Junior Management Science 8(3) (2023) 1040-1080

Junior Management Science

journal homepage: www.jums.academy

Enabling E-Mobility: How Electric Grids Can Support High EV Adoption with Residential PV and Battery Energy Storage Systems

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Abstract

Understanding the challenges electrical distribution grids will have to bear in the future is essential to take appropriate measures and ensure electrical grid infrastructure stability. This thesis deploys representative grid models for varying agglomeration scenarios and seasons to investigate the challenges and synergies that arise with high EV penetration rates, PV electricity generation and BESS. The central innovation lies in the developed large-scale model which considers time of year and agglomeration variation, all of which influence household and charging electricity demand, PV generation, as well as PV and EV penetration. Based on a large dataset on German mobility, a Markov chain is developed to sample a trip chain for each individual in the model. Based on the trip chain, EV energy demand and EV charging decisions are simulated. Household loads and PV generation are synthetically modelled to account for external influences. All load and generation profiles then interact with residential BESS and the resulting profile is deployed in three MATLAB MATPOWER grid models. An investigation of power flows showed that transformer thermal limits and feeder line thermal limits are the most critical components. Whilst rural grids are most vulnerable to increased loads through higher EV penetration rates, the mitigation potential with PV electricity generation and BESS is also highest. If every home that has an EV is equipped with a PV-BESS, the grid's capacity for maximum EV penetration increases by up to 50%.

Keywords: Electric vehicle charging; Photovoltaic systems; Electrical distribution grid; Battery energy storage system; Power flow analysis.

1. Introduction

Greenhouse gas emissions and energy supply insecurities necessitate a shift towards mobility and energy solutions without fossil fuel dependency. Recent geopolitical developments further highlighted the importance of energy independency. The transportation sector is responsible for 23% of the global energy related CO_2 emissions, with passenger road vehicles accounting for 44% of these emissions.[1] This has become an issue of great importance as the electrification of private transportation plays a significant role in achieving low-carbon targets. This introduces technical challenges for local power grids. Widespread integration of electrical vehicles (EV) in the distribution grid can lead to electrical equipment overloading and undervoltage issues. Furthermore, unpredictable energy price developments, energy dependencies, and carbon intensive energy generation might dampen the transition towards green mobility solutions and its environmental benefits. At the same time, prices for renewable power generation such as photovoltaic (PV) energy distinctly reduced over the last decades enabling the widespread adoption of PV systems.[2] These systems can have an opposite impact on electrical distribution grids – too much generation can lead to overvoltage issues and transformer overloading through reverse power flows. Together, the intense energy demand induced by EV charging operations and the surplus power generation by intermittent PV arrays might allow the mitigation of adverse effects on electrical distribution grids. This opportunity would forsake the need for costly infrastructure upgrades of the grid.

Understanding the loads electrical distribution grids will have to bear in the future is essential. Simulation models are needed to study the effect of high EV and PV penetration

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[1] Cf. IEA (2021b); Cf. IEA (2022).

[2] Cf. Our World in Data (2020).; Cf. Umweltbundesamt (2021a, p. 7).

DOI: https://doi.org/10.5282/jums/v8i4pp1040-1080

on electricity networks to derive suitable measures. Electrical grids need to be operated within specified limits to ensure smooth operation and compliance with required power quality standards.[3] McKinsey & Company estimates that the total annual electrical energy demand in Germany increases 8% over the current energy demand in an adoption scenario with 16 million EVs.[4] To develop a greater understanding on the impact of charging EVs on electrical distribution networks a detailed model to forecast the charging demands and subsequently its impact on the electrical distribution grid is required. The total electricity demand for charging operations strongly depends on the charging power, the battery capacity, and the total number of EVs. The latter is greatly influenced by consumers' adoption rate. An increasing number of governments defined target penetration rates of electric vehicles and subsequently adopted pro-EV policies to foster EV adoption.[5] The current government of Germany now aims towards a rapid reduction of CO_2 emissions and agreed on reaching a stock of 15 million electric cars until 2030.[6] This represents a 30-fold increase in the number of EV stock over the current stock, shifting energy demand from fossil fuels to electricity.[7] Further, technological advancements and changing consumer preferences increase consumers' adoption towards EVs.[8] The rapidly decreasing costs of battery capacity made the mass production of EVs with greatly improved maximum driving ranges feasible.[9] To cope with enhanced battery capacities and to keep charging times moderately, charging standards with increasing power limits have been developed.[10] Thus potentially increasing peak charging loads in electrical distribution grids. As a result, thermal limits of electrical distribution equipment might be exceeded, and power quality standards cannot be ensured.

The mitigation of these non-negligible impacts has caused considerable interest due to its importance for policy makers and distribution system operators (DSO). On the network side, DSO would need to perform costly infrastructure side upgrades to enable such high EV penetration rates. On the consumer side, a multitude of approaches, such as controlled smart charging or vehicle to grid applications have been discussed in literature.[11] As these solutions poses restrictions on the charging behavior and battery service life reductions, alternative solutions are highly interesting. Deploying residential PV systems are another option to decrease grids loads induced by EV charging.[12] Due to the intermittent nature of PV generation, synergies of this approach are restricted towards day times only. An opportunity to increase the synergies between EV charging and PV generation is given by deploying battery energy storage systems (BESS) in residential buildings. Thus, increasing the PV self-consumption as well as reducing unwanted surplus generation. This might reduce loads on distribution networks and thus decrease the need for infrastructure side distribution network upgrades.

This thesis deploys representative grid models for varying agglomeration scenarios and seasons to model the synergy potential between high EV penetration rates, PV electricity generation and BESS. Mobility and charging behavior, PV yield profiles, and household load profiles are synthetically generated to account for time of the year and agglomeration characteristics. The resulting electrical profiles are then deployed, and a power flow analysis is conducted in MATLAB using MATPOWER to determine effects on the electrical grid.

The following chapter reviews relevant literature to model and analyze the effect of high EV and PV penetration rates in electrical distribution grids and its interaction with BESS. Having reviewed existing work, the problem statement and the research gap is derived in chapter three. This thesis then continues by introducing the employed data, how it is preprocessed and how it parameterizes the model in chapter four. Based on this data pool, the next chapter focusses on the specific model development and how entities in the model are simulated. Chapter six illustrates the power flow results and analyzes them. The final two chapters cover the discussion of the results and limitations of the work, as well as the conclusion and future research opportunities.

2. Literature review

This section reviews recent literature on the topic of EVs, EV charging, and PV electricity generation. A thematic disaggregation into two subtopics allows the identification of relevant literature and promising methodologies and simulation techniques. First, EV adoption, driving and charging behavior as well as the charging impact on electrical distribution grids are reviewed. Second, the integration of renewable energy generation with PV systems in distribution grids is investigated. This concerns the environmental impact, the impact on the power grid as well as the interaction with BESS. Finally, the novel contribution of this thesis is derived.

2.1. EV deployment characteristics and electrical grid interaction

2.1.1. EV adoption trends

The steadily growing amount of EV sales and registrations contribute towards the goal of emissions' reduction in the transport sector.[13] In existing literature, the EV adoption has been extensively investigated in an attempt to assess influencing factors and to understand EV adoption. However, fluctuating and diverging market growth rates make predictions about future adoption rates challenging. An understanding of these factors is important to assess the impact of

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[3] Cf. DIN (1999).

[4] Cf. McKinsey & Company (2021).

[5] Cf. IEA (2021c).

[6] Cf. (Presse- und Informationsamt der Bundesregierung, 2021, p. 51).

[7] Cf. Kraftfahrt Bundesamt (2021b).

[8] Cf. Coffman, Bernstein, and Wee (2017, pp. 82–88).

[9] Cf. Our World in Data (2021).

[10] Cf. IEA (2021c).

[11] Cf. A. Dubey and Santoso (2015, pp. 1882–1890).

[12] Cf. ElNozahy and Salama (2014).

[13] Cf. Gohlke and Zhou (2021, p. 14); Cf. Kraftfahrt Bundesamt (2021a); Cf. Jochem, Rothengatter, and Schade (2016, p. 2); Cf. Jochem et al. (2016, p. 2).

charging EVs on electrical distribution grids, as the amount of total EVs greatly influences the demanded electrical energy. The following chapter will give an overview of recent EV adoption rate trends. Further, factors and characteristics influencing consumer's EV adoption rate are discussed.

In the past, the uptake of EVs grew steadily but remained relatively low and behind governmental expectations.[14] With sales shares in Germany below 3% until 2019 the EV share in total personal vehicle stock also remained very low and only reached a level of 0.64% in 2021.[15] This situation is predicted to change drastically as the growth of the EVs' sales share in Germany skyrocketed with more than 200% year over year growth, reaching 6.6% of total person vehicle sales in 2020.[16] With this rapid rise in consumers' EV adoption rate, the question arises which impacting factors exist and which shall be incorporated in the prediction of future penetration rates.

A review of major studies identified a multitude of factors that affect EV adoption rates.[17] Technological advancements such as decreasing plug-in electric vehicle (PEV) costs and range increases, as well as changing consumer preferences influence adoption rates significantly.[18] Additional factors include socio-demographics, mobility practices, policy interventions, and financial and non-financial incentives created by governmental institutions.[19] The latter are unpredictable in nature and thus an acknowledged constraint for forecasting models.[20] As many of these factors are country specific, significant discrepancies in the EV penetration of new vehicle sales across various countries emerged.[21]

Household-related factors have been extensively documented by existing research. The availability of home charging is suggested to influence PEV adoption, as many consumers prefer to charge at home.[22] This finding is backed by a field study of Patt et al. conducted in Switzerland.[23] Based on answers of 658 participants the relationship between the willingness to purchase a battery electric vehicle (BEV) and the ownership of a parking space was investigated.[24] The result indicates that residents who own their parking space are almost twice as likely to indicate a high willingness to purchase a BEV compared to those who park on the street.[25] This can have an influence on the spatial distribution of EV adoption, as urban areas tend to have significant less privately owned parking spaces then rural areas. To further understand spatial factors, Brückmann et al. investigated BEV adoption in Switzerland, where governmental support for EV adoption is low.[26] Minimizing the influence of political jurisdictions allows for a more precise analysis on spatial patterns of EV adoption. A combination of revealed preference data with the car holder's area of residence links consumer characteristics with spatial characteristics.[27] Their findings suggest that BEV adoption is neither driven by population density of residential areas nor by a higher availability of charging infrastructure.[28] Home-ownership, however, is a significant driver of current BEV adoption.[29] Even though home-ownership is strongly associated with parking space ownership, this finding might be explainable by the strong relationship between the individuals' level of income and their likeliness to adopt a PEV.[30] In other words, people owning homes are more likely to have a higher level of income and thus they are more likely to adopt a PEV. This theory is supported by Chen et al.[31] In their study 4,885 individuals from Denmark, Finland, Iceland, Norway, and Sweden were investigated according to their preferences and their willingness to adopt a PEV.[32] Their findings suggest that there is no significant difference in PEV adoption rates of non-rural and rural residents.[33]

Collectively, these studies suggest that the uptake of EVs will increase greatly driven by a multitude of factors such as technological advancements and decreasing costs. As financial incentives play a major role, significant discrepancies in the EV penetration of new vehicle sales across various countries emerged. Regardless of this, no significant spatial differences in the EV adoption between rural and non-rural residents were identified. Forecasting future penetration rates is important to understand when charging operations of EVs might lead to non-negligible impacts on electrical distribution grids. To further understand the impact of charging EVs it is important to ask when and where charging occurs, and what energy demands to expect. This is covered in the next section.

2.1.2. Driving and charging behavior

Literature that investigated the driving or charging behavior of individuals, or both, is mainly based on mobility data, time of use data, or charging point data. Depending on the deployed data source, current work mainly embodies two types of simulation frameworks: Agent-based electromobility simulations and charging point-based load simulations. First, agent-based electromobility simulations often entail socio-economic, behavioral, and spatial factors and can be implemented using various modelling techniques. Mobility and

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[14] Cf. IEA (2021c); Cf. Deutsche Bundesregierung (2009, p. 46).

[15] Cf. IEA (2021a).; Cf. Kraftfahrt Bundesamt (2021b).

[16] Cf. IEA (2021a); Cf. Kraftfahrt Bundesamt (2021b).

[17] Cf. Coffman et al. (2017).

[18] Cf. Coffman et al. (2017, pp. 82–88).

[19] Cf. Coffman et al. (2017, pp. 89–91); Cf. C.-f. Chen, Zarazua de Rubens, Noel, Kester, and Sovacool (2020, pp. 3–6).

[20] Cf. Ensslen, Will, and Jochem (2019, p. 85).

[21] Cf. Graham and Brungard (2021, p. 304).

[22] Cf. van der Kam, van Sark, and Alkemade (2020); Cf. Morrissey, Weldon, and O'Mahony (2016); Cf. Tal, Lee, and Nicholas (2018); Cf. Hardman et al. (2018).

[23] Cf. Patt, Aplyn, Weyrich, and van Vliet (2019).

[24] Cf. Patt et al. (2019, p. 3).

[25] Cf. Patt et al. (2019, p. 6).

[26] Cf. Brückmann, Willibald, and Blanco (2021).

[27] Cf. Brückmann et al. (2021, p. 2).

[28] Cf. Brückmann et al. (2021, p. 8).

[29] Cf. Brückmann et al. (2021, p. 10).

[30] Cf. C.-f. Chen et al. (2020, p. 11).

[31] Cf. C.-f. Chen et al. (2020).

[32] Cf. C.-f. Chen et al. (2020, p. 5).

[33] Cf. C.-f. Chen et al. (2020, p. 11).

time of use data can be used to extract temporal or spatial information to build models, such as Hidden Markov chains or other deterministic models. Second, charging point-based load simulations employ charging data to identify temporal or spatial charging patterns and to predict charging demands. In the past, simulations have been realized with a wide variety of modelling techniques, such as Monte Carlo simulations, decision trees, or multinomial logit models. The following chapter gives an overview of identified charging preferences derived from both data types as well as their chosen simulation frameworks. Further, novel contributions in literature with enhanced methodologies are discussed. These are built on these two simulation frameworks and refine or combine them to develop a model embracing multiple empirical data sources and to account for as many influential factors as possible.

A stochastic bottom-up modelling approach for predicting residential EV use, charging behavior, and resulting electrical load profiles was presented by Fischer at al.[34] Based on a large German mobility dataset, a Markov chain including the most significant influencing factors on residential charging behavior was developed.[35] The results suggest that car-type, charging infrastructure, day of the week and the agent's working times have the strongest influence on EV usage.[36] The agent-based electromobility simulation indicates peak electricity loads at 6:00 p.m. which can, depending on the charging power, increase the overall peak load of a household up to a factor of 3.6 compared to a household without EVs.[37] These findings are in line with the demand predictions of a conference paper based on the UK National Travel Survey and a study based on UK 2000 time of use survey data.[38] Both works were able to predict and observe temporal charging patterns with peak demands in the early evening. Recent work by Habib et al. extends the stochastic modelling approach based on mobility data by including various external factors, such as type of EVs based on market trends.[39] A subsequent Monte Carlo simulation was then carried out to develop the stochastic charging profiles.[40] The results confirm previous findings and suggest high peak loads by uncontrolled EV charging.[41] A partly acknowledged natural limitation of that approach is given by superimposing mobility behavior of internal combustion engine vehicles (ICEV) to EVs. A study in Norway's maturing electric vehicle market identified a stronger change in driving behavior after buying a BEV.[42] However, results also suggest that buyers of a BEV are in a stage of life, in which travel changes are more likely to occur, therefore clear conclusions cannot be drawn.[43]

An analysis of charging-point data was employed by Schäuble et al. They analyzed the charging behavior patterns of EV based on electric mobility studies of early adopters.[44] Empirical load profiles on data covering over 30,000 recorded charging operations between 2011 and 2015 in Germany and France are observed and subsequently synthetic load profiles are generated.[45] Results indicate that 60% of charging operations are completed at home with clear charging patterns differentiating weekdays and weekends.[46] Weekday charging peaks occur at 6:15 p.m., while charging load decreases to nearly zero from 2:30 a.m. to 5:30 a.m. in presence of fast charging.[47] Work based on Irish charging data from the years 2012 to 2015 also observed an accumulation of home charging events during evening times, highlighting temporal charging patterns.[48] However, dated data accommodating EVs with significantly smaller battery capacities than today's vehicles and the potentially unique charging behavior of early adaptors might lead to hardly generalizable results of both studies.[49] Therefore, more recent data should be employed.

Figenbaum analyzed data from two fast charging station providers with a total network of more than 1,500 stations in Norway.[50] Norway provides a great research environment as their EV fleet share is among the highest with 9.4% EVs of total passenger vehicles.[51] The results suggest, that only 4-6% of the total EV energy demand is provided by fast chargers.[52] Furthermore, a survey of Norwegian EV owners indicated that only 12% of owners charge at least once per week at public facilities and that 93% have access to charging at home.[53] These findings are supported by multiple other contributions which suggest, that most of the charging is done at home.[54] Nevertheless, public charging might play an indispensable role in urban areas, as less than 60% of urban US households can park on their own property.[55] First predictions in Germany estimate an out-of-home charging probability of 33% in metropolitan areas.[56] The majority of public charging points do not provide fast charging power.[57] A study conducted by van der Kam et al. based on more than one million charging operations at approximately 25,000 unique

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[34] Cf. Fischer, Harbrecht, Surmann, and McKenna (2019).

[35] Cf. Fischer et al. (2019, p. 10).

[36] Cf. Fischer et al. (2019, p. 17).

[37] Cf. Fischer et al. (2019, p. 14).

[38] Cf. Crozier, Apostolopoulou, and McCulloch (2018, p. 5); Cf. Wang and Infield (2018, p. 93).

[39] Cf. Habib et al. (2020, p. 301).

[40] Cf. Habib et al. (2020, p. 301).

[41] Cf. Habib et al. (2020, p. 305).

[42] Cf. Figenbaum and Nordbakke (2019, p. 53).

[43] Cf. Figenbaum and Nordbakke (2019, p. 20).

[44] Cf. Schäuble, Kaschub, Ensslen, Jochem, and Fichtner (2017).

[45] Cf. Schäuble et al. (2017, pp. 7–10).

[46] Cf. Schäuble et al. (2017, pp. 16–25).

[47] Cf. Schäuble et al. (2017, pp. 26–28).

[48] Cf. Morrissey et al. (2016, p. 263).

[49] Cf. Schäuble et al. (2017, pp. 17–18); Cf. Electric Vehicle Database (2021).

[50] Cf. Figenbaum (2020).

[51] Cf. Figenbaum (2020, p. 42).

[52] Cf. Figenbaum (2020, p. 48).

[53] Cf. Figenbaum and Nordbakke (2019, p. 26).

[54] Cf. Lee, Chakraborty, Hardman, and Tal (2020, p. 11); Cf. Thingvad, Andersen, Unterluggauer, Træholt, and Marinelli (2021, p. 10); Cf. Kleiner, Brokate, Blaser, and Friedrich (2018, p. 218); Cf. Baresch and Moser (2019, p. 388).

[55] Cf. Traut, Cherng, Hendrickson, and Michalek (2013, p. 143).

[56] Cf. Kleiner et al. (2018, p. 218).

[57] Cf. Chargemap (2022).

charge points in the Netherlands investigated public charging behavior.[58] Contrary to the findings of Chen et al., their results suggest a smaller charging impact induced by public charging.[59] The charging profile is smoother and does not include high gradients. Peak loads are observable at 9:00 a.m. and 6:00 p.m. and a base load by public charging piles is observable throughout the day.[60] Hence, public charging load peaks, based on this data, are not as pronounced as private home charging.

This section has illustrated a review of techniques used to simulate driving and charging behavior and discussed charging preferences. Both simulation frameworks lead to similar results regarding identified charging patterns. Most of the charging operations are executed between 6:00 p.m. and 9:00 p.m. on weekdays, while home charging plays a major role in providing most of the EV energy demand. These temporal patterns in charging demands raise the question of how the increased electricity consumption influences electrical distribution grids. This will be discussed in the next chapter.

2.1.3. Charging impact on distribution grids

Academic research investigated the EV charging impact on electrical grids for a considerable period of time, ranging from the early work of Taylor et al. over a decade ago to most recent work published this year.[61] It has been extensively evaluated in an attempt to characterize, classify and measure potential effects and to derive recommendations for grid operators and policy makers. Existing work differs significantly regarding the complexity and assumptions made to model the EV charging load, the network topology, and the investigated metrics of the charging impact. The following section provides an overview of chosen metrics and findings regarding the charging impact on electrical distribution grids.

