameters (EV usage patterns and SOC status) may affect the results. Fig. 7 presents 10 Monte Carlo simulation runs of the model with different EV arrival parameters for three days, i.e. EV availability ($A_{m,t}$, AA_m) from inhomogeneous Markov chains and SOC status (SOC_m^{ini}, SOC_m^{target}).

$$D_t^{pref} = \max\left\{Base_t | i+1 \le t \le W^i\right\} - Base_t, \ \forall t \tag{25}$$

Fig. 7(a) shows how EV charging load follows the preferred curve under 10 different EV parameters. Because of the charging target set by EV users, the EV charging load may not perfectly reach the value of the preferred curve but is able to follow the shape of the preferred curve under uncertainties. In Fig. 7(b), the black curve is the conventional load $Base_t$. The 10 colored curves above are 10 potential total demand curves out of 10 different EV arrival parameters. The area between each of the 10 colored curves and the base-load black curve is the EV charging load (cf. Fig. 7(a)). As can be seen, EV charging behaviors are more scheduled to off-peak hours in order to avoid higher peak load. The model also manages to cover the variation of the base load without further increasing the peak load. The difference between the 10 total load curves (10 color curves in Fig. 7) derives from the 10 Monte Carlo simulation runs of EV arrival parameters. This result serves as an example to show how the results would perform on different days. Morais et al. (2014) show similar results but EV uncertainties are not considered.

5.4. Application III: demand response for wind energy integration and control reserve market

A significant amount of wind energy has been curtailed in the past few years (Schermeyer et al., 2018) and recent literature also considers utilizing EVs for the integration of renewable energy (Schuller et al., 2015). With great temporal flexibility, EVs can be used to reduce the curtailment of wind and solar energy, which is *Application III* of our model.

In the case of potential wind energy curtailment, EV charging demand can adjust accordingly for the utilization of renewable energy. To achieve this goal, the preferred demand curve D_t^{pref} is again set to zero (cf. constraint (22)). Additionally, constraint (26) will be added to the proposed model. When a new rolling window starts, constraint (26) forces the total charging demand $D_{t,\omega}$ in the next few periods to be higher or lower than the previous charging demand D_{i-1} by a certain amount R. Scalar q determines the duration of the decrease periods. Exemplary results are shown in Fig. 8.

$$D_{t,\omega} = D_{i-1} + R, \ \ i \le t \le i+q, \ i \ge 2, \ \forall \omega \tag{26}$$

In Fig. 8(a), a demand increase R of 40 kW for 2 h from 7:45 to 9:45 of the first day is requested. For comparison, the reference charging demand (without R request) is also given. As extra EV charging demand is scheduled, EV charging demand after 10 a.m. is lower than the one in the reference case as a compensation. This

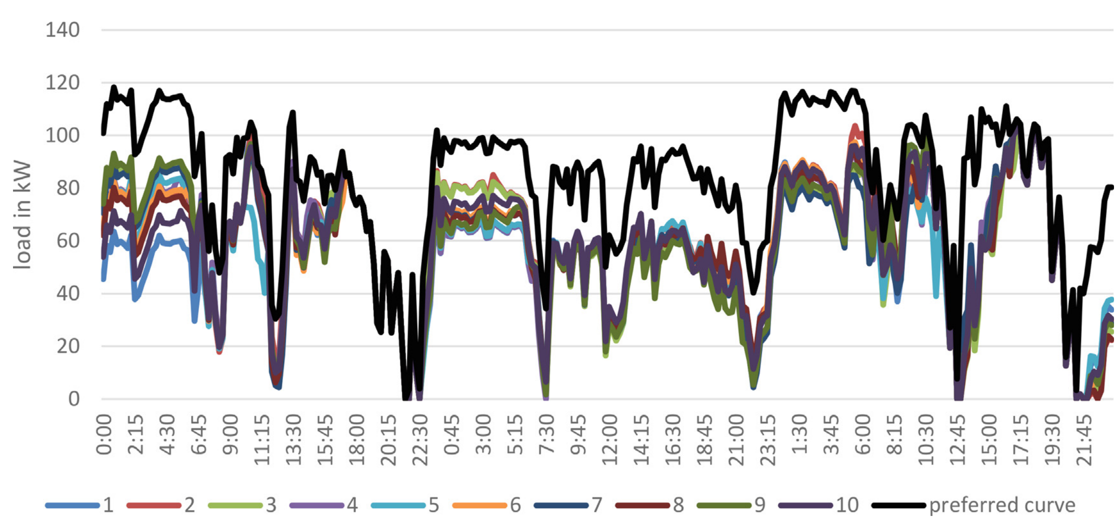


Fig. 7(a). EV charging load for peak shaving and valley filling under 10 Monte Carlo simulation runs (charging load - in color; preferred curve - black).

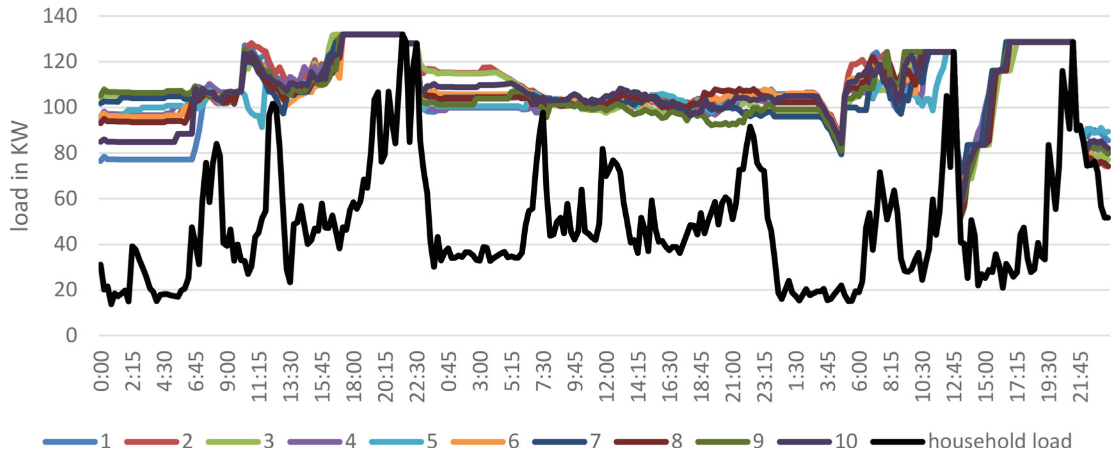


Fig. 7(b). Total load for peak-shaving and valley-filling under 10 Monte Carlo simulation runs (total load - in color; household load - black).

compensation effect is because the total EV demand within a time frame is fixed to some extent. Our proposed model distributes this compensation smoothly in the following periods and minimizes this side effect. Fig. 8(b) shows a mirrored example of Fig. 8(a) on the demand side, where R is set to be −40 kW between 7:45 and 9:45. When power import is needed because of wind energy curtailment, this problem can be temporarily solved by postponing EV charging, which provides an option to avoid high redispatch cost.

In Fig. 8(c), we further set R to be −50 kW between 7:45 and 10:45 to examine the impact of this application on EVs' final SOC. We find that all EVs' target SOC are completed in the reference case of Fig. 8 while eight charging tasks are not completed in the decrease case of Fig. 8(c). We compare the results of final SOC at departure of these two cases and present our findings in Fig. 9. We illustrate the charging availabilities of the eight tasks with gray bars and the decrease periods with blue shades (from 7:45 to 10:45 of the 1st day). As shown in Fig. 9, these eight charging tasks have relatively shorter availability periods (about 4 h) and the majority of their availability periods are in the decrease period (3 h, between 7:45 and 10:45). Because of this overlapping, these charging tasks have limited load shifting potentials beyond the decrease periods. In order to respond to the mandatory demand decrease, these eight charging tasks greatly reduce their charging power between 7:45 and 10:45. As their departure time is too early to outbalance this request, their charging tasks become incomplete.

Due to the possibility of uncompleted charging tasks, we further calculate the lowest R value for temporary decrease which can still complete all charging tasks. To achieve this, we adjust the original model ((1)–(18)) as follows.

$$\text{Min:}D_i^I + \sum_{\omega}\sum_{t=i+1}^{t=W^i} \pi_\omega \times \left(\left|D_{t,\omega}^I\right| + \left|D_{t,\omega}^{II}\right|\right) - \text{M} \times \overline{R} \tag{1a}$$

$$SOC_{m,t} \geq SOC_m^{target} \times (1 - AA_m),\ m \in EV^i,\ t = W^i \tag{10a}$$

$$SOC'_{s,t,\omega} \geq SOC_s^{target},\ t = W^i,\ s \geq i+1,\ \forall\omega \tag{17a}$$

$$D_{t,\omega} + \overline{R} = D_{i-1}^{ref},\ i \leq t \leq i+q,\ i \geq 2, \forall\omega \tag{27}$$

Objective (1) is replaced by (1a). Parameter M is set to be a large positive number. Variable $\overline{R}$ is the amount for temporary decrease and can be either positive or negative by definition. To minimize the objective, $\overline{R}$ will try to be as large as possible.

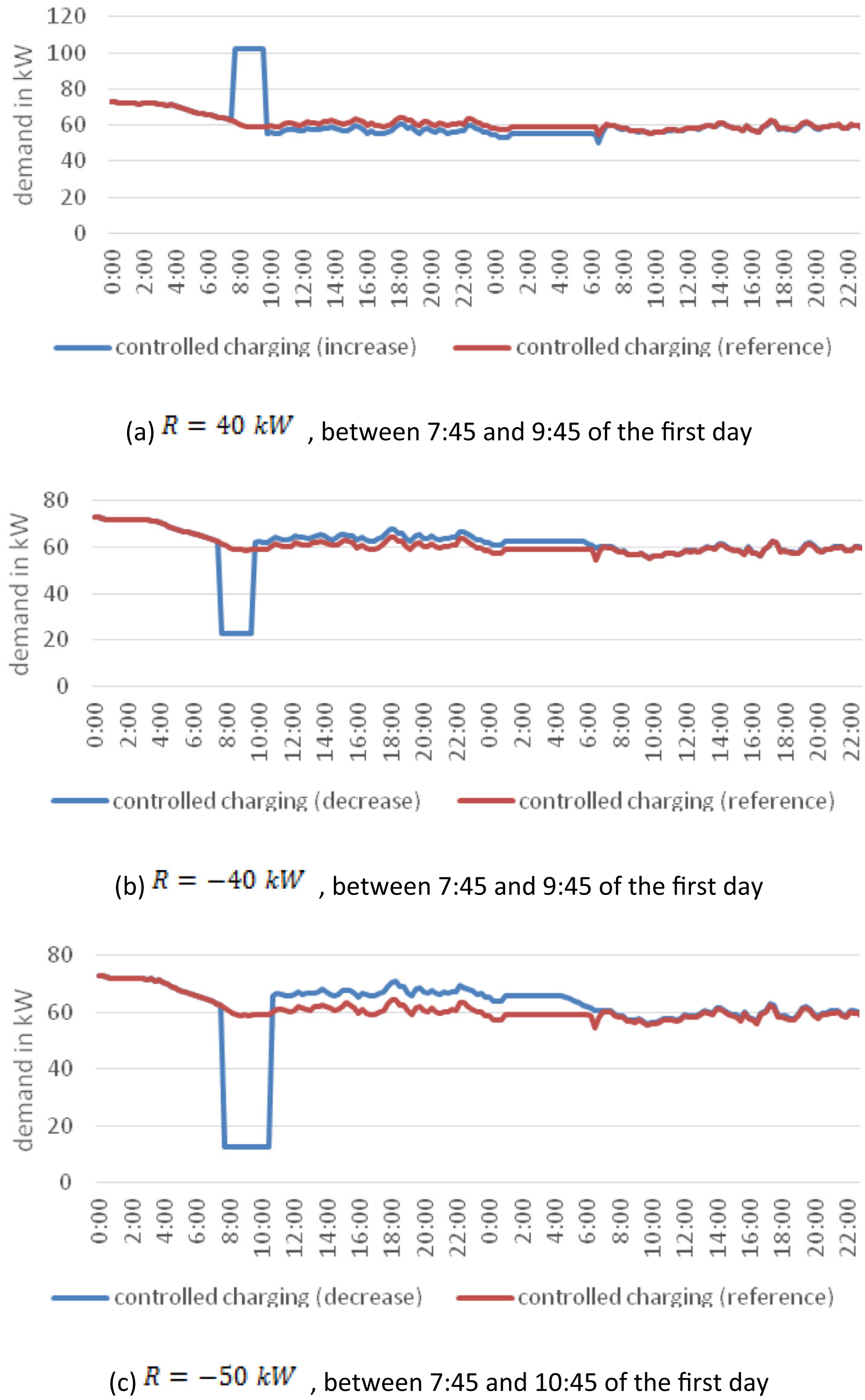
Constraint (10) and (17) are replaced by (10a) and (17a) respectively. We remove Gap_m and $Gap'_{s,\omega}$ from the constraints to guarantee that all charging tasks can be completed.

Constraint (25) is an additional constraint. Parameter D_{i-1}^{ref} is the total charging demand in the last period in the reference case (shown in Fig. 8). With constraint (25), the new model will force the total charging demand to be lower than D_{i-1}^{ref} by a certain amount $\overline{R}$ for a couple of periods. The new model includes objective (1a), constraints (2–9), (10a), (11–16), (17a), (18) and (27).

Fig. 10 shows the exemplary 2-day results of the lowest operating level (compared with the reference case) if we decrease the total charging demand temporarily for two or 3 h. The initial charging curve from ***Application I*** serves as a reference case before control reserve is provided. From either one of the two lowest operating level curves, we can see that this lowest operating level is time-variant because EVs parking at night have longer parking times and greater load shifting potentials. When we compare the two curves, we find that this lowest operating level is higher for longer decrease durations.

In Fig. 8(c), we have a decrease of 50 kW from 7:45 to 10:45 on the first day. While in Fig. 10, the $\overline{R}$ value for 3 h at 7:45 of the first day is 47.99 kW, which means uncompleted charging will happen if the decrease value is greater than 47.99 kW and lasts for 3 h. In order to justify the new model, we set R to be −47.99 kW from 7:45 to 10:45 and rerun the original model with constraint (24). We check if all EV charging tasks can be completed in this new decrease case. In Fig. 11, we compare the final SOC results of this new decrease case with the one in the reference case of Fig. 8. We illustrate the charging availabilities of the tasks with gray bars and the decrease periods with blue shades (from 7:45 to 10:45 of the 1st day).

In Fig. 11, the first eight tasks are the same as the ones in Fig. 9 and we see that seven tasks are still uncompleted (Tasks 1–3 and 5–8), which means the $\overline{R}$ value from the new model fails to guarantee that all charging tasks can be completed. This is because the new model can only guarantee that all EVs that are already connected at 7:45 can complete their charging tasks. Based on the EV patterns used, Task 8 is available from 8:15 to 11:30 and Task 9 from 8:15 to 11:45. These two EV arrive during the 3-h period and have limited availabilities for load shifting, which takes up the charging demand scheduled for other EVs (Task 1–3 and 5–8). As a result, some EV charging tasks are uncompleted. Even though our model considers uncertainties of future EVs, the total charging demand is



(a) $R = 40\ kW$, between 7:45 and 9:45 of the first day

(b) $R = -40\ kW$, between 7:45 and 9:45 of the first day

(c) $R = -50\ kW$, between 7:45 and 10:45 of the first day

Fig. 8. Synergy with wind energy integration.

controlled at a low level in the first 3 h of the decrease case so that the model does not schedule charging behaviors for future EVs within the decrease periods.

Despite the discussions above, the findings in Fig. 10 provide an upper bound for real-time charging demand decrease, which means uncompleted charging tasks will happen if the decrease level goes beyond $\overline{R}$. The findings may assist EVs in integrating renewable energy or bidding in control reserve markets. Fig. 10 can also serve as a quantification of EV load shifting potentials at different times of the day. Future work may focus on further improvements of the new model.

5.5. Future work

As a premise to our proposed model, we assume that all EV users accept the proposed charging strategy and that none of them will

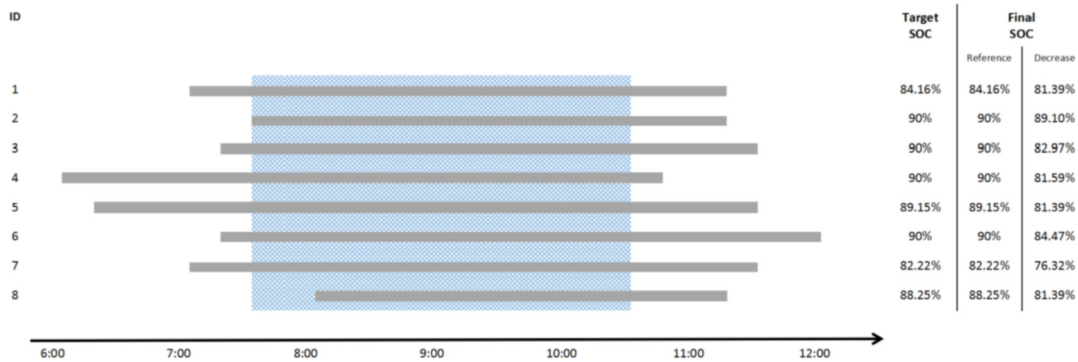


Fig. 9. Comparison of final SOC at departure, reference case of Fig. 8 and decrease case of Fig. 8(c).

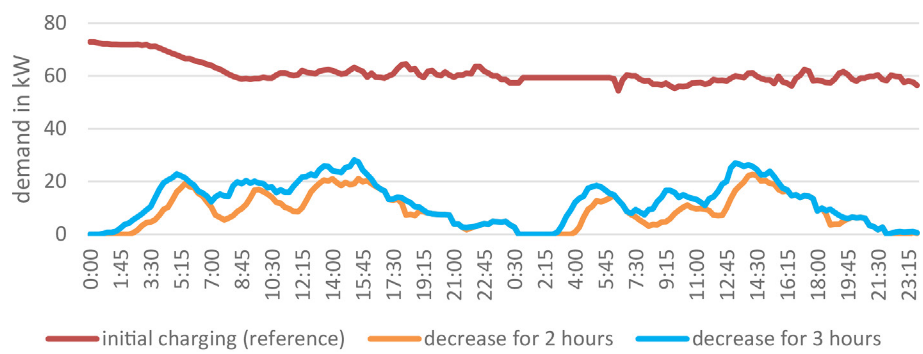


Fig. 10. Lowest operating level for temporary decrease.

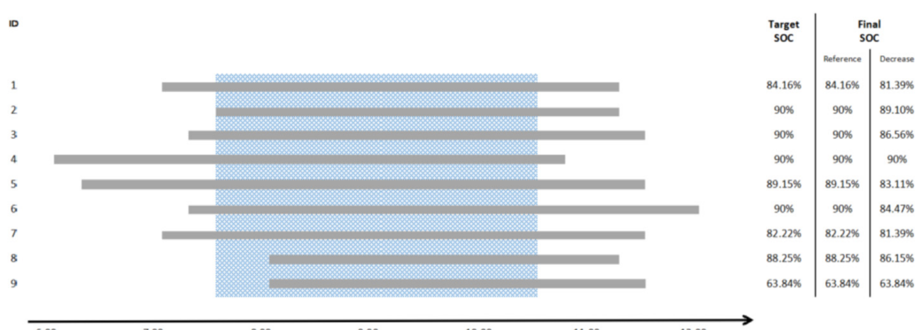


Fig. 11. Comparison of final SOC at departure, reference case of Fig. 8 and new decrease case ($R = -47.99\ kW$, between 7:45 and 10:45 of the 1st day).

leave earlier than at their guaranteed departure times. The simplifications above might not apply in reality and analyses of EV users' acceptance should be studied accordingly (Ensslem et al., 2013). Although we have taken into account the uncertainties of future EVs by either scenarios or valid assumptions, the EV driving profile with different maximum charging power in reality might be more difficult to consider than our simulation results, which might deteriorate the performance of the proposed model. Further exemplary results based on other EV database might be necessary. Since charging strategies may have a significant impact on the battery lifetime, additional concerns regarding the battery degradation could also be considered (X. Hu et al., 2016; Li et al., 2017). The applications of load flattening and peaking shaving can be further elaborated with constraints for grid bottleneck and transformer capacity limit and the synergy between EV charging and local renewable energy integration can also be further studied. As in Tan et al. (2016) and Zheng et al. (2019), the idea of V2G has been widely discussed in the current literature but is not yet included in our current model. The integration of V2G would increase model complexity and computational burden and would be an improvement of our work and the focus of future research.

6. Conclusion

This paper presents a two-stage SLP to address the EV charging scheduling problem in real time. We model the uncertainties in EV availability (arrival time and departure time) and SOC status upon arrival (initial SOC and target SOC). We consider the future EVs on an aggregated level to reduce computational burden. With this objective, the model can be easily applied for different optimization purposes.

Three potential applications are given. *Application I* flattens the total charging demand of an EV fleet throughout the day. A comparison between the controlled charging demand and an instant charging demand is presented. *Application II* is for peak shaving in coupling with household demand and manages to shift more charging demand to off-peak hours. *Application III* utilizes EVs for renewable energy integration where EV charging behaviors respond to the volatile output of renewable energy in real time, which can also serve as an example of participation in the control reserve market.

We show that future EVs may not complete their charging tasks when the down-regulation offer of total load is excessively provided and charging behaviors are greatly postponed. This is because we consider the uncertainties from future EVs but on an aggregated level. This aggregation decreases the computation complexity of the model and does not consider EVs which arrive in the near future with limited availabilities. Based on this, we further adjust the model and calculate the upper bound down-regulation offer at different times of the day and for different durations.

Author contributions

Zongfei Wang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization. **Patrick Jochem**: Validation, Resources, Investigation, Writing - Review & Editing, Supervision, Funding acquisition. **Wolf Fichtner**: Validation, Resources, Writing - Review & Editing, Supervision, 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.

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How many electric vehicles can one wind turbine charge?

A study on wind energy generation and electric vehicle demand correlation

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Summary
We propose an optimization model which schedules EV charging behaviors to maximally utilize wind energy and to alleviate the generation volatility. We compare the proposed charging strategy with other charging strategies. The performance is demonstrated by coupling the output of one wind turbine with an EV fleet. The simulated results show the necessity of smart charging strategy for wind energy integration and the challenge in alleviating wind generation volatility.

Keywords: battery electric vehicles, smart charging, renewable, optimization

1 Introduction

A growing number of countries have set targets to increase the market share of electric vehicles (EVs) and the integration of renewable energy into power system [1,2]. In this context, EVs are often expected to reduce carbon dioxide (CO_2) emission. However, such expectation depends on not only the electricity generation mix of the area but also the charging strategy of EVs. Considering the promising load shifting potential of EV [3], controlled charging can better utilize the renewable energy generation and lower CO_2 emissions [4].

[5] estimates the cost saving by the management of EV fleet based on a case study of California with high renewable integration. [6] develops a unit commitment and economic dispatch model to operate both conventional and wind generation unit under smart EV charging strategy to minimize operation cost. [7] applies fuzzy control theory and proposes a hierarchical controller to manage EV charging behaviors for wind power smoothing.

