Leveraging the Benefits of Integrating and Interacting Electric Vehicles and Distributed Energy Resources

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Leveraging the Benefits of Integrating and Interacting Electric Vehicles and Distributed Energy Resources

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Abstract

In this paper, benefits resulting from the interaction of electric vehicles and photovoltaic generation units are analyzed. In doing so, a bottom-up approach is developed to simulate the driving and charging behavior of electric vehicles. An economic analysis is then performed to determine key findings for households with photovoltaic systems and electric vehicles: First, smart electric vehicle charging concepts may allow households to achieve higher cost-saving potentials by increasing their share of self-consumption by 59% compared to the case of uncontrolled charging. Second, adopting more of a system-oriented perspective, smart electric vehicle charging concepts could react to times of peak load and thereby reduce the average peak-load increase due to electric vehicles to 27%. According to these findings, it may be beneficial for policy makers to encourage peak-load minimizing charging behavior by introducing, e.g., load-sensitive tariff schemes. Technical challenges arising from the peak-load impact of electric vehicles may be regarded as being a coordination problem. Finally, the analysis shows that the potential of electric vehicles to counteract extremes of reverse power flows due to high photovoltaic electricity generation is limited.

Keywords: electromobility; distributed energy resources; energy storage; electric vehicle charging; sector coupling; energy self-sufficiency

JEL classification: C15, C61, C63, D14, H20, R20

1. Introduction

The power supply system is facing an ongoing transition from centralized to more decentralized electricity generation. The increasing share of renewable power plants as well as an increasing number of small-scale

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generation units change the requirements for the existing energy system. At the same time, an electrification of the transport sector is underway, meaning that in the coming years the number of electric vehicles will increase significantly(see ,e.g., White House (2011); Federal Government of Germany (2009)).

As more and more vehicles begin to run on electricity instead of gasoline and diesel, the absolute electricity consumption as well as the temporal load structure will be increasingly affected by vehicle charging behavior. Yet battery storage in electrical vehicles may be harnessed for additional storage applications and grid services. Put simply, electric vehicle storage may be used to smooth out the highly volatile feed-in profiles from distributed energy sources. Imagine, for example, an electric vehicle storage that is used in combination with a photovoltaic (PV) system. On the one hand, the vehicle may be directly charged using renewable energy generation. Smart charging could help to reduce or even avoid the need for electricity to be purchased from the grid and thereby allow for cost-saving potential to be leveraged, depending on the underlying regulatory framework. On the other hand, electric vehicle storage could provide additional flexibility to the power supply system (see, e.g., Kahlen and Ketter (2015); Kahlen et al. (2017)) or even be used in the context of demand-side management and grid-relieving consumption behavior given, e.g., bidirectional charging.

Yet the rapidly growing share of photovoltaics in the energy mix has resulted in an electricity generation profile that is increasingly dichotomous. In other words, there may potentially be a few hours with very high electricity generation followed by hours with zero electricity generation if the sun suddenly stops shining. A high simultaneity of photovoltaic systems feeding-in electricity at the same time stresses the grid. However, as demand and renewable electricity generation do not perfectly coincide, the application of storage technologies may be beneficial in alleviating such grid issues. Research has yet to be conducted as to whether electric vehicles could serve as sufficient buffer storage. Heterogeneity in driving profiles, for example, makes it harder to determine to what extent electric vehicles could be charged using photovoltaic systems. Therefore, the concurrence of photovoltaic electricity generation and electric vehicle charging demand should be simulated via modeling techniques that account for differences in, e.g., the individual driving behavior.

In this paper, the interaction between photovoltaic generation and electric vehicle charging behavior is analyzed extensively. More specifically, two key aspects are investigated: First, the cost-saving potential of electric vehicles in helping to achieve a high share of self-consumption on an individual household level is simulated. Second, a system-oriented perspective is assumed and the peak-load impact of electric vehicles is analyzed. Consequently, the peak-load reduction potential of electric vehicles is determined relative to different charging concepts and incentive schemes.

In order to investigate the concurrence of photovoltaic electricity generation and electric vehicle charging demand, a bottom-up approach is developed. The model simulates electric vehicle driving and charging behavior in power supply systems with high penetration rates of electric vehicles. In quantifying the potential of electric vehicles to increase the self-consumption of photovoltaic electricity generation, it can be found that uncontrolled electric vehicle charging would result in a share of self-consumption that is rather comparable to a case without any storage. Here, the charging demand and photovoltaic electricity generation would only partially coincide. However, smart charging strategies designed to follow the generation from renewable energy sources (RES) may allow for a share of self-consumption of about 59%, 57% more than in the case of uncontrolled charging. This share of self-consumption is even higher than in the case of a stationary battery storage, as charging demand triggers an increase in the overall residential electricity demand. By analyzing the impact of socio-demographic characteristics of potential electric vehicle owners, the most relevant drivers of the simulation results can be identified. The share of self-consumption tends to be especially high if the vehicle is used less often and for comparitively shorter trips. Above all, being connected to the residential power socket during midday hours yields higher shares of self-consumption. As a consequence, unemployed and retired electric vehicle owners tend to exhibit high shares of self-consumption.

On a system level, uncontrolled and RES-oriented charging may trigger a significant increase in the peak load of the household in terms of the electricity purchased from the grid. The results show that the electric charging behavior in these two cases increases the household's peak load on average by between 69% and 84% of the available charging capacity. However, tariff schemes that incentivize peak-load minimizing charging behavior, such as those with peak-load pricing, may be beneficial in reducing the maximum charging demand of electric vehicles. In fact, load-sensitive tariffs could encourage electric vehicle charging to shift away from times of peak load, thereby reducing the average peak-load increase due to electric vehicles to 27%. Nevertheless, the simulation indicates that only limited potential exists to counteract the peak of reverse power flows from photovoltaic electricity generation. Therefore, complementary measures such as charging opportunities in addition to residential charging and efficient congestion management, especially on a distribution grid level, should be considered.

The results presented in this article enable a better understanding regarding the impact of increasing shares of electric vehicles on the power supply systems of today. As such, it may be beneficial for policy makers to implement load-sensitive tariff schemes to avoid technical issues linked to a strongly increasing peak load in local distribution grids. On a household level, there may be a business case to couple photovoltaic electricity generation with electric vehicle charging demand.

The remainder of this paper is structured as follows: The main literature background is depicted in Section 2. The modeling approach developed to simulate the charging behavior of electric vehicles is then presented in Section 3. In Section 4, the main model results are shown and discussed in detail. Finally, Section 5 concludes.

2. Literature Background

The European Union has committed to reducing greenhouse gas emissions by 80-95% by 2050 compared to 1990 levels (European Commission, 2012). In order to achieve these targets, strong efforts have been made to support investments into distributed renewable electricity generation (European Commission, 2013). In Germany, the share of renewable electricity generation accounted for 27.8% of the overall gross electricity production in 2015 (German Federal Government, 2015). Yet high shares of highly volatile distributed electricity generation, such as wind and solar power, may challenge the power supply systems of today. Especially if distributed generation units are operated in an uncontrolled manner without reactive power management, the voltage stability may be jeopardized and an increasing voltage level may be identified (Lopes et al., 2007). Furthermore, as stated in Lopes et al. (2007), the power quality may be affected by harmonic distortions and variations of the transient voltage. In order to alleviate these challenges, smart grid infrastructure has been rolled out (Blumsack and Fernandez, 2012). Nevertheless, there is an increasing need for grid services in order to guarantee the balance of demand and supply at each point in time. From a rather market-oriented perspective, forecast uncertainty triggers an additional need for short-term trading opportunities with preferably short contract duration (see, e.g., von Roon and Wagner (2009); Borggrefe and Neuhoff (2011); Knaut and Obermüller (2016); Knaut and Paschmann (2017)).