Initial work by Clement-Nyns et al. investigated the impact of charging plug-in hybrid electric vehicles (PHEV) on a residential distribution grid. Based on home arrival times the impact of home charging 8.8 kWh PHEV batteries with a 4 kW charger in an IEEE 34-node test feeder grid topology is simulated.[62] Therefore, they undertook a feeder level analysis as proposed by Taylor et al.[63] Different scenarios are realized by varying the EV adoption rate and subsequently, power losses and maximum voltage deviations are calculated.[64] The results suggest that the uncoordinated charging of batteries of PHEVs has a non-negligible impact on the distribution grid.[65] A lack of complexity in the simulation model for PHEV loads as well as the low battery capacity of PHEVs limit the work of Clement-Nyns et al. Nevertheless, later work, which explicitly focused on voltage deviations induced by additional EV charging loads, were able to confirm these results.[66] These papers by Ul-Haq et al. and Ma et al. both examined voltage characteristics of single nodes in more complex distribution networks: IEEE30 node system and a CIGRE low-voltage European distribution benchmark system respectively.[67]

Beside voltage deviations, a great extent of literature studied the influence of EV charging on distribution grid peak loads.[68] Wang and Infield simulated the charging impact predicted by a Markov Chain Monte Carlo simulation of vehicle use patterns in a single phase distribution network layout.[69] They employ load profiles for domestic households alongside the predicted EV charging profiles for both weekdays and weekends.[70] The results suggest that the EV charging loads occur at the same time as domestic base peak loads and thus total peak loads increase significantly for a single household with an EV.[71] Further, the voltage profile for the household in the distribution network, which suffers the most from the network impact due to its location, is investigated. All power flow analyses have been conducted with the dedicated network simulator "Open Distribution System Simulator" (OpenDSS).[72] An analysis of voltage bound violations predicts violations during weekdays with EV penetration rates of 30% and above.[73] Additionally, the thermal performance of the substation feeder is examined. The substation feeder is part of the distribution equipment. Distribution equipment is rated until a specific power load in kVA. Exceeding this power load can lead to shortened lifespans of the equipment or in extreme cases to thermal overloading and damage.[74] In the simulated scenario with EV penetration rates of 70% and above the specified line limit of 50 kW might be exceeded.[75] Applicability of results to a European environment might be difficult due to the simplified single phase distribution network layout, as most European distribution networks are based on three phase networks. Further limitations might be given since the chosen EV characteristics of a 2013 vehicle with a battery capacity of 18.8 kWh are already outdated compared to battery capacities of newly sold EVs.[76]

Habib et al. extended the model for the network load by developing a stochastic EV model incorporating additional

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[58] Cf. van der Kam et al. (2020, p. 7).

[59] Cf. van der Kam et al. (2020); Cf. J. Chen, Li, Yang, and Ma (2020).

[60] Cf. J. Chen et al. (2020, p. 9); Cf. van der Kam et al. (2020, p. 8).

[61] Cf. Taylor, Maitra, Alexander, Brooks, and Duvall (2009); Cf. Rahman, Khan, Khan, Mallik, and Nadeem (2022).

[62] Cf. Clement-Nyns, Haesen, and Driesen (2010, pp. 371–372).

[63] Cf. Taylor et al. (2009, p. 6).

[64] Cf. Clement-Nyns et al. (2010, p. 373).

[65] Cf. Clement-Nyns et al. (2010, p. 378).

[66] Cf. Ul-Haq, Cecati, Strunz, and Abbasi (2015, p. 56); Cf. Ma, Jiang, Chen, Dai, and Ju (2017, p. 503); Cf. Habib et al. (2020, p. 313).

[67] Cf. Ul-Haq et al. (2015, p. 54); Cf. Ma et al. (2017, p. 501).

[68] Cf. Muratori (2018); Cf. Zhang, Yan, Liu, Zhang, and Lv (2020); Cf. Pagani, Korosec, Chokani, and Abhari (2019); Cf. Calearo, Thingvad, Suzuki, and Marinelli (2019); Cf. Haider and Schegner (2021); Cf. Wang and Infield (2018).

[69] Cf. Wang and Infield (2018, pp. 86–92).

[70] Cf. Wang and Infield (2018, p. 92).

[71] Cf. Wang and Infield (2018, p. 93).

[72] Cf. Wang and Infield (2018, p. 92).

[73] Cf. Wang and Infield (2018, p. 93).

[74] Cf. Haque, Shafiullah, Nguyen, and Bliek (2016, p. 3).

[75] Cf. Wang and Infield (2018, p. 93).

[76] Cf. Wang and Infield (2018, p. 91); Cf. Electric Vehicle Database (2021).

parameters, such as varying EV types or charging powers.[77] Subsequently, households are differentiated by their size and a predefined number of EVs is assigned for each adoption rate scenario.[78] Households between 125 and 250 square-meters are simulated with one EV each, while the biggest categorized household with 500 square-meters is simulated with two EVs.[79] Household type dependent residential demands alongside charging demands are deployed in an extended version of the IEEE 13-node test feeder network.[80] Network characteristics are then analyzed in the power flow tool "DigSilent Power Factory" for different scenarios.[81] The investigated metrics include: Thermal limits of transformers, feeder losses, voltage behavior, and voltage unbalance factor.[82] The former two metrics address the distribution equipment in the network while the latter two are energy quality related measures. The simulation results illustrate that thermal limits of transformers are exceeded in case of 7.2 kW charging with a 40% penetration rate.[83] Furthermore, voltage drops exceed regulatory voltage limits in the 40% penetration rate scenario at around 7:00 p.m. for both scenarios with either a 1.9 kW charger or a 7.2 kW charger.[84]

In summary, existing literature analyzed the charging impact in simulated distribution networks by investigating peak charging loads, voltage deviations, and thermal power limits of grid components. The overall results suggest that there is a significant impact of EV charging on distribution grids in scenarios with higher EV penetration rates. Therefore, possibilities to mitigate this impact should be evaluated.

2.2. Charging with renewable energy sources

One possibility to mitigate the impact of EV charging on distribution grids, which is discussed in scientific research, is to employ distributed and renewable electricity generation.[85] The most common and economically feasible form of household level distributed electricity generation is provided by PV arrays. Latest advancements in PV modules efficiency and economies of scale led to a sharp decline in prices for PV systems.[86] This might render the widespread installation of PV arrays feasible for owners with EVs. Furthermore, PV as sustainable and emission free energy source can support the decarbonization of the transport sector. The following section will discuss the environmental impact charging of EVs with PV arrays. Further, the potential to charge EVs with the support of decentralized PV electricity as well as implications of widespread distributed and intermittent electricity generation and their impact on distribution grids is reviewed. Finally, research on the interaction of EV charging, PV arrays, and BESS is examined.

2.2.1. Environmental impact

The environmental impact of driving an EV mainly depends on the energy source used to generate the energy for the charging operation.[87] The energy mix describes the fraction of energy fed-in, based on a specific energy source divided by the total amount of fed-in energy in a year. The energy mix varies greatly between countries due the availability of natural resources.[88] In Germany, most of the produced energy currently relies on fossil fuels such as coal or natural gas.[89] Fossil fuel-based energy generation is known to emit a great extent of CO_2 and other emissions which are harmful to the environment. Calculations involving traded electricity as well as electricity in- and exports estimate, that 1 kWh of electrical energy consumed in Germany is responsible for 366 g of CO_2 emissions.[90] This value decreased steadily as the share of emission free renewable energy sources in the energy mix increased significantly over the past years.[91] Despite this, a great discrepancy in predicted CO_2 emissions over the lifetime of a EV between Germany and countries with comparatively lower emission energy production emerged.[92] Therefore, an acceleration of the decarbonization in the transport sector by exploiting the potential of renewable energy sources such as PV to charge EVs might be feasible.

Yang et al. conducted a comprehensive benefits analysis of an EV charging station with PV arrays.[93] They conducted a case study of an electric bus charging station in Beijing, China with a total charging output power of 354 kW, a 445 kW PV system, and an additional battery with a capacity of 616 kWh. The results suggest that, in addition to benefits for grid operators in terms of lower transmission losses, there is also a major environmental benefit.[94] The environmental benefit is calculated by considering the environmental cost of pollutants emitted during the energy generation process.[95] This implies a great reduction in emissions, however, the study did not provide exact figures.

Overall, results suggest that emission free PV energy has the potential to further accelerate the decarbonization of the transport sector. Existing studies, however, employed simplified models without considering grid interaction effects. Grid interaction is important as the amount of energy which can be fed back into the grid might be limited. How PV arrays interact with the grid and why fed-back of energy is limited is discussed in the next chapter.

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[77] Cf. Habib et al. (2020, p. 302).
[78] Cf. Habib et al. (2020, p. 302).
[79] Cf. Habib et al. (2020, pp. 303–305).
[80] Cf. Habib et al. (2020, p. 306).
[81] Cf. Habib et al. (2020, pp. 307–308).
[82] Cf. Habib et al. (2020, pp. 309–310).
[83] Cf. Habib et al. (2020, p. 311).
[84] Cf. Habib et al. (2020, p. 313).
[85] Cf. ElNozahy and Salama (2014); Cf. Mancini, Longo, Yaici, and Zaninelli (2020); Cf. Good, Shepero, Munkhammar, and Boström (2019).
[86] Cf. Our World in Data (2020).
[87] Cf. Hawkins, Singh, Majeau-Bettez, and Strømman (2013, pp. 56–59).
[88] Cf. eurostat (2022).
[89] Cf. Statistisches Bundesamt (2022).
[90] Cf. Umweltbundesamt (2021a, p. 10).
[91] Cf. Umweltbundesamt (2021a, p. 10).
[92] Cf. Gómez Vilchez and Jochem (2020, p. 10).
[93] Cf. Yang, Zhang, Zhao, and Wang (2021).
[94] Cf. Yang et al. (2021, p. 10).
[95] Cf. Yang et al. (2021, p. 6).

2.2.2. Impact on the power grid

Initial work published by ElNozahy and Salama focussed on the aggregated system-level impact of using PV electricity to charge PHEVs.[96] They deployed their model in a IEEE 123 node test feeder and simulated the impact of adding a 10 kW PV array to each household with a PHEV.[97] PV electricity generation, PHEV charging demands, and residential as well as commercial loads where stochastically modelled with Monte Carlo simulations.[98] This Monte Carlo based benchmark system allows to investigate the resulting impacts when PV arrays are used to charge PHEVs. Further, they investigated the probability of overloading different distribution equipment classes.[99] Analyzed equipment includes primary feeder, 25 kVA transformers, 50 kVA transformers, single phase laterals, and service drops. The results suggest that the inclusion of PV arrays reduces the probability of transformer overloading significantly while primary feeder, single phase laterals, and service drops are not likely to be overloaded even in the studied worst-case scenario.[100]

The introduction of distributed electricity generation can lead to power flows, which can change their direction. Reverse power flows can occur if a household produces more electricity than it consumes. For the electrical network this household now behaves like an electrical supply and no longer like an electrical sink. The household becomes an electrical prosumer. The feed-in of electrical energy by the household can lead to issues such as voltage rises or voltage phase imbalances.[101] As effects on distribution equipment by reverse power flows can be more severe, many DSOs limit the occurrence of reverse power flows.[102] High PV penetration rates in distribution networks increase the probability of reverse power flows, therefore, ElNozahy and Salam also investigated the occurrence of reverse power flows.[103] In the studied scenario with a PHEV and PV penetration rate of 52%, the simulated reverse power flow exceeded tolerable limits of transformers.[104] Excessive reverse power flows cannot only lead to overloading of distribution equipment but also to a rise of voltage above limits. To mitigate this effect, overvoltage prevention mechanisms, such as active power curtailment of the PV inverter, can be used.[105] In this scenario, power curtailment would have been necessary to avoid damages or a significant loss in lifespan of the transformers. This finding is reinforced by a later study which concluded that energy demand by both public and at home EV charging, does not significantly reduce the need of active power curtailment of widespread distributed generation with PV systems.[106] Nevertheless, overall findings of ElNozahy and Salama imply that PV arrays can meet part of the PHEV charging demand.[107] However, a weak chronological coincidence between PHEV charging demand and PV electricity production might reduce potential synergies.[108]. This is due to the fact that PV generation is strongest during daytimes where solar irradiation is strongest while PHEV charging demands peak in evenings.

This relationship was further supported by recent studies, which showed that the chronological coincidence between EV charging demand and solar energy availability can be weak and is influenced by seasonal dependencies.[109] Good et al. explicitly investigated the potential of PV energy for charging EVs during different seasons and calculated the solar fraction, which describes how much of the electrical load can be covered by solar power.[110] In their study approach, a solar fraction of 1 would imply that the complete energy demand of charging EVs can be supplied with PV energy. Their simulation results suggest a significant higher solar fraction during the month of July compared to the month of March.[111] This can be explained by the high latitude of the chosen research environment in Scandinavia, where day length differences between June solstice and December solstice are especially large. Thus, making the potential for EV charging with PV electricity season and latitude dependent. Further investigations are necessary to understand if it is feasible to charge EVs with PV electricity during the winter months in locations of high latitude.

Together, these studies outline that distributed PV electricity generation can play a role in mitigating EV charging demands. However, a weak chronological coincidence between PV electricity generation and EV charging demands as well as the influence of seasonality effects on solar irradiance can limit the mitigation potential. Furthermore, reverse power flows can occur, and active power curtailment measures might be necessary to avoid negative effects on the grid. Current literature is sparse and employed simulation models lack complexity and variability in EV type, time of the year, or PV penetration rates.

2.2.3. Interaction with battery energy storage systems

Having discussed how PV electricity impacts the power grid in scenarios with high EV adaption, this section addresses how energy storage systems (ESS) can support the integration of intermittent renewable energy sources.

Energy storage systems are a mean of storing excess electrical energy produced during periods of high electrical generation and low electrical loads. The stored energy can then be converted back to electricity to be used at times of high demand. ESS are increasingly used to balance electrical grids

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[96] Cf. ElNozahy and Salama (2014).
[97] Cf. ElNozahy and Salama (2014, p. 137).
[98] Cf. ElNozahy and Salama (2014, pp. 134–136).
[99] Cf. ElNozahy and Salama (2014, pp. 139–140).
[100] Cf. ElNozahy and Salama (2014, p. 140).
[101] Cf. Scott, Atkinson, and Morrell (2002, p. 510).
[102] Cf. Hatta, Asari, and Kobayashi (2009); Cf. von Appen, Braun, Stetz, Diwold, and Geibel (2013, p. 57).
[103] Cf. Hasheminamin, Agelidis, Salehi, Teodorescu, and Hredzak (2015, p. 1158); Cf. ElNozahy and Salama (2014, p. 140).
[104] Cf. ElNozahy and Salama (2014, p. 141).
[105] Cf. Tonkoski and Lopes (2011).
[106] Cf. Luthander, Shepero, Munkhammar, and Widén (2019, p. 715).
[107] Cf. ElNozahy and Salama (2014, p. 139).
[108] Cf. ElNozahy and Salama (2014, p. 139).
[109] Cf. Mancini et al. (2020, p. 21); Cf. Munkhammar, Widén, and Rydén (2015, pp. 140–141); Cf. Good et al. (2019).
[110] Cf. Good et al. (2019, p. 116).
[111] Cf. Good et al. (2019, p. 119).

and play a crucial role in the energy management of intermittent energy sources.[112] However, limited capacities of electrical distribution grids limit the load balancing capabilities of centralized ESS.[113] Therefore, power feed-in management measures of renewable sources are required to avoid negative effects on distribution grids.[114] In 2019 approximately 4% of feed-in wind and PV energy were curtailed in Germany.[115] This number is expected to increase with a rapidly growing share and distribution of renewable energy generation.[116] To further enhance the transition towards renewable energy sources residential ESS might be pivotal. Residential ESS are compact distributed ESS installed at the individual's household often coupled with devices connected to them such as energy management devices, control devices, and supervision devices.[117] Together, these can help shaving electrical peak loads of households and thus reduce loads on distribution grids while increasing the efficiency of renewable generation due a reduction of required power feed-in management measures.[118]

Figure 1 illustrates an classification of common distributed energy storage systems. Chen et al. provided an assessment of promising ESS systems.[119] Reviewed characteristics include the technical maturity, power rating, discharge time, storage duration, capital cost, cycle efficiency, energy density as well as life time.[120] A thorough analysis of these aspects did not yield a superior technology for energy storage, instead the technology should be chosen based on the application.[121] For small-scale and distributed PVs the application of battery energy storage systems (BESS) proved most promising.[122] In this category, lithium-ion cells provide the best combination of energy density, energy efficiency and power performance.[123] This is supported by the fact that lithium-ion cells experienced a sharp decline in price per kWh.[124]

To understand how the coupling of a BESS with distributed PV electricity generation affects the impact of uncontrolled EV charging in varying network topologies, Mancini et al. simulated multiple EV and PV penetration rates and employed the load curves in different distribution networks.[125] A 300 kWh battery with an 50 kW inverter was employed in low voltage distribution grids.[126] The DigSilent Power Factory simulation findings indicate that PV electricity and energy storage can increase the maximum feasible EV penetration in rural networks from 40% to more than 60%.[127] Further, EV induced peak charging loads are more critical in urban compared to rural networks.[128] Issues not addressed in this study include time of the year dependent variability in both EV loads and PV generation, as well as individual household level BESS. The latter should play a major role in mitigating charging loads.

A passively integrated residential BESS implies a charging process of the BESS whenever there is an energy surplus between produced PV electricity and consumed electricity or discharging when there is an energy deficit. Hong et al. studied how EV charging affects distribution transformer aging and how this can be mitigated with two integration approaches of PV energy.[129] This contribution modelled the EV mobility and different charging habits and powers based on the EV's battery's state of charge (SOC) in an apartment complex with 1,000 households.[130] The BESS is assumed to provide a capacity of 2 MWh while the PV arrays' modelled peak generation capacity equals 310 kW which is lower than the apartments base load during the day.[131] Integrating the PV energy without a BESS led to no reduction of simulated peak loads in the evening while BESS interaction enabled a 20% reduction of peak loads in an 30% EV penetration scenario.[132] This simulation demonstrates the supporting role of an BESS towards PV electricity to mitigate EV charging impacts. However, limited complexity in the employed simulation, undersized PV arrays, and no investigation of grid metrics limit the explanatory power of the study.

Overall, energy storage systems and especially BESS show a great potential in increasing synergies between PV electricity generation and EV charging loads by reducing peak loads, increasing PV self-consumption, and enhancing power quality. Employed simulations in current literature lack complexity in modelled EV loads, an investigation of residential BESS, and an impact assessment on electrical distribution grids.

2.3. Contribution

As the market of EV is rapidly developing with a 43% year-over-year increase in 2020 in global electric car stock the impact of wide range EV charging on electrical distribution grids is inevitable.[133] EV charging is characterized by temporal patterns, where individuals' charging activities cluster together such that peak loads coincide. Existing literature suggests that the most pertinent points are voltage drops below regulatory limits as well as electrical distribution grid equipment overloading induced by these peak demands. One

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[112] Cf. Rehman, Al-Hadhrami, and Alam (2015, p. 593); Cf. H. Chen et al. (2009, pp. 291–292).

[113] Cf. Hatta et al. (2009). Cf. Hawkins et al. (2013, p. 57); Cf. Scott et al. (2002, p. 510)

[114] Cf. Bundesnetzagentur (2022).

[115] Cf. Bundesnetzagentur (2021).

[116] Cf. Umweltbundesamt (2021b, p. 10).

[117] Cf. IEEE (2015).

[118] Cf. Novoa and Brouwer (2018, pp. 175–176).

[119] Cf. H. Chen et al. (2009).

[120] Cf. H. Chen et al. (2009, pp. 306–309).

[121] Cf. H. Chen et al. (2009, pp. 309–310).

[122] Cf. H. Chen et al. (2009, pp. 309–310).; Cf. Nair and Garimella (2010), p. 2126.

[123] Cf. Hall and Bain (2008, pp. 4353–4354).

[124] Cf. Our World in Data (2021).

[125] Cf. Mancini et al. (2020).

[126] Cf. Mancini et al. (2020, p. 12).

[127] Cf. Mancini et al. (2020, pp. 18–19).

[128] Cf. Mancini et al. (2020, pp. 14–16).

[129] Cf. Hong, Lee, and Kim (2020).

[130] Cf. Hong et al. (2020, pp. 11–12).

[131] Cf. Hong et al. (2020, pp. 11–12).

[132] Cf. Hong et al. (2020, p. 15).

[133] Cf. International Energy Agency (2021).