In this paper, we focus on tackling the uncertainties from EV during charging management for wind integration. We propose an EV charging scheduling model which aims to utilize more wind energy and to alleviate the volatility of wind generation. We demonstrate the proposed model with a simplified case where an EV fleet is supported by a local wind turbine. When wind generation is insufficient, EV charging demand will be supported by the grid. Compared with an instant charging strategy, we quantify the extra wind generation utilized by EVs. Compared with a myopic charging strategy which only aims to utilize more wind energy, we illustrate the function of wind volatility alleviation.

The remainder of this paper is organized as follows. Section 2 explains two controlled charging strategies and the respective optimization models. In section 3 we provide simulated results of wind energy utilization under different charging strategies. Section 4 concludes the paper.

2 Methodology

Two different controlled charging strategies are defined as follows and they both aim at utilizing wind energy for EV charging:

i. *Following charging strategy:* This charging strategy aims at having the total EV charging demand scheduled at the level of the wind turbine output so that wind energy can be utilized and its output volatility can be alleviated. With this objective, EVs that may arrive in the future should also be considered.

ii. *Myopic charging strategy:* This straightforward strategy only considers currently available EVs to maximize charging demand from wind energy. When possible, this myopic strategy will shift charging behaviour to periods with sufficient wind energy supply so that wind energy is maximally utilized and grid electricity use is limited.

2.1 Following charging strategy

The EV charging scheduling model we apply is based on [8], where the EV charging scheduling problem is formulated as a scenario-based two-stage linear programming model. The structure of the model is as shown in Fig.1. The objective of the model is to have the EV charging demand follow a target curve, which makes the model extensible for different applications. The model considers the uncertainties from future EVs' availability (i.e. arrival time and departure time) and their charging demand upon arrival (initial and final battery state of charge). The model optimizes charging behaviors for the next 24 hours with quarter-hour temporal resolution. Because new EVs will arrive in the future and join the optimization model, rolling window approach is applied and the model runs every quarter hour to update the charging scheduling solutions [9].

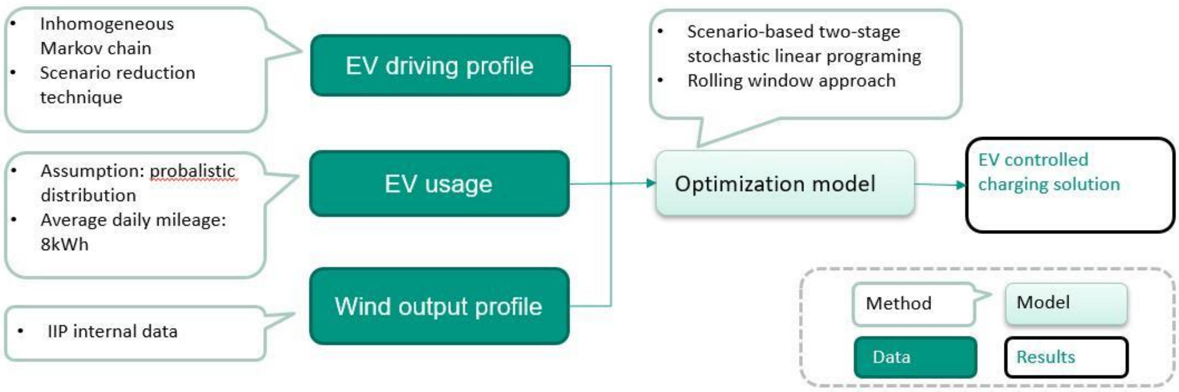

Figure 1: Model structure

In order to study the synergy between the generation of a wind turbine and a large amount of EVs (over 1000 EVs) over a time span of one month, we make some adjustments and simplifications to the original model above to shorten the calculation time.

In this paper, we take one empirically-based wind turbine output profile as the target curve so that the electricity for EV charging is more from wind energy. The objective formulation is as shown in eq. (1).

$$\text{Minimize: } \sum_{t=i}^{t=W^i}(D_t^{grid} + D_t^{cur}) + \sum_{t=i+1}^{t=W^i}\left|(D_t - G_t^{wind}) - (D_{t-1} - G_{t-1}^{wind})\right| \quad (1)$$

Subject to:

$$D_t^{grid} - D_t^{cur} = D_t - G_t^{wind} \qquad i \le t \le W^i \quad (2)$$

Indices/Sets:

t Time periods

Parameters:

i Starting period of the optimization model

W^i Ending period of the optimization model

G_t^{wind} Wind turbine generation in period t [kW]

Variables (non-negative, in italic):

D_t EV total charging demand in period t [kW]

D_t^{grid} EV charging demand by the grid in period t [kW]

D_t^{cur} Curtailed wind generation in period t [kW]

Eq. (2) shows the gap between EV total charging demand D_t and the current wind energy output G_t^{wind}. As objective (1) is a minimization problem and both charging demand by the grid D_t^{grid} and curtailed wind generation D_t^{cur} are non-negative variables, at least one of them is equal to zero. Therefore, the first summation of objective (1) aims at maximizing wind energy utilization and the second summation makes sure that EV charging demand could follow the output profile of the wind turbine. [10] explains the linearization of the second summation.

Furthermore, we simplify the model as a deterministic one and the number of future EV arrival is considered by its expected value instead of scenarios. The maximum charging power of EV is considered constant, regardless of EV's SOC [11]. The rest of the constraints are not adjusted, e.g. constraints for SOC and EV charging power.

The original model outperforms the simplified model when the actual number of EV arrival in the future greatly deviates from the expected value while the simplified model saves much computation time and the key findings are not affected.

2.2 Myopic charging strategy

In order to present the performance of the modified model above, we also propose another myopic optimization model which also aims at maximizing the EV charging demand by wind but in a more direct way. This reference model will only consider the currently available EVs for controlled charging and the follow objective is as shown in eq. (1a).

$$\text{Minimize: } \sum_{t=i}^{t=W^i} c(t) * (D_t^{grid} + D_t^{cur}) \quad (1a)$$

Parameters:

$c(t)$ Quasi price signal

Parameter $c(t)$ is not a real charging cost but just a time series of positive values which decrease over time. This myopic model only optimizes charging behaviors for the currently available EVs. With objective (1a) and parameter $c(t)$, this myopic will postpone the charging behaviors and limit charging power in early periods when EVs are charged with electricity from the grid and will charge EVs instantly and as much as possible when EVs use electricity from the wind turbine.

Except for the consideration of future EV arrival, all other constraints used for this myopic model are the same as the model discussed in Section 2.1.

Both following and myopic charging strategies are applied in the rolling window fashion. Every time each model only optimizes charging behaviors for the next 24 hours and neither of the two strategies has future information beyond that. Only the solutions for the first quarter hour will be implemented and then charging solution will be updated with latest information.

2.3 Flexible EV charging targets

It is also worth noting that in both models above we do not set fixed charging targets for EVs, as shown in eq. (3).

$$SOC_{m,t} \geq \mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}} \qquad \forall m, \mathrm{t} = \mathrm{dep_m} \wedge \mathrm{t} \leq \mathrm{W^i} \tag{3}$$

Indices/Sets:

m EVs currently available for charging scheduling

Parameters:

$\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ Starting period of the optimization model

$\mathrm{dep_m}$ Guaranteed departure time of EV m

Variables (non-negative, in italic):

SOC_{m,t_t} Battery SOC of EV m in period t [%]

We assume that the departure time of the currently available EVs is known to the model. The scheduled SOC at departure time $SOC_{m,t}$ could be greater than the charging target of each EV $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ and this constraint only applies to EVs that will depart within the next 24 hours (the optimization horizon).

Based on the SOC upon arrival and available time to charging scheduling, $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ is individually set by each charging service and will not exceed 90%. According to [10], EV charging power decreases when SOC reaches a certain level. As a result, if $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ is strictly set to 100%, EVs will take much longer to charge EVs.

Considering the focus of this paper, when the total charging demand D_t is below the wind turbine output, SOC at departure time will try to reach 100% to maximally utilized wind energy. When wind output is insufficient, SOC at departure time $SOC_{m,\mathrm{dep_m}}$ will just reach $\mathrm{SOC}_{\mathrm{m,t}}^{\mathrm{target}}$ (less than 100%) to limit the use of electricity from the grid.

3 Results and discussions

3.1 Data

With inhomogenous Markov Chains [12, 13] and test field EV usage data from [14], we get the transition matrix for EV usage behaviors and we assume that the transition matrix of each EV for weekdays is the same and so is the matrix for weekends. Then we generate usage data for 1008 simulated EVs for one month and assume that EVs are available for controlled charging service when the parking time is longer than three hours. The battery capacity of each EV is assumed to be 17.6 kWh with a maximum charging power of 5 kW. The initial SOC upon arrival is assumed to be uniformly distributed between 30% and 80%. The charging target is individually assigned considering the initial SOC and parking time of each charging service and will not exceed 90%. The wind output profile [15] is a simulation result for a 3 MW wind turbine with quarter-hour resolution based on wind speed data in 2015.

3.2 Integration of wind generation

With simulated usage data of 1008 EVs, we first test how much wind energy can be utilized under instant charging strategy which serves as a reference scenario for the two controlled charging strategies discussed in section 2, i.e. following charging strategy and myopic charging strategy. For instant charging strategy, we assume that EVs will start charging upon arrival with maximum charging power until they reach 100% SOC or they start their next trips.

We select the simulated wind output profile in four representative months of 2015 (January, April, July and October) and apply the two controlled charging strategies for a time span of each month. Summarized results of the four months are listed in Table 1 and time series EV charging demand under the three charging strategies are presented in Fig.2. Please note that only results of the first 15 days of April are presented in this paper due to page limit. With rolling window approach, Fig.2 is an accumulation of the first period solutions of 1440 iterations (96 iterations for one day).

Table1: Total charging demand under three charging strategies

	Following	Myopic	Instant
Total charging demand (MWh)	1329.33	1335.68	1424.59
Charging demand by wind (MWh)	1130.14	1132.57	907.26
Charging demand by wind ratio	85.02%	84.79%	63.69%
Unutilized wind ratio	55.00%	54.91%	63.87%
100% wind charging periods ratio	62.65%	73.87%	57.50%

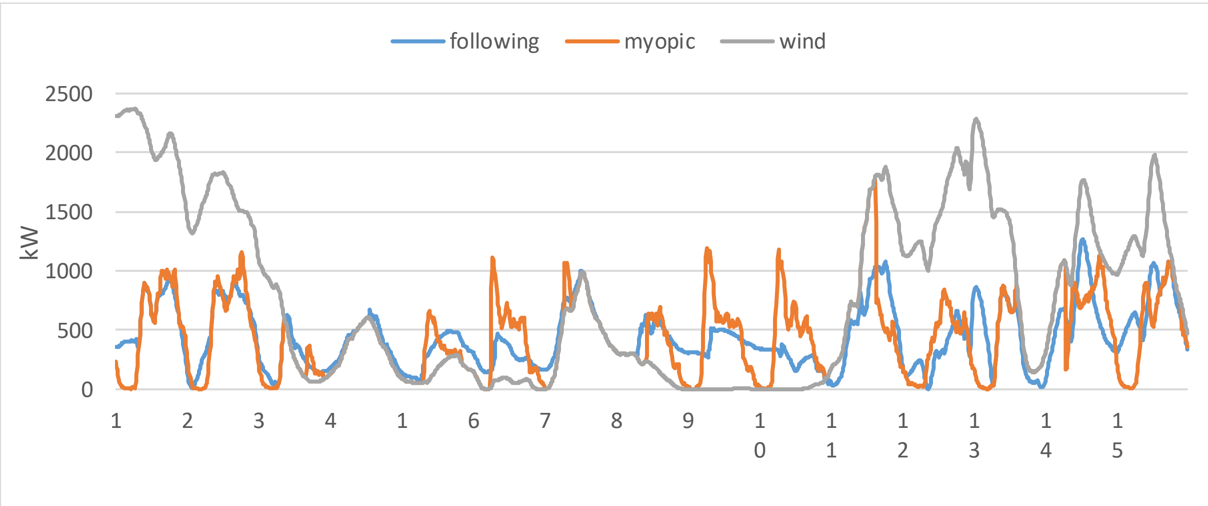

Figure2: Time series charging demand under three charging strategies (15 days)

In the four representative months of 2015, the average output of the 3 MW simulated wind turbine is about 0.85 MW and the total output is about 2511.67 MWh. In Table 1, the total charging demand under following and myopic charging strategies is lower than that under instant strategy because the two controlled charging strategies have no incentive to charge to full SOC during periods with insufficient wind energy supply. Despite less total charging demand, two controlled charging strategies make use of more wind energy for EV charging to satisfy charging targets and limit to the use of grid electricity.

Although their capabilities of utilizing wind energy are similar, the two controlled charging strategies schedule charging behaviors in different ways. In day 9 and 10 of Fig. 2, the myopic strategy postpones charging behaviors as late as possible when wind energy supply is insufficient and only charges EVs to satisfy their charging targets. As a result, a peak charging demand happens before a larger amount of EVs depart during similar periods (morning hours to workplace). When there is enough wind energy output and no postponed charging behaviors, the myopic strategy will behave like instant charging strategy, e.g. in day 1 and 2 of Fig. 2. In contrast, the following strategy tries to follow the shape of the wind energy output (e.g. in day 12 and 13) and tries to evenly schedule charging tasks when wind energy output is low (e.g. in day 9 and 10).

3.3 Alleviation of wind generation volatility

According to Table 1, the total wind energy supply is about 88% more than the total EV charging demand. However, even under the two controlled strategies where wind energy utilization is maximized, more than half of the total wind energy are unutilized.

The unutilized wind generation under two controlled charging strategies of Fig.2 is shown in Fig.3 and negative value means the amount of electricity charged by the grid. As discussed in Section 2.1, the following charging strategy considers information of EVs that will arrive in the future. In order to show the error of such estimation, Fig. 3 additionally shows a perfect foresight scenario where charging behaviors with one month are optimally scheduled to follow the wind output profile with full EV information in the optimization period. This perfect foresight serves as the upper bound of the following charging strategy.

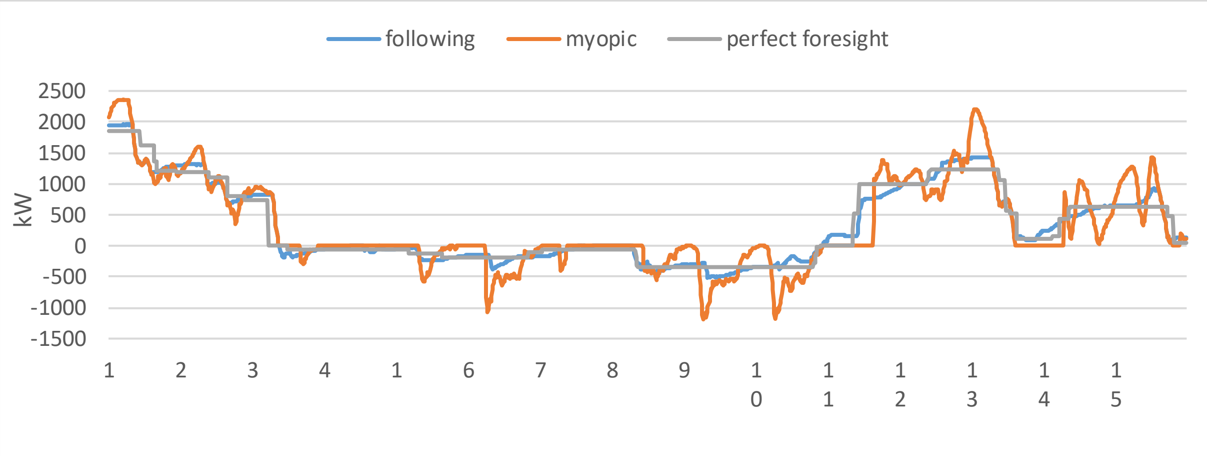

Figure 3: Alleviation of wind generation volatility under two controlled charging strategies (15 days)

As the myopic charging strategy has no further constraints for allocating EV charging demand, postponed charging with grid supply can result in charging demand spike (e.g. in day 9 and day 10 of Fig. 3) and the volatility of unutilized wind energy may not be alleviated (e.g. in day 12 and day 13 of Fig. 3). Since total EV charging demand tries to follow the wind output profile under following charging strategy, such volatility can be alleviated and the unutilized wind generation could be better integrated into the grid.

The performance gap between the following strategy and the perfect foresight scenario result from the modelling and the estimation and for future EVs' information, i.e. their arrival and departure time and initial and target SOC. If uncertainties from future EVs could be better modelled beyond the current following charging strategy model, the perfect foresight model would be the upper bound one could reach.

4 Conclusions

This paper aims at promoting the utilization of wind energy for controlled EV charging. We propose a linear programming optimization model to maximize the utilization of wind generation by the charging demand of local EVs. We test how much generation of a 3 MW wind turbine can be utilized by charging 1008 EVs. Compared with the instant charging strategy, we show that the propose model could increase the amount of charging demand by wind significantly. The proposed model can also alleviate the volatility of unutilized wind energy for better integration into the grid, which is demonstrated by comparison with a charging strategy which only considers maximizing the wind energy utilization. With a perfect foresight scenario, we show the upper bound of such alleviation. Further alleviation is limited by the number of EVs and their parking time. The option of vehicle-to-grid [16] might bring more possibilities to the field of renewable integration and emission reduction and would be the focus of our future work.

Acknowledgments

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Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies

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ABSTRACT

The growing market share of electric vehicles (EV) has increased the interest in charging strategies and their effects on the electricity system as well as their climatic soundness. However, the benefits of different charging strategies including Vehicle-to-Grid (V2G) on a large regional scale, e.g. in Europe, have not been analyzed sufficiently. This study examines the impact of different charging strategies on greenhouse gas (GHG) emissions from electricity generation and EV batteries in Europe in 2050. To consider indirect emissions and potentially additional battery degradation due to V2G, a model coupling concept is applied to link Life Cycle Assessment (LCA) with the electricity system model, PERSEUS-EU. Overall, EV could reduce the GHG emissions by 36% by simply replacing conventional cars. Controlled unidirectional charging and V2G add another 4 or 11 percentage points on the European level. However, for these gains an efficient implementation of V2G is required.

1. Introduction

The necessity of reducing greenhouse gas (GHG) emissions has already been widely recognized. Consequently, the European Commission has announced a series of long-term low-carbon policy plans and has explored pathways for key sectors, such as electricity and transport, to achieve GHG emission reductions by 80% to 95% by 2050 compared to the level of 1990 (European Commission, 2015). As one of the essential components, the transport sector has to reduce its GHG emissions by 54% to 67% in 2050 (European Commission, 2011). Currently, transport produces around a quarter of Europe's GHG emissions, with road transport having a share of over 70% (European Commission, 2016). This indicates the important role of innovative and green road transport measures in low-carbon mobility. Electric vehicles (EV) including battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) are considered to be one of such measures. BEV, in particular, are still regarded as zero-emission vehicles by the European legislation even though their indirect emissions might be significant (Jochem et al., 2015).

Emissions from upstream, downstream, and auxiliary processes are not included in these considerations (e.g. Teixeira and Sodré,

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Nomenclature

Indices and Sets

$ec \in EC$	Energy carriers
$ec \in EC^{re} \in EC$	Renewable energy carriers
$ec \in EC^{time} \in EC$	Balanced energy carriers for each time slice
$ec \in EC^{year} \in EC$	Yearly balanced energy carriers
$el \in EC$	Electricity
$no \in NO$	System nodes
$pc \in PC$	Processes
$pc \in PC^{re} \in PC$	Renewable processes
$pump \in PC^{ps} \in PC$	Pump process
$si \in SI \in NO$	Sinks of the graph structure
$so \in SO \in NO$	Sources of the graph structure
$t \in T$	Time slices
$turbine \in U^{ps} \in PC$	Turbine process
$u \in U$	Units
$u \in U^{PS} \subset U$	Pumped storage units
$y \in Y$	Years

Parameters

$\eta_{n,n',ec,y}$	Efficiency of flow between n and n′ for energy carrier ec in year y
$\eta_{n,n',ec}$	Efficiency of flow between n and n′ for energy carrier ec
$\eta_{pc,y}$	Efficiency of process pc in year y
$av_{u,y,t}$	Availability of unit u in time slice t in year y
$c^{fix}_{u,y}$	Fixed annual operation costs of unit u in year y
$c^{inv}_{u,y}$	Investment expenditures for commissioning unit u in year y
c^{lv}_{ec}	Load variation costs for units using energy carrier ec
$c^{var}_{pc,y}$	Variable operating costs of process p in year y
$ct_{ec,no,y}$	Capacity target of a node for the energy carrier for a year
$flh^{max}_{u,y}$	Maximum full-load hours of unit in year y
$flh^{min}_{u,y}$	Minimum full-load hours of unit u in year y
h_t	Number of hours of time slice t
$k^{exist}_{u,y}$	Initial capacity of unit u in year y considering shutdowns and life times
$np_{ec,no,y}$	Potential of a node for each energy carrier for a year
ph^{life}_{u}	Physical lifetime
$po_{ec,no,y}$	Maximum potential of energy carrier ec in node no in year y
pt_y	Production target in percentage for a year
r	Discount rate of future cash flows
$RT_{ec,no,y}$	Maximum potential
$rt_{ec,y}$	Production targets for renewable energy carrier ec in year t
$rt_{n,ec,y}$	Capacity expansion targets at node n for energy carrier ec in year y
sc_u	Secured capacity of unit u
sf	Factor for security of supply
$tr_{t-1,t}$	Number of transitions between time slice t-1 and t
$v_{u,y}$	Planned volume of a storage system in planning phase
$c^{fuel}_{ec,y}$	Fuel costs of energy carrier ec in year y

Variables

$Cap^{Max}_{u,y}$	Maximum installed capacity of generation unit u at the end of year y
$Cap^{Tot}_{u,y}$	Installed capacity of generation unit u at the end of year y
$FL_{no,no',ec,y,t}$	Level of the flow between node no′ and no in time slice t in year y
$FL_{no,no',ec,y}$	Level of the flow between node no′ and no in year y
$K^{new}_{u,y}$	Newly installed capacity of unit u in year y
$K_{u,y}$	Capacity of unit u in year y
$LV^{down}_{pc,ec,y,t-1,t}$	Load variation downwards between time slices t-1 and t in year y
$LV^{down}_{u,t-1,t,y}$	Load variation downwards between time slice t-1 and t in year y
$LV^{up}_{pc,ec,y,t-1,t}$	Load variation upwards between time slices t-1 and t in year y
$LV^{up}_{u,t-1,t,y}$	Load variation upwards between time slice t-1 and t in year y
$PL_{pc,y,t}$	Production level of process pc in time slice t in year y
$PL_{pc,y}$	Production level of process pc in year y
$SL_{u,y,t}$	Storage level of pumped storage units in time slice t in year y
$SOC_{ess,y,t}$	Charging level of storage system ess at the end of time slice t in year y

2018). Overall, GHG emissions of EV depend on the electricity mix used during charging as well as on the emissions from vehicle production and scrappage processes. Many studies (Bauer et al., 2015; Lewis et al., 2014; Nanaki and Koroneos, 2013; Orsi et al., 2016; Qiao et al., 2019; Shen et al., 2019; Casals et al., 2016) have already shown the large advantages of EV in climate change mitigation compared to conventional internal combustion engine vehicles (ICEV) and have confirmed the positive effect of renewable-dominated electricity systems compared to fossil-based ones for EV, even from a life cycle perspective. However, those studies mainly used the national or regional average annual electricity mix to calculate upstream GHG emissions of EV. Most studies consider neither the feedback effect which occurs due to the additional electricity demand by EV nor a timing effect which considers different charging strategies. However, controlled charging of EV affects the electricity mix and emissions considerably and is therefore addressed in the following.