As the electricity generation from photovoltaic power plants only partially coincides with demand, storage technologies may be beneficial in order to shift the volatile electricity generation into periods with high demand (Toledo et al., 2010). Otherwise, the photovoltaic electricity generation may exceed demand in individual hours (Denholm and Margolis, 2007). The utilization of energy storage may therefore allow households to reduce or even avoid purchasing electricity from the grid. As a consequence, cost savings potentials could be leveraged as the share of residential self-consumption increases (Kousksou et al., 2014). From a system point of view, one major issue regarding increased distributed generation is the high simultaneity of photovoltaic electricity generation being fed into local distribution grids. As a consequence, costly grid reinforcement may become necessary (German Energy Agency (dena GmbH), 2012). However, small-scale energy storage on a residential level may help to reduce these grid expansion needs (Zeh and Witzmann, 2014). Depending on the underlying regulatory framework, residential energy storage could be harnessed for grid services and thus may facilitate the large-scale integration of distributed generation units (Kousksou et al., 2014).

Although it is well known that small-scale electricity storage may facilitate the integration of residential photovoltaic generation units, a respective business case may be hard to find. High initial investment costs pose hindrances to investing into the respective energy storage systems (Nair and Garimella, 2010), especially for existing plants (Hoppmann et al., 2014). However, opportunities for electrification in the transportation sector have recently become more plentiful, with electric vehicles leading the path for decarbonization in the passenger vehicle segment. With a large-scale diffusion of electric vehicles to be expected within the next years, it is necessary to analyze whether vehicle storage may be harnessed for additional applications coupled with photovoltaic generation units. The literature so far provides detailed insights into the interaction of electric vehicles and smart grids as well as the major challenges that arise(see, e.g., Mwasilu et al. (2014), San Roman et al. (2011), Galus et al. (2013) and Garcia-Valle and Pecas Lopes (2013)). Yet, Richardson (2013) identifies a research gap surrounding the interaction of solar power and electric vehicles. More precisely, it is found that previous articles mainly focus on individual business cases lacking representativeness and generality. In Birnie (2009) and Li et al. (2009), for example, the authors analyze benefits from combining parking lots with solar photovoltaic panels. Furthermore, the respective business models for charging electric vehicles with photovoltaic electricity generation are discussed in Letendre (2009) and the technical feasibility of such concepts is the major topic in Gibson and Kelly (2010) and Kelly and Gibson (2011).

Complementing the existing literature, three major pillars surrounding the interaction of photovoltaic electricity generation and electric vehicles are addressed, all of which could support a beneficial integration of high numbers of electric vehicles into the power supply systems of today: First, the heterogeneity exhibited by electric vehicle users is analyzed with respect to its impact on the potential to couple phovotoltaic generation units and electric vehicle storage. The respective procedure allows to circumvent hindrances resulting from small samples and specific configurations. Second, detailed insights on major factors affecting the electric vehicle storage potential are developed. In doing so, the role of user characteristics is analyzed in more detail. Finally, adopting a system-oriented perspective, the peak-load impact of electric vehicles can be evaluated. Within the analyses, special focus is placed on the role of different charging concepts[1].

[1]More details on charging procedures and the respective impact on the grid integration of electric vehicles are presented in Müller et al. (2017). However, the authors adopt a grid operator's perspective and lack scalability as well as representativeness of their results.

3. Methodology

A bottom-up simulation approach is applied to model the electric vehicle driving behavior and the resulting charging demand. The driving profiles that can be observed today[2] may differ significantly from those to be expected with an increasing penetration rate of electric vehicles. The modeling approach developed especially allows driving profiles to be mimiced in a world with high diffusion rates of electric vehicles.

In a first step, the driving behavior of lightweight electric vehicles in the private transportation sector is modeled by the use of statistical information. Based on the simulated driving characteristics, the resulting charging behavior can then be derived. In the following, the individual steps are explained in more detail.

3.1. Modeling the Driving Behavior of Electric Vehicle Owners

3.1.1. Simulating Electric Vehicle Owner Characteristics

The derivation of weekly driving profiles is based on a preceding simulation of electric vehicle driver characteristics, and it is assumed that the owner is the only user of the electric vehicle. Interactions with secondary vehicles are not considered. The general program sequence is depicted in Figure 1. Initially, the age and gender of the vehicle owner are simulated based on general demographic data combined with information on car owners in Germany (Endlein et al., 2015). Depending on both parameters, the respective employment status can be derived[3] (Federal Statistical Office, 2017). If the simulated vehicle owner is employed, a random draw is conducted to derive the daily working time as well as to simulate whether the person works on weekends. Based on the previous characteristics, conclusions on the respective earnings may be drawn(Federal Statistical Office, 2015).

3.1.2. Simulating Weekly Driving Profiles

The simulation seeks to replicate recurrent typical driving patterns rather than considering one-time occasions such as holiday trips. General driver characteristics are linked to the resulting driving requirements based on statistical information referring to the usage of lightweight vehicles in the private transportation sector in Germany (infas, 2008). Unfortunately, the data does not differentiate between the driving behavior of electric vehicles and conventional cars. Yet, since this article considers rather high diffusion rates of electric vehicles, it is to be expected that electric vehicles will replace the driving patterns that are nowadays served by conventional cars. By linking driver characteristics and driving requirements, it is facilitated to account for a wide range of heterogeneity. The underlying driver characteristics are transferred into driving profiles

[2]For more details on early adopters, see, e.g., Rogers (2003) and Santini and Vyas (2012).

[3]Being employed may have a significant impact on the driving behavior if the electric vehicle is used to commute to work.