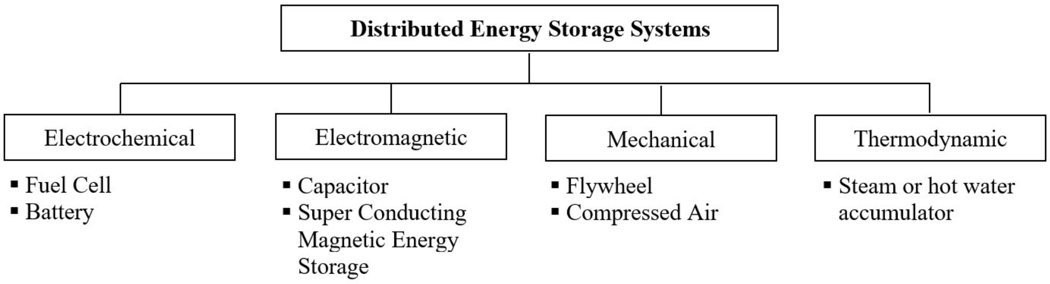

Figure 1: A classification of distributed energy storage systems.

potential approach to mitigate the impact of EV charging is widespread distributed PV electricity generation. Moreover, PV as a sustainable and emission free energy source decreases overall CO_2 emissions in the production of the required electrical energy. However, challenges such as the occurrence of reverse power flows and a weak chronological coincidence between PV electricity generation and EV charging demands could limit potential synergies. These challenges might be overcome by integrating BESS for prosumer households. Prosumer households with such a system of a PV array and BESS have a great a great potential in supporting electrical distribution grids and allowing widespread EV adoption. Despite this, current literature is lacking a thorough understanding of the role of BESS supported PV generation to charge EVs. Thus, understanding the real potential of decentralized power generation with PV systems is crucial to prepare electrical distribution grids for soaring energy demands induced by EV charging operations.

Table 1 provides an overview of the most important forementioned literature in terms of features chosen for simulations and evaluated metrics. These features play a major role in the chosen degree of simplification for the model and thus have a significant impact on the simulation results. In earlier studies, reasonable assumptions were made to model the EV penetration, charging load of EVs, and generation capacity of PVs, while few significant aspects were not covered. For instance, fixed PV penetration and sizing was presumed in ElNozahy and Salama, whereas the model of Mancini et al. assumes an uniform distribution of employed EV and PV units.[134] Both models employ stochastic modelling techniques to simulate charging and generation loads, nonetheless they do not account for different EV types or seasonal fluctuations in solar irradiance or energy consumption. Mancini et al. modelled a centralized BESS to store excess electrical energy generated by PV array but did not consider household level BESS.[135] Varying EV types were considered in the work of Habib et al., in which the impact of distributed PV electricity generation on distribution grids was not studied.[136] Simulations accounting for seasonal fluctuations in solar irradiance were presented by Good et al., however, no impact on electrical grids have been investigated.[137] Overall, no thorough analysis on the role of distributed PV systems in combination with BESS to mitigate the charging impact of high EV adoption rates on electrical distribution grids exists.

Therefore, this thesis contributes to existing research by enhancing the modelling approach and by considering all identified features of importance. First, an enhanced model of EV charging demands is employed. It comprises seasonality characteristics, EV fleet developments, and consumers' charging preferences, therefore combining, and applying findings of existing research. Second, varying household load profiles by aggregating demand with PV generation and a BESS are realized. Third, varying household load profiles are deployed in different network topologies and grid interaction metrics are investigated. So far, there is no existing literature that conduced a comprehensive distribution grid level analysis of all these system parameters.[138] This approach identifies the potential of PV arrays in combination with a BESS to support widespread EV adoption. Furthermore, the feasibility of this approach depending on the type of agglomeration can be deducted. This thesis will enable DSOs and policy makers to set the right course to prepare electrical distribution grids for a widespread EV adoption. The baseline developed by this thesis will help decision makers to identify promising solutions. These can eliminate or reduce the need for expensive infrastructure-side grid expansions.

3. Problem statement and scenarios

Having reviewed related work, this section now presents the main body of research of this thesis. First, the problem statement is described, and research questions are formulated. Next, the chosen simulation scenarios of this thesis and how they help to answer the research questions at hand are elaborated.

3.1. Research question

Existing work shows the importance of understanding EVs' charging impact on electrical distribution grids since this

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[134] Cf. ElNozahy and Salama (2014); Cf. Mancini et al. (2020).

[135] Cf. Mancini et al. (2020).

[136] Cf. Habib et al. (2020).

[137] Cf. Good et al. (2019).

[138] To the best of the authors knowledge.

Table 1: Summary of relevant literature.

Author	**Year**	**Country**^{a}	**A**	**B**	**C**	**D**	**E**
Clement-Nyns et al.	2010	BE	✓			✓	
ElNozahy and Salama	2014	US	✓	✓		✓	
Good et al.	2019	NO, SE	✓	✓			✓
Habib et al.	2020	PK	✓			✓	
Hong et al.	2020	CN		✓	✓		
Mancini et al.	2020	IT	✓	✓	✓	✓	
Mazzeo	2019	IT		✓	✓		
Novoa and Brouwer	2018	US	✓		✓	✓	
Schäuble et al.	2017	DE	✓				
Wang and Infield	2018	UK	✓			✓	
Yang et al.	2021	CN		✓	✓		
This thesis	2022	DE	✓	✓	✓	✓	✓

A: Charging behavior modelled
B: Distributed household level PV electricity generation modelled
C: BESS modelled
D: Grid impact investigated
E: Time of the year variation investigated
[a] Country code based on ISO 3166 Alpha-2

can have a serious impact on grid stability and power quality. Electrical grids can be supported by the extensive integration of decentralized power generation with PV systems and BESS to enable widespread EV adaption. Current literature is lacking an understanding of household-level PV systems with BESS. In particular, its impact throughout the seasons in mitigating distribution grid overloading in various network topologies induced by EV charging loads. Therefore, the following research questions are investigated:

1. ***How can the employment of residential PV generation support EV charging to mitigate charging impacts on the distribution grid in varying network topologies?***
2. ***How can the employment of passive residential PV-BESS support EV charging to mitigate charging impacts on the distribution grid in varying network topologies?***

Answering these research questions establishes a better understanding on the role of distributed electricity generation in supporting electrical distribution grids. Furthermore, it will allow policy makers and DSOs to derive suitable measures to prepare distribution grids for the increased electrical demands induced by the charging of EVs. Depending on the suitability of distributed PV electricity generation to mitigate the charging impact, consumers can be incentivized to adopt PV arrays. These incentives might be regional specific as different agglomeration types will reach infrastructure limits with varying EV penetration rates. As these research questions require a detailed analysis with varying assumptions, multiple simulation scenarios are proposed.

3.2. Simulation scenarios

To understand if and how distributed electricity generation with PV arrays can mitigate potential charging impacts multiple simulation scenarios with varying EV and PV penetration rates are deployed in three network architectures. The chosen scenarios reflect different short and long-term projections of EV penetration rates. A future case in 2030 with an EV vehicle stock of 15 million EVs is assumed. This aligns with the PEV adoption goal of the German government and results in an EV share of approximately 30% if the total vehicle stock of 48.2 million remains unchanged.[139] Further, variation in EV penetration and PV penetration are analyzed, to investigate the sensitivity of results. Urban, semi-urban, and rural grid architectures are employed to investigate if population density can have a significant impact on the availability of PV electricity generation. This might be due to spatial limitations in cities with high-rise buildings.

Owing to the fluctuations in solar irradiance based on the time of the year, different calendar weeks (CW) are considered.[140] These solar irradiance scenarios address the following four cases: First, average case solar insolation scenarios in between both solstices are deployed during CW12 in March and CW38 in September. Second, a best-case for PV electricity generation on the northern hemisphere during the June solstice in CW 26 is determined. And last, a worst-case scenario during the December solstice in CW51 is studied. With these four scenarios, the model covers the PV energy

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[139] Cf. Presse- und Informationsamt der Bundesregierung (2021); Cf. Kraftfahrt Bundesamt (2021a).

[140] All calendar weeks based on the year 2019.

generation under the most common solar insolation conditions. The paper is limited to these four conditions, as current research has recognized them as most information-intensive edge cases.

4. Employed data and identification of model parameters

This section describes what data is necessary to answer the research question at hand, how it is preprocessed and how it parameterizes the developed model.

4.1. Employed data to model charging loads

To enable the modeling of realistic charging loads, agents' mobility behavior needs to be simulated as well. The following section will describe the employed dataset to model the mobility behavior. Further, the characteristics of the simulated EVs and their charging characteristics are defined.

4.1.1. Mobility dataset and preprocessing

This thesis assumes that peoples' driving behavior does not depend on the propulsion type of the vehicle. Therefore, the following section will introduce, analyze, and preprocess a mobility dataset where personal vehicle trips are based on ICEVs.

The German Mobility Panel "Deutsches Mobilitätspanel" (MOP) conducted by the Karlsruhe Institute of Technology and the Federal Ministry of Transportation and Digital Infrastructure builds the foundation of the mobility behavior.[141] This dataset contains 70,796 recorded trips by 3,191 persons who live in 1,853 households. Each participant recorded all trips conducted during a time span of one specific week between September 2019 and March 2020. No influence of COVID-19 on the mobility dataset is expected as the last recorded trip was conducted on the 06/03/2020, a week before the German Government declared COVID-19 as pandemic. The recorded trips, inter alia, include detailed information of the trip purpose, start and arrival times as well as person and household related information. Of these recorded trips 32,223 trips have been conducted mainly by car with the person as main driver and are thus the only trips of interest. Further, residential information such as the community size of the household and the number of cars in the household is available.

Pre-processing of the data was necessary before employing it to parametrize the mobility model. Recorded departure and arrival times have an accuracy of 1 minute, which allows accurate tracking of mobility behavior. However, as all recordings are self-reported most arrival and departure times show a rounding bias resulting in approximately 75% of datapoints with a right-hand digit of 0 or 5. Therefore, all data points are rounded to 5-minute steps such that no 0-minute trips exit. Then, 305 trips to holiday flats or hotels as well as the corresponding household were removed as subsequent trips of members of the household would skew data. 31,942 car only trips remain where an explorative data analysis was conducted. Focusing on the travelled distance and the trip time it was observable that maximum values show a great deviation by multiple standard deviations of the mean values. As this thesis focuses on the average daily travel patterns, unreasonable long trips got excluded. Chosen thresholds for exclusion were the corresponding 99^{th} percentiles, resulting in a cutoff time duration of 130 minutes and above and a travelled distance of 200 km and above in one trip. Records based on the average speed of the trip were not excluded, as "stop&go" traffic can cause average speeds below 5 km/h and unreasonably high speeds are not present.[142] The final dataset contained 22,803 trips. 18,383 trips have been conducted on weekdays and 4,420 trips on weekends. The separation allows an independent identification of use patterns. Figure 2 illustrates selected probability distribution functions (PDF) for the vehicle trips differentiated by weekdays and weekends. Data for weekdays are denoted by solid red lines and weekends are shown as solid blue lines. Figure 2a. and 2b. depict the rolling average of the probability of departing and arriving at a specific timestep, respectively. A morning and evening driving peak can be observed during weekdays as portrayed by Figures 2a. and b. Furthermore, weekend driving patterns peaks around 11:00 a.m.

Considering all trips of an individual person results in individuals' mobility behavior for the period of one week. Each trip in the dataset essentially represents a transition between one location state to another. The MOP dataset contains twelve different trip purpose categories and thus spatial information can be derived from each trip purpose. To accurately depict the agents' charging behavior it is important to derive spatial information of the vehicle. This thesis assigns four states to each individual: Driving (D), Home (H), Work (W), Other (O).

Figure 3 demonstrates the pseudo code for the algorithm used to determine the state of each individual at each timestep. First, the initial state of an individual before conducting the first trip had to be determined as this was not part of the data. It was assumed that most individuals were at home at the beginning of their recording at 12:00 a.m. of a randomly chosen day of the week. Thus, the initial state was set to home except for the 29 individuals' whose first recorded trip had the purpose "homewards". These got initialized with the state other. After the initialization step, the trip information was employed to determine the subsequent states. Between departure and arrival time the state is set to driving. The state from the current trip until the beginning of the next trip was determined based on the purpose of the current trip. The trip purpose was encoded as follows:

1. **Work:** Way to work; way to training facility
2. **Home:** Homewards; way to second home
3. **Other:** Run an errand; leisure route; pick someone up/ drop someone off; other; other personal purpose

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[141] Cf. Karlsruhe Institute of Technology and Federal Ministry of Transportation and Digital Infrastructure (2020).

[142] Cf. Ohde, Ślaski, and Maciejewski (2016, p. 32).

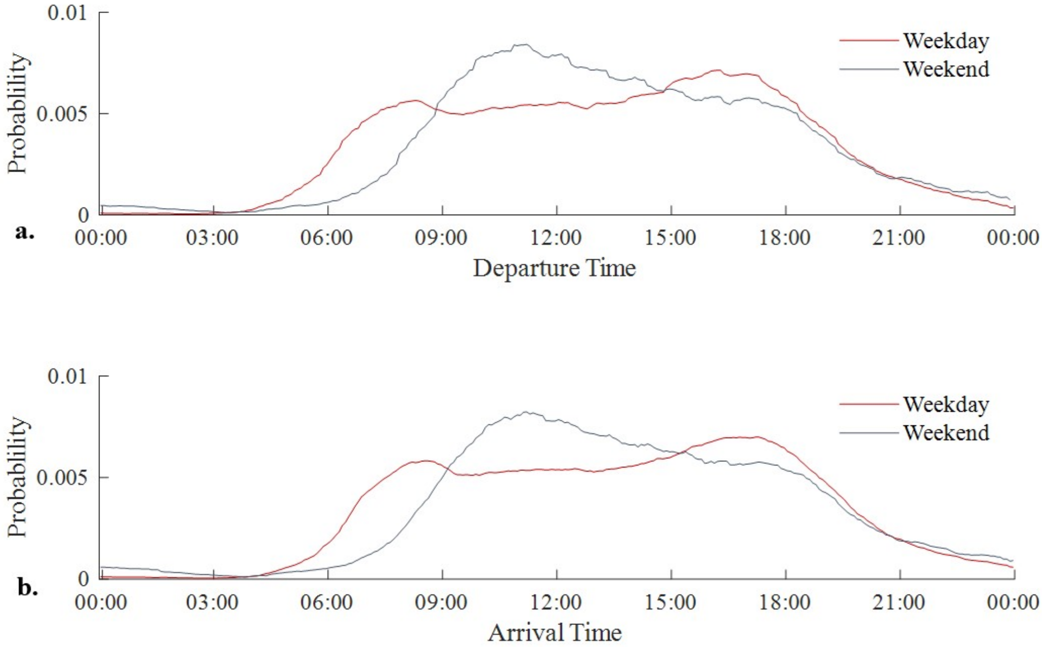

Figure 2: PDFs of vehicle trips differentiated by weekday and weekend. **a.** Departure time; **b.** Arrival time.

4. **Same state as the previous state:** Round-trip

The resulting state chain depicts the state of each individual at each timestep and allows to derive a mobility schedule of the vehicle. Figure 4 depicts the average state distribution for all individuals during an average weekday. Driving peaks in the morning and in the evening can be observed which confirms beforehand identified vehicle use patterns during weekdays. Furthermore, it is worth noting that the share of people in a working state during daytimes appears to be relatively low. This is due to the fact that the dataset represents the general public and includes the non-employable population as well.

4.1.2. EV characteristics

The following section describes EV characteristics and EV specifications used to model the energy consumption of electric vehicles. Further, different charging standards are introduced, and the charging power is specified. EV characteristics are defined on battery electric vehicles as presented in Table 2. This is due to two reasons: The most pertinent point is that their battery capacity is significantly larger compared to PHEVs. Moreover, this kind of vehicle already has predominant share in sales of non-ICEVs in Germany while showing a considerable growth in share.[143] Even though commercial vehicles and buses are considered crucial to the wider uptake of EVs, these vehicle categories scheme are not considered in this thesis.[144]

The battery capacity of EVs varies strongly and depends on the specific vehicle model. Segments group vehicles according to their size, vehicle structure or intended purpose and allow a better comparability between vehicles.[145] As each segment represents vehicles of a specific size and weight the battery capacity strongly correlates within segments. EVs in segments representing smaller vehicles such as “Mini” or “Small car” usually contain batteries of smaller capacities than EVs in segments for larger cars and thus require more frequent charging. Figure 5 exhibits newly registered personal vehicles in Germany in 2020 grouped by segment. Particularly striking is that segments for smaller cars prevail for newly registered EVs as 46% of these are small or mini cars, while these two segments only account for 20% of all newly registered personal vehicles.[146] This difference might be explainable by the fact that most of the offered EV models are still in higher price classes. Therefore, consumers with the intention to buy an EV might chose vehicles of smaller size as these suit their willingness to pay. For the chosen simulation, this thesis assumes that differences between EV and the overall segment mix level out and that the EV segment distribution equals the current distribution of overall vehicle sales. The segment “Other” is excluded, as it represents a great variety of vehicle types and assigning specific characteristics to this segment would not be reasonable.

Literature suggests that the average energy consumption per km of an EV generally increases with both weight and power but still varies a lot depending on the specific vehicle model.[147] This scattering of rated energy consumptions can

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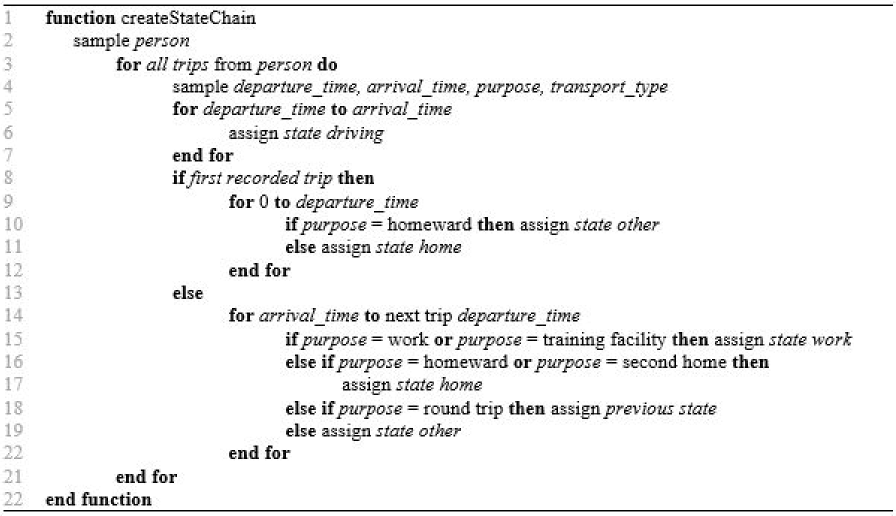
[143] Cf. Kraftfahrt Bundesamt (2021a).

[144] Cf. United Nations (2017, pp. 6–8). Excluded categories include N, M2, and M3 according to the European Union classification of vehicles.

[145] Cf. Kraftfahrt Bundesamt (2021c, p. 9).

[146] Cf. Kraftfahrt Bundesamt (2021b); Cf. Kraftfahrt Bundesamt (2021e).

[147] Cf. Weiss, Cloos, and Helmers (2020, p. 11).



```
function createStateChain
    sample person
        for all trips from person do
            sample departure_time, arrival_time, purpose, transport_type
            for departure_time to arrival_time
                assign state driving
            end for
            if first recorded trip then
                for 0 to departure_time
                    if purpose = homeward then assign state other
                    else assign state home
                end for
            else
                for arrival_time to next trip departure_time
                    if purpose = work or purpose = training facility then assign state work
                    else if purpose = homeward or purpose = second home then
                        assign state home
                    else if purpose = round trip then assign previous state
                    else assign state other
                end for
        end for
end function
```

Figure 3: Pseudo code to derive states from trip information.

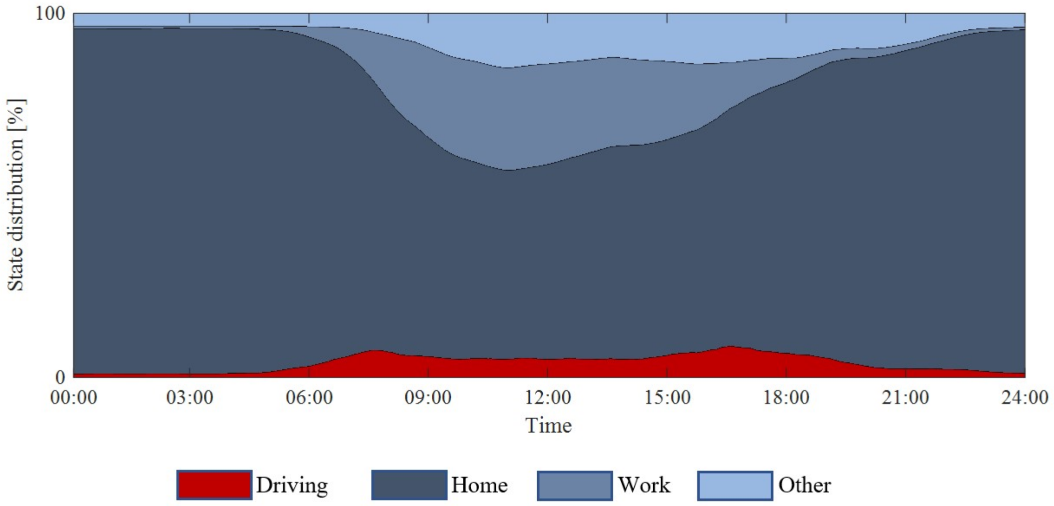


Figure 4: Average state distribution during a weekday.