From an energy system point of view, controlled charging is an acceptable demand-side flexibility option to cope with the challenges of an increasingly intermittent electricity generation from renewable energy resources (RES), such as wind and Photovoltaics (PV), and fluctuating demand (Richardson, 2013). The controlled charging strategies can be divided into unidirectional controlled charging, and bidirectional controlled charging (the so-called Vehicle-to-Grid (V2G) approach (Ghofrani et al., 2016)). V2G makes EV mobile storage, which feed electricity back into the grid, whenever possible and necessary from the system perspective.

Depending on the EV charging strategy chosen, the electricity mix generated for EV may vary, and so will the resulting impact on the electricity system and climate change in the future. This calls for an evaluation of GHG emissions of EV with different charging strategies, based on the electricity mix dedicatedly generated for EV. The idea to assess GHG emissions of EV is not new, and different charging strategies have also been considered, such as unidirectional charging (Jochem et al., 2015; Rangaraju et al., 2015) and even V2G (Colmenar-Santos et al., 2019; Lund and Kempton, 2008; Zhao et al., 2016, 2017; Noori et al., 2016). However, these assessments mainly focus on direct CO_2 emissions of electricity production during the vehicle usage phase, while emissions from upstream and downstream processes were neglected. Additionally, additional charging in V2G might cause an accelerated degradation of the EV batteries (Hoke et al., 2011) which may lead to higher GHG emissions. Consequently, it is crucial to consider GHG emissions from EV battery production, too.

This study aims to fill this knowledge gap, i.e. to systematically assess GHG emissions associated with both the generation of electricity mix during vehicle usage and EV battery production including V2G and the feedback effect of EV charging on the European electricity system. For this purpose, life cycle assessment (LCA) is coupled with an electricity system model, PERSEUS-EU. LCA is a holistic quantitative method for assessing the environmental impacts of a product or a service during the entire lifespan, i.e. from raw materials extraction, processing, production, and utilization to final disposal (International Organization for Standardization, 2006). It has been widely applied to evaluate electricity generation systems and generation technologies, especially for their GHG emissions. The PERSEUS-EU model is a bottom-up optimization model which represents the European electricity system (Fichtner et al., 1999). As a base model of the electricity system, it has been developed and applied by many researchers to analyze the integration of EV (Jochem et al., 2015; Babrowski et al., 2014; Heinrichs et al., 2014). Additionally, the environmental assessment framework of energy system analysis (EAFESA) (Xu et al., 2020) is applied as a guideline to couple both models. Consequently, the analysis identifies the effects of different EV charging strategies on climate change.

Although fuel cell electric vehicles (FCEV) are another important electrification option in road transport and hydrogen technology will be important for storage in the future energy system with high shares of RES, FCEV will not be considered by this study. The main reason is the still unclear market penetration of this technology as well as the unknown hydrogen share in the future energy system.

This paper is organized as follows: Section 2 gives an overview of current literature and Section 3 describes the methodologies, including description of models and their coupling, used data, and the scenarios. In Section 4, the results regarding GHG emissions from the generation of the electricity mix and battery production are presented and discussed, Section 5 contains uncertainty analyses of battery development and EV availability. Finally, Section 6 summarizes the main findings of the paper, makes policy recommendations, and presents critical reflections and an outlook.

2. Literature review

A shift from ICEV to EV will, ceteris paribus, increase the demand for electricity and might, consequently, increase installations of power plants (Hadley, 2006). Due to their technically seen high charging flexibilites (Babrowski et al., 2014) this additional load might be scheduled to hours of low demand or high supply of intermittent electricity supply by RES which increases system efficiency with little additional investments (e.g. Jochem et al., 2015; Richardson, 2013; Kristoffersen et al., 2011). This is especially true for V2G applications which decreases curtailment of electricity generation by RES and storage applications in the energy system (e.g. Hajimiragha et al., 2011; Colmenar-Santos et al., 2019). Especially, Colmenar-Santos et al. (2019) shows a comprehensive impact from V2G on the European energy system in the year 2050.

One main impediment to make use of these flexibilities, however, is the still low demand for EV in the large car markets (Vilchez and Jochem, 2020). According to a study of Geske and Schumann (2018), mainly ‘range anxiety’ and the ‘minimum range’ are important factors determining the willingness of German EV users to participate in V2G. The study concludes that if these concerns are addressed, e.g. by guaranteeing a certain lower bound for the range throughout the whole charging process, high participation rates might be achieved.

Some studies identified that a smart integration of EV into power markets might be profitable - especially in the long run. According to Li et al. (2020), the total net profit of V2G services in Shanghai is positive, at least for the EV users (in Shanghai power grid operators may not be able to role over the additional costs to their customers).

While the impact of EV on transmission grids seems rather unproblematic (e.g. Heinrichs and Jochem, 2016), the impact on distribution grids depends on many framework conditions (Held et al., 2019). Technically, a smart controlled charging could allow market penetrations of 100% and even improve the power quality in most distribution grids (cf. Ghofrani et al., 2016; Habib et al., 2015; Ma et al., 2012). An uncontrolled charging may, however, lead to increased line losses, transformer overloads and voltage limit violations (Habib et al., 2015; Gong et al., 2011).

Controlled charging strategy could also be an essential component of environmentally friendlier road transport, since charging with electricity from fossil power plants makes the environmental impact by EV worse than those of ICEV - especially, if the LCA impact from EV are included. Furthermore, different charging management strategies could facilitate the integration of intermittent RES into electricity grids (cf. Ghofrani et al., 2016; Huijbregts et al., 2017; Dallinger and Wietschel, 2012). But the impact of such strategies is strongly dependent on different assumptions such as technical limitations or socio-economic parameters as well as many others. Some studies try to estimate concrete economic and environmental effects. E.g. Szinai et al. (2020) analyzed for California a scenario with a share of 50% RES grid and the 5-million-EV target and quantify the added value from controlled charging in 2025. The study concluded that compared to uncontrolled charging with 0.95 million vehicles an expansion to 5 million ”smart” EV reduces the total system costs by up to 10% and declines the amount of RES curtailment by up to 40%. In addition, it is found that, residential smart charging supported by overnight time-of-use tariffs with added daytime periods are important policies which help to reach California's EV and RES goals. Similarly, Jochem et al. (2015) assessed CO_2 emissions of EV in Germany in 2030 for uncontrolled charging and optimized unidirectional controlled charging strategies. These studies do not consider V2G.

According to most studies, bidirectional controlled charging enhances these advantageous effects further. E.g. Kawamoto et al. (2019) analyzed the life cycle CO_2 emissions of EV in the U.S.A., European Union (EU), Japan, China, and Australia using country-specific parameters such as the vehicle's lifetime, driving distance, and CO_2 emissions associated with battery production. They emphasize, similar to other studies (e.g. Ellingsen et al., 2016; Helmers et al., 2020; Mayyas et al., 2017), that though the CO_2 emissions for the production process of EV outbalance those of ICEV, the excess can be compensated by the vehicle consuming electricity from clean energy sources. These findings are generally supported by Lund and Kempton (2008) who modeled the impact of V2G on the national energy system of Denmark in 2020. The analyses reveal that EV with overnight charging and even more with V2G, enhance the efficiency of the electrical energy system, reduce CO_2 emissions, and improve the ability to integrate wind power.

From this literature review it follows that there are still several research gaps with regard to several issues. We try to fill some of these gaps in the following by applying a comprehensive modeling approach which considers many of the already mentioned dimensions together:

1. Empirically-based and detailed controlled unidirectional and bidirectional charging strategies are implemented.
2. The expansion of RES is modeled endogenously in the energy system model and depends on the electricity demand by EV.
3. The geographical scope is extended to Europe and the time horizon to 2050.
4. While many studies consider only CO_2 emissions during the vehicle usage phase associated with the combustion of fossil fuels for electricity generation, we focus on GHG emissions and consider the life cycle perspective of EV (i.e. emissions from battery production and disposal), too.

3. Methodology

For the analysis of GHG emissions with different charging strategies, a model coupling concept is applied to combine LCA with an electricity system model. In Section 3.1 the used electricity system model PERSEUS-EU is presented, Section 3.2 focuses on the implementation of the EV module in PERSEUS-EU. Section 3.3 presents the LCA model. In Section 3.4 the coupling concept is demonstrated. Afterwards, the data are described in Section 3.5 and finally, the analyzed scenarios are presented in Section 3.6.

3.1. Electricity system model

The PERSEUS-EU model (Heinrichs, 2014) represents all power plants and energy flows of the electricity sector in 28 European countries (EU28 without the islands of Cyprus and Malta, but including Switzerland and Norway) using a linear optimization approach. The main decision variables of the optimization problem are the production level of existing electricity production capacities, investments in new capacities, and electricity exchange between neighboring countries.

The objective of the optimization problem is to minimize total system costs under a set of technical, ecological, and political constraints. The time horizon until 2050 is modeled. The base year 2015 is used for model calibration with historical data. Due to the computational restrictions, the characteristic years of 2015, 2020, 2030, 2040 and 2050 are calculated. An inner-year time resolution with 6 representative weeks in hourly resolution is applied to each year. A method, based on neural networks, presented in Yilmaz

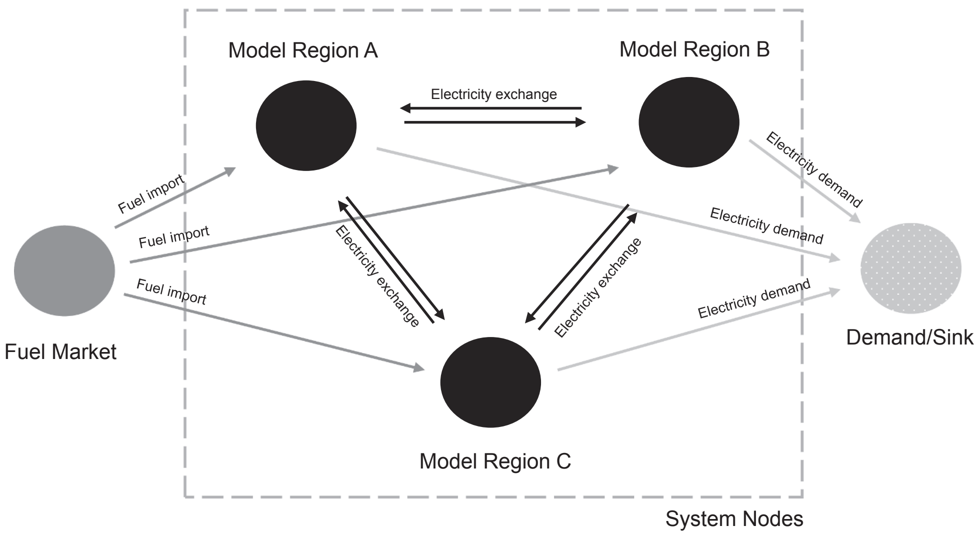

Fig. 1. PERSEUS model structure.

et al. (2019), is used to select the representative weeks and to create the time structure of the model.

In this study, the PERSEUS-EU model was further developed to analyze the different EV charging strategies. The implementation of the EV charging strategies and the main structure of the model are described in Section 3.2. The model equations can be found in the supplementary material of Appendix A and further details as well as a discussion in Heinrichs (2014). PERSEUS-EU is implemented as a linear program in GAMS and is solved with the CPLEX solver.

3.2. Implementation of the EV module in the PERSEUS-EU model

The model structure is based on a directed graph in which the system nodes are connected with each other by energy flows (see Fig. 1). In addition, we have a sink and a source node.

In PERSEUS-EU, each system node is a country. Several power plant technologies are available at the system nodes to generate electricity from different energy sources, e.g. gas. Exchange flows between the system nodes represent electricity exchange between the European countries. The sink node contains the energy demand of the modeled countries, which is to be covered by the inflows to this node. The source node supplies the graph with fuel from outside the system (e.g. gas imports from the world market). The energy inflows and outflows are balanced for each system node.

The electricity demand is represented by $FL_{no,si,el,y,t}$. The demand is the electricity (*el*) flow from each system node (*no*) to the sink node (*si*) in every year (*y*) and in each model time slice (*t*). An additional controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) is added to the model.

We define and formulate the calculation of the additional controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) as follows. Index t' denotes the original time slice of the uncontrolled demand and index t denotes the rescheduled time slice of that uncontrolled demand.

Eq. (1) defines the controlled charging strategy. Within a time span (the time between the time slice t' and $t' + shift^{max}$), charging and discharging are both allowed but the summation of the charging solutions ($Ctrl^{ch}_{no,si,el,y,t',t}$) and discharging solutions ($Ctrl^{dis}_{no,si,el,y,t',t}$) for time t' in time t must be equal to the uncontrolled demand of the starting time slice t'.

$$d^{ev}_{no,si,el,y,t'} = \sum_{t \in P_{t'}} (Ctrl^{ch}_{no,si,el,y,t',t} - Ctrl^{dis}_{no,si,el,y,t',t}) \quad \forall\ no \in NO^{sys}, \forall\ y \in Y, \forall\ t' \in T, P_{t'} = \{t', t'+1, ..., t' + shift^{max}\} \tag{1}$$

This implies that:

- The uncontrolled charging demand ($d^{ev}_{no,si,el,y,t'}$) must be covered within the considered time span, i.e. the next $shift^{max}$ hours.
- Discharging ($Ctrl^{dis}_{no,si,el,y,t',t}$) is allowed, but the discharging amount must be compensated before or after and within the same time span.

The net controlled EV demand ($FL^{ev}_{no,si,el,y,t}$) from the grid perspective is then defined by Eq. (2). After the uncontrolled EV charging demand is rescheduled to the next $shift^{max}$ hours by Eq. (1), we calculate the controlled net EV demand ($FL^{ev}_{no,si,elec,y,t}$). The net demand EV ($FL^{ev}_{no,si,elec,y,t}$) in time slice t is the summation of the charging and discharging solutions for the previous $shift^{max}$ hours. $FL^{ev}_{no,si,elec,y,t}$ is a free variable in the model and can be positive, zero, or negative.

$$FL^{ev}_{no,si,el,y,t} = \sum_{t' \in Q_t} \left(\frac{Ctrl^{ch}_{no,si,el,y,t',t}}{\eta_{ev}} - Ctrl^{dis}_{no,si,el,y,t',t} \cdot \eta_{ev} \right) \quad \forall\ no \in NO^{sys}, \forall\ y \in Y, \forall\ t \in T, Q_t = \{t - shift^{max}, t - shift^{max} + 1, ..., t\} \tag{2}$$

In Eq. (3), the total amount of charging ($Ctrl^{ch}_{no,si,el,y,t',t}$) and discharging ($Ctrl^{dis}_{no,si,el,y,t',t}$) demand in one time slice is limited by the total charging power ($Ctrl^{max}_{no,si,el,y,t}$) of EV available at time t. This power depends on the EV usage pattern, access to charging infrastructure, and user acceptance of controlled charging.

$$Ctrl^{max}_{no,si,el,y,t} \geqslant \sum_{t' \in Q_t} \left(\frac{Ctrl^{ch}_{no,si,el,y,t',t}}{\eta_{ev}} + Ctrl^{dis}_{no,si,el,y,t',t} \right) \quad \forall\ no \in NO^{sys}, \forall\ y \in Y, \forall\ t \in T, Q_t = \left\{ t - shift^{max}, t - shift^{max} + 1, ..., t \right\}. \tag{3}$$

In Eq. (4), the total discharging amount of a country (*no*) within every 24 h is limited by the amount of electricity available in the batteries of all EV in that country. This restriction is applied in a rolling window fashion and t^{start} is the starting time slice.

$$Discharge^{max}_{no,si,el,y} \geqslant \sum_{t \in R_{t^{start}}} \sum_{t' \in Q_t} Ctrl^{dis}_{no,si,el,y,t',t} \quad \forall\ no \in NO^{sys}, \forall\ y \in Y, \forall\ t^{start} \in T, R_{t^{start}} = \{t^{start}, t^{start} + 1, ..., t^{start} + 23\}, Q_t = \{t - shift^{max}, t - shift^{max} + 1, ..., t\}. \tag{4}$$

3.3. The LCA model

LCA converts material and energy inputs into environmentally relevant outputs per functional unit associated with all the stages of the life cycle of a product or service. Different environmental impact categories are distinguished, e.g. climate change. The functional unit is the utility of a product or service and is given in a physical unit (Cooper, 2003). The general formulation of an LCA model on the technological scale is described in Eq. (5):

$$h_{u,y,l} = \sum_{k \in K} \sum_{i \in I} \sum_{i' \in I} Q_{u,y,l,k} B_{u,y,k,i'} A_{u,y,i',i} \cdot f_{u,y,i} \quad \forall\, k \in K, \forall\, i \in I, \forall\, i' \in I \tag{5}$$

where $h_{u,y,l}$ represents the potential environmental impact in category l over the life cycle of technology u in year y in a functional unit, $Q_{u,y,l,k}$ is the characterization factor which reflects the relative contribution of emission k to the environmental impact in category l for technology u in year y, $B_{u,y,k,i'}$ represents the environmental output in emission k from process i' for technology u in year y. $A_{u,y,i',i}$ represents the linkage between the processes i' and i that shows how many products from the process i' are required in process i for technology u in year y. $f_{u,y,i}$ denotes the final demand in process i which specifies the functional unit for technology u in year y. K represents the set of all emissions, while I is the set of all processes.

Based on the above LCA model, Eq. (6) is used subsequently to assess a system containing multiple technologies.

$$Z_{y,l} = \sum_{u \in U} h_{u,y,l} \cdot E_{u,y} \quad \forall\, u \in U \tag{6}$$

where $Z_{y,l}$ is the total environmental impact in category l over the life cycle of all considered technologies in year y. $E_{u,y}$ equals the electricity generation or electricity charging amount from technology u in year y.

Several life cycle impact assessment (LCIA) methods are available to identify impact categories, category indicators, and characterization factors. The ReCiPe method (Huijbregts et al., 2017) is applied in this study. The impact category concerned is climate change, and the category indicator is GHG emissions (kg CO_2 eq.). The electricity generation technologies and EV battery technologies are included in the system under review, which defines the set of U. In addition, the geographical boundary is assumed to be a global market for the upstream processes and a European market for use and downstream disposal processes.

3.4. Model coupling

As already mentioned, the PERSEUS-EU model is used for modeling the European electricity system. The results, such as the electricity mix produced are then analyzed using LCA. In this case, the Environmental Assessment Framework for Energy System Analysis (EAFESA) is applied as a guide for coupling both models to overcome the challenges due to the differences of both models in terms of the system boundaries, databases, and assumptions (Xu et al., 2020). There are four steps in EAFESA, i.e., goal and scope definition, inventory analysis, impact analysis, and policy implication, which are inspired by ISO LCA guidelines (International Organization for Standardization, 2006). Fig. 2 presents the framework used for this paper.

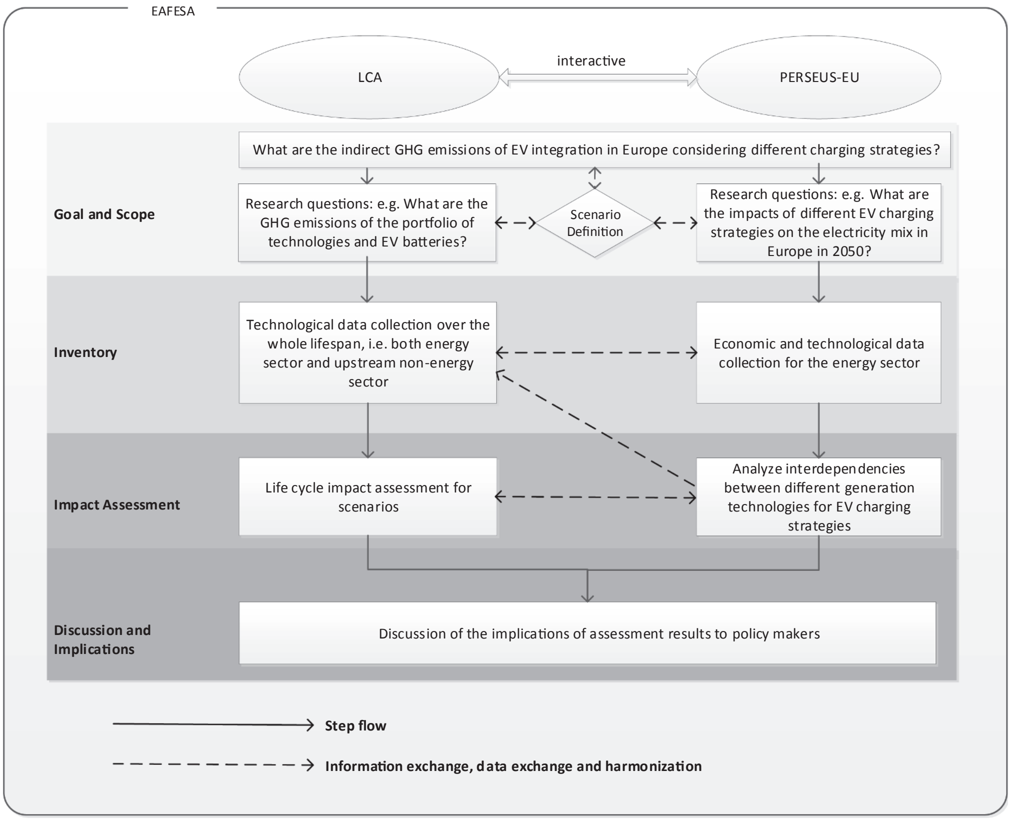

Fig. 2. Applying the EAFESA framework to guide model coupling between LCA and PERSEUS-EU.

In general terms, the technologies expected to exist in Europe by 2050 are defined first and matched between LCA and PERSEUS-EU considering technological development and progress. Secondly, some technologies aggregated in PERSEUS-EU are broken down in LCA, based on literature and expert knowledge. Technologies on the laboratory scale are not included. In this case, wind and PV energy technologies are especially relevant. Electricity generation from wind turbines is achieved by a mix of technologies: Asynchronous generators and synchronous generators. The latter are further subdivided into electrically excited direct drive, permanent magnet and high-temperature superconductors. PV technologies are conventional technologies based on crystalline cells and advanced technologies using thin-film cells. All assumptions about specific breakdowns of electricity generation technologies are obtained from Xu et al. (2020). Additionally, data are harmonized in terms of electricity mix, efficiencies, capacities, as well as life times.