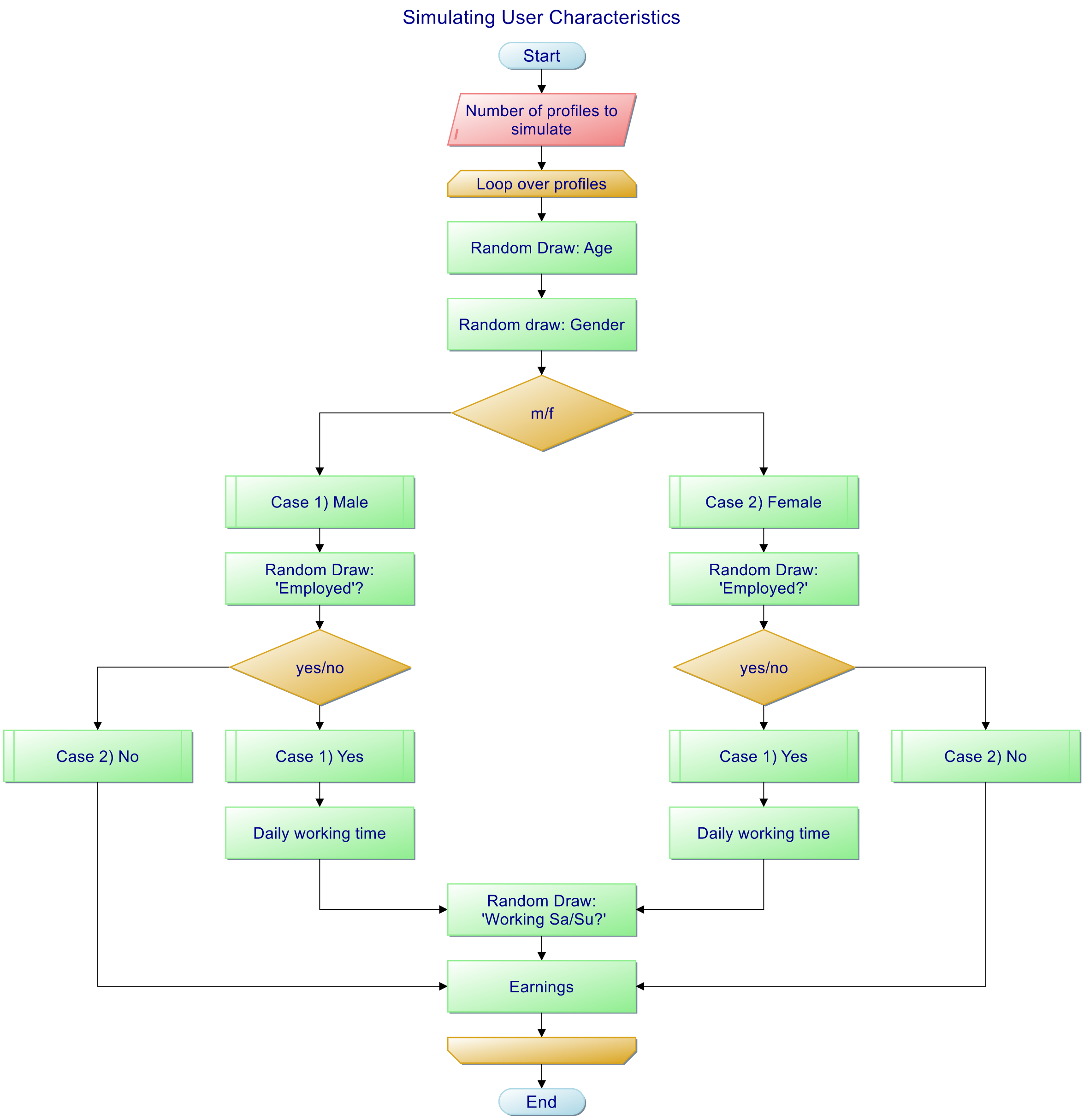

Figure 1: Program sequence simulating user characteristics

that are, so to say, customized as statistical data is broken down into specific user groups such as students, unemployed and employed persons. Further differentiation is made with respect to the age and gender.

The program sequence is illustrated in Figure 2. First, the employment status is transferred into the overall driving schedule. In doing so, a probability-weighted draw is conducted to check whether the car is used to go to work. In order to link specific trips to general employment characteristics, an additional random draw is applied referring to the period in which the daily working day beings. The procedure is based on a probability density function for the start of the work day.

Having dealt with possible commutes to work, focus is now placed on residual daily trips apart from working purposes. In a first step, the average number of trips per day is derived depending on the underlying user characteristics. In doing so, the corresponding driving distances can be extracted from statistical data. Within a loop, these trips are then iteratively transferred into the overall driving schedule. There is an initial probability-weighted draw with respect to a particular purpose for each trip under consideration. In general, ten types of purposes are differentiated which are, inter alia, related to leisure activities such as doing sports, honorary positions and cultural activities. Furthermore, shopping, personal dealings and accompaniment are considered. It is accounted for the fact that the probability of specific purposes may vary depending on the day of the week. For each trip it is then simulated whether the electric vehicle is used in the context of the purpose under evaluation. A criterion is applied which is based on statistics referring to the total number of days on which a car is used per week as well as to the general share of trips that are performed using passenger cars. Both data sets are extracted from infas (2008). If the current trip presupposes the use of the electric vehicle, it is to be simulated at which time the activity starts. In infas (2008), a rich set of data is provided with respect to the starting times for the purposes considered. However, as the temporal resolution (hourly) does not fit the purpose of modeling quarter-hourly profiles, probability density functions were derived from discrete statistical values using least-squares methods. Thereby, a continuous representation of probabilities for each point in time was achieved. Finally, based on the starting point, the average activity duration, and the respective driving time, the trip is transferred into the weekly driving schedule.

Within the iterative procedure, previous trips are always accounted for to avoid overlaps. The iterative procedure is repeated until there are no residual trips left. As a result, a weekly driving schedule with 15-minute temporal resolution is finally acquired. The schedule provides information on the purposes of all trips, the driving duration, and distances.

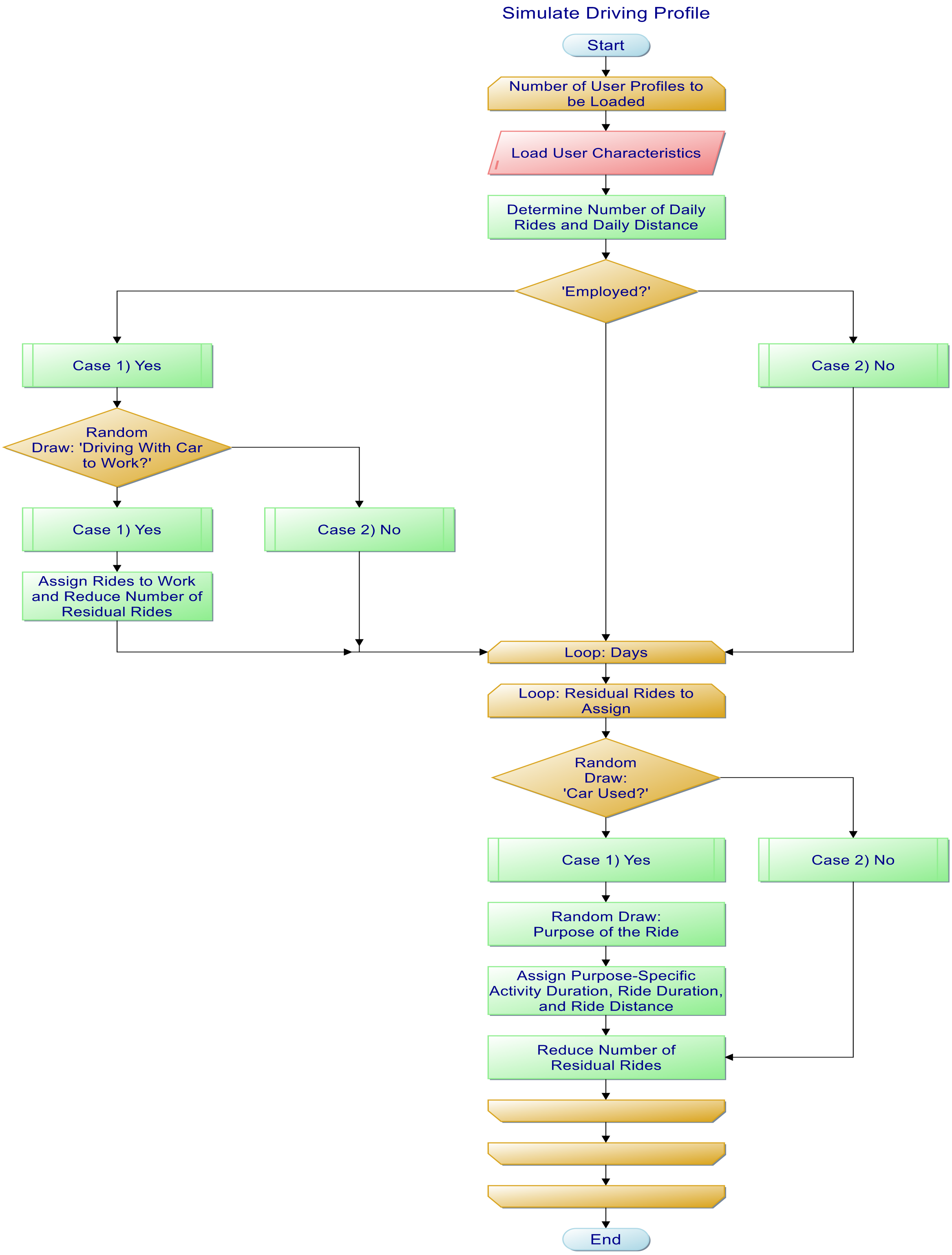

Figure 2: Program sequence simulating driving profile

3.2. Modeling the Charging Behavior of Electric Vehicles

The charging concepts considered within this paper comprise uncontrolled charging as well as charging strategies oriented to smart renewable energy sources (RES). Within the system analysis, a third charging concept is simulated to minimize the residential peak load. The individual concepts will be outlined in more detail below. The analysis is restricted to assuming that the only charging opportunity is provided by a residential power outlet or wallbox.