Table 2: A classification of personal transport vehicles by type.

Type	**Internal combustion engine vehicle (ICEV)**	**Fuel cell electric vehicle (FCEV)**	**Hybrid electric vehicle (HEV)**	**Plug-in hybrid electric vehicle (PHEV)**	**Battery electric vehicle (EV)**
Power source	Fossil Fuel	Hydrogen	Fossil Fuel	Fossil Fuel & Electricity	Electricity
Battery	-	-[a]	1-5 kWh	5-30 kWh	15-110 kWh
Example	Volkswagen Golf Mk7	Toyota Mirai 2019	Toyota Prius	Mercedes C 300 e	Tesla Model S

[a] Usually non-plug-in batteries included for recapturing breaking energy and smoothing power delivery.

also be seen in Table 4, where the selected EV models for this thesis are presented. As rated energy consumptions tend to represent the best-case scenario, real life energy consumption results of the ADAC Ecotest are chosen.[148] For each segment the top selling EV model in Germany of the year 2021 was

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[148] Cf. ADAC (2022).

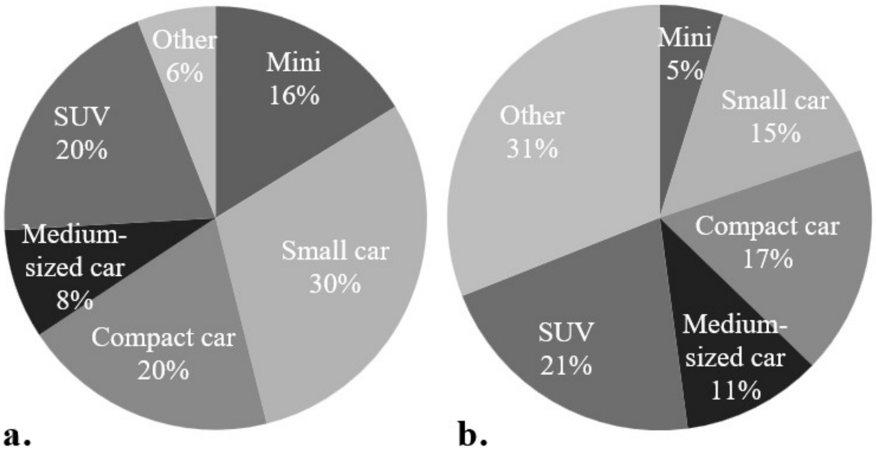

Figure 5: Registration of new vehicles in Germany 2020 grouped by segment. **a.** EV only; **b.** All vehicle types. Own illustration based on Kraftfahrt Bundesamt.

Cf. Kraftfahrt Bundesamt (2021b); Cf. Kraftfahrt Bundesamt (2021e).

Table 3: Share of households with private car by agglomeration type.

	Rural [%]	Semi-urban [%]	Urban [%]
Share of households with private car	89	86	77

Cf. Karlsruhe Institute of Technology and Federal Ministry of Transportation and Digital Infrastructure (2020).

chosen.[149] To prolong life expectancy and to avoid harmful under- or overcharge events of the battery, vehicle manufacturers limit the amount of total battery capacity which can be used. The simulation of the battery charge in this thesis is built upon the usable battery capacity only.

An additional factor which has a significant influence on the average energy consumption of an EV is the ambient temperature.[150] Ambient temperature affects energy efficiency of an EV by influencing both auxiliary loading, such as cabin and battery thermal management, and battery output energy losses.[151] Existing work suggests that the total energy consumption increases significantly with decreasing ambient temperatures.[152] Most recent literature identified that the trip range at low temperatures from 0°C to 15°C is 28% lower than driving at moderate temperatures from 15°C to 25°C.[153] The simulation scenarios in this thesis cover different seasons, implying varying ambient temperatures. To model the effect of the additional energy consumption during colder months a consumption factor is introduced. This consumption factor represents a simplification of actual temperature dependencies, as the ambient temperature influences various other mechanical factors such as the air density, air resistance, rolling resistance, or tire pressure. Based on average ambient temperatures, a consumption factor of 1.25 is assumed for the December scenario, implying an additional energy consumption of 25%.[154] The March and September cases include a consumption factor of 1.15, while the June case assumes unaltered rated energy consumption. Further, a temperature and state of charge independent self-discharge rate of 1% per day is assumed to account for the energy consumed by electronics. Other potentially influencing factors on energy consumption such as the trip distance, individual driving styles, average speed, or the batteries state of charge are excluded in the context of this thesis.[155]

4.1.3. Charging characteristics

The core metric influencing the charging load on electrical distribution grids is the charging power. This section describes common charging standards and locations and defines the underlying characteristics of EV charging.

A wide range of charging technologies and power levels based on either 1-phase AC, 3-phase AC or DC power supplies exist. For each technology, different standardized connector types are used in the European Union, such as the EN 62196

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[149] Cf. Kraftfahrt Bundesamt (2021d).

[150] Cf. Al-Wreikat, Serrano, and Sodré (2022, p. 1); Cf. Liu, Wang, Yamamoto, and Morikawa (2018); Cf. Qi, Yang, Jia, and Wang (2018, p. 371).

[151] Cf. Liu et al. (2018, p. 331).

[152] Cf. Iora and Tribioli (2019, p. 12); Cf. Liu et al. (2018, p. 329).

[153] Cf. Al-Wreikat et al. (2022, p. 1).

[154] Cf. Climate-Data (2022).

[155] Cf. Qi et al. (2018, p. 371); Cf. Bingham, Walsh, and Carroll (2012, p. 34).

Table 4: Selected EV specifications by segment.[a]

Segment	**Mini**	**Small car**	**Compact car**	**Medium-sized car**	**SUV**
Selected model	Volkswagen e-UP	Renault Zoe ZE40 R110	Volkswagen ID.3 Pro	Tesla Model 3 Long Range Dual Motor	Audi e-tron 55 quattro
Battery capacity [kWh]	36.8	54.7	62	82	95
Battery usable [kWh]	32.3	41	58	76	86.6
Rated energy consumption[b] [kW/100 km]	14.5	17.5	15.5	14.7	22.4
ADAC Ecotest energy consumption [kW/100 km]	17.7	20.3	19.3	20.9	25.8

[a] Cf. Electric Vehicle Database (2021); Cf. ADAC (2022).

[b] Based on the Worldwide Harmonised Light Vehicle Test Procedure (WLTP).

Type 2 for regular AC charging.[156] The "Ladesäulenverordnung" of the German Federal Ministry for Economic Affairs and Climate Action adopted on 17th March 2016 laid down the requirement to adopt the EU standard.[157] This regulation enforced the European connector standard EN 62196 Type 2 in Germany for AC charging. The Type 2 connector provides between 3.6 kW and 43 kW power.

Literature identified home charging as the prevalent mode of charging.[158] Fast chargers and high power chargers for range extensions are excluded, as they only account for 1-2% of the charging operations and many EV types still do not support maximum charging powers.[159]

Table 5 provides an overview of charging locations that are either in scope or out of scope for the modelling of EV charging demands in this thesis. The charging location home includes privately owned garages or parking spaces, as well as parking spaces for residential buildings. As an 11 kW 3-phase AC charger provides a good compromise between moderate charging times and economical CAPEX, this thesis assumes that chargers installed at home provide a charging power of 11 kW. The charging power demanded by the EV is not constant, as it depends on the SOC.[160] Furthermore, the charging efficiency also tends to decrease with higher SOCs, reaching maximum charging losses of 20% for SOCs above 80%.[161] As both these factors strongly depend on the specific EV model and literature regarding these is sparse, this thesis excludes these factors and assumes a constant grid side charging power of 11 kW. Average charging losses are considered and an average in literature identified charging efficiency of 90% is assumed for the whole charging process.[162]

4.2. Employed data to model household and house loads

The following section will provide an overview of impacting variables on household electricity consumption, and what assumptions and underlying data sources are chosen to model the household load profiles. Subsequently, characteristics of a house depending on the type of agglomeration are presented.

4.2.1. Household load characteristics

Household electricity consumption is mainly determined by human activities.[163] Thus, the temporal and spatial ordering of human activities have a huge influence on the electricity demand of a household. This has implications on the formation of temporal patterns as some energy intensive activities cluster together, such as the preparation of food, and therefore peak electricity demands occur.[164] Further, the electricity consumption is determined by climate conditions as it varies between cold and hot climates mainly due to the use of air conditioning and heating devices.[165] To forecast and account for the energy demand of electrical consumers, averaged load profiles, such as standard load profiles, based

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[156] Cf. International Electrotechnical Commission (2014); Cf. International Electrotechnical Commission (2016).

[157] Cf. Bundesanzeiger Verlag (2016).

[158] Cf. Baresch and Moser (2019, p. 388).

[159] Cf. Baresch and Moser (2019, p. 393); Cf. Kleiner et al. (2018, p. 218); Cf. Lee et al. (2020), p. 11; Cf. Thingvad et al. (2021, p. 10).

[160] Cf. Figenbaum (2020, p. 41).

[161] Cf. Kostopoulos, Spyropoulos, and Kaldellis (2020, p. 423).

[162] Cf. Sears, Roberts, and Glitman (2014, p. 256).

[163] Cf. Torriti (2017, p. 46).

[164] Cf. Torriti (2017, p. 46).

[165] Cf. Park, Yang, Miller, Arjunan, and Nagy (2019).

Table 5: Charging locations.

	In scope	Out of scope			
Charging location	Home	Public fast and high power charger	Commercial parking	Curbside	Workplace
Electrical power range [kW]	3.6 - 22	50 - 350	11 - 50	11 - 22	3.6 - 43
Selected EV charging power [kW]	11	-	-	-	-

on past data are mainly used. Figure 6 depicts standard load profile curves for a week in December and June of the consumption type household (H0). Temporal patterns are visible with pronounced load peaks each evening.

To accurately model household loads, it is important to consider different household sizes and their distribution. The average household size in Baveria, Germany tends to increase with decreasing community size.[166] This implies that households in rural areas are on average larger than in urban areas. Table 6 illustrates the household size distribution according to the type of agglomeration.

4.2.2. House parameters

Having reviewed the electrical load of a single household the electrical load at a supply point needs to be determined. To define the electrical load of a house, the number of households per building needs to be considered. Table 7 gives an overview on the distribution of the number of households depending on the type of agglomeration. The data suggests that the share of single family homes is significantly higher in rural areas while the share of multifamily buildings is higher in urban areas. This is expected and can have a significant influence on the PV generation potential.

4.3. Employed data to model PV generation

The potential PV electricity generation capacity can be expressed in different ways. This thesis focusses on the technical potential, which accounts for the generation potential given technical constraints as well as geographical depending solar irradiance data. The economic potential – the share of houses with the capacity to invest in a PV system – is not considered. The following section introduces the underlying statistical data to determine the PV generation potential per residential house.

4.3.1. Available rooftop area

The core metric influencing the PV generation potential is the area of the PV arrays and therefore the available area to install PV arrays is crucial. Large rooftop PV installations can reach peak power generation capacities of up to 10 MWp.[167] For single residential households, photovoltaic systems below 10 kWp are most common and average installation capacities increased over the last years and reached 7.5 kWp for all newly installed systems below 10 kWp.[168] At the same time the number of PV systems between 10 and 15 kWp showed a YoY growth of 248%.[169] This is further supported by the reform of the German renewable energy act (EEG) which increased the exemption limit of the EEG apportionment from 10 kWp to 30 kWp.[170] Estimates of the PV installation potential based on the available rooftop area in German residential areas showed the need to distinguish between different types of buildings.[171] This thesis considers residential buildings only and differentiates between single family buildings, double family buildings, and multifamily buildings. Because the rooftop area was calculated based on, inter alia, the average size of an apartment, an analysis of average apartment sizes depending on the type of agglomeration was conducted.[172] This analysis separated apartment sizes depending on residential building type and type of agglomeration. Results suggested no significant differences in apartment sizes. Therefore, the average German roof area was used for all agglomeration types and is given in Table 8 for slanted and flat roofs. Flat roofs are defined as roofs with an inclination below 5° and its share is roughly 10% of residential rooftop construction types.[173]

Next, a reduction in available rooftop area for PV installations due to constructional constraints such as existing solar thermal systems, ventilation systems or chimneys was considered. Unsuitable azimuth angles of the direction of slanted roofs further reduce the available area. This is expressed by a utilization factor which determines the share of the roof area that is suitable for an PV array. Multiplying the roof utilization factor for photovoltaic systems with the average rooftop area results in the average available rooftop area for PV in-

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[166] Cf. Bayrisches Landesamt für Statistik (2021).

[167] Cf. Bundesnetzagentur (2021).

[168] Cf. EUPD Research (2020); Cf. Bundesnetzagentur (2021).

[169] Cf. EUPD Research (2020).

[170] Cf. Bundesministerium für Wirtschaft und Klimaschutz (2021).

[171] Cf. Mainzer et al. (2014).

[172] Cf. Mainzer et al. (2014, p. 719); Cf. Statistisches Bundesamt (2011); Cf. Bundesamt für Bauwesen und Raumordnung (2010).

[173] Cf. Fechner (2020, p. 16).

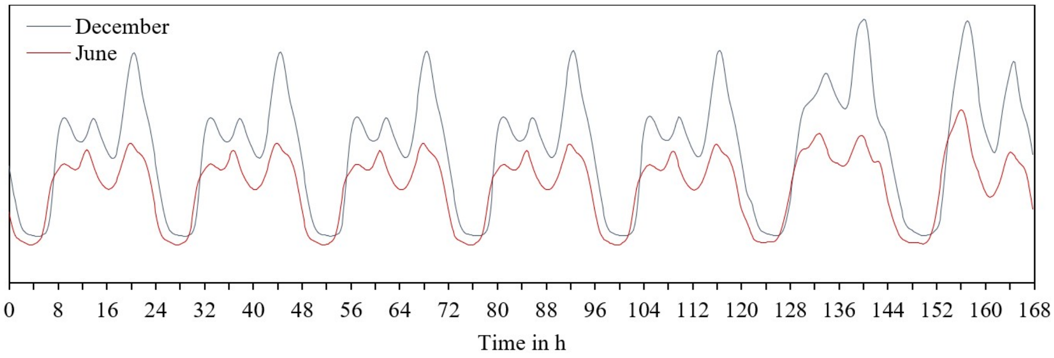

Figure 6: Standard load profiles for households, where a time of 0 equals Monday 12:00 a.m. Own illustration.

Cf. Stadtwerke Groß-Gerau (2021).

Table 6: Household sizes depending on agglomeration types.[a]

Persons per household	Rural [%]	Semi-urban [%]	Urban [%]
1	35	40	54
2	35	33	27
3	14	12	10
4	12	11	7
5 or more	4	4	2

[a]Cf. Bayrisches Landesamt für Statistik (2021); Cf. Bundesamt für Bauwesen und Raumordnung (2010).

Table 7: House types depending on agglomeration types.[a]

Households per building	Rural [%]	Semi-urban [%]	Urban [%]
1	68	57	48
2	10	13	10
3-6	14	20	14
7-12	7	7	17
13 or more	1	3	11

[a]Cf. Statistisches Bundesamt (2011); Cf. Bundesamt für Bauwesen und Raumordnung (2010).

Table 8: Average German rooftop area.[a]

	Flat roof [m^2]	Slanted roof [m^2]
Single family buildings	141.4	113.7
Double family buildings	143.9	130.2
Multi-family buildings	135.7	207.3

[a]Cf. Mainzer et al. (2014, p. 720).

stallations, which is given in Table 10.

This thesis does not consider façade PV installations as these are usually only considered for new- or reconstructions and a lower economical yield as well as security constraints do not render them suitable for most building owners.[174]

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[174] Cf. Fechner (2020, p. 24).

Table 9: Average roof utilization factor and share of rooftop types.[a]

	Flat roof [%]	Slanted roof [%]
Roof utilization factor for photovoltaic systems	27	29
Rooftop type of residential buildings	10	90

[a]Cf. Mainzer et al. (2014, p. 720); Cf. Fechner (2020, p. 16).

Table 10: Average available rooftop area for PV installations.

	Available rooftop area for PV installation	
	Flat roof [m^2]	Slanted roof [m^2]
Single family buildings	38	33
Double family buildings	38	38
Multi-family buildings	36	60

4.3.2. PV generation capacity

Based on the available rooftop area the potential peak power capacity of the PV system can be calculated. The average module efficiency increased over the past years and newly sold silicon-based PV systems reach nominal module efficiencies of more than 20%.[175] This implies that 20% of the exposed solar irradiation can be converted to electricity. Even though the efficiency negatively correlates with the operating temperature, temperature dependencies are not considered in the context of this thesis.[176] Based on system power densities of 200 W/m^2 for modern PV arrays the average potential PV peak power as given in Table 11 is achievable for rooftop solar installations.[177]

The potential yield of the PV system depends on a multitude of additional factors, such as other performance losses, the tilt angle, azimuth angle, and solar irradiance. These factors need to be parametrized before the PV generation profiles can be simulated.

The overall efficiency of the PV system is further reduced by conversion losses as well as obscuration through soiling or other objects and buildings.[178] This performance loss is set to 10% for this thesis. The tilt angle influences both the possible yield of a PV system as well as the required surface area to install multiple PV panels.[179] Optimal tilt angles for latitudes between 40°N and 70°N range between 29° and 40°.[180] Higher tilt angles require greater spacing between multi row PV array installations. This required spacing between PV systems is already considered with the utilization factor for the rooftop area calculation. The tilt angle is set to 30° while the azimuth angle is set to 180° (facing perfectly southwards) which is in line with the mean for most PV systems as identified by Pfenninger and Staffell.[181]

The solar irradiance strongly depends on meteorological events as well as the location. Larger latitudes lead to a strong occurrence of seasonality patterns. Figure 7 illustrates the PV generation capacity in Munich simulated with MERRA-2 data from 1980 until 2019.[182] The MERRA-2 data contains satellite imagery-based information and assimilation of, inter alia, aerosol and meteorological data.[183] The illustration confirms both the occurrence of seasonality patterns in potential PV yield as well as the strong influence of meteorological events. The latter is unpredictable and can lead to huge fluctuations in the electric energy generated as depicted by the light blue area.

4.4. Parameters of the BESS

Literature investigated varying BESS capacities and their feasibility to deploy them in residential buildings. While some literature investigated the potential of used EV batteries as BESS, this thesis will select a battery configuration based upon currently available products.[184] The "Tesla Powerwall" was selected with an energy capacity of 13.5 kWh and an overall charging efficiency of 90%.[185] This efficiency was set for a charging cycle, while discharging was assumed to be without any significant losses.

5. Model development

This chapter presents the selected modelling methodology. For each scenario a suitable simulation is developed. Multiple partial models are required to conduct an in-depth analysis of the individual factors. These partial models cover the following aspects: (1) Model of EV charging loads, (2)

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[175] Cf. Fraunhofer Institute for Solar Energy Systems ISE (2020, p. 44).

[176] Cf. S. Dubey, Sarvaiya, and Seshadri (2013).

[177] Cf. Trinasolar (2020).

[178] Cf. Fraunhofer Institute for Solar Energy Systems ISE (2020, p. 44).

[179] Cf. Fraunhofer Institute for Solar Energy Systems ISE (2020, p. 44).

[180] Cf. Yunus Khan et al. (2020, pp. 520–521).

[181] Cf. Pfenninger and Staffell (2016, p. 1254).

[182] Cf. Pfenninger and Staffell (2016).

[183] Cf. NASA (2022).

[184] Cf. Heymans, Walker, Young, and Fowler (2014).

[185] Cf. Tesla (2022).

Table 11: Rooftop PV installation potential.