3.5. Data

The power plant data are based on the WEPP database (Platts, 2015). For the techno-economic parameters of future power plant investment options, data based on DIW (2013) are applied. The development of electricity demand for EU countries is based on the EU Reference Scenario 2016 (Capros et al., 2016). The discount rate in the target function is set to 5%.

We make optimistic assumptions regarding RES in order to achieve high shares of RES in 2050. The CO_2 emission price path is based on the 450 ppm scenario of World Energy Outlook (International Energy Agency, 2016), which reaches 160 Euros per ton in 2050. Furthermore, investments in coal-fired power plants are not allowed, which leads to a phase-out of coal-fired power plant capacities over time.

The strongly growing development of EV for the 28 European countries from 2015 to 2050 is derived from the centralized high-RES scenario of the REFLEX project (Reiter et al., 2017). The average mileage of a car is based on the constant assumption of 12,000 km/year and the empiric average gross electricity efficiency is assumed to be 20 kWh/100 km (Jochem et al., 2015). The uncontrolled EV charging load curve is adopted from the Reference Scenario of Babrowski et al. (2014) with an assumption of 6.3 kWh charging power on the average. The EV can be charged at home or at the workplace. Additionally, a plug-in of every other day is assumed (i.e. 50% availability of EV). The daily discharge limit of each connected EV is set to a maximum of 10 kWh for V2G.

The life cycle inventory (LCI), i.e., data for both the technologies under review as well as upstream and auxiliary systems for the generation of electricity mix, is taken from Xu et al. (2020). The LCI of the EV battery is obtained from Notter et al. (2010), which is based on lithium-ion batteries. The EV battery life time is set to guarantee 150,000 km in Notter et al. (2010). Considering V2G will increase the battery charge and discharge volumes, the original battery life in terms of mileage (150,000 km, cf. Notter et al. (2010)) is not guaranteed anymore. Hence, we limit the lifetime of the battery in terms of energy throughput (i.e. 30,000 kWh, which equals 150,000 km without V2G). The battery survives for the whole lifetime (i.e. 30,000 kWh) and dies at 30,001 kWh. Consequently, V2G leads in our model to higher battery demand. The weight of the 40 kWh battery is 300 kg (Notter et al., 2010).

3.6. Scenarios

Three scenarios with different charging strategies and a reference scenario without EV is calculated. In all these scenarios, we calculate endogenously the expansion and electricity production of all power plant technologies, including RES. Detailed information

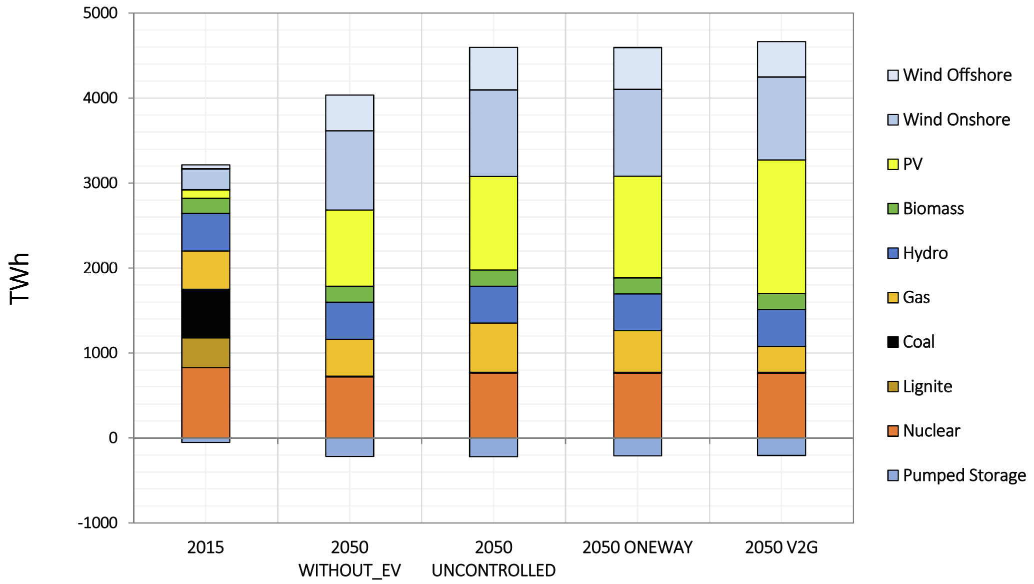

Fig. 3. The electricity mix in 2015 and for different EV charging strategies as well as the WITHOUT_EV scenario in 2050.

on the four scenarios is given below:

- **WITHOUT_EV:** A hypothetical reference scenario without any EV and consequently none charging demand from EV is assumed.
- **UNCONTROLLED:** The EV charging process starts whenever the EV is connected to the grid. For this, a fixed electricity demand curve from the EV is added to the demand curve used in the WITHOUT_EV scenario.
- **ONEWAY:** The charging task at a certain time span is to be accomplished within the next 12 h only.
- **V2G:** Similar to the ONEWAY scenario, the charging task at a certain time span is to be accomplished within the next 12 h but discharging is also allowed during this period. This scenario provides the highest degrees of freedom to the energy system.

4. Results and discussion

This chapter presents and discusses the results of the four Scenarios and mainly focuses on the direct and life cycle related GHG emissions.

Fig. 3 presents the electricity mixes of the different EV charging scenarios as well as the WITHOUT_EV scenario in 2050 and the electricity mix in 2015. Comparing the electricity mixes in all scenarios, the amount of RES in 2050 is higher than in 2015 due to high CO_2 prices, coal phase-out, and declining costs of RES. In 2050, electricity production by coal-fired power plants is close to zero in all scenarios. However, the share of electricity produced by gas-fired power plants is not eliminated in 2050, even increases in the UNCONTROLLED scenario compared to in 2015 due to the need for flexible electricity generation. The amount of renewable and flexible conventional electricity production varies in all scenarios, as the different EV charging strategies allow different levels of flexibility for the system.

In 2050, total electricity production is 15% higher in the UNCONTROLLED scenario than in WITHOUT_EV due to the increased demand by EV. In the UNCONTROLLED scenario, electricity generation from gas is higher despite further investments in RES. This is due to the intermittent characteristic of RES. In the hours when there is no wind and solar, gas-fired power plants are operated predominantly. In the ONEWAY scenario, electricity production from RES is higher than in the UNCONTROLLED scenario. Much cheaper electricity from RES is obtained by shifting the charging time to the hours of higher electricity production from RES. Then, less gas-fired electricity is produced.

Due to the efficiency losses in EV charging and discharging, total electricity production in the V2G scenario is slightly higher than in the ONEWAY scenario, whereas electricity production by gas-fired power plants is much lower. Similar to the ONEWAY scenario, the demand is shifted to the hours of increased electricity production from RES. In addition, the electricity production from PV is significantly higher by about 30%. In return, electricity production not only from gas-fired power plants but also from wind power is declining. PV is cheaper than other technologies and therefore the EV are charged with electricity from PV as much as possible and discharged during the night hours for decreasing electricity generation by fossil fuels.

Fig. 4 demonstrates the direct and life cycle GHG emissions associated with electricity production for the UNCONTROLLED, ONEWAY, and V2G Scenarios compared to WITHOUT_EV in 2050 and the base year 2015. The significant reduction in GHG emissions is due to the high share of renewable power in 2050. However, a shift from direct emissions by the electricity generation to life cycle emissions can be observed. Since there is no direct emissions of RES-based power generation, the share of direct emissions in the life cycle emissions decreases from 75% in 2015 to 23–35% in 2050. Hence, the share of direct emissions in the life cycle emissions decreases along with the shares of RES-based power generation.

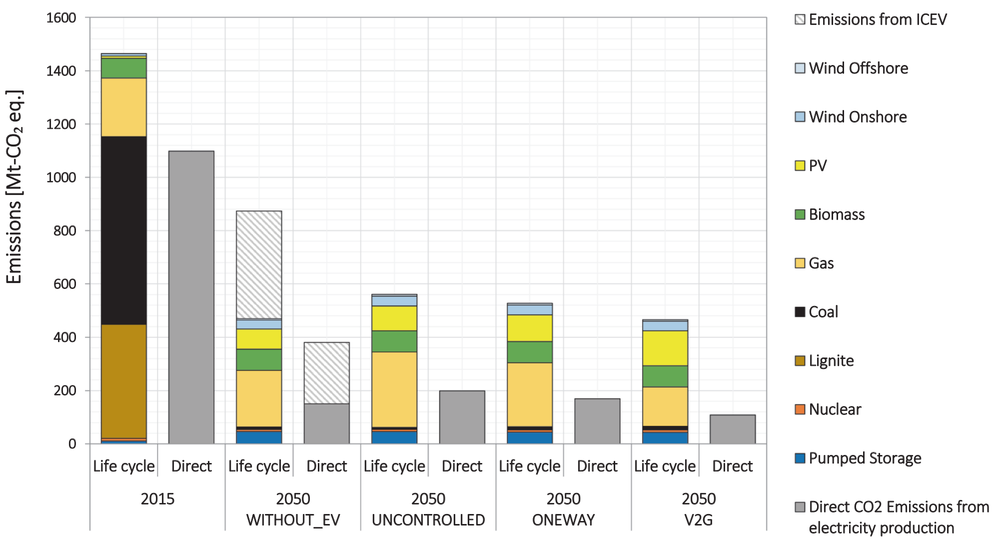

Fig. 4. The direct and life cycle GHG emissions associated with the production of electricity in the UNCONTROLLED, ONEWAY, and V2G scenarios compared to WITHOUT_EV in 2050 and the base year 2015.

In 2050, the life cycle GHG emissions of electricity production are 19% (90 Mt CO_2-eq.) higher in the UNCONTROLLED scenario than in the WITHOUT_EV scenario, which is mainly due to the increased electricity demand by EV and the resulting higher gas-fired electricity production. However, in the WITHOUT_EV scenario, a non-electrified equal number of ICEV (approx. 210 million) at 90 g CO_2/km would lead to about 230 Mt CO_2-eq. of direct emissions and about 400 Mt CO_2-eq. of life cycle emissions in 2050, as shown in Fig. 4. So the electrification of the transport sector helps to reduce the emissions in our framework assumptions, even with uncontrolled charging.

The life cycle GHG emissions are lower (by 6% in ONEWAY and 17% in V2G) in the two controlled charging scenarios compared to the UNCONTROLLED scenario, meaning that both controlled charging strategies have a positive impact on global climate change. The V2G Scenario leads to a greater decrease in GHG emissions than the ONEWAY Scenario, with the emissions being even lower than in the WITHOUT_EV Scenario. Considering that the WITHOUT_EV Scenario assumes a world with ICEV only, the V2G scenario shows a significant reduction of GHG emissions.

Fig. 5 illustrates the difference in life cycle GHG emissions for the UNCONTROLLED, ONEWAY, and V2G Scenarios compared to WITHOUT_EV in 2050 without considering the reduction in emissions by replacing ICEV.

Using the WITHOUT_EV scenario as a reference, the life cycle GHG emissions of the UNCONTROLLED and ONEWAY scenarios are higher by 90 Mt CO_2-eq. and 57 Mt CO_2-eq., respectively, whereas emissions in the scenario V2G are 4 Mt CO_2-eq. lower. The lower flexibility of the UNCONTROLLED and ONEWAY scenarios compared to the V2G scenario results in the use of gas-fired power generation technology, which produces most of the emissions in the UNCONTROLLED scenario and the ONEWAY scenario. When looking at the gas-fired power plants from a life cycle perspective, it is found that the most important emission source is the gas combustion process (over 85%), followed by gas leakage during transport via the long-distance pipeline (8%). Compared to the scenario WITHOUT_EV, GHG emissions associated with PV-based power generation increase by 17 Mt CO_2-eq. (UNCONTROLLED), 24 Mt CO_2-eq. (ONEWAY), and 56 Mt CO_2-eq. (V2G). The GHG emissions from PV are mainly due to the processes of PV panel production (65%) and mounting system production (31%).

With increasing flexibility of the charging options, the importance of pumped storage power plants decreases slightly as well with controlled charging. Compared to the scenario WITHOUT_EV, the emissions are higher by 0.3 Mt CO_2-eq. in UNCONTROLLED, but, lower by 1.7 Mt CO_2-eq. in ONEWAY and by 2.3 Mt CO_2-eq. in V2G, respectively.

Considering the potential risk of accelerated battery degradation due to additional charging and discharging in V2G, Fig. 6 illustrates the life cycle GHG emissions associated with both additional electricity production and EV battery production separated. GHG emissions caused by the EV battery are identical in the UNCONTROLLED and ONEWAY scenarios since the power demand of EV is only shifted in the ONEWAY scenario. Obviously, the V2G scenario is associated with an accelerated battery degradation and increased emissions from battery production. The reduced GHG emissions associated with the electricity generation do more than compensate the increased emissions associated with the EV battery and this scenario, consequently, shows the lowest GHG emissions.

5. Uncertainty analyses

To examine the potential impacts of variations of some important inputs on the systematic performance, a series of uncertainty analyses are performed.

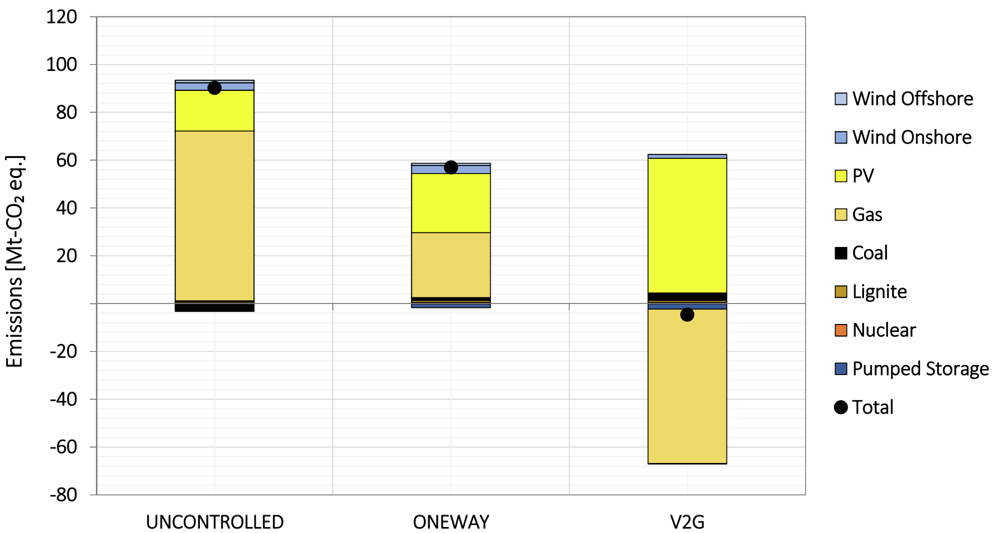

Fig. 5. The differences in the life cycle GHG emissions from electricity production and EV battery production for the UNCONTROLLED, ONEWAY, and V2G compared to the WITHOUT_EV Scenario in 2050.

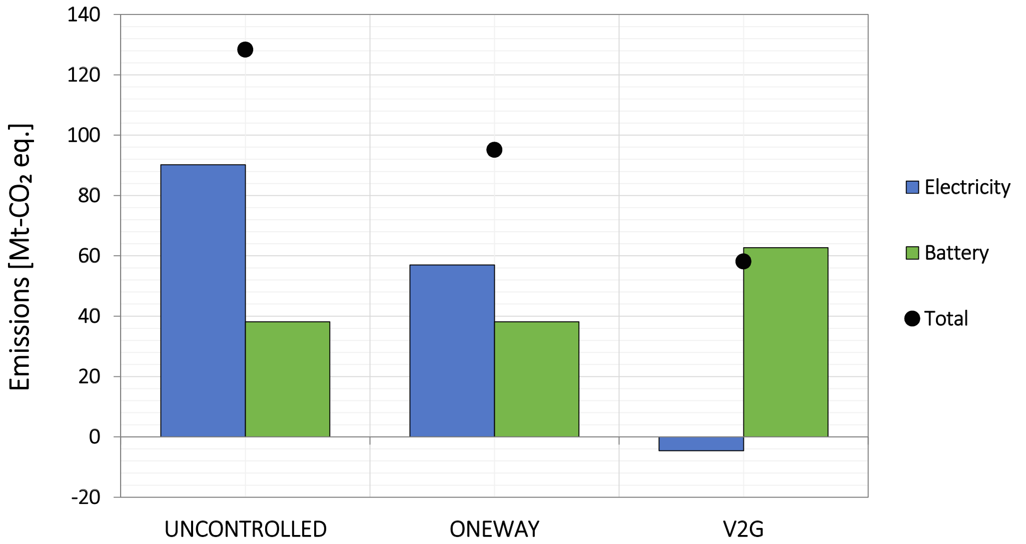

Fig. 6. The difference in the life cycle GHG emissions from electricity generation (blue) and EV battery production (green) for UNCONTROLLED, ONEWAY and V2G Scenarios compared to WITHOUT_EV in 2050. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Lithium-ion batteries are normally considered the best energy storage technology for EV and are already widely applied in EV. Even though post-lithium battery technologies attracted attention in recent years, they still face tremendous challenges in their realization. In this context, the present study is based on the assumption that the future EV will depend highly on lithium-ion batteries.

However, technological development and progress of lithium-ion batteries are required to improve energy security, reduce petroleum dependence, and lower GHG emissions. An important parameter characterizing technological development is a higher energy density in the future compared to the current situation. The battery's energy density is projected to increase by about 140% to around 320 Wh/kg by 2030 (Thielmann et al., 2013). This higher energy density will reduce the GHG emissions of the EV batteries to 42% compared to the current situation, when assuming that this development will continue in a linear way until 2050. This would further enhance the positive effects of EV charging strategies in reducing GHG emissions. Battery life time is another important parameter to characterize technological development. Although lithium-ion batteries are considered mature, attempts to achieve a better cycle life are continuing. In Virya and Lian (2017), a good cycle life (over 10,000 cycles) is demonstrated with the development

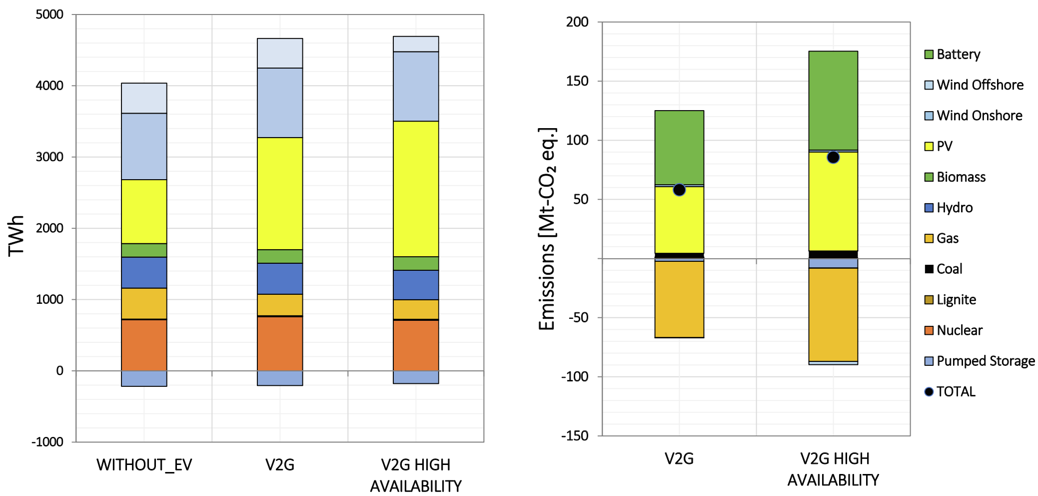

Fig. 7. The electricity mixes (left) and the difference in life cycle GHG emissions (right) in the V2G scenario with different EV availabilities compared to the WITHOUT_EV Scenario in 2050.

of a neutral polymer electrolyte containing lithium chloride and polyacrylamide. The state-of-the-art achievement (Virya and Lian, 2017) is still in the experimental stage, but shows a significant improvement compared to our assumption, i.e., 30,000 kWh of the total battery charge amount for a 40 kWh battery, which is basically in line with the 1,000 full cycle equivalents with 90% Depth of Discharge (DoD). In case of a longer cycle life (from 1,000 cycles to 10,000 cycles), the GHG emissions of batteries should reduce by up to 90%, assuming a constant scaling effect.

Apart from the technological development and progress of lithium-ion batteries, another important uncertainty analyzed is the EV availability. As mentioned before, 50% of all the EV are assumed available everyday. Increasing the availability of EV from 50% to 100% would provide more flexibility with the same number of EV. In this case, maximum discharge into the grid also doubles.

Fig. 7 illustrates the electricity mixes and the life cycle GHG emissions in V2G in 2050 for the different EV availabilities. At a higher EV availability, electricity production from gas-fired and offshore wind power plants decreases while more electricity is produced by PV (see Fig. 7, left). Compared to the original V2G scenario with a lower EV availability, GHG emissions from gas-fired power plants decrease in the scenario with higher EV availability. However, there is not a large decrease associated with gas-fired electricity production, as there are still days when not enough electricity is generated from RES even with more EV availability. In our framework assumptions, V2G can advance or postpone the demand for 12 h. To further reduce gas-fired power generation, long-term storage technologies, such as hydrogen, are required.

Furthermore, total emissions increase in the higher EV availability scenario (see Fig. 7, right). This is caused by two reasons. The first one is due to the higher usage of the batteries. The second is that more electricity production from wind technologies is shifted towards PV technologies. From the LCA-based analysis, PV technologies produce more emissions than wind technologies, when generating the same amount of electricity.

6. Summary and conclusions

Electric vehicles might be a corner stone in the energy transition of passenger transport. For this reason, greenhouse gas emissions and the impact from controlled charging strategies hereon are already widely discussed in academia. This study focuses on different charging strategies, namely, uncontrolled charging, unidirectional controlled charging, and bidirectional charging (Vehicle-to-Grid), and their impacts on greenhouse gas emissions caused by electricity production and electric vehicle batteries in Europe in 2050. For the analyses, life cycle assessment is combined with an energy system model, PERSEUS-EU. To our knowledge, this is the first attempt to analyze the Vehicle-to-Grid charging strategies in the European electricity system and their greenhouse gas emissions by a coupled approach.

The framework assumptions made with respect to renewable energy sources are optimistic, e.g. high CO_2 costs, cost reduction of renewable technologies and phase-out of coal-based electricity production. In 2050, all scenarios reach a very high share of renewable energy sources and deep decarbonization. The results show uncontrolled charging increases electricity production from natural gas slightly. The two controlled charging strategies, however, reduce dependence on gas-fired electricity production and increase the amount of electricity produced by renewable energy sources (mainly photovoltaic). Flexibilites from Vehicle-to-Grid exceeds that of unidirectional charging, as charging cannot only be postponed, but electric vehicles can be used as mobile storages in the electricity system.

Emissions from uncontrolled charging are higher than those of both controlled charging strategies. The emissions are lower in unidirectional charging, and even further decreased by Vehicle-to-Grid, due to the increasing use of electricity from renewable energy sources. Taking into account the degradation of electric vehicle batteries, however, Vehicle-to-Grid may cause more emissions only due to enhanced battery degradation. Nevertheless, in our scenario bidirectional charging still outperforms the unidirectional charging in terms of greenhouse gas emissions at least when the overall flexibility is restricted.