Individual households are considered which possess both a photovoltaic generation unit as well as an electric vehicle. The respective investment costs are neglected within the analysis and sunk costs are assumed as the focus of this article is placed on the interaction and the beneficial operation of both devices rather than on the general investment decision.[4] It is assumed that the installed capacity of the photovoltaic power plant equals 10 kW_{inst}, which is a typical parameterization for a residential consumer in Germany (Bundesnetzagentur, 2017). The absolute value as well as the temporal structure of the photovoltaic electricity generation are derived from solar irradiation data for Germany. More precisely, the respective data refers to the test reference year provided by the German meteorological service[5] (Wetterdienst, 2011). The hourly data may be interpolated in order to obtain a time series with 15-minute temporal resolution. With respect to the conventional residential load, it is initially assumed that the yearly electricity consumption equals 4,500 kWh per household. The respective load structure is derived from reference load profiles for a four-person household(Ingenieure, 2008). Within the scope of this paper, several sensitivity analyses are conducted considering different load profiles, which are attributable to specific socio-economic characteristics.

Households aim to minimize the overall costs of their electricity purchase from the grid. A constant residential electricity tariff is assumed equal to 31.5 ct/kWh. Photovoltaic electricity generation that is not used for residential appliances (self-consumption) but rather fed back into the grid is remunerated with a constant feed-in premium of 11.1 ct/kWh. As total costs are not within the scope of the analysis, the absolute values of the assumptions made do not impact the results. Only the relative cost structure plays a crucial role. More specifically, the assumptions refer to a case in which self-consumption is always preferred compared to electricity purchased from the grid. Regarding the electric vehicles, a storage capacity of 25 kWh and a specific energy usage of 20 kWh/100km are considered. Finally, perfect foresight with respect to load, driving needs and electricity generation of the photovoltaic generation unit is assumed.

[4] Furthermore, the opportunity to increase the photovoltaic generation capacity is neglected. As residential customers today are rather less charged relative to their system capacity, peak-load reduction potentials do not result in additional photovoltaic generation capacity becoming more economic.

[5] The data refers to *'Region 5'* in Germany, which is, for example, close to Cologne.

3.2.1. Charging Concepts

The most relevant characteristics of the three charging concepts considered should be briefly discussed. First, the classification 'uncontrolled charging' refers to the case in which smart charging algorithms which allow to react to a selective load at specific points in time are not available. Instead, the vehicle is charged with the maximum available charging capacity until the storage limit is reached, whenever connected to a charging station. In the context of this paper, this is the single-phase maximum residential charging load available, equal to 3.7 kW.

In a second step, households are able to apply smart charging algorithms which support the cost optimization problem by enabling a profitable interaction of photovoltaic electricity generation and electric vehicle charging demand ('RES-oriented charging'). Simply put, the electric vehicle is primarily charged if the sun is shining. This concepts yields a linear optimization problem for each residential decision maker considered. A detailed overview on the optimization problem is presented in Section Appendix.1.

Assuming a system-oriented perspective, it is finally seeked to analyze the theoretical peak-load reduction potential without explicitly implementing the underlying charging procedure. The peak load ($peak\_load$) which is stressing the grid is therefore endogeneized and embodies the objective function which is to be minimized. In doing so, it is accounted for both the peak of electricity purchased from the grid as well as reverse power flows resulting from high amounts of photovoltaic electricity generation that are fed back into the grid. Therefore, the target function (1) is included:

$$\begin{aligned} &minimize\, z = peak\_load \\ &\qquad with\ \ 1)\ \ peak\_load \geq ev\_charging\_load\_grid_t + residential\_load_t \\ &\qquad\qquad\ \ 2)\ \ peak\_load \geq pv\_to\_grid_t, \end{aligned} \tag{1}$$

where electricity purchased from the grid comprises both conventional residential load ($residential\_load_t$) as well as the electric vehicle charging load (ev_charging_load_grid$_t$). Photovoltaic electricity generation that is fed back into the grid is embodied by the term $pv\_to\_grid_t$.

4. Results

In this section, benefits resulting from the interaction of electric vehicles and photovoltaic generation units are analyzed to determine key findings for households with photovoltaic systems and electric vehicles: First, the economic analysis addresses the research question whether smart electric vehicle charging concepts may allow households to achieve higher cost-saving potentials by increasing their share of self-consumption. Second, adopting more of a system-oriented perspective, the peak-load impact of electric vehicles as well as the capability of electric vehicles to contribute to a peak-load reduction is simulated. It is abstained from grid calculations due to the individual character of grid configurations. Yet, the economic results may form the basis for further technical analyses.

4.1. Self-Consumption

4.1.1. Reference Case

In analyzing the self-consumption potential of individual households, two benchmark cases are initially derived to provide a comparative basis for the further results. In this analysis, the first benchmark is considered as a household without any storage device. As a second benchmark, a stationary battery storage device with a 3 kW load limit and a loading capacity equal to 6.6 kWh is considered. The efficiency of the storage device is assumed to amount to 95%. The optimization results are depicted in Table 1.

Reference case simulation results

	Case a: No storage	Case b: Stationary storage
Self-Consumption	27.5%	52.0%
Share Demand Provided by PV	39.6%	55.3%

Table 1: PV usage characteristics

Supporting the general applicability of the modeling approach as well as the validity of the data, these results are well in line with those presented in the existing literature. In Luthander et al. (2015), the authors present an overview on simulation-based analyses with focus on the share of self-consumption. The respective results range between 25% and 38%. Furthermore, the authors state that households may achieve an even larger share of self-consumption, ranging between 45% and 65%, if the photovoltaic power plant is combined with a stationary battery storage.

4.1.2. The Impact of Electric Vehicles on the Residential Share of Self-Consumption

Uncontrolled Charging

To begin with, the impact of uncontrolled charging concepts is simulated for 1,000 different driving profiles. In doing so, the influence of electric vehicle charging processes on the general residential load structure can be evaluated. Figure 3[6] presents a boxplot for the average hourly residential electricity demand across all simulated profiles. The red marker shows the mean overall residential load including the charging load. The green boxes bound the 25% and 75% quantile thresholds. Additionally, the dashed lines

[6]These are averages across all 15-minute time intervals within each hour over the whole year simulated.

mark the 10% and 90% thresholds. Finally, the lowest line reflects the conventional residential electricity demand without electric vehicles. In order to offer an intuition for times of higher shares of self-consumption, the photovoltaic electricity generation in representative summer and winter weeks are also given[7].