	PV installation potential rooftop	
	Flat roof [kWp]	Slanted roof [kWp]
Single family buildings	7.6	6.6
Double family buildings	7.6	7.6
Multi-family buildings	7.2	12

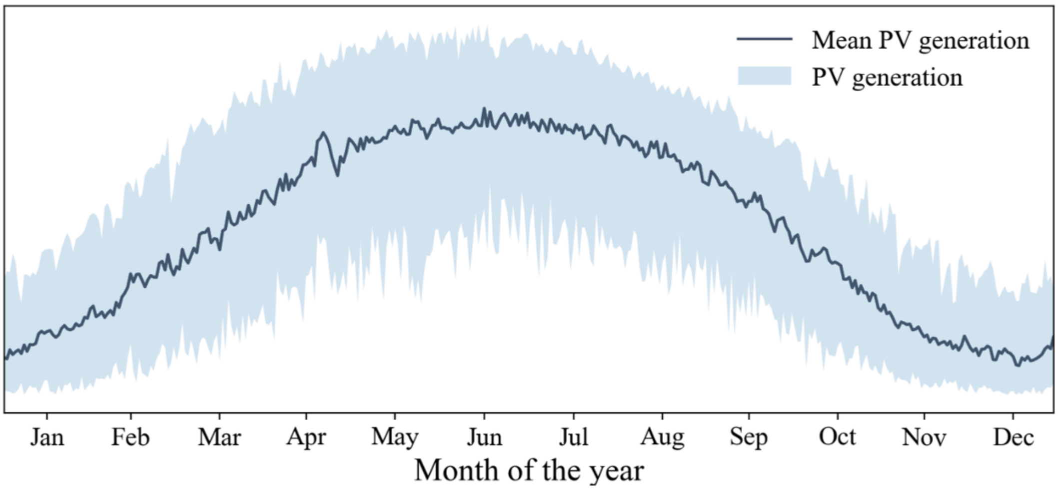

Figure 7: Yearly PV power generation over 40 years in Germany. Based on Pfenninger and Staffell. Own illustration.

Cf. Pfenninger and Staffell (2016).

Model of house load profiles, (3) Model of PV generation capacity, and (4) Model of the BESS. The results of the former three partial models represent the electrical load profile of an individual house which then represents a node in the low voltage (LV) distribution grid. For specific simulation scenarios a further forth model of the BESS interacts with the load profile.

Figure 8 illustrates the flowchart and the relationship between the input data in yellow boxes and the final output in red. Boxes colored in blue represent significant intermediate results. A simulation period of one week is chosen to account for day of the week dependencies in behavior. First, a Markov chain state and trip sequence is generated. Based on this, EVs and their charging behavior are simulated. An aggregation of household load profiles, EV charging profiles, PV generation profiles as well as a simulation of the BESS results in the electrical profile of a house. This house is then deployed as a node in selected grid topologies. The power flow problem is solved with MATLAB MATPOWER to investigate the resulting grid metrics.

5.1. Model of EV charging loads

Chapter 2.1.2 provided an overview on approaches to simulate EV charging loads. In general, both charging load simulation frameworks, namely agent-based electromobility simulations and charging point-based load simulations led to similar results. However, charging point-based load simulations are comparatively more limited, as charging point data is sparser and the inclusion of external factors is limited. Literature has shown that external factors, such as ambient temperature, EV types, or spatial and temporal mobility behavior can have a significant impact on the energy demand of EVs.[186] In contrast, the inclusion of external factors in agent-based electromobility simulations follows a simpler logic and spatial charging locations can be modelled. Therefore, this thesis simulates EV charging loads by carrying out this methodology.

5.1.1. Model of mobility behavior

To enable the modeling of realistic charging behavior, agents' mobility behavior needs to be simulated as well. An accurate depiction of travel behavior can be achieved by scheduling the activities of an agent in both time and space with suitable methodologies such as trip chaining. Trip chaining is a common approach applied in traffic modelling.[187] A trip chain consists of two or more trips linked to each other. Hence, a household usually begins the day by a home to non-home trip. Subsequently several non-home trips can be linked to this initial trip whereas each trip has an assigned time and space variable. This allows to identify

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[186] Cf. Fischer et al. (2019, p. 14); Cf. Tal and Dunckley (2016, 54); Cf. Hu, Wu, and Schwanen (2017, p. 6).
[187] Cf. McGuckin and Nakamoto (2004).

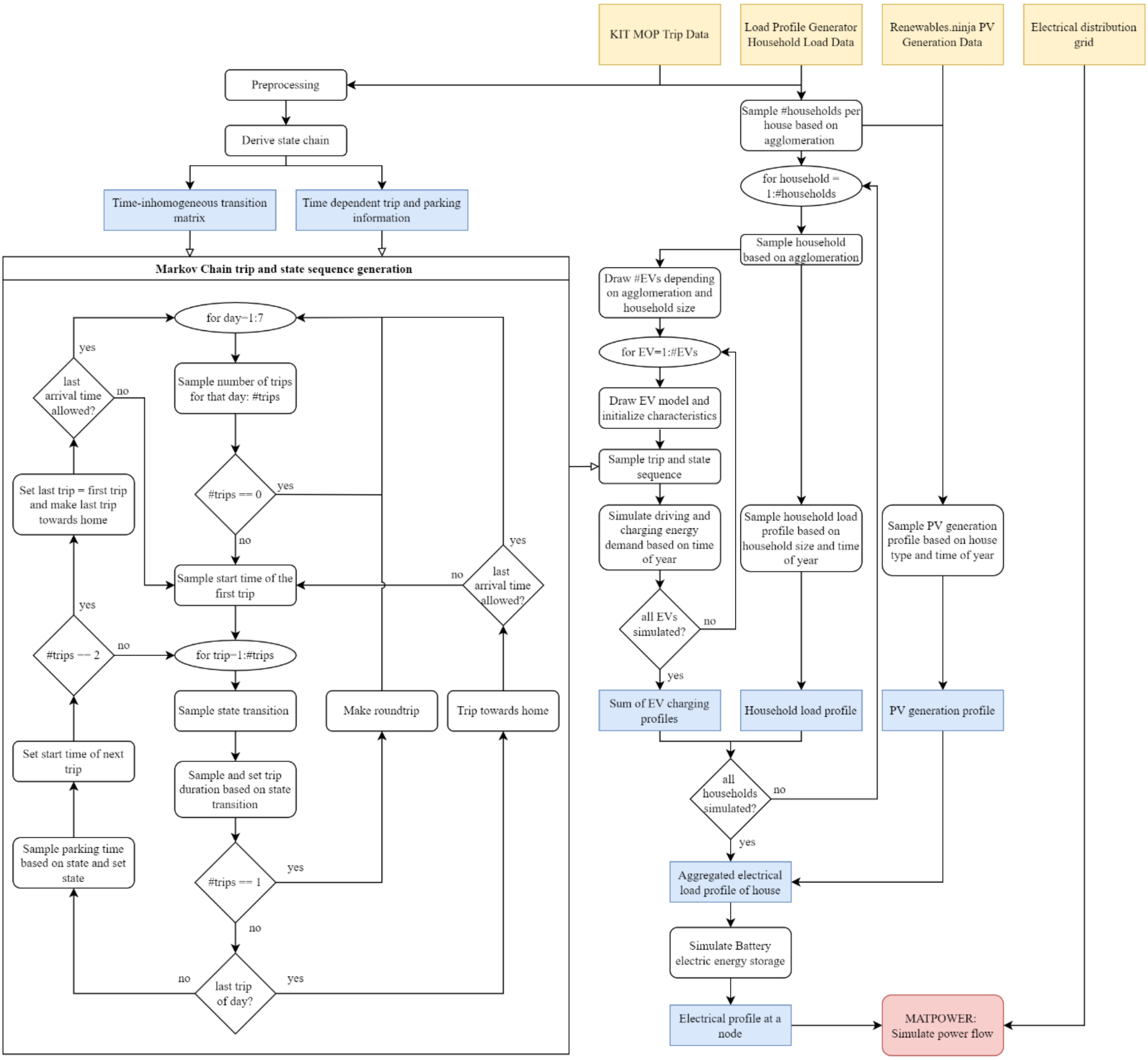

Figure 8: Flowchart of model.

the agents' daily mobility schedule. Related work usually employed probability distributions for mobility related time data, space data or both, to randomly sample and simulate single agents.[188] By employing this approach Fischer et al. were able to create probability distribution functions of weekday departure and arrival times as well as activities. Synthetic driving schedules were then created with time-inhomogeneous Markov Chains.[189] This approach allows to simulate the vehicle state at each time step.

This thesis employs Markov Chain simulations, as a numerical approach, to create synthetic mobility schedules. A Markov Chain can be defined as a stochastic memoryless process, where the specific state x at the point in time t only depends on the state at time *t-1*. This is expressed by Equation (1).

$$P\left(x_t \mid x_{t-1}, x_{t-2}, \ldots, x_0\right) = P(x_t \,| x_{t-1}) \tag{1}$$

The Markov Chain is mainly characterized by the transition operator $T(x_{t+1}|x_t)$ which provides the probability of arriving at state x_{t+1} at time $t+1$ given the chain state x_t at time t. As the associated transition operator is not constant and depends on the given timestep a time-inhomogeneous Markov Chain is necessary. The transition operator can be converted to a matrix form in $C \times S \times S$ scale, where C describes the

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[188] Cf. Habib et al. (2020, p. 303); Cf. Wang and Infield (2018, p. 87); Cf. ElNozahy and Salama (2014, pp. 135–136).

[189] Cf. Fischer et al. (2019, pp. 10–11).

chain length which equals the number of timesteps, and S describes the number of possible states. To accurately depict the agents' behavior the following spatial states were considered: Home (H), Work (W), Other (O). This results in the transition matrix as depicted in Equation (2).

$$T_c = \begin{bmatrix} P^c_{H\to H} & P^c_{H\to W} & P^c_{H\to O} \\ P^c_{W\to H} & P^c_{W\to W} & P^c_{W\to O} \\ P^c_{O\to H} & P^c_{O\to W} & P^c_{O\to O} \end{bmatrix} \tag{2}$$

The agents state transition probability of arrival at work in $c+1$ given being at home in c is now given by $P^c_{H\to W}$. During any time step in the chain C, the sum of probabilities given a specific state is always 1. Furthermore, it is assumed that each person only has one workplace and one home. This is reflected in the transition matrix as the state transition probability from home to home and work to work are 0 for all timesteps. To generate the car usage and locations the algorithm proposed by Fischer et al. is used and slightly adopted.[190] First, for an agent and each day of the week, the number of trips is randomly sampled depending on car usage data. In a second step, the time of the first departure for the current day is sampled. The time-inhomogeneous Markov Chain now constructs a sequence of trips and determines the spatial transitions between each trip. The parking durations at each spatial location are randomly sampled based on a state and time of week depending on parking probability distribution. Trip durations of the first and the last trip of a day are equal if the total number of trips for this day equals two. The last trip of the day ends at home and the trip sequence for an agent on that day is accepted if the last arrival time is before a predefined time. The predefined time is sampled from a fitted distribution to the final homewards trips of each day. For this a Burr Type XII distribution was chosen. To ensure that arrival times are not too restricting and to account for differences in agents' daily schedules only arrival times after 4:00 p.m. are considered to fit the distribution. Figure 9 shows the probability distribution which sets the predefined times for weekdays and weekends. The weekday distribution with a solid blue line and is more restricting regarding the latest arrival time and peaks at around 17:00 while the weekend distribution shows a higher variance.

Benchmarking the generated trips chains with the input data trip chains yielded results showing only slight deviations of average trip duration and frequency. This is displayed in Table 12. Temporal driving patterns are observable in the resulting average state distribution for a weekday as depicted in Figure 10.

5.1.2. Model of EV charging behavior

Based on the mobility behavior the energy demand of the EV and subsequently the charging operations of a household can be modelled. Depending on the household size, the type of agglomeration, and the EV penetration rate the number of EVs for a single household is sampled.

Each EV of the household then gets a random mobility schedule assigned. An affine relationship between the distance travelled and the energy consumed is used to estimate the energy consumption of an EV. The travelled distance is modelled by sampling a time of the day dependent speed from the original trip dataset for each timestep during the duration of the trip. The energy consumed during one timestep is calculated with Equation (3).

$$P_{consumed} = v * P_{car} * C * \frac{1}{60} \tag{3}$$

where v equals the sampled velocity for that timestep in km/h, P_{car} the energy consumption of the car in kW/km, and C the consumption factor based on the time of the year. Based on the consumed energy and the self-discharge of the EV the batteries SOC gets adjusted accordingly. The self-discharge also applies when the EV is not used.

The likelihood of a charging operation depends on multiple factors. This thesis considers: (1) the availability of a charging station, (2) the parking duration and, (3) the agent's behavior depending on the current SOC. In the context of this thesis only charging at home is assumed. This is done as it represents a worst-case scenario for the residential distribution grid as all the required energy is drawn from that grid. Therefore, charging is only feasible if the EV is parked at home.

In the next step the parking period is considered. The probability to plug in an EV is only considered if the parking time exceeds a certain period. This period is set to 10 minutes. Finally, the agent's behavior depending on the current SOC is modelled based on range anxiety, the fear of running out of energy, as a core metric. A study showed that most individuals start to feel uncomfortable at a 25% SOC or less.[191] To account for larger battery capacities of modern EVs the range anxiety is parametrized with 20% in the context of this thesis. Therefore, agent's whose EV have a SOC below 20% are almost 100% likely to connect their EV to a charger given that the former two conditions are fulfilled. This behavior is modelled with a logistic function.[192] Equation (4) and Figure 11 depict the logistic function that represents the connection probability depending on the state of charge. The point of indifference is set to 60%, based on the empirically observed median SOC at the beginning of a charging operation.[193] The SOC at the beginning of the week is randomly initialized with a SOC value obtained after one week of simulation.

$$p_{charge}(SOC) = \min\left(1, 1 - \frac{1}{1 + e^{-0.15*(SOC-0.6)}}\right) \tag{4}$$

$$P_{charged} = P_{charger} * \eta * \frac{1}{60} \tag{5}$$

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[190] Cf. Fischer et al. (2019, p. 11). Specifically algorithm 1 and 2.

[191] Cf. Philipsen, Brell, Brost, Eickels, and Ziefle (2018, pp. 488–489).

[192] Cf. Fischer et al. (2019, p. 11).

[193] Cf. Schäuble et al. (2017, pp. 16–17).

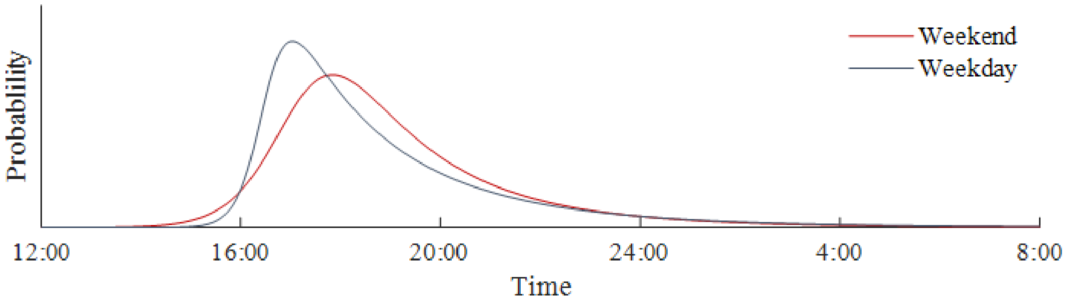

Figure 9: Burr Type XII probability distributions to draw predefined maximum arrival times.

Table 12: Benchmarking of driving time and trip frequency of data against model.

		Model	**Data**	**Deviation**
Average daily driving time [min]	Total	40.37	40.2	0.17 (0.4%)
	Weekday	45.35	45.27	0.08 (0.2%)
	Weekend	27.93	27.5	0.43 (1.6%)
Average trip frequency [trips/day]	Total	2.08	2.09	-0.01 (-0.5%)
	Weekday	2.34	2.36	-0.02 (-0.8%)
	Weekend	1.42	1.42	0 (0%)

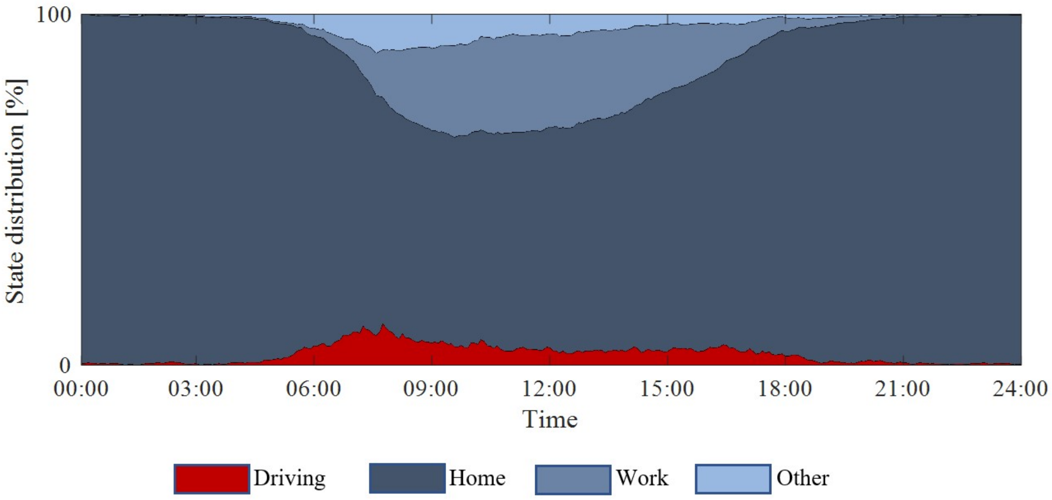

Figure 10: Average simulated state distribution of agents during a weekday.

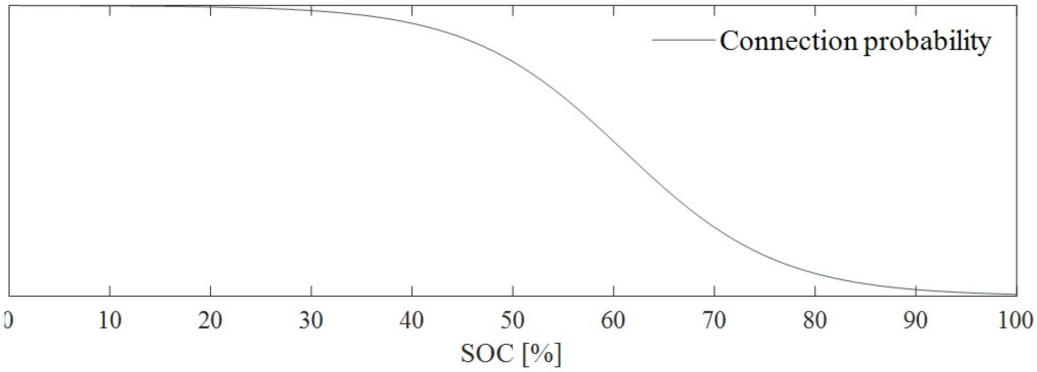

Figure 11: Connection probability with a=1.

The energy charged at one timestep for the EV is calculated with Equation (5), where $P_{charger}$ is the rated power of the charger in kWh and η is the charging efficiency of the overall charging operation. The resulting charging loads equal $P_{charger}$. Aggregation of all charging loads for each EV of a household results in the overall charging loads of this household.

5.2. Model of house load profiles

Standard load profiles have been widely used for research in energy systems. However, recent literature suggests that the use of such profiles yields misleading results especially in settings with intermittent energy sources.[194] Alternatives are provided by reference load profiles or synthesized residential load profiles. The former usually depicts reference data of one specific household. Unfortunately, publicly available reference load profiles are spare and thus empirical sampling of households to simulate multiple households is not feasible. On the other hand, synthesized residential load profiles allow the generation of random household behavior as well as the definition of household characteristics and desired activities and behaviors. Due to these benefits, this thesis realizes the modelling of household load profiles with synthetic load profiles.

Pflugradt and Muntwyler developed a synthetic load profile generator that simulates the behavior and activities of the residents to generate the load profiles for the whole household.[195] Their load profile generator is available free of charge and has been widely used and validated in a great extent of literature.[196] The energy consumption can be simulated in time intervals down to 1 minute for self-defined households. Further, it includes 60 predefined and validated German households based on a survey, measurements, and appliance use statistics. These predefined households are used to generate a set of 1, 200 households for each time of the year while incorporating meteorological data for the location Munich. This thesis assumes that all households do not rely on electricity as source of heating, as only roughly 5% of households in Germany use this source of heating energy.[197]

To develop the electrical load profile of a house, the loads of individual households are aggregated. First, depending on the agglomeration type, household load profiles based on the number of residents per household are sampled. Second, the number of households per house are selected based on the type of agglomeration. Then, household load profiles of the houses' residents (including EV charging demand) are aggregated to obtain the electrical load profile of the house.

5.3. Model of PV generation profiles

To model the PV generation profiles the PV profile generator provided by Pfenninger and Staffell is used.[198]

Figure 12 illustrates the model of PV generation in two different stages. In the first stage, the PV capacity per residential building type is estimated. This parametrization of the PV model has been done in section 5.3. In the second stage, the PV generation simulator provided by Pfenninger and Staffell is parametrized accordingly to generate time of the year and building type depending on PV generation profiles. The generated PV profiles apply on a building level. In total PV profiles for 40 years are generated which are then later randomly drawn to capture variation in PV electricity generation.

PV systems with peak powers above 7 kWp need to have active power curtailment measures in Germany to ensure grid stability.[199] This can be implemented with additional smart meters or alternatively with limiting the maximum output power to 70% of the theoretically achievable peak power. As smart meter installations are often not economically feasible for such small PV installations, most residential PV systems in Germany are curtailed to 70% of peak power.