The results of the uncertainty analysis reveal that further technical progress in electric vehicle batteries is of particular needed to increase the benefits of reducing life cycle greenhouse gas emissions. A complete elimination of emission-intensive generation, such as electricity generation from gas, is not possible due to the days and longer periods without sufficient electricity generation from RES. Further scenario analyses may integrate hydrogen as an additional storage system, which may lead to further decreasing greenhouse gas emissions but may show other disadvantages as a lower system efficiency and lower benefits from Vehicle-to-Grid.

Still, our work is subject to the following limitations: Not every single EV or EV fleet is modeled in detail. The EV are represented by aggregated loads or flexibilities for each country. In addition, the costs of EV batteries are not taken into account, as this study focuses on GHG emissions. Another important limitation is that network restrictions are not considered. For charging of the EV, mechanisms in distribution and transmission grid level should be in place to avoid network congestion or even collapse. A detailed analysis with a network model should be performed. The degradation level of a battery is assumed to depend linearly on the accumulated amount of charge. This assumption is applied to all batteries. However, the battery life is significantly affected by a variety of complex factors, e.g. temperatures at which a battery is charged, the state of charge, the charging rate, etc. (Hoke et al., 2011). Differences in battery life result in different life cycle emissions. These factors are usually not considered in macro-scopic energy system models, and, hence, might be an interesting topic for further studies. Hydrogen in the energy system model in combination with fuel cell electric vehicles might even lead to stronger decarbonization effects. However, market success of hydrogen is still subject to several uncertainties, which is why fuel cell electric vehicles have not been considered in this study.

Appendix A. PERSEUS equations

Objective function

$$min \sum_{y \in Y} (\frac{1}{1+r})^{y} \cdot \left(\begin{array}{l} \sum_{so \in SO} \sum_{no \in NO} \sum_{ec \in EC} FL_{so,no,ec,y} \cdot c^{fuel}_{so,no,ec,y} \\ + \sum_{u \in U} (K_{u,y} \cdot c^{fix}_{u,y} + K^{new}_{u,y} \cdot c^{inv}_{u,y}) \\ + \sum_{pc \in PC} \left(\begin{array}{l} PL_{pc,y} \cdot c^{var}_{pc,y} \\ + \sum_{t \in T} \left(\begin{array}{l} LV^{up}_{pc,y,t-1,t} \\ + LV^{down}_{pc,y,t-1,t} \end{array} \right) \cdot c^{lv}_{pc} \end{array} \right) \end{array} \right)$$

Energy balance restrictions

$$\sum_{no' \in NO} FL_{no',no,el,y,t} + \sum_{pc \in PC_{no}} PL_{pc,y,t} = \sum_{no' \in NO} \frac{FL_{no,no',el,y,t}}{\eta_{no,no',y}} \quad \forall \; no \in NO^{sys}, \forall \; y \in Y, \forall \; t \in T$$

$$\sum_{no' \in NO} FL_{no',no,ec,y} + \sum_{pc \in PC_{no}} PL_{pc,y} \cdot \lambda_{pc,ec} = \sum_{no' \in NO} \frac{FL_{no,no',ec,y}}{\eta_{no,no',y}} + \sum_{pc \in PC_{no}} \frac{PL_{pc,y} \cdot \lambda_{pc,ec}}{\eta_{pc,y}} \quad \forall \; no \in NO^{sys}, \forall \; ec \in EC, \forall \; y \in Y$$

$$PL_{pc,y} = \sum_{t \in T} PL_{pc,y,t} \quad \forall \; pc \in PC, \forall \; y \in Y$$

$$FL_{no',no,el,y} = \sum_{t \in T} FL_{no',no,el,y,t} \quad \forall \; no', \; no \in NO, \forall \; y \in Y$$

Capacity restriction

$$K_{u,y} \cdot av_{u,y,t} \cdot h_t \geqslant \sum_{pc \in PC_u} PL_{pc,y,t} \quad \forall \; u \in U, \forall \; y \in Y, \forall \; t \in T$$

Capacity expansion restriction

$$K_{u,y} = k^{exist}_{u,y} + \sum_{y'=y-\tau_u}^{y} K^{new}_{u,y'} \quad \forall \; u \in U, \forall \; y \in Y$$

Load variation restriction

$$LV_{pc,y,t-1,t} = \left| \frac{PL_{pc,y,t}}{h_t} - \frac{PL_{pc,y,t-1}}{h_{t-1}} \right| \cdot tr_{t-1,t} \quad \forall \; pc \in PC, \forall \; y \in Y, \forall \; t \in T$$

Storage restrictions

$$SL^{pss}_{u,y,t} = SL^{pss}_{u,y,t-1} + \frac{PL^{pump}_{pc,y,t}}{h_t} - \frac{PL^{turb}_{pc,y,t}}{h_t} \cdot \frac{1}{\eta^{turb}} \quad \forall \; pc \in PC_u, \forall \; u \in U^{pss}, \forall \; y \in Y, \forall \; t \in T$$

$$SL^{pss}_{u,y,t} \leqslant s^{max}_u = \frac{K_{u,y}}{\kappa^{max}_u} \cdot s^{max,0}_u \quad \forall \; u \in U^{pss}, \forall \; y \in Y, \forall \; t \in T$$

Generation adequacy restriction

$$max(FL_{no,si,el,y,t}) \cdot sf \leqslant \sum_{u \in U^{conv}_{no}} (K_{u,y} \cdot av_{u,y}) + \sum_{u \in U^{re}_{no}} (K_{u,y} \cdot sc_u) \quad \forall \; no \in NO, \forall \; y \in Y, \forall \; t \in T$$

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METHODS, TOOLS, AND SOFTWARE

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Integrating vehicle-to-grid technology into energy system models

Novel methods and their impact on greenhouse gas emissions

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Abstract

The electrification of the transport sector plays a key role in the global energy transition and it is of great necessity to assess emissions induced by electric vehicles in the long term for effective policy-making. Typical life cycle assessment may not consider the impact of electric vehicle integration in future electricity systems adequately, or the time-dependent characteristics of electricity generation mix and EV charging patterns. The solution requires modeling methods to integrate electric vehicle into energy system models, especially with vehicle-to-grid option. However, relevant methods have not been evaluated, yet. This integration is mathematically ambitious especially for huge and heterogeneous fleets of electric vehicles and brings energy system models to their computational limits. So far, current studies have proposed several aggregation methods for the load from electric vehicle charging, which simplify the original problem but may provoke bias. In our contribution, we propose a novel method of integrating vehicle-to-grid compliant electric vehicles into energy system models and demonstrate its feasibility by comparing it with two recent others from the literature. Taking the performance of the individual modeling method as the benchmark, we improve one of the two methods from the literature with updated parameters and additional constraints. We apply all three aggregation methods in a simple energy system model for comparing and analyzing their performances from multiple aspects, that is, solution accuracy, computational complexity, parameter requirement, and their impact on greenhouse gas emissions. Finally, we discuss the reasons behind the differences and give recommendations for further research.

KEYWORDS
electric vehicles, energy system modeling, industrial ecology, life cycle assessment (LCA), renewable energy integration, vehicle-to-grid

1 | INTRODUCTION

Electric vehicles (EV) are considered to be a crucial and proactive player in the transport and energy transition and a cornerstone of mitigation options in road transportation, as promoted by policy-makers, relevant industries, and the academia (IEA, 2020). Kasten et al. (2016) have projected that the electricity demand from EV charging may account for 9.5% of the total electricity demand in the European Union by 2050. Considering such high level of penetration, EV will influence the future electricity system. In the first instance, this additional demand seems to be an additional burden for the electricity system. However, the batteries of EV might also provide a huge load shifting potential and can, consequently, influence the energy transition (Rupp et al., 2019), especially with vehicle-to-grid technology (V2G) (Babrowski et al., 2014). Therefore, it is of great necessity to analyze how EV may synergistically contribute to emission reduction in the long term and how this process might be accelerated by effective policy instruments (Märtz et al., 2021).

For future-oriented and interdisciplinary studies, long-term life cycle assessment (LCA) on EV emissions may be faced with the following methodological challenges. The typical practice is to use annual average electricity mix by scenarios and considers the total of EV electricity demand (e.g., Burchart-Korol et al., 2020; Cox et al., 2018; García-Sánchez et al., 2013; Krause et al., 2020; Naranjo et al., 2021; Wolfram & Wiedmann, 2017; Wu et al., 2018; Xiong et al., 2019; Xue et al., 2021; Zhang & Hanaoka, 2021). However, such an option may not explicitly consider the impact of EV integration on the future electricity generation investment and could not consider the time-dependent character of electricity mix or EV charging patterns. In response to these deficiencies, an emerging trend is to combine LCA for EV with energy system modeling, as suggested by Arvesen et al. (2021), Jochem et al. (2015), and Weis et al. (2016). This calls for the development of novel modeling methods, which dynamically combines LCA approaches with energy system modeling and considers sophisticated and empirical charging demand of EV including their flexibilities for providing V2G.

Due to the computational burden, it may not be possible to model each individual EV separately in large-scale energy system models as in small-scale EV charging scheduling problems (e.g., Wu & Sioshansi, 2017; Wang et al., 2020). Accordingly, it is required to develop aggregated EV modeling methods, which should not be biased toward the underlying load shifting potential.

However, only exact methods for aggregating the multiple feasible solution spaces (polytopes) of individual EV (such as the Minkowski sum) may avoid aggregation errors, but the resulting optimization problems are unfortunately NP-hard (Ried et al., 2020). This makes modeling of large-scale and heterogeneous EV fleets highly challenging and a compromise seems unavoidable. Recent literature has developed various aggregated modeling methods to integrate flexibilities from EV into energy system models. Classified by the freedom of controlling EV demand in energy system models, aggregated EV modeling methods can be progressively classified into the following three categories:

1. EV demand is exogenously given (i.e., no endogenously decided flexibility).
2. EV demand is endogenously decided by the model, but V2G option is not considered.
3. EV demand is endogenously decided by the model, with V2G option considered.

In the first category, Arvesen et al. (2021) assess EV emission in Europe in 2050 by introducing multiple assumed EV charging patterns into a power system model. In the second category, Jochem et al. (2015), who base the EV aggregation modeling on Heinrichs (2013), calculate the electricity mix of EV charging and the corresponding greenhouse gas (GHG) emissions under different charging strategies in Germany in 2030. Schill and Gerbaulet (2015) investigate how various EV charging modes would affect the utilization of coal-based power plants and the consequential CO_2 emission. In the third category, Chen et al. (2018) calculate the emissions of various types of EV under different wind penetration levels in the city of Beijing in 2020. Xu et al. (2020b) investigate how different charging strategies may impact the GHG emission of EV in a Europe-wide scale from a life cycle perspective.

As a common practice in the literature, the proposal of a new idea or method should be accompanied by its demonstration. However, the feasibility of aggregated EV modeling methods is often indirectly assured either by empirical judgement or by explanations on how an aggregated EV constraint resembles one in individual EV modeling. Furthermore, even if all presented constraints are feasible, it does not mean that all presented constraints are sufficient to model the aggregated EV adequately, especially when their impacts on the results in energy system models (such as resulting unit commitment of power plants or emissions) are focused on. Since aggregated EV modeling is a simplification of individual EV modeling, its feasibility can be theoretically proven by comparing its performance with that of individual EV modeling. Unfortunately, such a way of proving might not be computationally possible for a large-scale energy system model and is rarely seen in the literature, which is the reason why we combine LCA with a simple energy model.

As EV has become an unignorable player in the future energy system, it is of great importance and necessity to analyze the feasibility of aggregated EV modeling methods and to improve their performance wherever possible. In response to such a concern, this paper contributes to the current literature in the following aspects:

1. We propose a novel aggregated EV modeling method and compare it with two alternative types of methods from the literature by taking the performance of individual EV modeling method as a benchmark.
2. Based on empirical data, we design a simple energy system model as a testbed to analyze the feasibility of the three aggregated EV modeling methods and to make potential modifications and improvements on existing methods.
3. We comprehensively present the performance of three selected methods (including solutions for electricity mix, reduction of GHG emission, parameter requirement, and computational complexity) and make recommendations for the selection of these methods by the focuses of potential researchers and modelers.

The remainder of the paper is organized as follows. Section 2 introduces three different EV aggregation methods as well as the idea of the considered testbed for comparing the methods. Sections 3 presents the data and parameter setting of the paper. Section 4 analyzes the feasibility of the modeling methods, compares their performances, and makes suggestions for further improvements. Section 5 concludes the paper.

2 | METHODOLOGY

First, a novel method is originally proposed in Section 2.1. Second, Sections 2.2 and 2.3, respectively, introduces two alternative aggregation methods from the recent literature. Finally, the simple energy system model, our testbed for the aggregation methods, is explained in Section 2.4. All parameters are lowercase, and all variables are uppercase. Please refer to Supporting Information S1 for detailed nomenclature.

2.1 | Aggregated EV modeling Method A: Dynamic EV fleet

The starting point of **Method A** is to model all individual EV as one aggregated EV while the battery capacity is dynamic. Being dynamic means that the arrivals and departures of individual EV affect the capacity of this aggregated EV (Škugor & Deur, 2015). Although this starting point is also shared by Fattori et al. (2014) and Sterchele et al. (2020), the specific formulations differ between each other.

The core variable is the time-dependent energy content of all grid-connected EV batteries, that is, the aggregated energy level value V_t^{en}, which is given in kWh, and therefore should not be confused with the state of charge (SOC), which is given as a percentage from the total capacity (the latter may vary over time in this case).

$$V_t^{en} = v_0^{en} + \left(V_t^{ch} - V_t^{dis}\right) \quad t = 1 \tag{A1}$$

$$V_t^{en} = V_{t-1}^{en} + \left(V_t^{ch} - V_t^{dis}\right) + v_t^{en,arr} - v_t^{en,dep} \quad t > 1 \tag{A2}$$

Equations (A1) and (A2) define the energy level of the aggregated EV (V_t^{en}). Specifically, Equation (A1) defines the energy level of the first time slice, including a predefined energy content of the aggregated EV in the initial period $t = 0$ (v_0^{en}). Equation A2) shows the development of the aggregated energy level over time. V_t^{en} depends on the aggregated energy level from the previous period (V_{t-1}^{en}), the difference of charging (V_t^{ch}) and discharging energy (V_t^{dis}) of the current period and the difference of energy content between new arrivals ($v_t^{en,arr}$) and departing EV ($v_t^{en,dep}$).

The controlled charging strategy, which provides load flexibility to the energy system model, is defined by Equations (A3) to (A5), which are uniquely proposed in this paper and can significantly improve the solution performance. Their functions are further illustrated in Supporting Information S1. Parameter $v_{t^a}^{task}$ is the aggregated EV charging task, which is latest due at time slice t^a, is the sum of the required charging tasks from all individual EV departing at t^a. Equation (A3) allows $v_{t^a}^{task}$ to be fulfilled by charging and discharging behaviors prior to t^a or at t^a. $V_{t^a,t}^{ch}$ and $V_{t^a,t}^{dis}$ are, respectively, the charging and discharging energy of the aggregated EV which is scheduled at t and to complete the charging task due at t^a. Take one individual EV, which arrives at 8 a.m., departs at 5 p.m. and requires a charge of 5 kWh, as an analogy. This individual EV can schedule charging and discharging behaviors between 8 a.m. and 5 p.m. to fulfill its charging task, that is, net charge 5 kWh, no later than 5 p.m. (t^a).

Unlike one individual EV which has the charging task due at only one time slice, the aggregated EV has constant charging tasks due in different time slices. Therefore, the charging or discharging energy at t (V_t^{ch} or V_t^{dis}) of the aggregated EV are composed of charging or discharging behaviors for charging tasks due at different time slices ($t^a \in P_t$), as formulated by Equations (A4) and (A5), respectively.

$$v_{t^a}^{task} = \sum_{t \in Q_{t^a}} \left(V_{t^a,t}^{ch} - V_{t^a,t}^{dis}\right) \quad \forall t^a \tag{A3}$$

$$V_t^{ch} = \sum_{t^a \in P_t} V_{t^a,t}^{ch} \quad \forall t \tag{A4}$$

$$V_t^{dis} = \sum_{t^a \in P_t} V_{t^a,t}^{dis} \quad \forall t \tag{A5}$$

V_t^{ch} and V_t^{dis} are defined as energy flows from the EV side. For the aggregated EV, charging and discharging behavior (V_t^{ch} and V_t^{dis}) can happen at the same time. In Equation (A6), V_t^{ch} and V_t^{dis} are jointly limited by the number of individual EV connected to the grid at t (v_t^{No}), where p^{max} is the maximum charging or discharging power of one individual EV and η is the efficiency.

$$\frac{V_t^{\text{ch}}}{\eta} + V_t^{\text{dis}} \leq v_t^{\text{No}} \times p^{\max} \times \Delta t \quad \forall t \tag{A6}$$

The net EV charging demand from the grid side $D_t^{\text{EV,ctrl}}$ considering efficiency η is given by Equation (A7) and represents a free variable, which can be positive, zero or negative.

$$D_t^{\text{EV,ctrl}} = \frac{V_t^{\text{ch}}}{\eta} - V_t^{\text{dis}} \times \eta \quad \forall t \tag{A7}$$

Equations (A8) and (A9) limit V_t^{en} by the capacity of the aggregated EV ($k_t^{\text{agg,EV}}$) and minimum and maximum SOC allowed ($s_t^{\text{agg,min}}$ and $s_t^{\text{agg,max}}$). As discussed before, the capacity of the aggregated EV is dynamic so $k_t^{\text{agg,EV}}$ is time dependent. Detailed settings of these parameters ($k_t^{\text{agg,EV}}$, $s_t^{\text{agg,min}}$ and $s_t^{\text{agg,max}}$) are further discussed in Section 3.3.

$$V_t^{\text{en}} \geq k_t^{\text{agg,EV}} \times s_t^{\text{agg,min}} \quad \forall t \tag{A8}$$

$$V_t^{\text{en}} \leq k_t^{\text{agg,EV}} \times s_t^{\text{agg,max}} \quad \forall t \tag{A9}$$

2.2 | Aggregated EV modeling Method B: Aggregated boundary

The key idea of **Method B** is to aggregate individual vehicles by their arrival time and to limit the behavior of this EV fleet by summing up the boundaries of its composing individual EV, which is separately proposed by Hahn et al. (2013) and Zhang et al. (2017). As discussed in Section 1, this method has been applied by Chen et al. (2018) and Szinai et al. (2020), where EV are integrated into large-scale energy system models. Please note that our introduction of Method B below captures only the key idea and features of this type of method but may not cover all the details in the literature.

For Method B, let charging trajectory denote the cumulative charging energy of one (individual or aggregated) EV, including both charging and discharging behaviors. For an individual EV, the upper bound of the charging trajectory can be calculated by instant charging upon arrival and as much as possible until departure. The lower bound can be calculated by first discharging if possible, and then charging as late as possible to the required minimum SOC level at departure set by EV user. This required level by departure in the lower bound can be lower than the fully charged level in the upper bound. For an individual EV, any charging trajectory between the upper and lower bound is a feasible trajectory.

In Method B, individual EV with the same arrival time are aggregated as one. The charging trajectory boundary for the aggregated EV is calculated by summing up the upper and lower bounds of its component individual EV, as in Equations (B1) and (B2). $V_{t^{\text{b}},t}^{\text{ch}}$ and $V_{t^{\text{b}},t}^{\text{dis}}$ are the charging and discharging decision of the aggregated EV in time slice t respectively, with t^{b} as the arrival time slice. $\sum_{t=t^{\text{b}}}^{t^{\text{c}}} (V_{t^{\text{b}},t}^{\text{ch}} - V_{t^{\text{b}},t}^{\text{dis}})$ denotes the charging trajectory of the aggregated EV at time slice t^{c} and is limited by the upper bound $v_{t^{\text{b}},t^{\text{c}}}^{\text{lv,max}}$ and lower bound $v_{t^{\text{b}},t^{\text{c}}}^{\text{lv,min}}$.

$$\sum_{t=t^{\text{b}}}^{t^{\text{c}}} \left(V_{t^{\text{b}},t}^{\text{ch}} - V_{t^{\text{b}},t}^{\text{dis}} \right) \leq v_{t^{\text{b}},t^{\text{c}}}^{\text{lv,max}} \quad \forall t^{\text{b}}, t^{\text{c}} \geq t^{\text{b}} \tag{B1}$$

$$\sum_{t=t^{\text{b}}}^{t^{\text{c}}} \left(V_{t^{\text{b}},t}^{\text{ch}} - V_{t^{\text{b}},t}^{\text{dis}} \right) \geq v_{t^{\text{b}},t^{\text{c}}}^{\text{lv,min}} \quad \forall t^{\text{b}}, t^{\text{c}} \geq t^{\text{b}} \tag{B2}$$

Similar to Equation (A6), Equation (B3) limits the charging and discharging power by the number of individual EV connected.

$$\frac{V_{t^{\text{b}},t}^{\text{ch}}}{\eta} + V_{t^{\text{b}},t}^{\text{dis}} \leq v_{t^{\text{b}},t}^{\text{No}} \times p^{\max} \times \Delta t \quad \forall t^{\text{b}}, \forall t \tag{B3}$$

Equation (B4) defines the net EV charging demand from the grid side.

$$D_t^{\text{EV,ctrl}} = \sum_{t^{\text{b}}} \left(\frac{V_{t^{\text{b}},t}^{\text{ch}}}{\eta} - V_{t^{\text{b}},t}^{\text{dis}} \times \eta \right) \quad \forall t \tag{B4}$$

Method B+ keeps the formulations of Method B and only modifies the upper bound of the charging trajectory. In Method B+, the upper bound is when the individual EV first charge as much as possible upon arrival and then has to be only at the required minimum SOC level by departure. While in Method B, the individual EV can depart with maximum SOC level if possible.

Based on Method B+, **Method B**++ additionally considers the constraints Equations (B5) to (B7). Another temporal dimension t^{d} is introduced, and $v^{task}_{t^{b},t^{d}}$ denotes the charging task of the aggregated EV fleet with arrival time t^{b} and is due at time t^{d}. Equation (B5) guarantees that $v^{task}_{t^{b},t^{d}}$ is exclusively fulfilled by charging and discharging behaviors before departure time. Equations (B6) and (B7) further decompose charging and discharging behavior ($V^{ch}_{t^{b},t}$ and $V^{dis}_{t^{b},t}$) into fractions with additional index t^{d}. The necessity and improvement of Method B+ and Method B++ are further in Supporting Information S1.

$$v^{task}_{t^{b},t^{d}} = \sum_{t=t^{b}}^{t^{d}} \left(V^{ch}_{t^{b},t,t^{d}} - V^{dis}_{t^{b},t,t^{d}} \right) \quad \forall t^{b}, t^{d} \geq t^{b} \tag{B5}$$

$$V^{ch}_{t^{b},t} = \sum_{t^{d}} V^{ch}_{t^{b},t,t^{d}} \quad \forall t^{b}, \forall t \tag{B6}$$

$$V^{dis}_{t^{b},t} = \sum_{t^{d}} V^{dis}_{t^{b},t,t^{d}} \quad \forall t^{b}, \forall t \tag{B7}$$

2.3 | Aggregated EV modeling Method C: Postponed charging

Method C is proposed in our previous work (Xu et al., 2020b) to analyze the European-wide EV emissions. Formulations with brief explanations can be found in Supporting Information S1. The main idea of the controlled charging strategy in Method C is that a certain amount of uncontrolled EV demand can be postponed within the next several hours. Therewith, it is a strong simplification of reality but decreases data requirements and computing efforts. Even though we do not know how controlled charging is accepted by EV users, this may still be a suitable approach for generating scenarios.