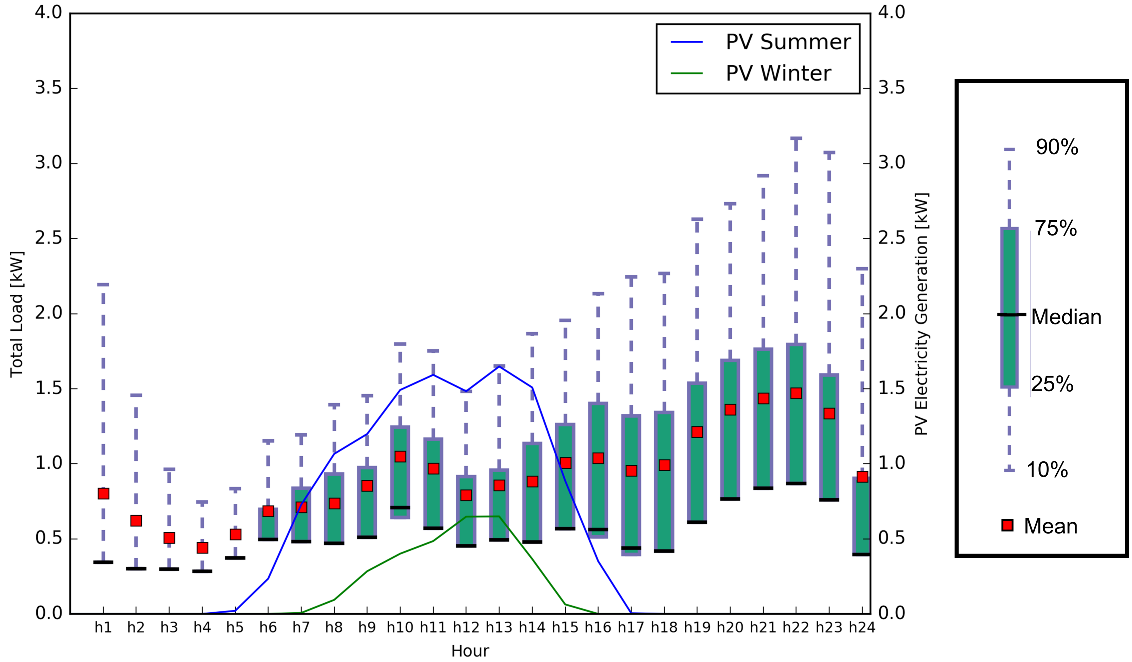

Figure 3: Impact of uncontrolled ev charging demand on residential load profiles compared to the pv generation (3.7 kW)

Uncontrolled charging concepts tend to trigger higher residential loads in the early evening hours. These results may be traced back to typical working times: When people get home from work, they plug in their electric vehicle and charge their storage device. As indicated in Figure 3, the charging load tends to coincide with high conventional residual loads, which could lead to an increased peak-load level (analyzed in more detail in Section 4.2). Furthermore, with regards to the self-consumption potentials, photovoltaic electricity generation and the electric vehicle charging load only partially coincide and therefore limit the amount of photovoltaic electricity that can be directly used to charge the vehicle.

To provide quantitative support for the previous observations, the numeric simulation results referring to both the share of self-consumption and the share of residential electricity demand that may be covered by photovoltaic electricity generation are shown in Table 2. The findings reveal that the average share of self-consumption only slightly increases (+30% relative increase; +8.7% absolute) compared to the benchmark

[7] These weeks are determined by a least-mean-squares procedure applied to the difference of residential load and photovoltaic electricity generation in each week of the year.

without any storage device (Section 4.1.1). This is due to two reasons: First, the electric vehicle storage is characterized by limited availability. Second, uncontrolled charging concepts allow for self-consumption potentials being leveraged solely coincidentally. However, the value distribution of the simulation results also reveals that, in individual cases, households may achieve a share of self-consumption that is even higher than in the case of the second benchmark with a stationary battery storage. Such a finding may be due to the fact that electric vehicles cause an overall increase in the residential electricity demand as a result of their charging needs. As such, the share of demand that is covered by photovoltaic electricity generation significantly decreases compared to the benchmark case without electric vehicles, even though self-consumption increases. In addition, it is worth stressing that there are also driving profiles which exhibit hardly any additional self-consumption potential. These driving profiles reveal a higher probability of vehicles not being located at the place of residence in the midday hours, e.g., due to work requirements.

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Self-Consumption	27.5%	28.1%	34.8%	50.2%	69.7%	36.2%	6.9%
Share Demand PV	12.4%	17.3%	29.4%	32.7%	40.3%	27.1%	5.3%

Table 2: Results in the case of uncontrolled charging on a household level

RES-Oriented Charging

Prior findings suggest that the application of smart charging algorithms that seek to interact charging processes and photovoltaic electricity generation may allow for additional cost-saving potentials to be leveraged. By achieving higher shares of self-consumption, households may be able to save on their electricity costs. Figure 4 depicts the impact of RES-oriented charging on the resulting residential demand profiles. It is observed that, compared to uncontrolled charging, the charging load tends to be shifted into midday periods in order to benefit from the interaction of photovoltaic electricity generation and charging demand. As a consequence, the average share of self-consumption, especially in the midday hours with high solar power availability, may increase significantly[8].

The optimization model from Section Appendix.1 is applied yielding the results in Table 3. The mean share of self-consumption increases by 59% compared to the case of uncontrolled charging. Therefore, the

[8]As the objective function is meant to target high shares of self-consumption, households are indifferent when to charge their vehicle whenever the sun is not shining. Thus, an arbitrary prevalence of charging processes in night periods may be identified. In the real-world, however, residential customers may prefer charging their vehicle as early as possible due to range anxiety. Nonetheless, the temporal structure of charging processes in periods without photovoltaic electricity generation does not impact the following results. Detailed insights into the concurrence of photovoltaic electricity demand and electric vehicle charging demand in individual hours may be found in Section Appendix.4.

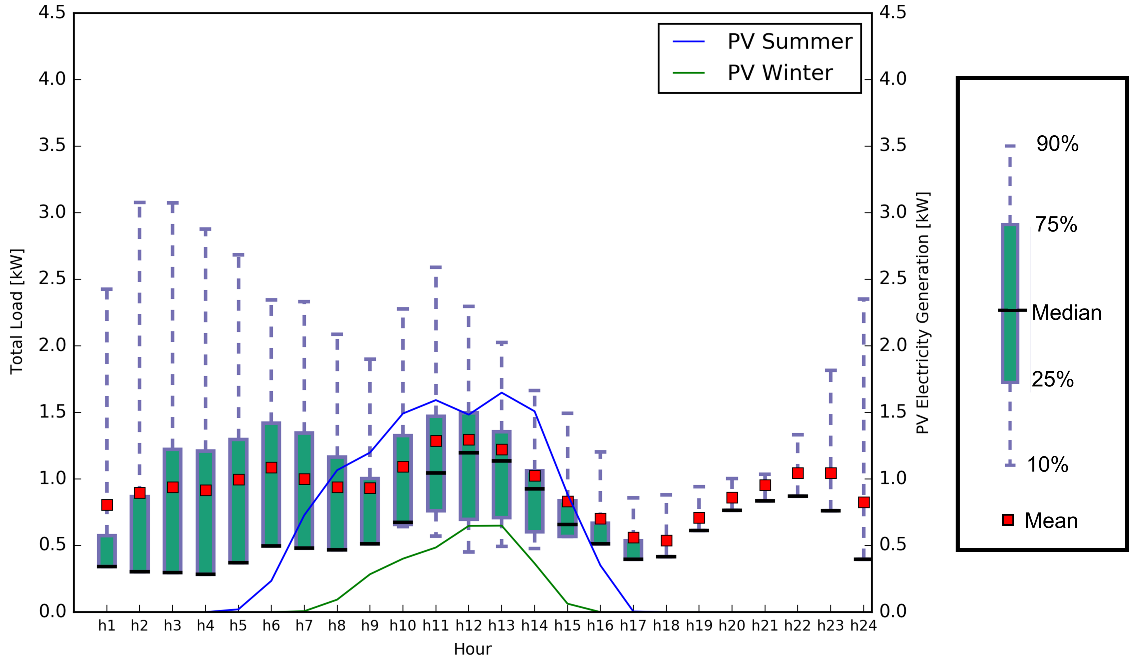

Figure 4: Impact of RES-oriented ev charging demand on residential load profiles compared to pv generation (3.7 kW)

share of self-consumption is on average about 11% higher than in the benchmark case with a stationary storage device but no electric vehicle. Overall, the mean self-consumption potential now amounts to 57.6%, which is at least double the achievable level without any storage device. Additional residential load that stems from charging processes may be scheduled such that directly charging the vehicle with photovoltaic electricity generation becomes feasible. At the same time the targeted driving behavior is not impacted. The results clearly emphasize the importance of appropriate charging algorithms to support the interaction of electric vehicles and photovoltaic generation units.