To estimate reasonable PV penetration rates, it is important to consider the share of EV owners with suitable rooftop areas, that own or are willed to invest in PVs. Empirical results suggest that PV owners in Austria are 21% more likely to purchase an EV in the next five years compared to non-EV owners. Moreover, 43% of EV drivers in the UK already own solar panels and 14% plan to buy solar panels in the near future.[200] This increases the overall likelihood that EV drivers are simultaneously owners of PV arrays. Latest results suggest that the conditional probability of owning a PV system is 31% higher when the owner also owns an EV.[201] This conditional probability is applied in this thesis while holding average PV penetration rates constant.

Average PV penetration rates shows great spatial differences in Germany. While rural areas in south Germany show penetration rates above 20% for small PV installations, some areas in north Germany have penetration as low as 3%.[202] Latest analysis suggest great development potentials due to many unused rooftop areas with suitable azimuth angles and rooftop geometry.[203] Therefore, PV penetration rates of 30% are assumed as reasonable for a future 2030 scenario.

5.4. Model of the battery energy storage system

The BESS integration mainly depends on the total power energy demand of the house. The calculation of the total energy profile of the house at a specific timestep is given in

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[194] Cf. Linssen, Stenzel, and Fleer (2017, p. 2024).

[195] Cf. Pflugradt and Muntwyler (2017).

[196] Such as Cf. Huang, Sun, Lovati, and Zhang (2021); Cf. Haider and Schegner (2020); Cf. Lopez, Rider, and Wu (2019).

[197] Cf. BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. (2019).

[198] Cf. Pfenninger and Staffell (2016).

[199] §9 EEG.

[200] Cf. Cohen, Azarova, Kollmann, and Reichl (2019, p. 575); Cf. CleanTechnica (2019).

[201] Cf. Cohen et al. (2019, p. 574).

[202] Cf. EUPD Research (2022).

[203] Cf. EUPD Research (2022).

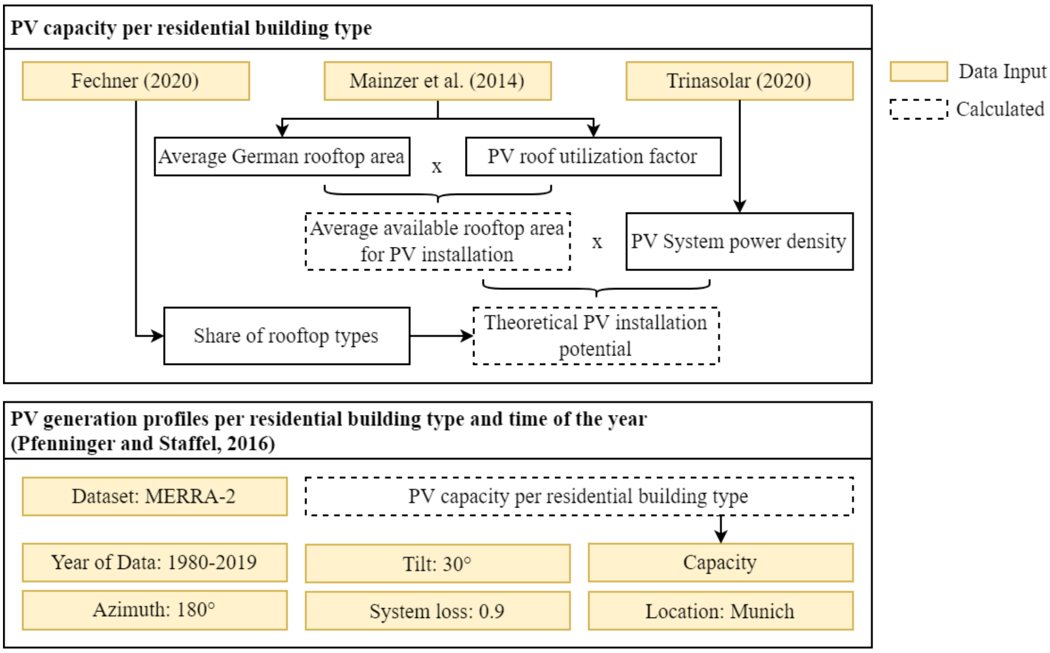

Figure 12: Model of PV generation.

Equation (6).

$$P_{house} = P_{PV} - P_{HH} \tag{6}$$

where $P_{HH} = \sum_j^h P_{HH}^j$ equals the sum of all household loads including EV loads in this specific house. P_{PV} represents the electrical PV yield of the PV system. All values only represent a specific timestep.

In a passive integration approach the following strategy is applied: If P_{house} at a given timestep is greater 0, the excess energy is used to charge the BESS. If the BESS already has a SOC of 100% then the house acts as an electrical supply and provides energy to the grid. If P_{house} is smaller 0, energy from the BESS is consumed to supply the house loads. If the SOC of the BESS is 0% then the house acts as an electrical sink and draws power from the grid. The SOC at the beginning of the week is initialized with a random SOC, which is obtained after one week of simulation.

5.5. Model of the distribution grids

This section describes the selected grid models, how simulated loads are integrated into the grid and the power flow methodology.

Representative networks grid model based on street maps and DSOs data are employed for varying agglomeration types to model electrical distribution grids.[204] SimBench distribution grids are based on typical German LV grid topologies and statistically represent average German grids.[205] The node layout of the selected grid is displayed in Figure 13 and Table 13 illustrates corresponding grid characteristics. All lines are realized as cables with diameters ranging between 150 mm^2 and 240 mm^2. In the power flow model, each supply point is realized as a simulated house. An exception is the urban grid, where more than one house can be connected to a supply point. Average grid lines differ greatly with an average feeder length of 367.5 m in the rural grid, 298.3 m in the semi-urban grid and 154.3 m in the urban grid respectively. Therefore, it is expected that voltage deviations are highest in the rural grid.

The load flow simulation is carried out with MATLAB MATPOWER.[206] All power flows in the context of this thesis are solved with Newton's method while all reactive limits are enforced. As the time horizon is very large the analysis is conducted semi-dynamically by parametrizing and solving a static grid power flow problem for each individual timestep. Investigated grid metrics are: (1) Maximum transformer loading and reverse power flows, (2) line loadings, and (3) voltage deviations. The maximum transformer loading is specified by the individual transformer's characteristics. Excess PV generation can lead to undesired reverse power flows, resulting in the transformer feeding energy from the LV grid to the MV grid. Maximum line loadings are calculated based on the maximum specified current of the line which mainly depends on the conductor material, the line diameter and the type of installation. All lines are installed in earth resulting in maximum current of 270 A for the NAVY 4x150 mm^2 line and 357 A for the 4x240 mm^2 line. Maximum power loadings of the line can then be calculated with Equation (7).

$$P = V * I * \sqrt{3} \tag{7}$$

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[204] Cf. Meinecke, Thurner, and Braun (2020); Cf. Sarajlic and Rehtanz (2019).

[205] Cf. Meinecke, Sarajlić, et al. (2020, p. 9).

[206] Cf. Zimmerman, Murillo-Sanchez, and Thomas (2011).

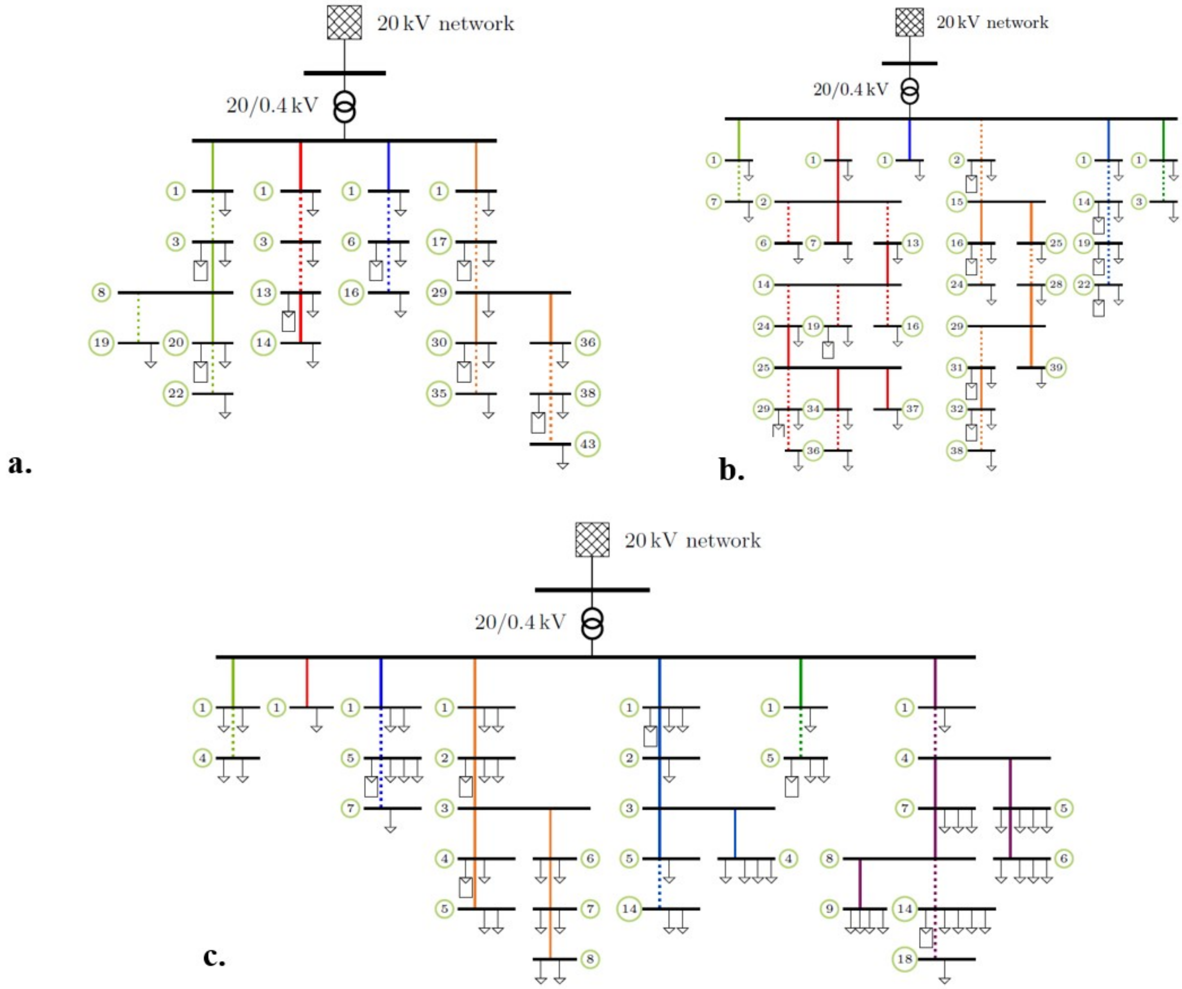

Figure 13: Illustration of selected grid topologies. **a.** Rural LV grid13 model; **b.** Semi-urban LV grid model; **c.** Urban LV grid model.

Cf. Sarajlic and Rehtanz (2019, p. 4).

Table 13: Characteristics of selected 0.4 kV distribution grids.[a]

	Rural grid (LV02)	**Semi-urban grid (LV05)**	**Urban grid (LV06)**
Transformer Sr	1x250 kVA	1x630 kVA	1x630 kVA
Line type	NAVY 4x150 mm^2	NAVY 4x240 mm^2	NAVY 4x240 mm^2
Overall line length	1.47 km	1.79 km	1.08 km
Number of supply points	93	104	53
Number of feeders	4	6	7

[a] Cf. Prettico, Gangale, Mengolini, Lucas, and Fulli (2016, pp. 40–48).

where P is power in Watt, V is the voltage of the line in Volts and I is the specified current of the line in Ampere. Line overloads mainly occur in feeders near the transformer. Maximum voltage deviations are defined in EN 50160 for German power grids. Voltage levels below 0.9 p.u. and above 1.1 p.u. are unsatisfactory and 95% of the 10-minute mean values for a week must obtain these limits.[207] Grid loads are deployed with a fixed power factor $cos(\varphi)0.93$ for individual loads,

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[207] Cf. DIN (2020).

while PV generation is assumed to have a power factor of 1.0.[208]

6. Impact of EV charging on distribution grids

Electrical load profiles are realized with the model such that each agglomeration scenario is populated with the respective number of households. This results in an average of 189 simulated households for the rural grid, 420 households in the semi-urban grid and 444 households in the urban grid. Solving the power flow problem allows an analysis of the grid metrics of interest. Owing to the natural fluctuations of the simulation results each scenario is simulated for 200 iterations. Based on this information, percentiles on how likely it is that a specific metric is violated, can be derived. This is important as distribution grids are not designed to withstand concurrent peak loads of all consumers in the grid. Instead, maximum capacities are calculated with a concurrency level and thus very small probabilities of grid metric violations are tolerated.[209]

The following section presents the results of the power flow analysis. First, results in the rural grid are introduced, influences of time of year variation and chosen grid metrics are discussed. Subsequently, the semi-urban power flow and the urban power flow are analyzed based on selected cases.

6.1. Rural grid

In this case a mean of 189 households is simulated for a period of one week. Figure 14 illustrates the median value of the deployed electrical profiles for the March case with an assumed EV and PV penetration level of 30%. The solid blue line depicts household loads, while the solid orange line illustrates the sum of household and EV charging loads. Household loads peak at 202 kW, which is 80.8% of the transformers capacity and in line with the grid load specifications of Sim Bench.[210] Results align with existing literature and indicate strong temporal patterns in household and EV charging loads. Load profiles show a great deviation between weekdays and weekends. While overall household loads are higher during weekends, additional EV charging loads during weekends are not as pronounced. Weekday peak loads increase by 25% due to EV charging and by 16% during weekends.

a. PV generation and reverse power flows

The solid yellow line in Figure 14 indicates the PV yield. Comparing this profile with load profiles confirms literature findings of weak chronological coincidences between PV generation and electrical peak loads, especially during weekdays. This leads to excess PV electricity generation which is fed back into the grid by the house supply point. This can be beneficial when neighboring supply points still demand electrical energy. However, if total PV yield surpasses total loads in the distribution grid, reverse power flows in the transformer occur. This is illustrated in Figure 15. The shaded area depicts the energy which is fed back into the medium voltage grid. The extend of excess energy strongly depends on the time of year, as shown by 15a, 15b, 15c, and 15d. The occurrence of these reverse power flows is not desired and might be limited by DSOs. Besides already considered curtailment measures, such as limiting PV generation to 70% of the peak power, further curtailment can be necessary. In the case without BESS, PV generation between 9:15 a.m. and 2:45 p.m. needs to be curtailed in June to eliminate the occurrence of reverse power flows. By introducing household BESS part of the excess energy can be stored. This is illustrated in Figure 16 which indicates the power flow into the battery as negative values and the power output of the battery as positive values. This additional energy storage and exchange significantly reduces the occurrence of reverse power flows as illustrated in the worst-case June scenario in Figure 16. First, the BESS are charged beginning at 7:00 a.m. when the net sum of generated electricity is higher than the electrical demand. During afternoon the average electrical demand of the houses start to surpass the PV generation. The overall sum of power outflow is higher than the power inflow as early as 3:00 p.m. and peaks at 7:15 p.m. Afterwards, the BESS is still able to supply the houses with energy, which indicates that the capacity of the BESS can sufficiently support electrical loads in the rural grid.

b. Transformer loads

An investigation of transformer limits for varying EV penetration rates indicates that maximum transformer loadings can be exceeded in certain simulation iterations. Figure 17 illustrates the mean transformer use factor for a weekday with varying EV penetration rates. The use factor is calculated with Equation (8).

$$Usefactor = \frac{P_{actual}}{P_{max}} \tag{8}$$

where P_{actual} represents the actual load in Watt and P_{max} equals the specified maximum power limit in Watt. A use factor of 1 indicates a load equal to the specified maximum load and is thus the critical threshold.

Based on mean values transformer limit violations are observable with 60% EV penetration as depicted with the yellow line. Grid loads can be of high volatility. Therefore, individual simulation iteration results are analyzed. Figure 18 illustrates the use factor of the transformer for all simulation iterations with an 30% EV penetration. The solid black line depicts the median value of all simulation iterations of the selected scenario. The red shaded area equals the respective percentiles where each shade represents a 5-percentile step. The simulation result shows that 20-percentile of simulations exceed the transformer limits with 30% EV penetration on Sunday. Limit violations occur during a very short period during weekdays in case of grid loads without PV and BESS interaction. Figure 18(b) and 18(c) illustrate the effect of additional PV arrays and BESS interaction respectively. The

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[208] Cf. Meinecke, Sarajlić, et al. (2020, p. 5).

[209] StromNEV §16 II Anlage 4.

[210] Cf. Sarajlic and Rehtanz (2019, p. 3).

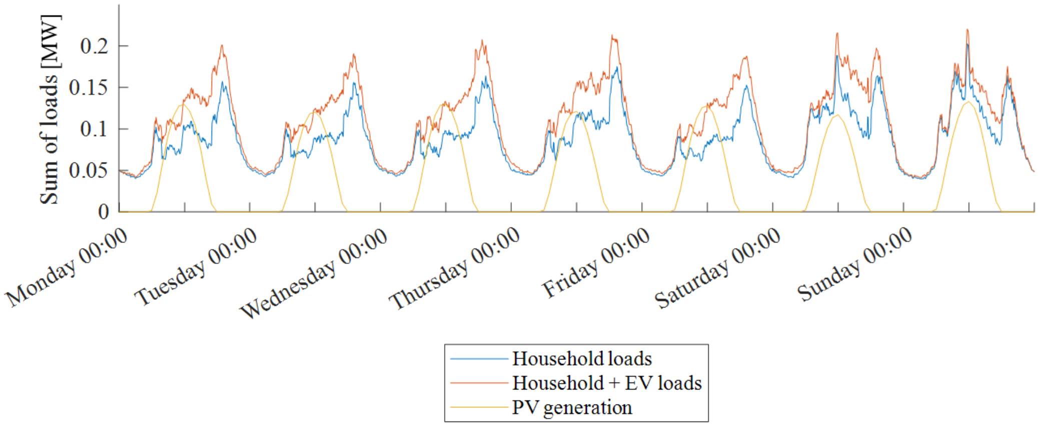

Figure 14: Median of deployed electrical load profiles for the rural grid in March with 30% EV and PV penetration.

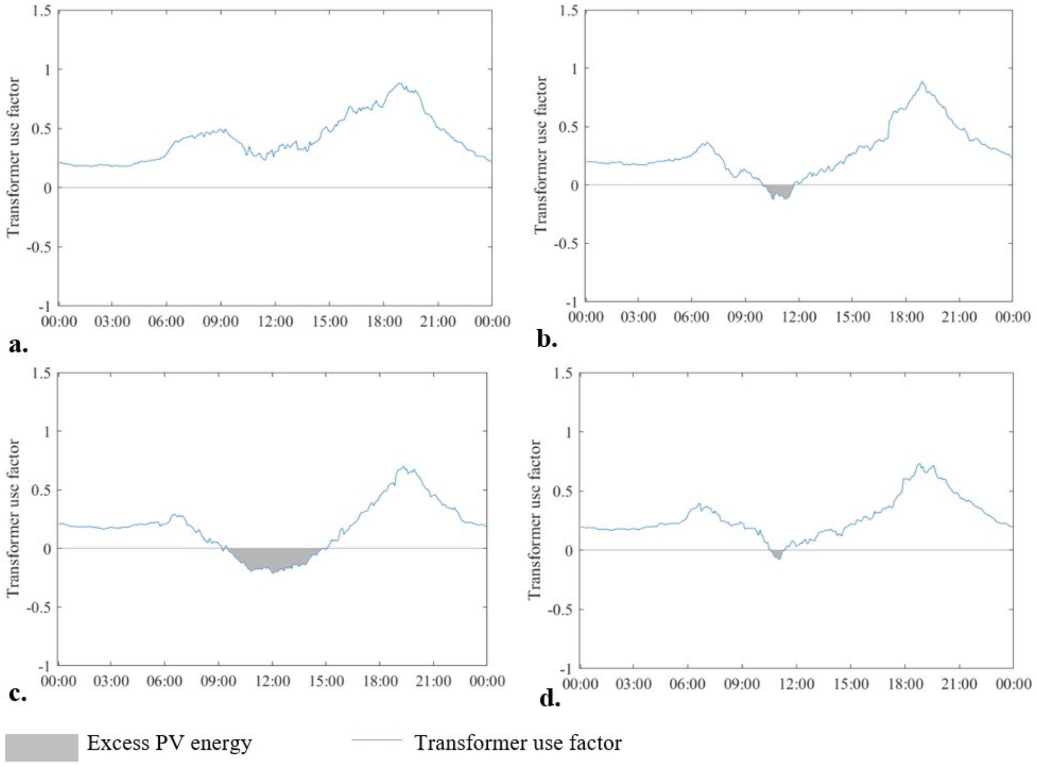

Figure 15: Excess PV energy with 30% PV penetration **a.** December; **b.** March **c.** June, **d.** September.

results demonstrate two things: First, the mitigation potential of solely adding PV generation is limited during weekdays but very effective on weekends. This is in line with findings of existing literature. Second, BESS can shave peak loads during time of days with little to no PV yield. This is visible in Figure 18c, where no transformer limit violations are observable.

c. Line loads

Next, loads of feeder lines depending on the EV penetration rate and time of year are investigated. Line limits can be exceeded at EV penetration rates of 40%. Most critical are the lines after the step-down transformers in long branches, as these must bear the load of all following houses in this feeder branch. Line limit violations in general are considered more critical than transformer overloading, as line temperatures cannot be precisely monitored and thus line limits are conservatively sized.[211] The line use factor of the most critical branch in the rural grid with 30% EV penetration is illustrated in Figure 19 for a period of one week. The lines still have enough capacity to cope with additional EV charging loads.