2.4 | Testbed for different EV aggregation methods

To test and analyze the performances of EV aggregation methods from multiple aspects, we design a simple capacity investment model for a country without any exchange to other countries as follows. Equation (TB1) is the model objective and minimizes the total cost, including investment cost ($\sum_{ec} c^{inv}_{ec} \times K_{ec}$), generation cost ($\sum_{ec} \sum_{t} c^{gen}_{ec} \times G_{t,ec} \times \Delta t$) and the fuel cost ($\sum_{ec} \sum_{t} c^{fuel}_{ec} \times G_{t,ec} \times \Delta t$). Equation (TB2) is the energy balance constraint, where the demand side includes a base demand d^{base}_{t} (demand without EV) and a flexible EV demand $D^{EV,ctrl}_{t}$. Equation (TB3) limits the generation of a certain energy carrier $G_{t,ec}$ by the investment capacity K_{ec} and the current availability $a_{t,ec}$.

$$\min : \sum_{ec} c^{inv}_{ec} \times K_{ec} + \sum_{ec} \sum_{t} c^{gen}_{ec} \times G_{t,ec} \times \Delta t + \sum_{ec} \sum_{t} c^{fuel}_{ec} \times G_{t,ec} \times \Delta t \tag{TB1}$$

$$d^{base}_{t} + D^{EV,ctrl}_{t} = \sum_{ec} G_{t,ec} \times \Delta t \quad \forall t \tag{TB2}$$

$$G_{t,ec} \leq K_{ec} \times a_{t,ec} \quad \forall t, \forall ec \tag{TB3}$$

We then separately apply EV aggregation Methods A, B, and C to the energy system model above and compare their results with the individual consideration of EV (formulations can be found in Supporting Information S1). Meanwhile, we combine the designed simple capacity investment model with LCA model to assess the GHG emissions. The model coupling applies the Environmental Assessment Framework for Energy System (EAFESA) to handle the challenges due to the differences of both models in system boundaries, databases as well as model assumptions (Xu et al., 2020a). LCA is to evaluate the environmental impacts throughout the entire process chain of a product system, that is, "from cradle to grave," which allows the assessment conducted switching from a direct emission perspective to a life cycle perspective (International Organization for Standarization, 2004). The target product system for the LCA analysis is the electricity system considered in our designed capacity investment model as well as the extra use of EV battery due to V2G. The ReCiPe method is applied for the life cycle impact assessment (Huijbregts et al., 2017).

As the modeling resolution and parameter availability are different in these methods, our focus is not merely to horizontally compare the three aggregation methods, but more to analyze how each aggregation method affect the results and whether, following the same way of aggregation, the respective modeling methods could be further improved.

3 | DATA

3.1 | Testbed: Energy system model and life cycle assessment

The proposed model is to decide the optimal capacity portfolio of one country, considering the option of V2G. Three generation technologies are selected as energy carriers, that is, gas, PV, and wind. Even though the model should not represent a certain country, some characteristics are referring to Germany. The following parameters are derived from Heinrichs (2013): the base demand profile d_t^{base} of Germany in 2050, investment, generation and fuel cost of different energy carriers (c_{ec}^{inv}, c_{ec}^{gen}, and c_{ec}^{fuel}) and the profiles of different energy carriers ($a_{t,ec}$). Four representative weeks with hourly resolution are selected to represent the four seasons of the year (Yilmaz et al., 2019).

For the LCA, the life cycle inventory (LCI) is based on the Ecoinvent 3.3 database (Treyer & Bauer, 2016). Furthermore, data of technologies for the generation of electricity mix is obtained from the ReFlex project (Brown et al., 2019), while the LCI of the EV battery is from Xu et al. (2020b), which assumed the battery life time subject to a fixed throughput (30,000 kWh), that is, V2G would lead to a higher battery demand. The functional unit of the electricity generation (gas, wind, and PV) and storage (the EV battery) technologies is 1 kWh.

3.2 | EV specifications

The scenario of EV integration is based on Reiter et al. (2017) and refer to Germany 2050, which projects a 71% EV market share among passenger cars. The annual mileage equals 12,000 km with an electricity efficiency of 20 kWh/100 km (Jochem et al., 2015) so that the EV charging task is about 9% of the total electricity demand. The capacity of the batteries is assumed to be 40 kWh with 5 kWh maximum charging or discharging power limited by the vehicle or the charging infrastructure. EV usage patterns are generated by inhomogeneous Markov chains (Iversen et al., 2017; Widén et al., 2009) and the transition matrix is derived from the iZEUS project (iZEUS, 2012; Schäuble et al., 2017) where usage patterns of an EV fleet are recorded for over 6 months. The setting of SOC for each individual EV is to make sure that the consequential daily energy consumption of an individual EV on average could match the setting of annual mileage of electricity efficiency stated above. The arrival SOC for an individual EV are assumed to be uniformly distributed between 30% and 80%. The corresponding departure SOC is subject to its arrival SOC and parking duration with an upper limit of 90%. When parking, the maximum SOC allowed is 100% (further information on EV SOC setting in Supporting Information S1). For this paper, 2000 individual EV usage patterns are generated with a duration of 4 weeks. The base demand d_t^{base} is scaled down to match these 2000 EV. Investment cost c_{ec}^{inv} is scaled down by annuity to match the optimization horizon of four weeks (detailed calculation in Supporting Information S1).

3.3 | Parameter setting in aggregate EV modeling methods

Parameters additionally required for the three aggregation methods are calculated from the parameters of the individual EV (cf. Section 3.2). As the focus of the paper is to analyze and compare the difference in modeling methods, the disturbance from parameter uncertainties is excluded by using the perfect information from individual EV. Detailed settings of the parameters additionally required by aggregated EV modeling methods can be found in Supporting Information S1, which are derived from individual EV information used in individual modeling method. The availabilities of these parameters in practice are further discussed in Section 4.5.

4 | RESULTS AND DISCUSSIONS

4.1 | Analysis of Method A

For our energy system model, we assume an ambitious decarbonization target for 2050. We apply a high CO_2 price (160 €/ton) based on the 450 parts per million (ppm) scenario of World Energy Outlook (IEA, 2016). This comparatively high CO_2 price encourages the use of renewable energies over fossil fuel electricity production technologies. Considering the generation profile, fuel cost, generation cost and investment cost

TABLE 1 Modeling error of EV behaviors in different aggregation methods (in kWh)

	Charging		Discharging	
	RMSE	AME	RMSE	AME
Method A: dynamic EV fleet	528	299	846	442
Method B: aggregated boundary	585	381	758	483
Method B++	**332**	**183**	**555**	**260**
Method C: postponed charging	803	523	866	481

Mathematical formulations of charging and discharging behaviors are in Supporting Information S1.

comprehensively, PV is the cheapest technology and gas is the most expensive one in our price setting (cf. Supporting Information S1). The model tends to invest more in PV and wind over gas to minimize the total cost, especially with the option of V2G.

For comparison, Figure 1a,b, respectively, select and show the time-dependent electricity mix and EV behaviors in Method A and individual modeling. EV discharging energy, as a measurement of V2G usage, are taken as generation units in Figure 1 and therefore are positive values. Figure 1c shows the hourly capacity factor of PV and wind during the same periods. Taking the solutions of individual modeling in Figure 1b as the benchmark, Method A in Figure 1a captures the key features of EV behaviors in individual modeling. Specifically, EV demand is shifted to noon hours to utilize PV in both. When there is sufficient PV in spring and summer, EV can even charge more than necessary so that they can discharge in the following night hours to reduce the use of expensive electricity generation by natural gas. Gas power plants are mainly operating during summer and autumn when there is insufficient PV and wind in the evening and night hours and only serve as a supporting technology during the other two seasons. It is also during these hours when the EV charging and discharging behaviors in Method A do not resemble the solutions in individual modeling that well. Such mismatch is partially due to the information loss during aggregation. Furthermore, the hourly capacity factor of PV and wind in Figure 1c can be taken as a guidance of how EV should schedule the charging and discharging behaviors. When gas is the main generating technology, EV have less incentives to charge or discharge in any specific hours since these alternative solutions are evaluated equally in terms for the total cost. This leads to multiple optimal solutions.

4.2 | Impacts of different EV aggregation methods on the results by the energy system model

Figure 2 illustrates how EV modeling methods affect the key solutions in energy systems, including electricity mix, EV demand and total cost. Figure 2 introduces Method A— in which Equations (A3) to (A5) are excluded from Method A to better illustrate their functions. Equations (A3) to (A5) additionally introduces the parameter $v_{t^a}^{task}$, the charging tasks of EV departing at time t^a, and ensures that the tasks can be completed within a time window in advance (12 hours in our setting). For the departure peak in the mornings (e.g., leaving home for work), these constraints (Equations (A3) to (A5)) assure that the charging tasks are completed during the previous nights. At nights when there is insufficient wind generation, these EV tasks are more supported by gas and discharging from other EV. Therefore, the generation from both gas and EV discharging increase from Method A— to Method A and are closer to the benchmark solutions in individual modeling.

In Method B, the upper bound for EV charging trajectory is defined much higher than the actual case (individual modeling), which means that Method B overestimates its potential of V2G usage. The total discharging energy from EV in Method B (460 MWh) is much higher than that in individual modeling (330 MWh) so that Method B can use less electricity generated by gas and more by PV and wind to reach a much lower total cost (226.0 thousand euro). Compared with Method B, Method B+ reduces the solution space for EV charging trajectory by lowering the upper bound, resulting in less generation by EV discharging and renewable energy, more usage of gas generation and finally higher total cost.

Method B+, Method B++, and individual modeling methods share the same upper and lower bound. The additional constraints Equations (B5) to (B7) further shrink the solution space so that the total cost increases from 236.7 thousand euro in Method B+ to 237.3 thousand euro in Method B++. The functions of Equations (B5) to (B7) are similar to Equations (A3) to (A5), so the generation from gas and EV discharging also increase from Method B+ to Method B++ and are closer to the solutions in individual modeling. Therefore, the main contribution of the additional constraints in Method B++ seems to better approximate of the EV load shifting potential.

Method C predefines an uncontrolled EV charging profile and allows for postponed charging by 12 hours. For the uncontrolled demand around evening periods, they cannot be fully shifted to periods with high PV generation (noon hours next day). Therefore, PV generation in Method C is much lower than those in other modeling methods and more gas technology is used. By comparing the overall solutions of different methods, Figure 2 shows that Method A and Method B++ lead to the closest unit commitment values by the individual modeling and, therefore, seem to be most appropriate for applications in energy system models in terms of solution accuracy.

Table 1 quantitatively compares the individual EV charging patterns over time with each EV aggregation method separately. Specifically, we take the EV charging and discharging solutions from individual modeling as the perfect results and calculate the root mean square error (RMSE)

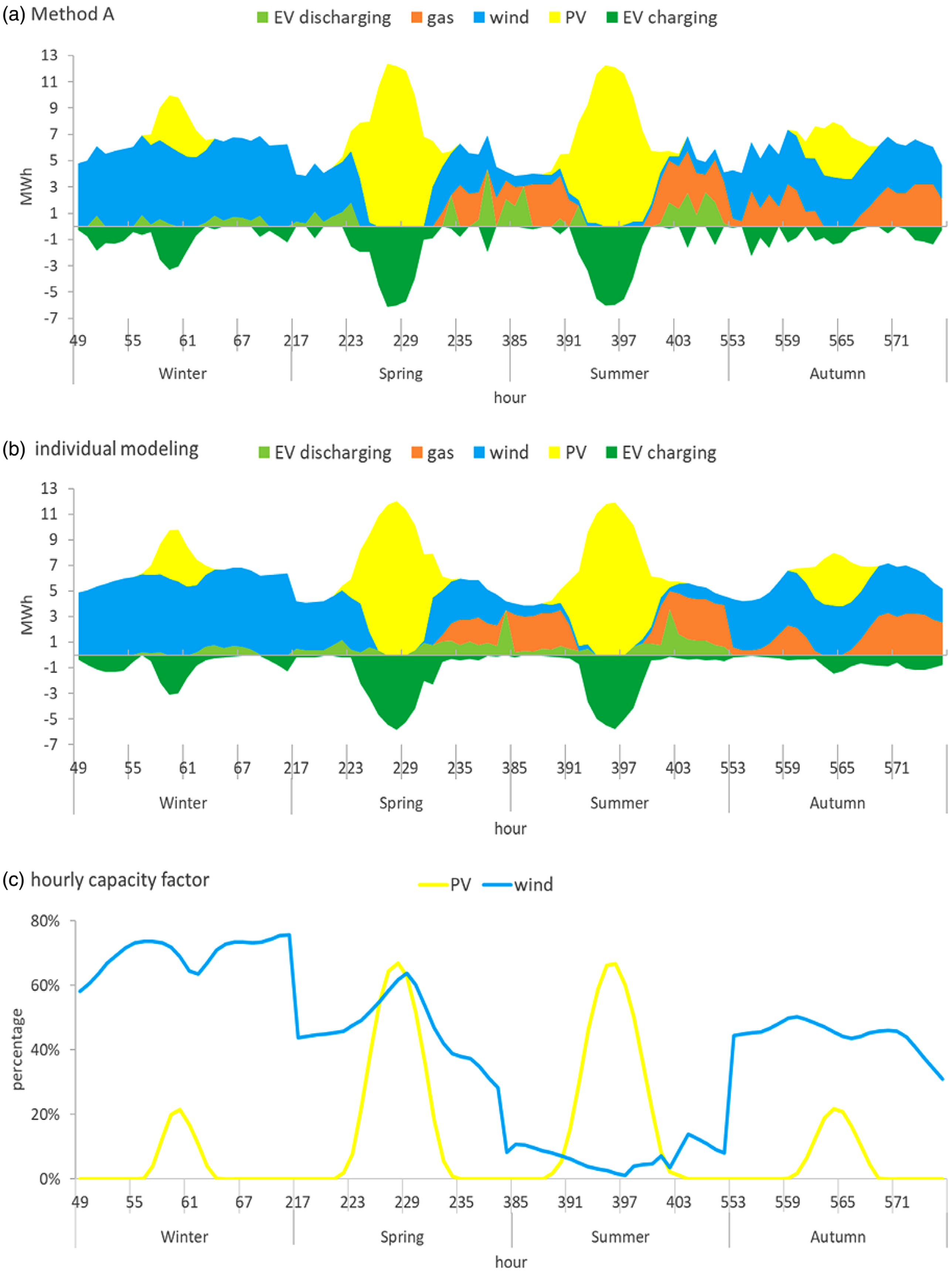

FIGURE 1 Time-dependent electricity mix. (a) Solutions of Method A (dynamic EV fleet). (b) Solution from individual modeling, which serve as the benchmark. (c) Hourly capacity factor of PV and wind for reference. Due to space limit, four Wednesday solutions are selected as representatives of the four weeks. The underlying data for this figure, including the complete data for the weeks, can be found in Supporting Information S2

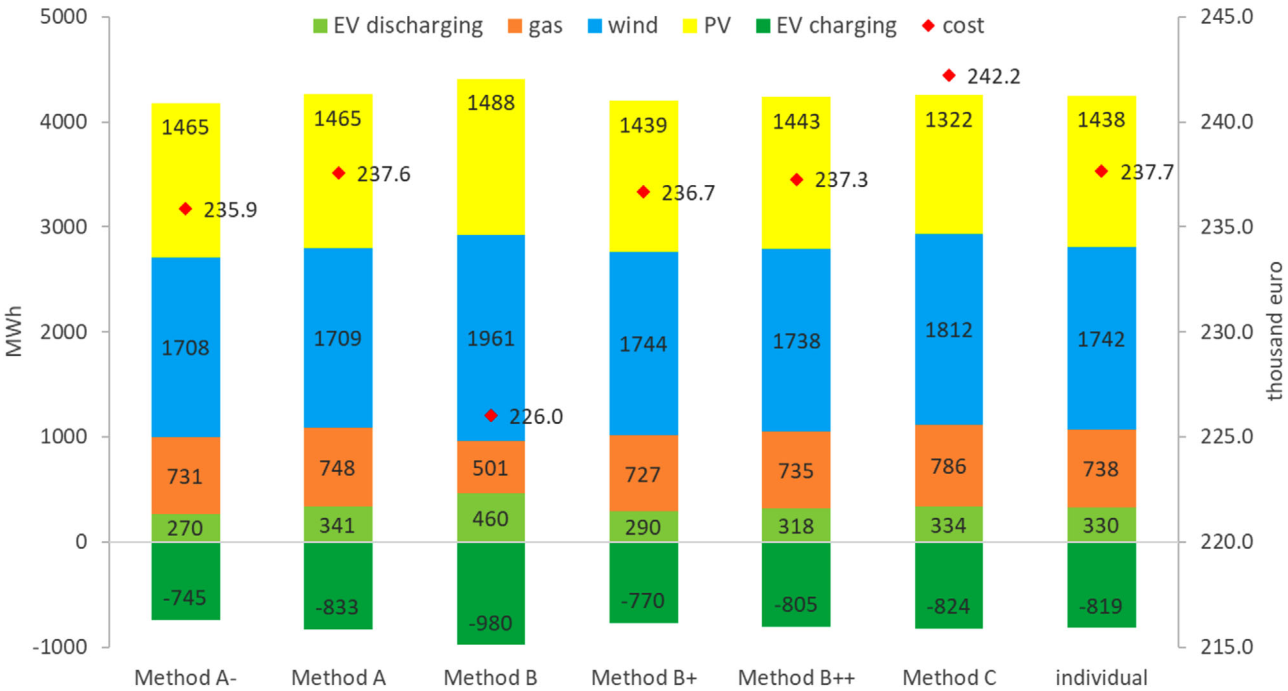

FIGURE 2 Electricity mix, EV charging demand, and total cost in different EV modeling methods. The electricity mix are presented in stacked columns as positive values on the primary *y*-axis, the EV charging demand as negative values on the primary *y*-axis and the total costs in scatter plot on the secondary *y*-axis. The difference between EV charging and EV discharging from the EV side is the EV charging tasks, which is a constant value proportional to EV annual mileage and same for all methods. Here, EV charging and discharging values are shown from the grid side considering efficiency so that their differences under different methods vary slightly. (Method A: dynamic EV fleet; Method B: aggregated boundary; Method C: postponed charging). The underlying data for this figure can be found in Supporting Information S2

and absolute mean error (AME) of each EV aggregation method. Again, Method B++ convinces the most. Method A does not perform as well as Method B++, which can be expected because Method B series aggregate individual EV by their arrival time and have a higher modeling resolution than Method A. Therefore, if properly modelled (e.g., Method B++), Method B series should have a better performance than Method A. The performance of Method C is the worst as its modeling is based on a predefined uncontrolled EV demand and does not capture as much as individual EV information as in Method A or Method B series.

4.3 | Impacts of different EV aggregation methods on assessment of emission reduction

Figure 3 shows the life cycle GHG emissions due to the application of V2G by different EV modeling methods, taking uncontrolled charging as a reference. We see the same trends in both EV aggregation and individual modeling methods. Compared with uncontrolled charging, EV charging strategies significantly save the emissions from gas and instead, increase the emissions from low-carbon wind and PV technologies as well as from EV battery. Although V2G increases the use of EV batteries, which comes in line with a higher depreciation, the resulting impact from EV on GHG emissions overall is still positive. However, the application of the different aggregation methods leads to different results which may over- or underestimate the resulting reductions. While Method B overestimates the load shifting potential and therefore expects significantly more GHG reduction, Methods A and C show much closer values to the individual consideration.

4.4 | Computational complexity

The computational complexity of different aggregated EV modeling methods is yet another important aspect as it might significantly influence solvability of the model. Table 2 shows the number of variables and equations required by different methods and their solving time in terms of cplex clock time and ticks.

Method A aggregates all individual EV as one by considering the dynamic capacity of this aggregated EV and has the lowest model execution time among the three methods. In Method B series, EV are aggregated by their arrival time, which means the number of time slices will make extra

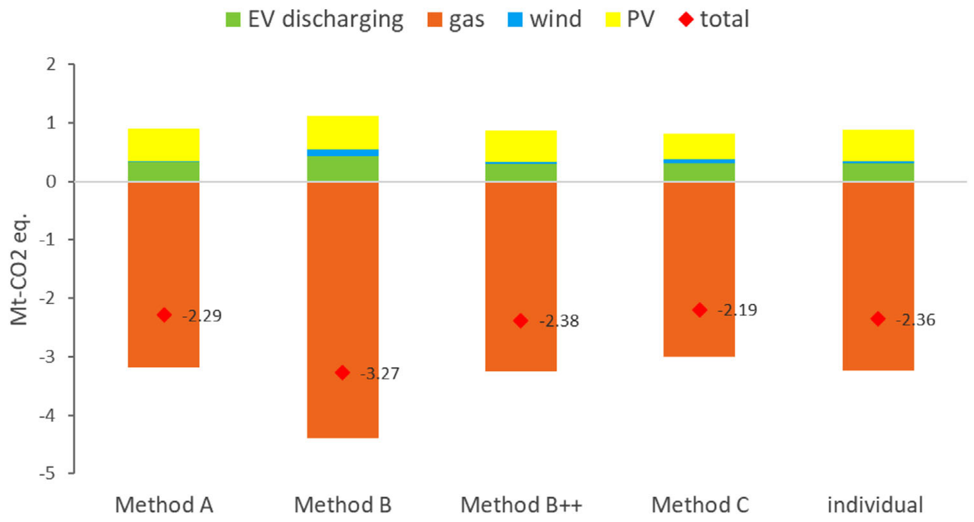

FIGURE 3 Assessment of emission reduction by different EV aggregation methods (Method A: dynamic EV fleet; Method B: aggregated boundary; Method C: postponed charging). The underlying data for this figure can be found in Supporting Information S2

TABLE 2 Computational complexity of different EV modeling methods

	No. of binary variables	No. of continuous variables	No. of equations	Cplex time (s)	Deterministic ticks
Method A: dynamic EV fleet	0	29,442	12,769	**0.76**	**541.50**
Method B: aggregated boundary	0	915,270	559,721	140.40	47,429.37
Method B++	0	8,170,264	707,813	968.39	329,271.23
Method C: postponed charging	0	**27,558**	**10,081**	0.87	692.22
Individual modeling	2,709,504	8,136,581	684,679	991.48	155,861.22

Cplex time of the same method may vary considering the current load of the platform (both hardware and software). However, ticks are considered to be consistent measures for the same platform (GAMS Development Corporation, 2018). With the same platform for all EV modeling methods, ticks can offer a precise comparison.

contribution to the complexity of the method if the applied model has a longer time span or higher temporal resolution. The addition of Equations (B5) to (B7) in Method B++ greatly increases the number of variables and equations required and the solving time in exchange of improvement in solution performance. The model size and execution time of Method C are also relatively low as it merely postpones the uncontrolled charging profile and empirically limits the EV discharging amount.