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Self-Consumption	29.9%	39.5%	59.3%	70.3%	79.0%	57.6%	9.5%
Share Demand PV	16.2%	22.2%	50.8%	59.1%	60.2%	44.8%	13.5%

Table 3: Results in the case of RES-oriented charging on a household level

Apart from the average values, the cost-saving potential of smart charging algorithms is found to strongly depend on the underlying driving behavior. If an individual driving profile is rather restrictive, the share of self-consumption may even correspond to the benchmark case without any storage device, i.e., a minimum share of self-consumption equal to 29.9%. Therefore, the impact of particular socio-demographic characteristics on the achievable share of self-consumption is analyzed in detail within the next subsection.

4.1.3. Decoding Socio-Demographic Impact Factors

Six different types of households are considered, each of which exhibits different socio-demographic characteristics. The analysis focuses on RES-oriented charging in order to analyze what types of households are more likely to benefit from shifting their charging demand relative to the feed-in profiles from photovoltaic power plants. The simulation procedure is based on the use of synthetic load profiles which are customized depending on the individual socio-economic characteristics. The profiles were generated with a load profile generator (Pflugradt, 2017) and taken from Feridarova (2015)[9]. The driving profiles which are assigned to the individual households furthermore comply with the underlying socio-economic characteristics. Details on the exact specifications are presented in Table 4.

Case specification

Case	Household Characteristics	Electric Vehicle Driver	Consumption/a
Case 1	Couple (no child), age: both 38, with work	Male (38), employed	3,281 kWh
Case 2	Family (child), age: both parents 45, with work	Male (45), employed	3,455 kWh
Case 3	Family (child), age: both parents 42, unemployed	Female (42), unemployed	3,977 kWh
Case 4	Single (child), with work	Female (31), employed	2,616 kWh
Case 5	Couple, both retired	Male (72), retired	3,856 kWh
Case 6	Multigenerational home, working couple, 2 children, 2 seniors	Male (68), retired	8,475 kWh

Table 4: Socio-demographic characteristics

Simulation results

Case	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Case 1	22.1%	30.1%	44.4%	59.0%	67.5%	43.6%	9.2%
Case 2	28.9%	34.3%	49.6%	63.6%	73.5%	49.7%	9.6%
Case 3	32.7%	37.5%	52.3%	67.9%	75.1%	52.7%	9.0%
Case 4	20.2%	29.6%	41.9%	59.4%	67.2%	42.7%	9.7%
Case 5	45.1%	49.2%	52.9%	65.0%	74.6%	54.3%	5.3%
Case 6	68.2%	73.1%	81.1%	84.0%	85.8%	79.9%	3.6%

Table 5: Results in the case of RES-oriented charging on a household level for different socio-economic specifications

Analyzing the share of self-consumption for the individual socio-demographic cases considered, as presented in Table 5, conclusions on the most relevant impact factors can be derived. For example, a relatively high share of self-consumption can be identified if the electric vehicle driver is retired (*Case 5* and *Case 6*). A retired couple, on average, may achieve a share of self-consumption of about 54.3%. The corresponding value distribution, what means the range between the minimum and maximum target figure in all simulated

[9]The exact data is accessible via Waffenschmidt (2015).

cases, is flat. The underlying reason for this result is most likely that retired drivers tend to exhibit relatively short mean daily driving distances. Statistics reveal that the group of retired people examined in this study has an average daily driving distance of 23 km, which is approximately a third of the driving distance for employed persons between 30 and 50 years old. In addition, the driving purposes of retired people tend to be related to activities with shorter duration. Within this analysis, shopping activities with an average residence time of 15 minutes constitute a significant share of all trips. As a consequence, the vehicle may be assumed being connected to the residential power outlet a large part of the midday hours if the sun is shining.

Apart from being connected to the residential power outlet during the midday hours, the corresponding charging demand is a further core issue. With respect to the retired drivers, for example, a rather small charging demand limits the potential to charge the electric vehicle with photovoltaic electricity generation. Overall, the highest share of self-consumption may be achieved if the vehicle is assigned to a multi-generational household since the conventional electricity demand in midday hours is rather high. In contrast, employed persons with long working hours exhibit a significantly lower self-consumption potential. Oftentimes, in this case, the vehicle is not connected to the residential charging station when the sun is shining. The socio-demographic groups that fall under this category are, for example, a family in which both parents work (*Case 1* and *Case 2*) as well as the employed single (*Case 4*). Here, the self-consumption potential is on average between 9% and 45% lower than for the retired group considered. On the other hand, there are households with barely any additional cost-saving potential related to electric vehicles, illustrated by the 5% quantile thresholds shown in the tables. These findings may be traced back to the concurrence of trips and photovoltaic electricity generation along each day. Finally, the average self-consumption potential of an unemployed family (*Case 3*) is similar to the one of the retired drivers considered. However, a wider distribution of the simulated share of self-consumption is observed. As a family on average exhibits a higher number of daily trips, the temporal structure is crucial.

4.2. Peak-Load Impact and Peak-Load Reduction Potential

4.2.1. The Impact of Different Charging Concepts

Uncontrolled Charging

In a first step, the peak load impact of electric vehicles is analyzed in the case of uncontrolled charging concepts. It is account for both the peak of residential load that is met by electricity purchased from the grid and the minimum of the residual load, equal to the total residential load minus the photovoltaic electricity generation. The simulation procedure is repeated iteratively for 1,000 driving profiles. The numeric results are illustrated in Table 6. As a benchmark, the values for the case without an electric vehicle ('No EV') are listed as well.

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	4.47	4.47	5.42	5.96	5.96	5.34	0.46
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.69	-5.62	-5.26	-5.67	0.04
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table 6: Peak-load impact in the case of uncontrolled charging

Uncontrolled charging on average drives the peak load to increase by 3.08 kW or 136%. Relative to the charging load, it may be concluded that electric vehicle charging processes under uncontrolled charging can yield a peak load increase amounting to 83% of the available vehicle charging capacity. The relative increase is robust to alternative charging capacities. In the case of 2.3 kW, for example, the average peak load increases by 78% of the charging capacity (see Section Appendix.2). Due to a frequency of charging processes in the early evening, when the conventional load tends to be very high, the peak load of residential appliances and electric vehicle charging tend to coincide. Even the minimum peak-load increase is equal to 60% of the vehicle charging capacity. However, the maximum amount of electricity fed back into the grid is only reduced to a negligible extent. There appears to be a need to analyze whether differing charging concepts may be suitable to reduce the peak-load impact identified as well as to reduce the peak of electricity fed back into the grid.