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[211] Cf. Nesti, Nair, and Zwart (n.d.).

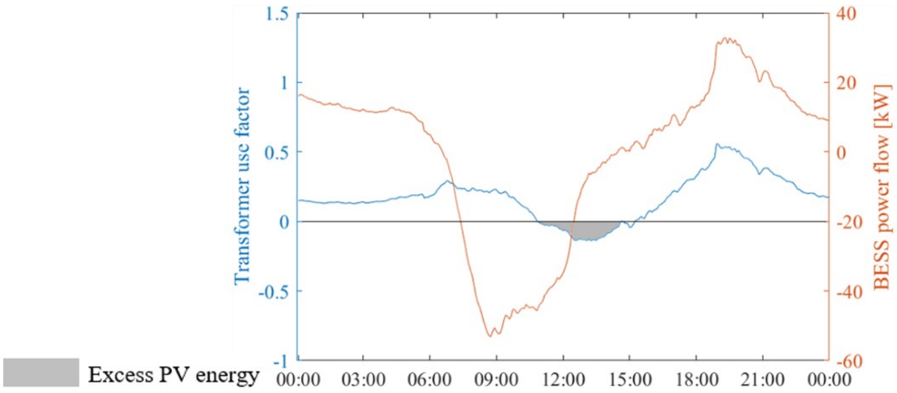


Figure 16: BESS interaction and transformer use factor in the rural grid in June.

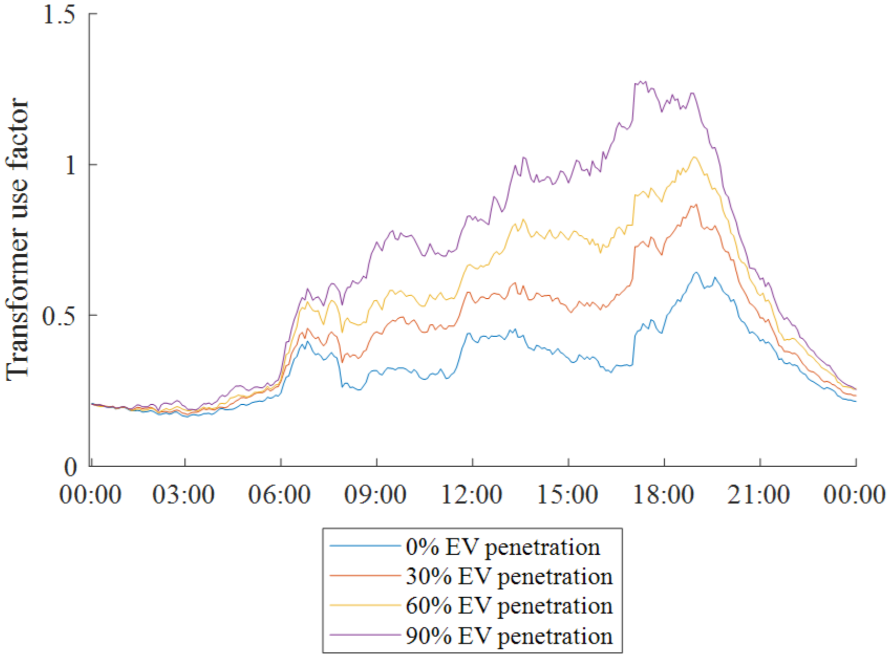


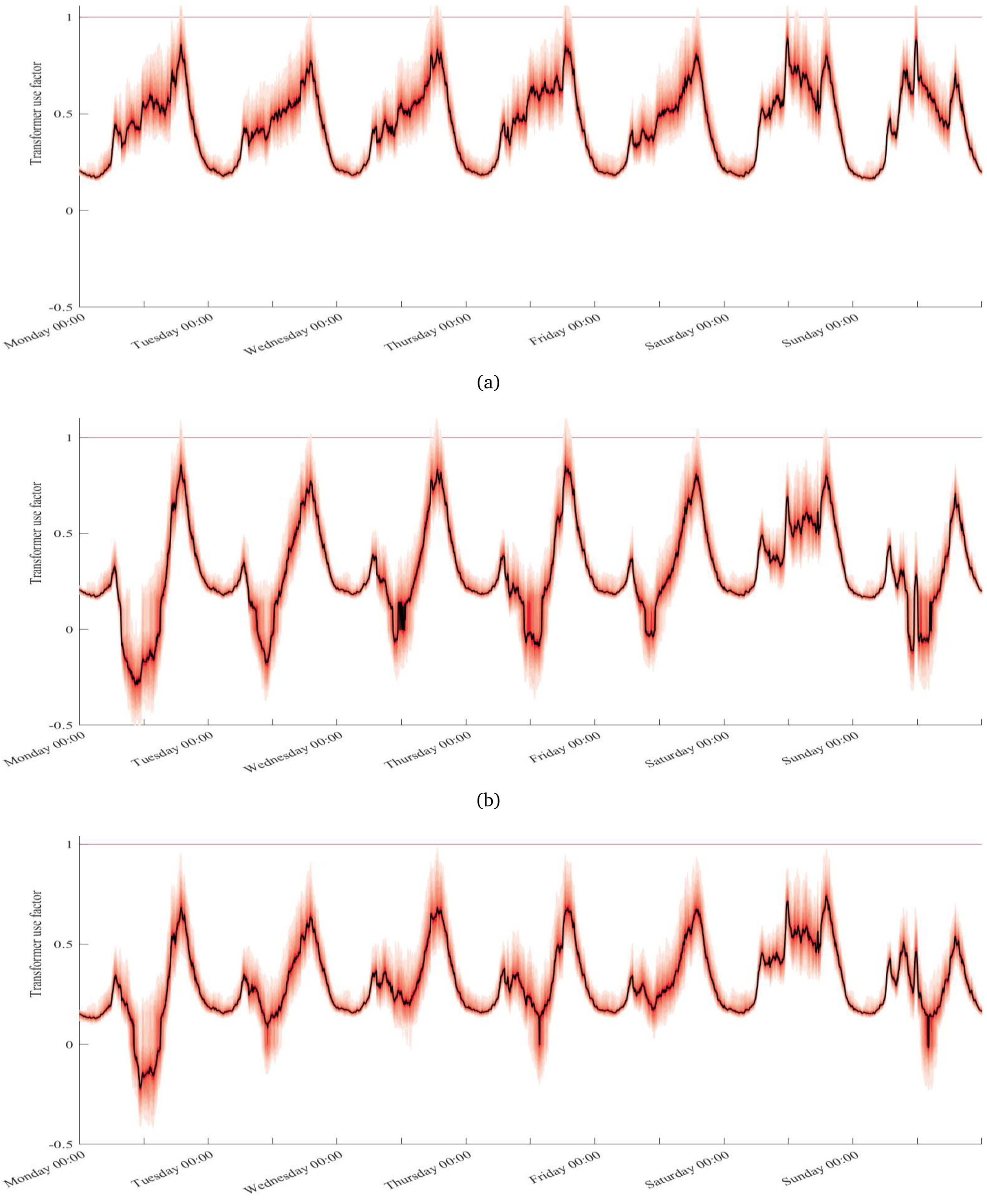
Figure 17: Mean transformer use factor for a weekday in the rural grid with varying EV penetration rates.

d. Bus voltages

Minimum bus voltages have been monitored and are presented in Figure 20 for an 30% EV penetration scenario in March. Under voltage issues are most likely to occur in the last line of the feeder branch with the highest overall line length. In general, voltage deviations appeared to be moderate and increasingly an issue with very high EV penetration rates. During the simulation period the moments of under voltage occurrences were counted. For investigated EV penetration rates of up to 75% no under voltage occurrences were observable.

e. Sensitivity of load mitigation

To understand the full potential of EV charging load mitigation with PV and BESS, simulations are carried out for varying time of years, PV penetration, and EV penetration. Figure 14 illustrates the sensitivity of the line limit violations in case of PV and BESS interaction. Numbers indicate the percentile of simulations where a limit violation occurred. December represents the worst-case scenario, as PV generation is low and electrical consumption by households and EVs is larger. Higher PV penetration rates as well as seasons with high solar irradiation significantly improve the mitigation potential of residential PV arrays with BESS. Figure 14 also indicates that rural lines in the SimBench grid are generously dimensioned for transmitting a high amount of power. Compared to Figure 15 where the sensitivity of transformer limit violations in case of PV and BESS interaction is displayed, violations of line limits are much rarer than transformer limit violations. Figure 15 indicates that with 40% EV penetration most simulated iterations exceed line limits in the December case, while this share significantly reduces with higher PV penetration rates and more solar irradiation in June. Limit



(a)

(b)

(c)

Figure 18: Rural transformer use factor in March. **a.** Household and 30% EV penetration; **b.** Household and 30% EV + PV penetration; **c.** Household and 30% EV + PV + BESS penetration.

violations occur for lower EV penetration rates mainly on weekends while for EV penetration rates above 50% the most critical violations occur during weekday evenings.

Together, these simulations suggest that the rural grid cannot reliably withstand EV penetration rates above 30%. Limit violations occur in the rural MV-LV transformer. Line limits as well as undervoltage limit violations only occur at higher EV penetration rates. Additional PV generation is not able to mitigate the loads effectively due to weak chronological coincidence. Paring a PV system with BESS greatly increases the mitigation potential. However, low solar irradiation in months with shorter daytimes limit the effect. Higher PV penetration increases the supporting potential but on the other hand introduces stronger reverse power flows.

6.2. Semi-urban grid

The semi-urban grid loads are realized with 420 simulated households containing approximately 1,530 individuals. Figure 21 illustrates the median value of the deployed electrical profiles for the March case with an assumed EV and

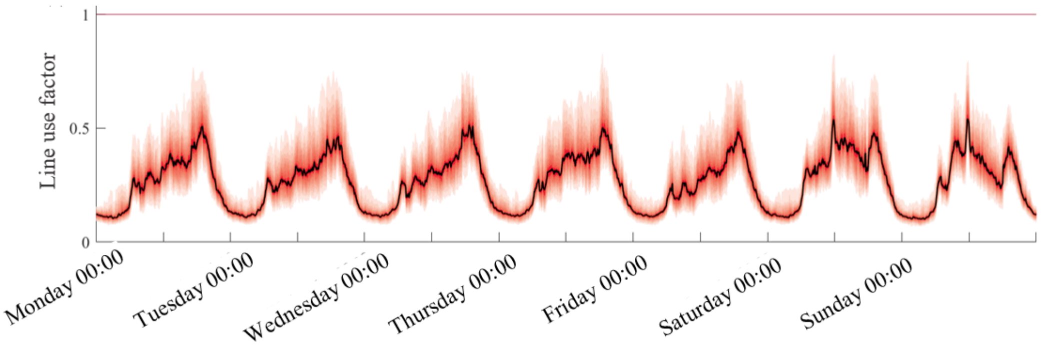


Figure 19: Use factor of critical line in rural grid with 30% EV penetration.

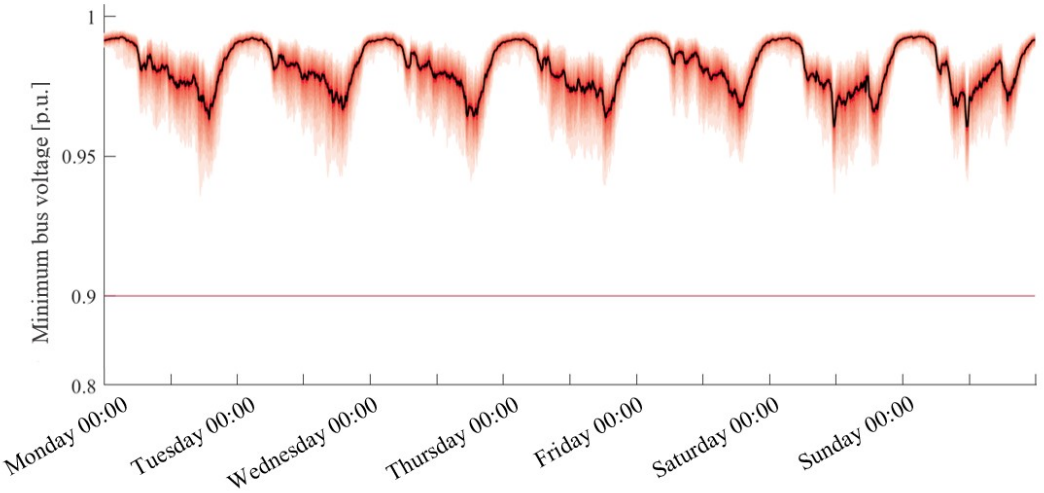


Figure 20: Minimum bus voltages in rural grid with 30% EV penetration.

Table 14: Percentile of simulation iterations with rural line limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	1	0	0	0
30	2	0	0	0
40	4	3	0	0
50	7	5	1	0
60	11	6	4	1
70	20	19	11	8

a.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	5	2	0	0
50	9	4	1	0
60	14	5	3	0
70	21	16	9	2

b.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	1	0	0	0
50	2	0	0	0
60	4	0	0	0
70	6	0	0	0

c.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	5	1	0	0
50	9	3	1	0
60	14	5	2	0
70	20	16	7	1

d.

PV penetration level of 30%. Household loads peak at 433 kW which is 69% of the transformer's capacity. Therefore, the semi-urban grids' household base load is not as high as the rural grids' load. 30% EV penetration leads to an approximately 23% increase in peak loads during weekdays and is comparable to the peak load increase in the rural grid.

a. PV generation and reverse power flows

The PV generation per household is significantly smaller compared to the rural grid. This is due to the conditional probability on the number of households per house. Therefore, reverse power flows do not occur in the median case in March with 30% EV and PV penetration. This is an important finding in the understanding of the maximum feasible PV penetration rate to minimize the occurrence of reverse power flows.

b. Line loads

Table 15: Percentile of simulation iterations with rural transformer limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]

a.

	0	30	60	90
0	0	0	0	0
10	25	7	1	0
20	43	21	7	3
30	54	39	24	12
40	64	45	36	30
50	71	51	45	41
60	74	59	52	49
70	85	67	59	55

b.

	0	30	60	90
0	0	0	0	0
10	3	0	0	0
20	9	0	0	0
30	17	0	0	0
40	35	19	9	7
50	51	34	26	21
60	64	43	38	34
70	74	55	49	45

c.

	0	30	60	90
0	0	0	0	0
10	1	0	0	0
20	9	0	0	0
30	24	0	0	0
40	37	0	0	0
50	47	3	0	0
60	54	8	0	0
70	63	11	1	0

d.

	0	30	60	90
0	0	0	0	0
10	3	0	0	0
20	8	2	0	0
30	17	6	0	0
40	34	20	8	6
50	50	33	25	19
60	63	41	36	31
70	73	52	46	41

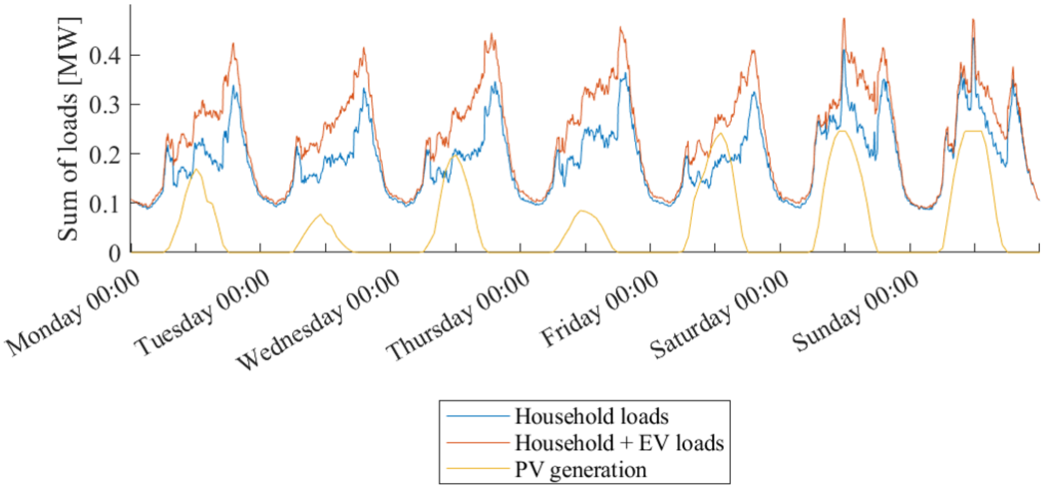


Figure 21: Median of deployed electrical load profiles for the semi-urban grid in March.

The relatively higher transformer capacity influences results such that transformer overloading's are not as likely to occur. On the other hand, line limit violations increase earlier in frequency with higher EV penetration rates. Line limits are illustrated in Figure 22 for an EV penetration rate of 30%. The mitigation impact of additional PV and BESS are not as pronounced as in the rural grid. While peak line loadings are slightly reduced, the influence is weaker.

c. Bus voltages

Undervoltage issues were not observable for all investigated EV penetration rates. This is most likely due to the high number of feeders and relatively low line length in combination with generously dimensioned line diameters.

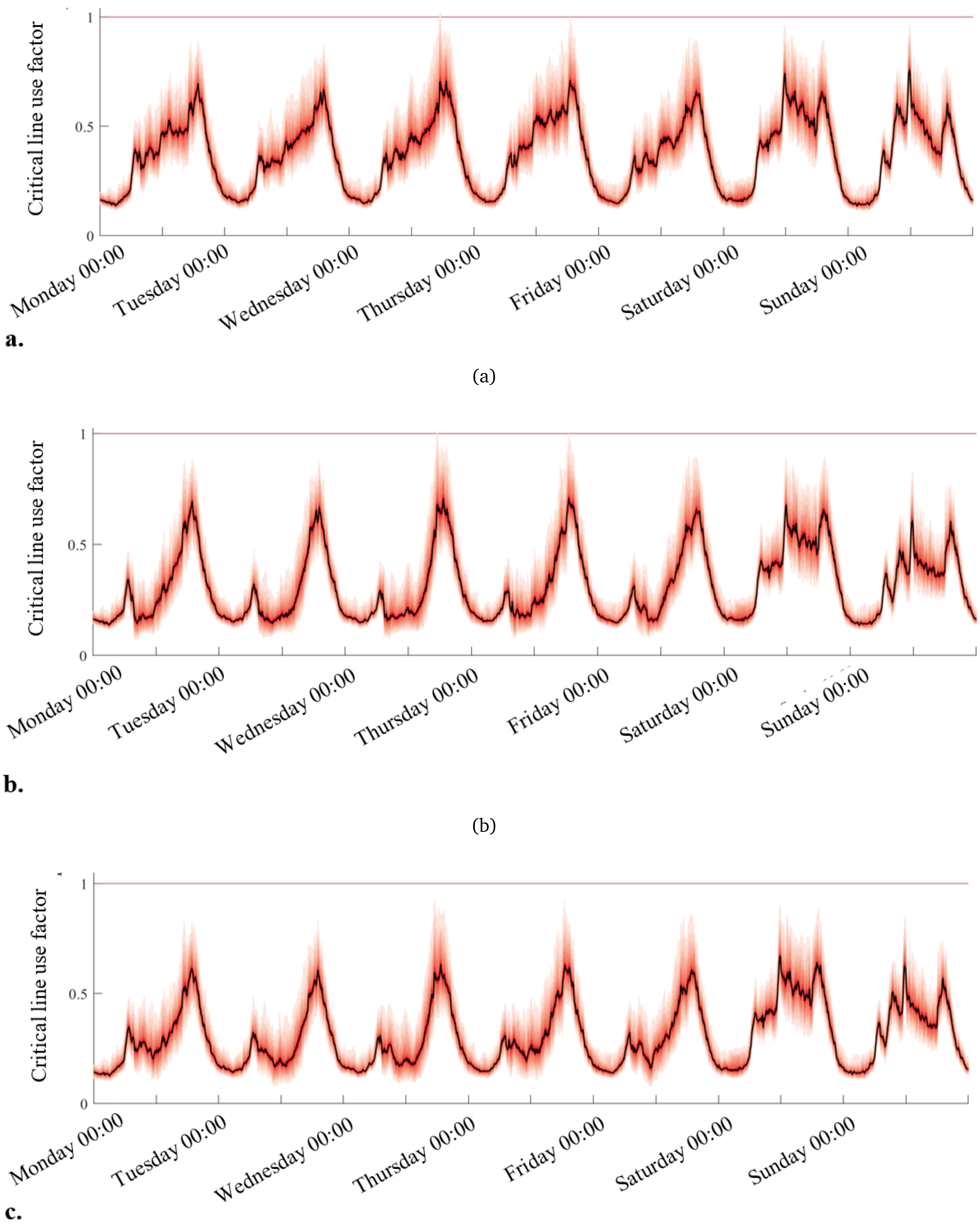
d. Sensitivity of load mitigation

Figure 16 illustrate the percentile of simulation iterations where line limits got violated. First violations occur with EV penetration rates as low as 10% in December. Higher PV penetration rates as well as seasons with higher solar irradiance significantly reduce the likelihood of limit violations for low EV penetration rates. Compared to the rural grid, the semi-urban grid step down transformer is not as likely to be overloaded, as shown in Figure 17. First limit violations occur at 20% EV penetration. Further, the June scenario mitigates transformer limit violations due to additional charging loads, completely for investigated EV penetration rates of up to 70%.