The binary variables in individual modeling method are the charging and discharging decision of individual EV. Therefore, the individual model is a mixed integer linear programming problem, while all aggregation methods are only linear programming. The execution time in individual modeling is even shorter than in Method B++, because only two thousand individual EV are considered for this comparison. The number of individual EV has a major impact on the solving time in individual modeling but does not significantly contribute to the model size of aggregation methods.

4.5 | Parameter requirement

Large-scale energy system models often face with the uncertainty from parameters, as they commonly use parameters based on historical data from statistics, projections for future scenarios, and assumptions. Table 3 lists the parameters required in different aggregation methods, classified by their current availabilities in literature. Being available in the literature means that there have been literature focusing on the simulation of these aggregated parameters based on historical or statistical data.

Based on statistics from multiple sources, Babrowski et al. (2014) simulate country-specific charging load curves of EV, including the uncontrolled EV demand curve $d_{te}^{EV,unctrl}$ and time-dependent EV availability (v_t^{No}). Assuming the same EV capacity, $k_t^{agg,EV}$ is also available ($k_t^{agg,EV} = v_t^{No} \times k^{ev}$). Wulff et al. (2020) also develop a transport model which generates EV demand profile and number of EV charging at time and location by considering charging costs and infrastructure availability. With a comprehensive survey on driver behavior, Propfe and De Tena (2010) develop a method to

TABLE 3 Parameters required by aggregation methods and their availabilities in literature (Method A: Dynamic EV fleet; Method B: aggregated boundary; Method C: postponed charging)

	Required parameters	Availability	Exemplary literature
Method A	v_t^{No}, $k_t^{agg,EV}$	Based on current EV usage data and assumptions	Babrowski et al., 2014; Wulff et al., 2020
	$s_t^{agg,min}$, $s_t^{agg,max}$	Based on current surveys	de Tena & Pregger, 2018; Propfe & De Tena, 2010
	$v_t^{en,arr}$, $v_t^{en,dep}$, $v_{t^a}^{task}$	Based on EV studies, but no simulation tool developed	Schäuble et al., 2017
Method B series	$v_{t^b,t^c}^{lv,max}$, $v_{t^b,t^c}^{lv,min}$, v_{t^b,t^d}^{task}, $v_{t^b,t}^{No}$	Based on EV studies, but no simulation tool developed	Schäuble et al., 2017
Method C	$d_{t^e}^{EV,unctrl}$, v_t^{No}	Based on current EV usage data and assumptions	Babrowski et al., 2014; Wulff et al., 2020

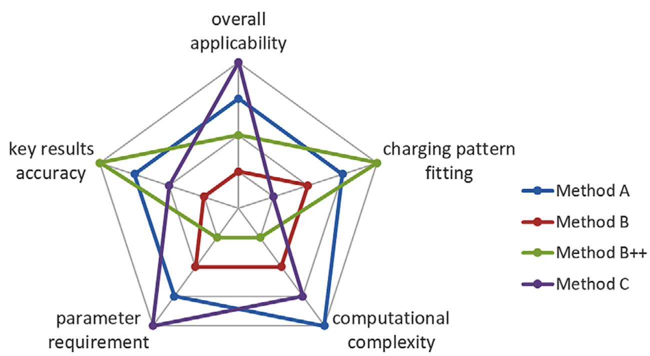

FIGURE 4 Various performance of EV aggregation methods. The farther the distance from the center, the better the performance. For each aspect, the distance between the methods only shows their relative rankings but does not represent the quantification of their performances. (Method A: dynamic EV fleet; Method B: aggregated boundary; Method C: postponed charging)

calculate the SOC boundary of the aggregated EV within a day, which can be used for the settings of $s_t^{agg,min}$ and $s_t^{agg,max}$ in this paper. By contrast, Schäuble et al. (2017) present comprehensive EV usage data from several electric mobility studies, including the plugged-in and plugged-out time of individual EV with their respective SOC status. This data could be used to provide corresponding aggregated parameters in Method A and Method B series in Table 3, but no simulation tool is developed in their paper. In practice, $v_{t^b,t^c}^{lv,max}$ and $v_{t^b,t^c}^{lv,min}$ in Chen et al. (2018) are derived from simple summation of assumed individual EV information (SOC upon arrival and charging window).

Consequently, we conclude that the required data for all three methods is available, although further development of some simulation tools are still necessary. Some, for example, the future market share, the future battery capacity, willingness to participate in V2G services as well as the future charging patterns (cf. autonomous vehicles), are still based on uncertain assumptions. This may still lead to the conclusion of using Method C or A instead of more sophisticated methods as long as these uncertainties remain.

4.6 | Discussion

Figure 4 illustrates the performances of different EV aggregation methods from various aspect. With the improvements in Section 2.2, Method B++ has the highest accuracy in key results and the lowest fitting error of EV charging pattern. The cost of such improvements, however, are the highest parameter requirement and the computational complexity. Compared with Method B++, Method A has slightly worse results, but shows significant time savings and lower requirement on empirical data. For Method C, its computing time is close to that in Method A and it requires the least on parameters. Even though the results of Method C are not as accurate as those in Method A or Method B++, it is so far the most applicable EV aggregation method. The applicability of Method A is mainly limited by its additional requirement on parameters. The applicability of Method B++ is both limited by parameter requirement and computational complexity. Please note that the ranking for the overall applicability focus on the current applicability. As the novel Method A and B++ would require some specially designed parameters (those commented with no simulation tool developed in Table 3). Since the test system in the paper has access to all the individual EV parameters (e.g., arrival and departure time and the corresponding SOC), the generation of these parameter is possible in the test case but might not be possible (so far to our knowledge) to acquire in real applications where the statistics of EV are highly aggregated and in predefined forms. The successful application of Method A and B++ in the future would require further simulation tools for these parameters.

5 | CONCLUSION

In this paper, we introduce three aggregation methods for considering vehicle-to-grid services by electric vehicles in (multi-)national energy system models. Method A (dynamic EV fleet) and Method B (aggregated boundary) are related: While Method A aggregates all vehicles as a dynamic EV fleet, Method B aggregates vehicles by their arrival time. Method C (postponed charging) is a strongly simplified aggregation method, as it allows to postpone the uncontrolled charging task to a later slot. By using the same notation, we make these methods comparable. To identify the differences, all these methods are applied in a simple energy system model and benchmarked with an individual consideration of load flexibilities from electric vehicles.

First, we experienced shortcomings of Method B from literature and extend this method accordingly, which resulted in Method B++. No clear advice can be drawn out of our comparison of method performances in four aspects, that is, key results accuracy (electricity mix and GHG reduction), charging pattern fitting, computational complexity, and parameter requirement. General recommendations are summarized for interested researchers and modelers as follows:

1. Method A has no obvious weaknesses and reaches a balance between result accuracy and computational complexity, which is recommended for researchers with no strong focus on either side.
2. Method B++ has the best result accuracy at the cost of the highest modeling resolution and a significant increase in computational time, which might be more suitable for problems with smaller geographical or temporal scales or strong focus on accurate modeling of EV usage patterns.
3. Due to the advancement in formulation, both Method A and Method B++ require parameters of particular forms which might not be explicitly available from statistical data or simulation tools so far to our knowledge. The accessibility of detailed EV data from statistics or field test might be a prerequisite for their applications.
4. Method C has relatively lower but still convincing solution performance in exchange of the simplicity in application and the low requirement on empirical data, which could be a practical option for large-scale or already sophisticated models (e.g., multi-national or multi-sectoral).

Finally, we would like to mention that the results of our analysis may depend on our applied energy system model and further implementation of the aggregation methods into other energy system models would be highly appreciated. The aim of the comparisons above is not to select the best EV aggregation method, but rather to highlight the differences from the modeling perspective and to inspire further research in this field.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supporting information of this article.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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Summary

This supporting information consists of 8 sections. Section 1 describes the nomenclature used for the formulations in the paper and in this supporting information. Section 2 illustrates the necessity and improvement of Method B+ and Method B++. Section 3 explains the formulations of Method C in the main article. Section 5 describes a general individual EV modeling method. Section 5 shows the formulations of the parameters required by aggregated EV modeling methods of the main article. Section 6 provides the cost settings used in the main article. Section 7 provides mathematical formulations of charging and discharging behaviors by different modeling methods. Section 8 provides further information on the setting of EV battery state of charge (SOC). Detailed data of the figures and tables provided in Supporting information S1 can be found in Supporting information S2 online (https://doi.org/10.1111/jiec.13200).

1. Nomenclature

Indices:

ec	energy carrier	
m	electric vehicle	
t	time	
t^a	alias of t, used in Method A	
t^b, t^c, t^d	alias of t, used in Method B/B+/B++,	
t^e, t^f	alias of t, used in Method C,	

Parameters:

$a_{\mathrm{t,ec}}$	time-dependent capacity factor of energy carrier	[%]
$b^{\mathrm{arr}}_{\mathrm{m,t}}$	EV arrival status; equal to 1 if EV m arrives at t, otherwise 0	[binary]
$b^{\mathrm{park}}_{\mathrm{m,t}}$	EV parking status; equal to 1 if EV m is parking at t, otherwise 0	[binary]
$b^{\mathrm{park}}_{\mathrm{m,t^b,t^c}}$	EV parking status with arrival time at t^b; equal to 1 if EV m is parking at t^c, otherwise 0	[binary]
k^{ev}	battery capacity of one single EV	[kWh]
$k^{\mathrm{agg,EV}}_{\mathrm{t}}$	battery capacity of aggregated EV at t	[kWh]
$c^{\mathrm{inv}}_{\mathrm{ec}}$	investment cost of energy carrier	[€/kW]
$c^{\mathrm{gen}}_{\mathrm{ec}}$	generation cost of energy carrier	[€/kWh]
$c^{\mathrm{fuel}}_{\mathrm{ec}}$	fuel cost of energy carrier	[€/kWh]
$d^{\mathrm{base}}_{\mathrm{t}}$	base demand (demand without EV) at t	[kWh]
$d^{\mathrm{EV,unctrl}}_{\mathrm{t^e}}$	uncontrolled EV demand at t^e	[kWh]
$v^{\mathrm{No}}_{\mathrm{t}}$	number of EV available at t	
$v^{\mathrm{No}}_{\mathrm{t^b,t}}$	number of EV with the same arrival time t^b and available at t	
$v^{\mathrm{dis,max}}$	maximum EV discharging energy amount	[kWh]

$v_{\mathrm{m,t^a}}^{\mathrm{task}}$	individual EV charging task due at $\mathrm{t^a}$	[kWh]
$v_{\mathrm{m,t^b,t^d}}^{\mathrm{task}}$	individual EV charging task classified by arrival time is $\mathrm{t^b}$ due at $\mathrm{t^d}$	[kWh]
$v_{\mathrm{t^a}}^{\mathrm{task}}$	aggregate EV charging task due at $\mathrm{t^a}$	[kWh]
$v_{\mathrm{t^b,t^d}}^{\mathrm{task}}$	aggregate EV charging task by arrival time is $\mathrm{t^b}$, due at $\mathrm{t^d}$	[kWh]
v_0^{en}	the initial energy level of aggregated EV	[kWh]
$v_{\mathrm{t}}^{\mathrm{en,arr}}$	EV energy which arrives at t	[kWh]
$v_{\mathrm{t}}^{\mathrm{en,dep}}$	EV energy which departs at t	[kWh]
$v_{\mathrm{t^b,t^c}}^{\mathrm{lv,min}}$	minimum energy level of EV aggregated by the same arrival time $\mathrm{t^b}$ at $\mathrm{t^c}$	[kWh]
$v_{\mathrm{t^b,t^c}}^{\mathrm{lv,max}}$	maximum energy level of EV aggregated by the same arrival time $\mathrm{t^b}$ at $\mathrm{t^c}$	[kWh]
p^{max}	maximum charging/discharging power of one EV (before energy loss)	[kW]
$s_{\mathrm{m,t}}^{\mathrm{arr}}$	initial SOC status of electric vehicle m upon arrival at t	[%]
$s_{\mathrm{m,t}}^{\mathrm{dep}}$	target SOC of electric vehicle m at departure time t	[%]
$s_{\mathrm{m,t}}^{\mathrm{ub}}$	upper bound of SOC status of electric vehicle m upon arrival at t	[%]
$s_{\mathrm{m,t}}^{\mathrm{lb}}$	lower bound of SOC status of electric vehicle m upon arrival at t	[%]
$s_{\mathrm{t}}^{\mathrm{agg,min}}$	minimum SOC of aggregated EV at t	[%]
$s_{\mathrm{t}}^{\mathrm{agg,max}}$	maximum SOC of aggregated EV at t	[%]
s^{max}	maximum SOC of electric vehicle	[%]
Δt	length of time interval	[hour]
η	EV charging/discharging efficiency	[%]
θ	percentage of non-shiftable EV demand	[%]

Variables (non-negative):

K_{ec}	capacity investment of energy carrier	[kW]
$V_{\mathrm{m,t}}^{\mathrm{ch}}$	charging energy of EV m at t (from EV side)	[kWh]

$V_{\mathrm{m,t}}^{\mathrm{dis}}$	discharging energy of EV m at t (from EV side)	[kWh]
$V_{\mathrm{t^a,t}}^{\mathrm{ch}}$	part of the charging energy of aggregated EV at t, to satisfy EV charging task due at $\mathrm{t^a}$ (from EV side)	[kWh]
$V_{\mathrm{t^a,t}}^{\mathrm{dis}}$	part of the discharging energy of aggregated EV at t, to satisfy EV charging task due at $\mathrm{t^a}$ (from EV side)	[kWh]
$V_{\mathrm{t^b,t,t^d}}^{\mathrm{ch}}$	part of the charging energy of EV aggregated by the same arrival time $\mathrm{t^b}$, scheduled at t, to satisfy EV charging task due at $\mathrm{t^d}$ (from EV side)	[kWh]
$V_{\mathrm{t^b,t,t^d}}^{\mathrm{dis}}$	part of the discharging energy of EV aggregated by the same arrival time $\mathrm{t^b}$, scheduled at t, to satisfy EV charging task due at $\mathrm{t^d}$ (from EV side)	[kWh]
$V_{\mathrm{t}}^{\mathrm{en}}$	energy level of aggregated EV at t	[kWh]
$V_{\mathrm{t^b,t}}^{\mathrm{ch}}$	charging energy of EV aggregated by the same arrival time $\mathrm{t^b}$ at t (from EV side)	[kWh]
$V_{\mathrm{t^b,t}}^{\mathrm{dis}}$	discharging energy of EV aggregated by the same arrival time $\mathrm{t^b}$ at t (from EV side)	[kWh]
$V_{\mathrm{t^e,t}}^{\mathrm{ch}}$	controlled charging energy at t, postponed for uncontrolled demand at $\mathrm{t^e}$ (from EV side)	[kWh]
$V_{\mathrm{t^e,t}}^{\mathrm{dis}}$	controlled discharging energy at t, postponed for uncontrolled demand at $\mathrm{t^e}$ (from EV side)	[kWh]
$V_{\mathrm{t}}^{\mathrm{ch}}$	charging energy of aggregated EV at t (from EV side)	[kWh]
$V_{\mathrm{t}}^{\mathrm{en}}$	discharging energy of aggregated EV at t (from EV side)	[kWh]
$G_{\mathrm{t,ec}}$	generation power of energy carrier at t	[kW]
$S_{\mathrm{m,t}}$	battery SOC of EV m at t	[%]

Variables (free):

$D_{\mathrm{t}}^{\mathrm{EV,ctrl}}$	controlled EV net charging demand at t (from the grid side)	[kWh]

Variables (binary):

$B_{\mathrm{m,t}}^{\mathrm{ch}}$	charging decision of EV m at t; equal to 1 if EV charges, otherwise 0	[binary]
$B_{\mathrm{m,t}}^{\mathrm{dis}}$	discharging decision of EV m at t; equal to 1 if EV discharges, otherwise 0	[binary]

Sets:

X	EV availability set	$X = \{(\mathrm{m},\mathrm{t}) \mid b_{\mathrm{m,t}}^{\mathrm{park}} = 1\}$
Y	EV arrival set	$Y = \{(\mathrm{m},\mathrm{t}) \mid b_{\mathrm{m,t}}^{\mathrm{arr}} = 1\}$
Z	EV departure set	$Z = \{(\mathrm{m},\mathrm{t}) \mid b_{\mathrm{m,t}}^{\mathrm{dep}} = 1\}$
P_{t}	collection of EV charging task	$P_{\mathrm{t}} = \{\mathrm{t^a} \mid \mathrm{t^a} = \mathrm{t}, \mathrm{t}+1, \dots, \mathrm{t}+11\}$
$Q_{\mathrm{t^a}}$	dispatch of EV charging task	$Q_{\mathrm{t^a}} = \{\mathrm{t} \mid \mathrm{t} = \mathrm{t^a}-11, \mathrm{t^a}-10, \dots, \mathrm{t^a}\}$
$R_{\mathrm{t^e}}$	decomposition of uncontrolled EV demand	$R_{\mathrm{t^e}} = \{\mathrm{t} \mid \mathrm{t} = \mathrm{t^e}, \mathrm{t^e}+1, \dots, \mathrm{t^e}+11\}$
S_{t}	recomposition of uncontrolled EV demand	$S_{\mathrm{t}} = \{\mathrm{t^e} \mid \mathrm{t^e} = \mathrm{t}-11, \mathrm{t}-10, \dots, \mathrm{t}\}$
$U_{\mathrm{t^f}}$	rolling window for EV discharging limit	$U_{\mathrm{t^f}} = \{\mathrm{t} \mid \mathrm{t} = \mathrm{t^f}, \mathrm{t^f}+1, \dots, \mathrm{t^f}+23\}$

Please note that this nomenclature applies to all the formulations in the main article and in the supporting information. All parameters (in lowercase letters), variables (in uppercase letters), superscripts and subscripts which are jointly used by different modeling methods are harmonized. All variables in the paper are defined as non-negative variables, unless otherwise specified.

2. Further analysis for the functions of Method B+ and Method B++

As discussed in the main article, the proposal and the application of aggregated EV modeling methods are commonly found together in one paper focusing on energy system models, so it is difficult for researchers to directly demonstrate the feasibility of their proposed methods by comparing with the individual modeling method. With the test model from Section 2.4 in the main article, this section presents and improves the performance of Method B by comparing its solutions with those in individual modeling. Such a practice can be taken an example of how to develop and improve aggregate EV modeling methods.

2.1. Method B+: modified boundary of charging trajectory

Method B aggregates individual EV by their arrival time. Figure S1 shows the charging trajectory of one aggregated EV fleet with the arrival time at hour 1. This aggregated EV is composed of 33 individual EV and its parking duration depends on the maximum parking duration out of these 33 individual EV, which is 38 hours in this case. According to the definitions of the upper and lower bound of Method B in Section 2.2 in the main article, they do not converge to one ending point in Figure S1. This aggregated EV would be fully charged at departure (hour 38) by the upper bound and would be only charged to the required level by the lower bound.

This setting enables the model to flexibly decide the charging task at departure. Naturally, such charging flexibility is feasible for one individual EV in a single charging service. However, our proposed test model in Section 2.4 (and most energy system models) optimizes over a long time span and the total EV charging task is considered to be a fixed value (proportional to EV annual mileage). If such flexibility setting is allowed, certain balancing constraints should have been additionally introduced. For instance, EV might charge more than necessary during a charging event when electricity prices are low and charge less in the next charging service, while the total EV charging tasks over the optimized time span is a fixed value (Nahmmacher et al. 2016)

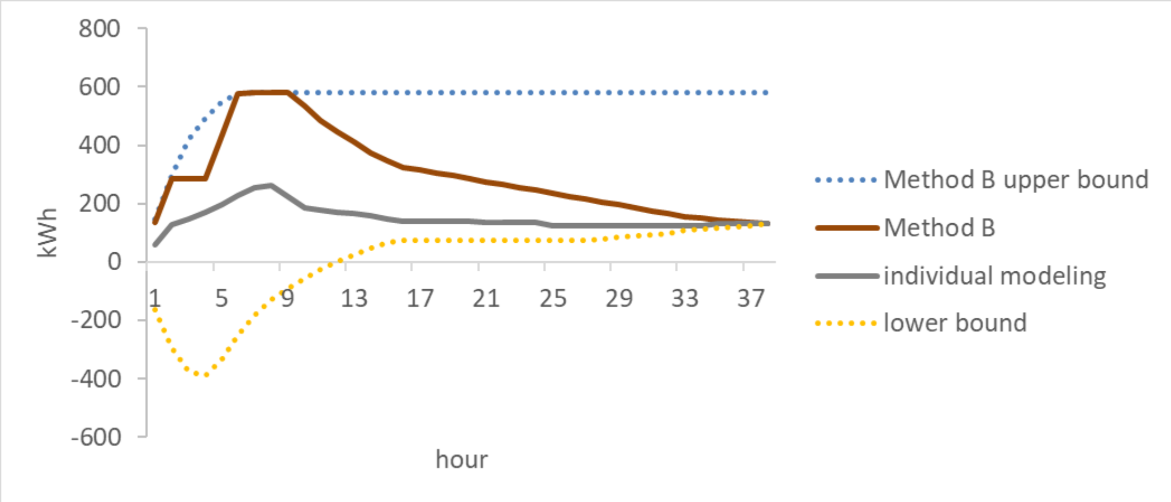

Figure S1 Exemplary charging trajectory result of Method B (arrival at hour 1 of the model horizon)

Moreover, most energy system models minimize the total cost so that it may not be the optimal solution to charge EV more than necessary. In fact, the optimal solution of our model is only achieved when all the charging trajectories converge to the lower bound (the necessary EV demand), which also means the upper bound of Method B enlarges the feasible set of the charging trajectory. Figure S1 shows the optimal charging trajectory of Method B, compared with the summation of the optimal solution of the same 33 EV in individual modeling. The solution of Method B greatly deviates from that of the individual modeling and the upper bound of Method B is not an active constraint of the individual modeling solution, implying that EV charging trajectories in individual modeling are not actually limited by such an upper bound.