RES-Oriented Charging

As self-consumption of electricity directly reduces the amount of electricity fed back into the grid, is is now analyzed whether RES-oriented charging may help to avoid additional stress posed to the distribution grid. Detailed descriptive statistics on the simulation results are listed in Table 7.

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	5.19	5.85	5.96	4.80	1.23
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.68	-5.68	-5.68	-5.42	-5.21	-5.64	0.09
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table 7: Results in the case of RES-oriented charging on a household level

Although leveraging cost-saving potentials on an individual household level may be possible, applying RES-oriented charging algorithms on average may not significantly reduce the peak load of reverse power flows. On the other hand, the average peak load related to electricity purchased from the grid increases by 69% of the available charging capacity what is, in the case of 3.7 kW, 2.5 kW. Such peak-load impact is only slightly lower than in the case of uncontrolled charging. The question arises as to whether incentive schemes such as dynamic pricing and peak-load pricing may be suitable to leverage peak-load reduction potentials that are not encouraged by flat tariff schemes.

Peak-Load Minimizing Electricity Charging Behavior

The theoretical peak-load reduction potential that may be achieved when supporting peak-load minimizing behavior is now examined. In doing so, the peak load is endogenized within the target function, analogous to Section 3.2.1. The results are illustrated in Table 8.

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	2.81	4.47	5.96	2.88	0.71
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.62	-2.60	-1.68	-5.07	1.0
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table 8: Results in the case of peak-load minimizing charging behavior

It can be observed that the impact of electric vehicle charging processes on the resulting peak load of electricity purchased from the grid may be reduced to a large extent if incentivized in an appropriate way. In this case, the average peak load only increases by 0.62 kW or 27.4%. As the peak load in our simulation results occurs in the early evening hours, the vehicle tends to be connected to the domestic power outlet for a longer time in these periods. A driver may, for example, think about coming home from work and using the vehicle the next morning again. Therefore, significant load-shifting potential can be identified. The charging demand may be distributed along a certain time period such that the peak-load impact is rather small. Simply put, the impact of electric vehicle charging processes on the electricity load is a coordination problem.

Yet, the residential peak of negative power flows caused by photovoltaic electricity generation may only be reduced to a limited extent. The absolute peak load on average is merely reduced from 5.7 kW to approximately 5.1 kW, which is about 17% of the available charging load. Only 5% of all households are essentially able to significantly counteract the maximum of photovoltaic electricity generation which is fed back into the grid. Thus, our results yield an indication that, under the analyzed framework, the stress posed to the grid by simultaneous photovoltaic electricity generation may not be reduced by interacting electric vehicles with distributed energy sources. This result may be due to the fact that a significant share of vehicles tends to be parked away from the place of residence at noon when the solar power availability reaches its maximum, e.g., when people are at work. The results emphasize the importance of alternative charging opportunities, such as public charging stations, in order to leverage peak-load reduction potentials on a distribution grid level.

To deepen the understanding of these results, additional sensitivity analyses provide further insights. Regarding the impact of alternative charging capacities, the potential to minimize the peak-load impact of electric vehicles only slightly ($\leq$ 10%) changes under the assumption of a charging load equal to 2.3 kW or 11 kW (Section Appendix.3). This finding indicates significant load-shifting potential. Households are subject to a lack of coordination as well as zero incentives to alter their charging behavior. On the other hand, charging with high loads to meet the driving requirements is only a minor issue.

Furthermore, conclusions can be drawn regarding the potential impact of range anxiety. A scenario is considered in which electric vehicle drivers target a minimum storage level of 50% in each period (see Section Appendix.5). The results depict that the average peak load impact increases from 27% to 38%. However, it is imaginable that in a worst case scenario range anxiety may trigger a charging behavior that is comparable to uncontrolled charging. Thus, it may be beneficial to reduce hindrances that favor range anxiety such as providing sufficient charging infrastructure. Finally, the peak-load reduction potential is analyzed in terms of different socio-economic groups (see Section Appendix.6). The results reveal that the average peak-load increase due to electric vehicle charging demand ranges from 0% in the case of the retired group to 48% for the working couple. In the case of the retired group, the vehicle tends to sit at home for longer periods such that the load-shifting potential is significant. In the case of working people, the driver may wish to charge the vehicle in the early evening hours shortly after coming home from work in order to drive to a leisure activity directly afterwards. Consequently, the respective load-shifting potential may be limited.

5. Conclusion

In this paper, the interaction of electric vehicles and photovoltaic generation units is analyzed. Two key aspects are examined in detail: First, emphasis is placed on the cost-saving potential of electric vehicles which results from helping individual households to achieve a significantly higher share of self-consumption. Second, a system perspective is adopted and the impact of electric vehicles on the residential peak load is analyzed. Within the analyses, special focus is placed on the influence of different charging concepts.

From a methodological point of view, a bottom-up simulation approach is developed to model the electric vehicle driving and charging behavior. The model allows for scalability such that the charging behavior in future power supply systems with high diffusion rates of electric vehicles can be mimiced.

Regarding the simulation results, in the case of uncontrolled charging, there are limited opportunities to increase the share of self-consumption by charging the vehicle with photovoltaic electricity generation. The share of self-consumption is rather comparable to a case without any storage device and photovoltaic electricity generation and charging demand would only partially coincide. In contrast, smart charging strategies designed to shift charging demand into periods with high solar power availability may allow to achieve an average share of self-consumption which is about 59% higher than in the case of uncontrolled charging. Sophisticated charging concepts may hence allow for significant cost-saving potentials to be leveraged on an individual household level.

In a second part of the analysis, a system perspective is taken and the peak-load impact of electric vehicles is simulated in detail. Uncontrolled charging concepts as well as charging designs which support the concurrence of photovoltaic electricity generation and electric vehicle charging demand may cause an increase in the residential peak load ranging from 69% to 84% of the available charging capacity. In order to avoid the resulting technical issues, tariff schemes incentivizing peak-load minimizing charging behavior may be beneficial. In fact, such load-sensitive tariff schemes could encourage electric vehicle drivers to shift their charging demand away from peak-load times. Thereby, the average peak-load impact of electric vehicles could be decreased to 27%. These results are robust with respect to alternative charging capacities. However, the simulation results yield an indication that the potential to counteract the peak of reverse power flows from photovoltaic electricity generation is limited. Consequently, complementary charging opportunities, such as public charging stations, and an efficient congestion management could be crucial prerequisites to efficiently integrate electric vehicles into the power supply systems of today.

In future research it may be worth analyzing selected model assumptions in more detail. First, it could be expected that households exhibit a specific price elasticity with respect to their driving and charging behavior. However, such data has yet to be collected and evaluated. Second, only residential charging opportunities are considered within the scope of this article. Broadening the scope of the analyses to additional charging opportunities, such as charging at work, may provide valuable insights. Finally, the model could be extended to account for uncertainty.