Overall, the semi-urban grid seems more robust dimensioned compared to the rural grid. Critical components are primarily lines. Transformer limits as well as undervoltage limit violations only occur at higher EV penetration rates. PV arrays with BESS help to reduce loads on grids. 30% penetration of the forementioned increases the maximum feasible EV penetration rate by 10% in the worst-case in December and 40% in the best case in June.

6.3. Urban grid

The urban grid loads are realized with 444 individual simulated households connected to 53 supply points of the grid. Therefore, this grid is the most complex in terms of number of simulated individuals. At the same time loads are spatially concentrated on a smaller number of supply points with short line distances in between. Figure 23 illustrates the median value of the deployed electrical profiles for the March case with an EV and PV penetration level of 30%. House-



(a)

(b)

(c)

Figure 22: Semi-urban line use factor in March. **a.** Household and 30% EV penetration; **b.** Household and 30% EV + PV penetration; **c.** Household and 30% EV + PV + BESS penetration.

Table 16: Percentile of simulation iterations with semi-urban line limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	3	0	0	0
20	7	2	0	0
30	12	5	0	0
40	21	8	5	0
50	35	24	22	16
60	55	53	49	48
70	64	62	58	55

a.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	2	0	0	0
30	5	0	0	0
40	12	5	1	1
50	19	10	6	4
60	26	17	13	11
70	47	38	34	28

b.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	1	0	0	0
20	3	0	0	0
30	5	0	0	0
40	12	0	0	0
50	18	2	0	0
60	25	5	0	0
70	40	10	0	0

c.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	2	0	0	0
30	5	0	0	0
40	12	5	1	1
50	18	10	5	4
60	25	16	12	9
70	46	37	33	26

d.

Table 17: Percentile of simulation iterations with semi-urban transformer limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	1	0	0	0
30	3	1	0	0
40	18	8	5	2
50	33	24	21	16
60	50	49	46	43
70	61	60	58	55

a.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	3	0	0	0
50	9	3	2	1
60	17	8	5	2
70	45	27	21	17

b.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	1	0	0	0
50	5	0	0	0
60	12	0	0	0
70	21	0	0	0

c.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	2	0	0	0
50	7	3	1	0
60	16	8	4	1
70	45	26	19	15

d.

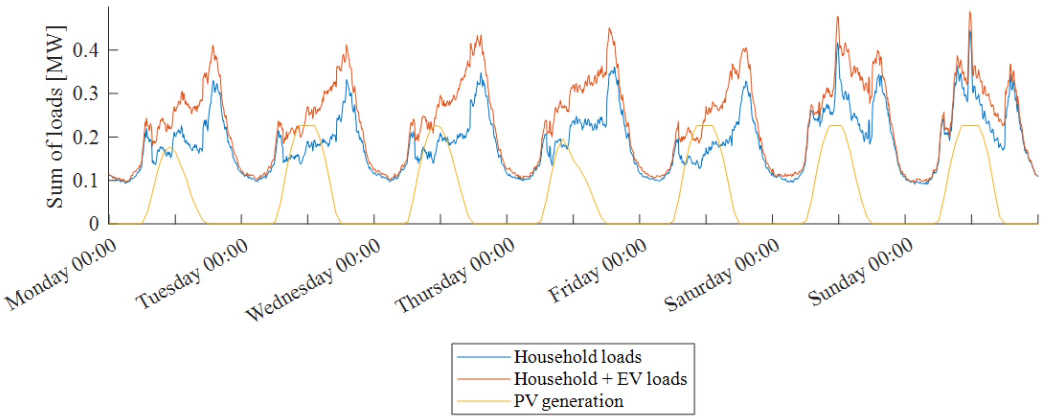


Figure 23: Median of deployed electrical load profiles for the urban grid in March.

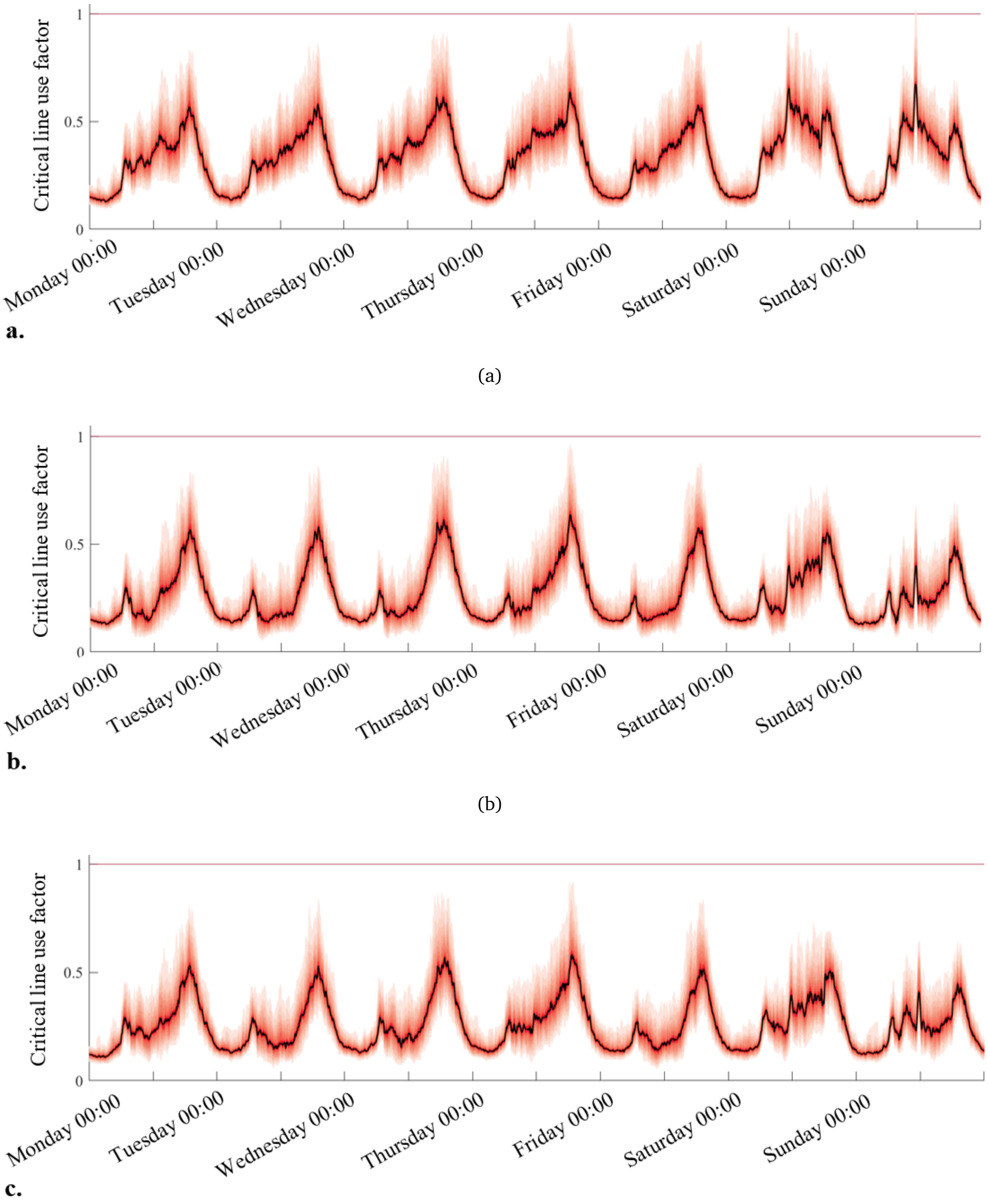
hold loads peak at 440 kW which is 70% of the transformer's thermal capacity.

a. PV generation and reverse power flows

The overall PV yield per household in this type of grid is the smallest. This is due to the high number of multifamily homes. Integrating additional EV charging loads leads to no reverse power flows in the March case even without a BESS. This is beneficial as higher PV penetration rates can be implemented without the need of any curtailment measures.

b. Line loads

An investigation of transformer and line load limits indicates that transformers are not the most critical component in the grid. This is due to the smaller use factor of the transformer in the base-case without EV loads. An analysis of line use factors over the simulation period of one week in March is presented in Figure 24. Line limits are most likely to be exceeded at weekends in a scenario with 30% EV penetration. Compared to the former two investigated grids, more volatility in deployed loads is observable in the urban grid. This is due to the relatively high number of simulated households



(a)

(b)

(c)

Figure 24: Urban line use factor in March. **a.** Household and 30% EV penetration; **b.** Household and 30% EV + PV penetration; **c.** Household and 30% EV + PV + BESS penetration.

and individuals. This leads to a higher likelihood of extreme cases where multiple peak loads coincide. A small percentile of simulations exceeds line load limits with 30% EV penetration. The addition of a PV array with BESS significantly reduces the median line use factor for the whole week, while worst-case peaks remain relatively unchanged. This might be due to the constant size of the BESS which is independent of the house size. Multi-home houses are therefore more likely to deplete the stored energy before the evening peak load occurs.

c. Bus voltages

An analysis of the voltage behavior suggests that undervoltage issues do not occur in the urban grid. This is owed to the short feeder line lengths and thus voltage drops are not as significant. The worst-case scenario for line voltages are high and focused loads in branches. Figure 25 illustrates minimum line voltages in the urban grid during December with an EV penetration rate of 75% and no PVs.

d. Sensitivity of load mitigation

To understand how varying EV and PV penetration rates

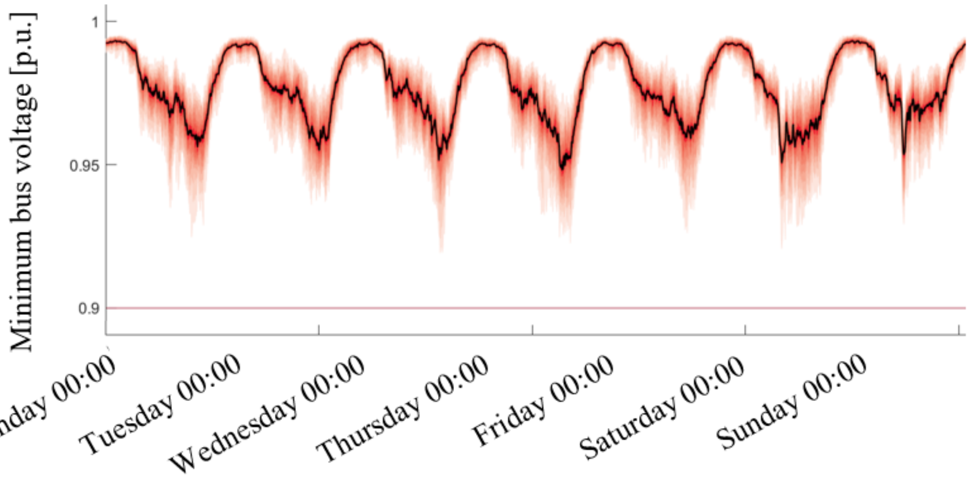


Figure 25: Minimum bus voltage in the urban grid in December with 75% EV penetration.

Table 18: Percentile of simulation iterations with urban line limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	1	0	0	0
20	4	1	0	0
30	10	3	0	0
40	19	10	7	1
50	29	18	12	4
60	40	29	14	11
70	51	39	17	15

a.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	1	0	0	0
30	3	0	0	0
40	9	3	1	0
50	14	6	3	1
60	17	9	6	4
70	32	12	9	7

b.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	1	0	0	0
40	8	0	0	0
50	13	0	0	0
60	16	0	0	0
70	19	5	5	1

c.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	1	0	0	0
30	3	0	0	0
40	9	3	1	0
50	13	6	2	1
60	16	8	5	3
70	31	12	8	6

d.

Table 19: Percentile of simulation iterations with urban transformer limit violations with PV and BESS. **a.** December; **b.** March; **c.** June; **d.** September.

PV and BESS penetration [%]

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	1	0	0	0
20	5	0	0	0
30	12	0	0	0
40	27	5	0	0
50	40	16	4	3
60	51	31	12	10
70	65	48	35	34

a.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	1	0	0	0
40	7	0	0	0
50	12	2	1	1
60	17	5	4	3
70	40	16	11	7

b.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	2	0	0	0
50	7	0	0	0
60	16	0	0	0
70	23	2	0	0

c.

EV penetration [%]	0	30	60	90
0	0	0	0	0
10	0	0	0	0
20	0	0	0	0
30	1	0	0	0
40	6	0	0	0
50	12	1	1	1
60	17	4	4	3
70	38	15	10	6

d.

influence the results, a sensitivity analysis was conducted for urban grid loads as well. This is depicted in Figure 18 and Figure 19. Compared to the base-case without PV, the 30% PV and BESS penetration case increased maximum feasible EV penetration by approximately 10% in December and 50% in June. These results cast new light on the potential of EV charging load mitigation with PV arrays depending on the time of year.

The urban grid is more robust compared to the rural grid. Even though this grid has the lowest PV generation capacity per household, the addition of PV and BESS still mitigated grid overloading's induced by additional EV charging successfully. With increasingly higher EV penetration rates line limits are violated first, afterwards the urban transformer limits are exceeded.

7. Discussion

This section summarizes the findings and contributions made and discusses potential implications as well as limitations.

7.1. Potential of PV and BESS to mitigate EV charging loads

The developed simulation models allowed to study the impact of high EV penetration, PV penetration as well as BESS interactions in varying grid topologies and time of year. Extensive results show that the presence of PV arrays have the potential to mitigate EV charging impact, especially during weekends. The intermittent nature of PV generation however limits the mitigation potential for peak loads which occur on weekdays in the evening. This result ties well with previous studies.[212] A promising finding was that BESS can leverage the potential of PVs to mitigate the charging impact. Further, they contribute to improved electrical quality as well as higher PV self-consumption by reducing the need for power curtailment measures. In general, maximum feasible EV penetration rates increased by 10% - 50% while the need for active power curtailment measures was reduced. With the addition of PV arrays in combination with BESS, grids can be sufficiently supported to handle EV charging loads of the targeted EV penetration of 30% for 2030. Especially, as some DSOs allow a temporarily loading of 130% of maximum steady-state loading for MV/LV transformers.[213] This however reduces the lifetime of the transformer.[214]

The results also demonstrated that for this thesis employed measures and assumptions regarding PV penetration and BESS are not enough to support the long-term goal of 100% electrification in the transport sector. One weakness is that the potential to mitigate charging impacts strongly depends on time of year dependent solar irradiance. While PV generation in summer months has the potential to generate enough electricity to mitigate evening charging loads, this is not the case in December. Here, higher PV penetration rates as well as bigger BESS are required to support grids sufficiently.

Critical grid components are transformers in the rural grid, and feeder lines in the semi-urban and urban grid. Limit violations mainly occur in feeder lines as well as MV/LV transformers. These findings are in accordance with findings reported by previous studies.[215] Contrasting to existing literature voltage deviations are not as likely to occur.[216] This is mainly due to two reasons. First, SimBench lines in rural grids (which are most prone to undervoltage issues) are generously sized compared to other LV rural grids.[217] Second, the investigated power flow assumes balanced loads and therefore single-phase overloading and thus resulting undervoltage is more unlikely. Further implications of this assumption and other limitations are discussed in the next section.

7.2. Limitations and uncertainties

One limitation of the implementation is that only home charging is assumed. Therefore, charging loads are probably overestimated as the whole EV energy demand is supplied by the residential distribution grid. Furthermore, this thesis modelled the grid loads symmetrically. Because a three phase 11 kW AC charger was set as the charging standard it was assumed that all additional loads in the grid are balanced. In practice, smaller chargers might be used as well. These draw power from one or two phases and might introduces significant imbalances requiring an investigation of grid imbalances as this can have an influence on results.[218]

Other limitations are given in the simulation of driving and household behaviors. Both these behaviors are not linked to each other therefore reducing load overlapping. It might be expected that an agent arrives at home, connects the EV, and begins to perform energy intensive household tasks. Therefore, charging loads and energy intensive household loads might coincide more frequently. This is supported by the fact that it was assumed that the number of charging ports equals the number of EVs in a household. It is likely that a household only invests in one EV charging station instead of owning a charger for each EV. These limitations are apparent in many existing simulations. Furthermore, this thesis assumes that all households regardless of role in the society follow the same mobility behavior. This was done because the mobility dataset was too sparse to categorize individuals in specific groups.

While reverse power flows have been investigated, uncertainties regarding the occurrence of overvoltage have not been addressed in this study. This is due to limitations of MATLAB MATPOWER to model renewable energy sources. Because of this potential limitation, this thesis treated excess PV energy, as energy which should be curtailed.

In conclusion, some limitations might increase the impact of EV charging on distribution while other limitations reduce the impact. The results in general, provide a better understanding of the exact interactions between EV charging loads, distributed PV energy generation and BESS. A differentiation between agglomeration scenarios and time of year enables a holistic view on the issue at hand.

8. Conclusion

New energy challenges and greenhouse gas emissions necessitate a shift towards mobility and energy solutions without fossil fuel dependency. The presence of EVs will introduce substantial challenges for distribution grids, on the one

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[212] Cf. Luthander et al. (2019); Cf. ElNozahy and Salama (2014).

[213] Cf. Meinecke et al. (2019).

[214] Cf. Gray and Morsi (2017); Cf. Hong et al. (2020).

[215] Cf. Wang and Infield (2018); Cf. Habib et al. (2020); Cf. Clement-Nyns et al. (2010).

[216] Cf. Ul-Haq et al. (2015); Cf. Ma et al. (2017); Cf. Clement-Nyns et al. (2010).

[217] Cf. Prettico et al. (2016).

[218] Cf. Held et al. (2017, pp. 8–10).

hand. Distributed and emission free PV electricity generation on the other hand, provides a unique opportunity to support distribution grids. Understanding EV charging loads and fed in distributed electricity into electrical distribution grids is therefore essential. This thesis deployed representative grid models for varying agglomeration scenarios and seasons to model the synergy potential between high EV penetration rates, PV electricity generation and BESS.

Results show that the presence of PV arrays with BESS have the potential to mitigate EV charging impacts. In general, maximum feasible EV penetration rates can be increased by 10% - 50% depending on the grid topology and the time of year. At the same time active power curtailment measures which might be necessary due to excess PV energy can be reduced. With the addition of PV arrays in combination with BESS, grids can sufficiently support EV charging loads of the targeted EV penetration of 30% for 2030 in Germany. Whilst rural grids are most vulnerable to increased loads through higher EV penetration rates, the mitigation potential with PV electricity generation and BESS is also highest. This is due to the spatial conditions as well as population density. The simulation results suggest that the feasible PV yield per household in rural areas is significantly higher than the PV yield in urban areas. Semi-urban and urban grids on the other hand are more robustly dimensioned in Germany and transformer overloading is not as likely to occur.

Limitations in the mitigation potential are given due to the intermittent nature of PV generation and the strong dependence on seasonality patterns. EV penetration rates of 50% and above are not supportable with the current grid infrastructure and the assumed PV and BESS specifications. To cope with days of low PV yield, the BESS might also require charging energy from the grid. Therefore, it can be guaranteed that BESS have enough stored energy to shave critical peak loads. Governmental incentives might be required to increase PV adoption rates, to achieve necessary PV penetration rates and to support the widespread installation of BESS. Recent price reductions for battery capacity as well as affordable BESS by extending used EV batteries' lifetime increases the feasibility of widespread BESS installation.[219] Future research should investigate if the integration of widespread PV with BESS also proves economically feasible by comparing investment costs, energy cost savings, and practicability of alternative measures.

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[219] Cf. Heymans et al. (2014).

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