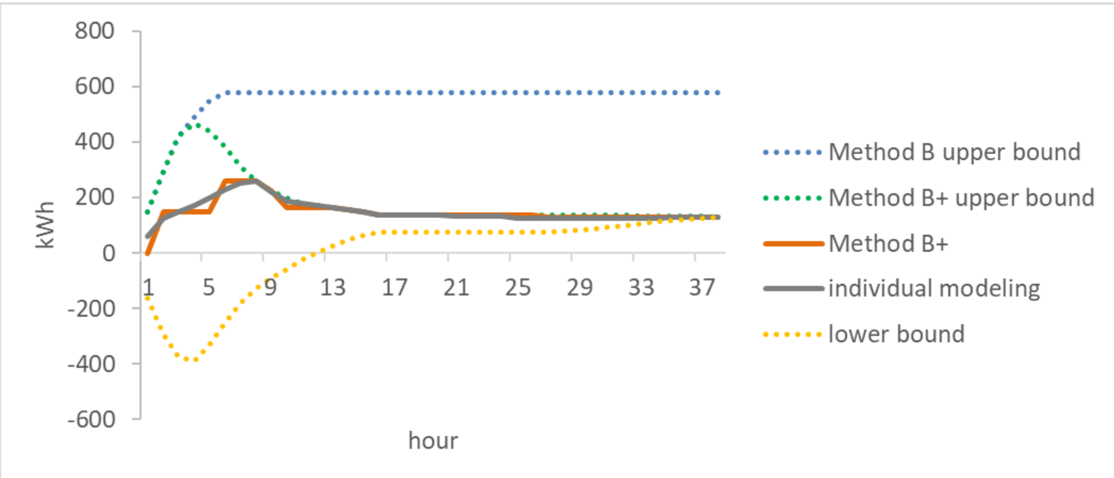

Figure S2 Exemplary charging trajectory result of Method B+ (arrival at hour 1 of the model horizon)

Our modified upper bound for Method B is to fix the charging trajectory at departure only to the necessary value, which is calculated by first instant charging as much as possible and then discharging as late as possible to the necessary level. Let Method B+ denote Method B with our modified upper bound and the corresponding results are presented in Figure S2. Our modified upper bound converges to the lower bound and is also an active constraint for the individual modeling solution, justifying the setting of the modified upper bound.

2.2. Method B++: additional constraints for the charging task

The key idea of Method B is the aggregation of the individual EV constraints. Method B+ keeps this idea and only modifies the upper bound by how the individual EV are in fact limited in individual modeling. However, there is one untold assumption for this boundary aggregation method, i.e., since any charging trajectory between the upper and lower bound of one individual EV is a feasible trajectory, any charging trajectory between the aggregated upper and lower bound is also a feasible trajectory for the EV fleet.

We illustrate the potential problem of this assumption in Method B (and Method B+) with the optimal charging trajectory of Method B+ at another arrival time (cf. Figure S3) and the corresponding detailed charging/discharging behavior (cf. Table S1). We take the aggregated EV arriving at hour 40, which is composed of 149 individual EV with a maximum parking time until hour 86.

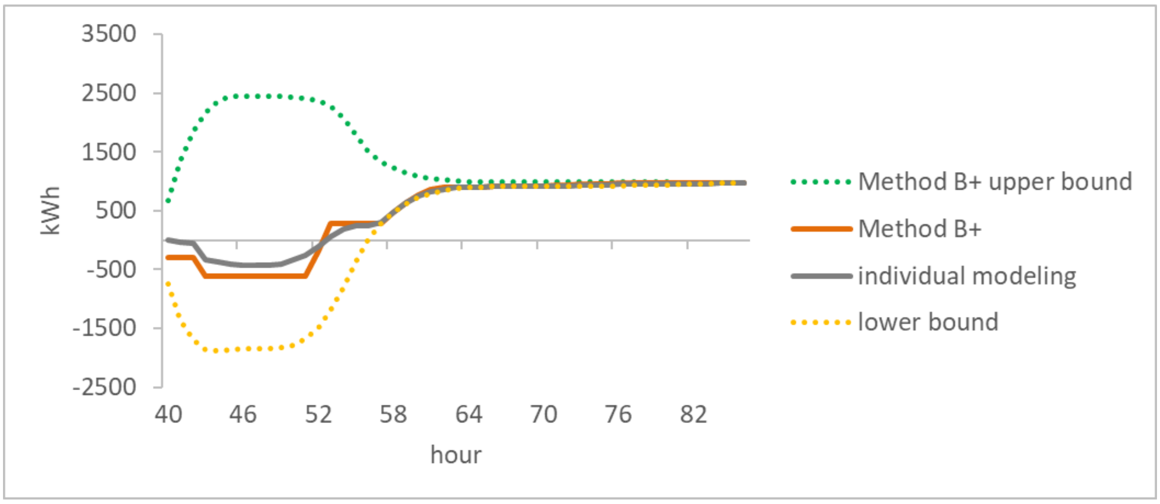

Figure S3 Exemplary charging trajectory result of Method B+ (arrival at hour 40 of the model horizon)

hour		**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**...**
No. of plugged-in EV		149	149	149	149	140	137	136	134	...
Method B+	Charging behavior	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
	Discharging behavior	-291.9	0.0	0.0	-327.6	0.0	0.0	0.0	0.0	...
	Cumulative charging trajectory	-291.9	-291.9	-291.9	-619.5	-619.5	-619.5	-619.5	-619.5	...
Individual modeling	Charging behavior	22.5	0.0	0.0	1.3	0.0	0.0	0.0	0.0	...
	Discharging behavior	-19.8	-33.1	-29.3	-267.3	-38.2	-45.0	-25.0	0.0	...
	Cumulative charging trajectory	2.7	-30.4	-59.7	-325.7	-363.9	-408.9	-433.9	-433.9	...

Table S1 Charging/discharging behavior of Method B+ in kWh (arrival at hour 40 of the model horizon)

Figure S3 shows that, although the aggregated EV fleet and the 149 individual EV have the same upper and lower bounds, their optimal charging trajectories are different. As defined in Section 2.2 of the main article, charging trajectory is the cumulative charging energy, including both charging and discharging behaviors which are allowed to schedule at the same time. To better illustrate the shortcoming of Method B, Table S1 separately presents a fraction of the detailed charging and discharging behaviors and their cumulative sum are the optimal charging trajectories in Figure S3, together with the time-dependent quantity of plugged-in individual EV composing the aggregated EV fleet. As can be seen from Table S1, 9 individual EV start to depart from hour 44, and 15 out of 149 individual EV have left the aggregated EV fleet by hour 47. In individual modeling, the charging task of these departing EV are fulfilled and reflected by the charging energy at hour 40 (22.5 kWh) and hour 43 (1.3 kWh). In Method B+, however, there is no charging energy before hour 47, which means that charging tasks of the individual EV are not properly considered by Method B+ and that they may depart without being charged at all. The simple aggregation of individual boundaries in Method B (B+) cannot guarantee a feasible set for the aggregated EV fleet.

We alleviate this problem by introducing additional constraints Eq. (B5) to (B7) which consider the charging tasks from individual EV. The idea and formulations are derived from Eq. (A3) to (A5). Let Method B++ denote Method B+ with additional constraints Eq. (B5) to (B7). The charging trajectory results of Method B+ and Method B++ are compared in Figure S4, with the charging trajectory result from individual modeling as a benchmark. Table S2 separately presents a fraction of the detailed charging and discharging behaviors of the optimal charging trajectories of Method B++ in Figure S4. Compared with the solutions of Method B+ in Table S1, Method B++ has charging energy at hour 40, 42 and 43 prior to the EV departure at hour 44. These results show that Method B++ further considers the charging tasks and gives better approximation of the individual EV modeling method.

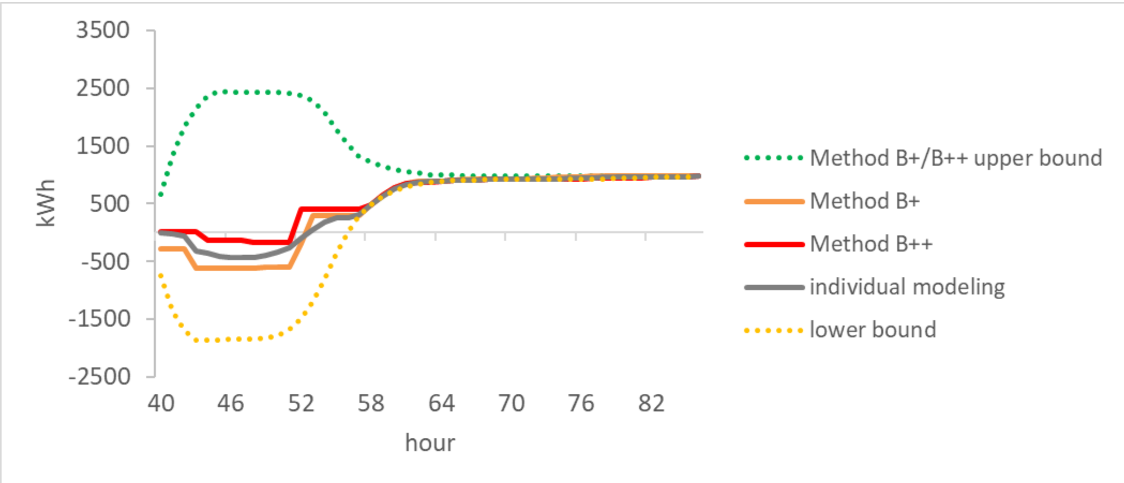

Figure S4 Exemplary charging trajectory results of Method B+ and Method B++ (arrival at hour 40 of the model horizon)

hour		**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**...**
No. of plugged-in EV		149	149	149	149	140	137	136	134	...
Method B++	Charging behavior	7.2	0.0	5.1	11.5	0.0	0.0	0.0	0.0	...
	Discharging behavior	0.0	0.0	-1.0	0.0	-163.1	0.0	0.0	0.0	...
	Cumulative charging trajectory	7.2	7.2	11.3	22.8	-140.3	-140.3	-140.3	-140.3	...
Individual modeling	Charging behavior	22.5	0.0	0.0	1.3	0.0	0.0	0.0	0.0	...
	Discharging behavior	-19.8	-33.1	-29.3	-267.3	-38.2	-45.0	-25.0	0.0	...
	Cumulative charging trajectory	2.7	-30.4	-59.7	-325.7	-363.9	-408.9	-433.9	-433.9	...

Table S2 Charging/discharging behavior of Method B++ in kWh (arrival at hour 40 of the model horizon)

3. Formulations of aggregated EV modeling Method C: postponed charging

Controlled charging strategy constraints

$$d_{t^e}^{EV,unctrl} = \sum_{t\in R_{t^e}} (V_{t^e,t}^{ch} - V_{t^e,t}^{dis}) \qquad \forall t^e \qquad (C1)$$

$$V_{t^e,t}^{ch} \geq d_{t^e}^{EV,unctrl} \times \theta \qquad \forall t^e, t = t^e \qquad (C2)$$

Controlled net charging demand constraint

$$D_t^{EV,ctrl} = \sum_{t^e\in S_t} \left(\frac{V_{t^e,t}^{ch}}{\eta} - V_{t^e,t}^{dis} \times \eta\right) \qquad \forall t \qquad (C3)$$

Charging/discharging power limit constraint

$$\sum_{t^e\in S_t} \left(\frac{V_{t^e,t}^{ch}}{\eta} + V_{t^e,t}^{dis}\right) \leq v_t^{No} \times p^{max} \times \Delta t \qquad \forall t \qquad (C4)$$

Total discharging limit constraint

$$\sum_{t\in U_{t^f}} \sum_{t^e\in S_t} V_{t^e,t}^{dis} \leq v^{dis,max} \qquad \forall t^f \qquad (C5)$$

This method is applied and discussed in detail in our previous work (Xu et al. 2020). As a brief explanation, Eq. (C1) allows $d_{\mathrm{t^e}}^{\mathrm{EV,unctrl}}$, the uncontrolled EV demand at $\mathrm{t^e}$, to be postponed to the next 12 hours and Eq. (C2) ensures that a certain portion (θ) of the uncontrolled demand is not shiftable. Eq. (C1) and (C2) decompose $d_{\mathrm{t^e}}^{\mathrm{EV,unctrl}}$ into $V_{\mathrm{t^e,t}}^{\mathrm{ch}}$ and $V_{\mathrm{t^e,t}}^{\mathrm{dis}}$ and Eq. (C3) restructures $V_{\mathrm{t^e,t}}^{\mathrm{ch}}$ and $V_{\mathrm{t^e,t}}^{\mathrm{dis}}$ into controlled demand $D_{\mathrm{t}}^{\mathrm{EV,ctrl}}$. Eq. (C4) limits the total charging and discharging power by EV availability, which is similar to Eq. (A6) and (B3). In a rolling window fashion, Eq. (C5) sets a cap ($v^{\mathrm{dis,max}}$) for the total amount of discharging energy in a fixed time span (e.g., 24 hours), which serves as an indirect constraint for EV capacity.

4. Formulations of individual EV modeling method

Battery SOC balance constraints

$$S_{\mathrm{m,t}} \times k^{\mathrm{ev}} = s_{\mathrm{m,t}}^{\mathrm{arr}} \times k^{\mathrm{ev}} + (V_{\mathrm{m,t}}^{\mathrm{ch}} - V_{\mathrm{m,t}}^{\mathrm{dis}}) \qquad \forall(\mathrm{m,t}) \in Y \qquad \text{(D1)}$$

$$S_{\mathrm{m,t}} \times k^{\mathrm{ev}} = S_{\mathrm{m,t-1}} \times k^{\mathrm{ev}} + (V_{\mathrm{m,t}}^{\mathrm{ch}} - V_{\mathrm{m,t}}^{\mathrm{dis}}) \qquad \forall(\mathrm{m,t}) \in X \setminus Y \qquad \text{(D2)}$$

Controlled net charging demand constraint

$$D_{\mathrm{t}}^{\mathrm{EV,ctrl}} = \sum\nolimits_{\mathrm{m}} \left(\frac{V_{\mathrm{m,t}}^{\mathrm{ch}}}{\eta} - V_{\mathrm{m,t}}^{\mathrm{dis}} \times \eta\right) \qquad \forall(\mathrm{m,t}) \in X \qquad \text{(D3)}$$

Charging/discharging power limit constraints

$$\frac{V_{\mathrm{m,t}}^{\mathrm{ch}}}{\eta} \leq p^{\mathrm{max}} \times B_{\mathrm{m,t}}^{\mathrm{ch}} \times \Delta t \qquad \forall(\mathrm{m,t}) \in X \qquad \text{(D4)}$$

$$V_{\mathrm{m,t}}^{\mathrm{dis}} \leq p^{\mathrm{max}} \times B_{\mathrm{m,t}}^{\mathrm{dis}} \times \Delta t \qquad \forall(\mathrm{m,t}) \in X \qquad \text{(D5)}$$

$$B_{\mathrm{m,t}}^{\mathrm{ch}} + B_{\mathrm{m,t}}^{\mathrm{dis}} \leq 1 \qquad \forall(\mathrm{m,t}) \in X \qquad \text{(D6)}$$

EV energy level limit constraints

$$S_{\mathrm{m,t}} \leq s^{\mathrm{max}} \qquad \forall(\mathrm{m,t}) \in X \qquad \text{(D7)}$$

$$S_{\mathrm{m,t}} \geq s_{\mathrm{m,t}}^{\mathrm{dep}} \qquad \forall(\mathrm{m,t}) \in Z \qquad \text{(D8)}$$

5. Further parameter settings for EV aggregation methods

Aggregated parameters used in each aggregation method are shown in Table S3 with their respective definitions as follows.

	PARAMETERS
METHOD A	$v_{\mathrm{t}}^{\mathrm{No}}$, $k_{\mathrm{t}}^{\mathrm{agg,EV}}$, $s_{\mathrm{t}}^{\mathrm{agg,min}}$, $s_{\mathrm{t}}^{\mathrm{agg,max}}$, $v_{\mathrm{t}}^{\mathrm{en,arr}}$, $v_{\mathrm{t}}^{\mathrm{en,dep}}$, $v_{\mathrm{t^a}}^{\mathrm{task}}$
METHOD B/B+/B++	$v_{\mathrm{t^b,t^c}}^{\mathrm{lv,max}}$, $v_{\mathrm{t^b,t^c}}^{\mathrm{lv,min}}$, $v_{\mathrm{t^b,t^d}}^{\mathrm{task}}$, $v_{\mathrm{t^b,t}}^{\mathrm{No}}$
METHOD C	$d_{\mathrm{t^e}}^{\mathrm{EV,unctrl}}$, $v_{\mathrm{t}}^{\mathrm{No}}$

Table S3 Additional parameters required by EV aggregation methods

$$v_{\mathrm{t}}^{\mathrm{No}} = \sum_{\mathrm{m}} b_{\mathrm{m,t}}^{\mathrm{park}} \qquad \forall \mathrm{t} \qquad \text{(P1)}$$

$$k_{\mathrm{t}}^{\mathrm{agg,EV}} = \sum_{\mathrm{m}} b_{\mathrm{m,t}}^{\mathrm{park}} \times k^{\mathrm{ev}} \qquad \forall \mathrm{t} \qquad \text{(P2)}$$

$$s_{\mathrm{t}}^{\mathrm{agg,min}} = \sum_{\mathrm{m}} s_{\mathrm{m,t}}^{\mathrm{lb}} \qquad \forall \mathrm{t} \qquad \text{(P3)}$$

$$s_{\mathrm{t}}^{\mathrm{agg,max}} = \sum_{\mathrm{m}} s_{\mathrm{m,t}}^{\mathrm{ub}} \qquad \forall \mathrm{t} \qquad \text{(P4)}$$

$$v_{\mathrm{t}}^{\mathrm{en,arr}} = \sum_{\mathrm{m}} s_{\mathrm{m,t}}^{\mathrm{arr}} \times k^{\mathrm{ev}} \qquad \forall \mathrm{t} \qquad \text{(P5)}$$

$$v_{\mathrm{t}}^{\mathrm{en,dep}} = \sum_{\mathrm{m}} s_{\mathrm{m,t}}^{\mathrm{dep}} \times k^{\mathrm{ev}} \qquad \forall \mathrm{t} \qquad \text{(P6)}$$

$$v_{\mathrm{t^a}}^{\mathrm{task}} = \sum_{\mathrm{m}} v_{\mathrm{m,t^a}}^{\mathrm{task}} \qquad \forall \mathrm{t^a} \qquad \text{(P7)}$$

$$v_{\mathrm{t^b,t^c}}^{\mathrm{lv,min}} = \sum_{\mathrm{m}} s_{\mathrm{m,t^c}}^{\mathrm{lb}} \times b_{\mathrm{m,t^b,t^c}}^{\mathrm{park}} \qquad \forall \mathrm{t^b}, \forall \mathrm{t^c} \qquad \text{(P8)}$$

$$v_{\mathrm{t^b,t^c}}^{\mathrm{lv,max}} = \sum_{\mathrm{m}} s_{\mathrm{m,t^c}}^{\mathrm{ub}} \times b_{\mathrm{m,t^b,t^c}}^{\mathrm{park}} \qquad \forall \mathrm{t^b}, \forall \mathrm{t^c} \qquad \text{(P9)}$$

$$v_{\mathrm{t^b,t^d}}^{\mathrm{task}} = \sum_{\mathrm{m}} v_{\mathrm{m,t^b,t^d}}^{\mathrm{task}} \qquad \forall \mathrm{t^b}, \forall \mathrm{t^d} \qquad \text{(P10)}$$

$$v_{\mathrm{t^b,t^c}}^{\mathrm{No}} = \sum_{\mathrm{m}} b_{\mathrm{m,t^b,t^c}}^{\mathrm{park}} \qquad \forall \mathrm{t^b}, \forall \mathrm{t^c} \qquad \text{(P11)}$$

6. Cost assumptions of the energy system model

	INVESTMENT COST (€/MW)	GENERATION COST (€/MWH)	FUEL COST (€/MWH)	ECONOMIC LIFETIME (YEAR)
GAS (COMBINED CYCLE)	865,000	3.6	40	15
PV	417,000	1	0	20
WIND (ONSHORE)	1,179,000	5	0	20
WIND (OFFSHORE)	1,955,000	5	0	20

Table S4 Cost assumptions of different generation technologies considered in the main article

The original investment costs in Table S4 are scaled down by the annuity method to match the scale of the test system. First, the value of each payment of investment cost is calculated by

$$specific\ annual\ payment = specific\ investment\ cost \times \frac{r}{1-(1+r)^{-n}} \qquad \text{(S1.6.1)}$$

where the annual interest rate r is assumed to be 5%, and the number of periods n is the economic lifetime of each type of power plant.

Take gas powerplant as an example, the annual payment is

$$865000\ \frac{€}{MW} \times \frac{1\ MW}{1000\ kW} \times \frac{5\%}{1-(1+5\%)^{-15}} \approx 88.34\ €/kW \qquad \text{(S1.6.2)}$$

For a payment of 4 weeks over a year, the payment is assumed to be

$$\frac{4\ \text{weeks}}{52\ \text{weeks}} \times 88.34\ €/kW \approx 6.41€/kW \qquad \text{(S1.6.3)}$$

7. Mathematical formulations of charging and discharging behaviors by different modeling methods

	CHARGING BEHAVIOR	DISCHARGING BEHAVIOR
METHOD A	$\sum_{t^a \in P_t} V_{t^a,t}^{ch}$	$\sum_{t^a \in P_t} V_{t^a,t}^{dis}$
METHOD B SERIES	$\sum_{t^b} V_{t^b,t}^{ch}$	$\sum_{t^b} V_{t^b,t}^{dis}$
METHOD C	$\sum_{t^e \in S_t} V_{t^e,t}^{ch}$	$\sum_{t^e \in S_t} V_{t^e,t}^{dis}$
INDIVIDUAL MODELING	$\sum_{m} V_{m,t}^{ch}$	$\sum_{m} V_{m,t}^{dis}$

Table S5 Formulations of charging and discharging behaviors by modeling methods

8. Further information on EV SOC setting

The setting of SOC for each individual EV is to make sure that the consequential daily energy consumption of an individual EV on average could match the setting of annual mileage (12,000 km) and electricity efficiency (20 kWh/100 km) in the paper, which is

$$12000\ km \times \frac{20\ kWh}{100\ km} \times \frac{1}{365\ day} \approx 6.58\ kWh/EV \cdot day \qquad \text{(S1.8.1)}$$

With inhomogeneous Markov chains, we have simulation results for the arrival and departure time of 2000 EV consecutively for 28 days, with hourly resolution. The arrival SOC for an individual EV is assumed to be uniformly distributed between 30% and 80%. The departure SOC is determined by

$$SOC_i^{departure} = min(SOC_i^{arrival} + T_i^{parking} \times \alpha, 90\%) \quad \text{(S1.8.2)}$$

As in Eq. (S1.8.2), the departure SOC of each charging event i is dependent on the arrival time of the event ($SOC_i^{arrival}$) and its parking duration ($T_i^{parking}$) so that it can be achieved by departure time. The coefficient α makes sure that the charging task is dependent on the parking duration of the charging event, with an upper limit of departure SOC being 90%. The value of α is not empirical or universal, but strongly dependent on the parameter setting of the EV fleet (EV arrival and departure time, parking times per day and battery capacity). Specifically in this paper, α is set to 0.0106 so that the energy demand from EV charging by SOC is about $16.48\%/EV \cdot day$, i.e., together with our assumed batter capacity of 40 kWh, the daily energy consumption per EV in our setting becomes

$$40\ kWh \times 16.48\% \approx 6.59\ kWh/EV \cdot day \quad \text{(S1.8.3)}$$

As a result, our setting of daily EV energy consumption from the individual perspective (Eq. S1.8.3) matches that from the macro perspective (Eq. S.8.1). This method is derived from Wang et al. (2020).

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