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Appendices

Appendix.1. Model Description: Renewable Energy Resources (RES-)Oriented Charging

Model parameters	Dimension	Description
$binary\_connected_t$	$\in \{1,0\}$	Binary whether car is connected to charging station
$distance_t$	100km	Distance driven with the electric vehicle in a certain time period
$domestic\_charging\_limit$	kW	Maximum load for domestic charging
$efficiency\_charging$	%	Storage efficiency when charging and discharging
ev_energy_usage	kWh/100km	Specific energy usage of electric vehicles
$feed\_in\_premium$	EUR/kWh	Feed-in premium for photovoltaic electricity generation
min_load	%	Minimum load of electric vehicle storage
$pv\_instcap$	kW_{inst}	Installed capacity of the pv generation unit
$pv\_availability_t$	kW/kW_{inst}	Relative available pv electricity generation
$residential\_demand_t$	kW	Overall residential demand for domestic appliances
$storage\_capacity$	kWh	Storage capacity

Table .9: Parameters of the optimization model

Model variables		
Abbreviation	Dimension	Description
$dummy\_charging_t$	kW	Dummy reflecting charging needs apart from residential charging
$ev\_charging\_load\_grid_t$	kW	Quarter-hourly vehicle charging load (grid)
$ev\_discharging_t$	kW	Discharging the electric vehicle for residential electricity consumption
$pv\_to\_grid_t$	kW	PV electricity generation fed back into the grid
$pv\_to\_consumption_t$	kW	PV electricity generation used for conventional residential load apart from charging
$pv\_to\_vehicle_t$	kW	PV electricity generation used for electric vehicle charging
$residential\_load\_gridt$	kW	Residential load besides vehicle charging that is served by electricity purchased from the grid

Table .10: Variables of the optimization model

The decision maker faces a cost minimization problem. Electricity purchased from the grid either for residential appliances or charging the vehicle is brought to account with the residential electricity price. Furthermore, photovoltaic electricity generation could be fed back into the grid being remunerated with a fixed feed-in premium (.1).

$$\begin{aligned} minimize\, z = & el\_price_{res} \cdot \frac{1}{4} \cdot \left[ev\_charging\_load\_grid_t + residential\_load\_grid_t\right] \\ & - feed\_in\_premium \cdot \frac{1}{4} \cdot pv\_to\_grid_t \\ & + 1000 \cdot dummy\_charging_t \end{aligned} \tag{.1}$$

Since only residential charging opportunities are considered, a dummy variable $dummy\_charging_t$ is included reflecting that if there are periods in which residential charging is not sufficient to meet the driving requirements, alternative charging stations are expected to be available. The respective costs are assumed to be very high.

In general, perfect foresight with respect to the photovoltaic electricity generation is assumed. The respective generation is non-dispatchable. However, three possible applications are considered which comprise directly charging the vehicle ($pv\_to\_vehicle$), serving residential electricity consumption ($pv\_to\_consumption$) and feeding back into the grid (pv_to_grid) (.2).

$$pv\_to\_grid_t + pv\_to\_vehicle_t + pv\_to\_consumption_t = pv\_instcap \cdot pv\_availability_t \tag{.2}$$

The electric vehicle is incorporated by implementing a respective vehicle storage equation. The storage level in each time period directly depends on its preceding level. Whenever the vehicle is used for driving purposes, the storage level is furthermore reduced by the respective energy usage which is depending on the specific energy consumption ev_energy_usage as well as the distance driven (.3). Whenever the vehicle is located at home, it may be charged by the use of the domestic charging station ($ev\_charging\_load\_grid$) or directly from photovoltaic electricity generation ($pv\_to\_vehicle$). In both cases, efficiency losses (95% efficiency) are considered. Finally, the vehicle storage may also be discharged in order to supply residential electricity consumption ($discharging\_load\_ev\_grid$).

$$\begin{aligned} storage\_level_t =& storage\_level_{t-1} - ev\_energy\_usage \cdot distance_t \\ &+ efficiency\_charging \cdot pv\_to\_vehicle_t \\ &+ efficiency\_charging \cdot ev\_charging\_load\_grid_t \\ &- \frac{discharging\_ev_t}{efficiency\_charging} \end{aligned} \tag{.3}$$

The storage level may not exceed a certain threshold which is determined by the storage capacity (.4)

$$storage\_level_t \leq storage\_capacity \tag{.4}$$

The constraint (.5) refers to a minimum storage level .

$$storage\_level_t \geq storage\_capacity \cdot min\_load \tag{.5}$$

In the first time period the storage is assumed to be half-full. Furthermore, a restriction is included such that the storage level is at least half-full in the last period under consideration.

As outlined in the previous section, all charging and discharging opportunities are finally restricted by charging bounds which are illustrated in Equation (.6), Equation (.7) and Equation (.8).

$$0 \leq ev\_charging\_load\_grid_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{.6}$$

$$0 \leq discharging\_ev_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{.7}$$

$$0 \leq pv\_to\_vehicle_t \leq domestic\_charging\_limit \cdot binary\_connected_t \tag{.8}$$

The parameter $binary\_connected_t$ determines whether the vehicle is connected to the domestic power outlet in a specific period. Thus, it controls for whether the electric vehicle may be charged. The parameter is assigned in an upstream process depending on the position of the vehicle which is directly resulting from the underlying driving profile. It is assumed that the vehicle is connected to the charging opportunity whenever the vehicle is located at home.

Finally, each household faces a given demand profile. Demand may be supplied by electricity purchase from the grid, self-consumption of photovoltaic electricity generation or discharging the electric vehicle (.9).

$$\begin{aligned} residential\_demand_t = & pv\_to\_consumption_t \\ & + residential\_load\_grid_t \\ & + ev\_discharging_t \cdot binary\_connected_t \end{aligned} \tag{.9}$$

Appendix.2. Sensitivity Analyses: The Impact of Charging Capacity in the Case of Uncontrolled Charging

The simulation results for the case of a charging capacity equal to 2.3 kW are presented in Table .11.

Simulation results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	3.07	3.09	4.03	4.56	4.56	4.05	0.44
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.69	-5.45	-5.24	-5.67	0.06
Minimum Residual Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table .11: Simulation results (2.3 kW)

Appendix.3. Sensitivity Analyses: The Impact of Charging Capacity in the Case of Peak-Load Minimizing Charging Behavior

The simulation results for a charging capacity of 2.3 kW are presented in Table .12 and in Table .13 in terms of a charging capacity equal to 11 kW.

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	2.26	2.26	2.81	3.33	4.56	2.67	0.37
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.62	-2.6	-1.67	-5.06	1.0
Minimum Residual Load No EV [kW]	-5.67	-5.67	-5.67	-5.67	-5.67	-5.67	0.0

Table .12: Simulation results (2.3 kW)

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Residual Load [kW]	2.26	2.26	2.81	6.18	11.77	3.06	1.73
Peak Residual Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Residual Load [kW]	-5.69	-5.69	-5.62	-2.6	-1.67	-5.06	1.0
Minimum Residual Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table .13: Simulation results (11 kW)

Appendix.4. Analyzing the Temporal Structure of the Impact of Different Charging Concepts on the Share of Self-Consumption

Figure .5 and Figure .6 illustrate the coincidence index of photovoltaic electricity generation and the electric vehicle charging demand for each hour in a representative summer week. The coincidence index is determined as the hourly average share of self-consumption that is achieved accounting for conventional load as well as electric vehicle charging load.

First, Figure .5 refers to weekdays (Mo-Fr). The green line marks the photovoltaic electricity generation in a representative summer week.

On the other hand, Figure .6 depicts the respective results for the weekend.

Appendix.5. The Impact of Range Anxiety on the Peak-Load Impact and the Peak-Load Reduction Potential of Electric Vehicles

Simulation Results

Target Figure	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Peak Load [kW]	2.26	2.26	2.81	4.60	5.96	3.12	0.94
Peak Load No EV [kW]	2.26	2.26	2.26	2.26	2.26	2.26	0.0
Minimum Load [kW]	-5.69	-5.69	-5.62	-2.60	-1.68	-5.07	1.0
Minimum Load No EV [kW]	-5.69	-5.69	-5.69	-5.69	-5.69	-5.69	0.0

Table .14: Results peak load minimizing charging behavior with 50% minimum load

Appendix.6. The Impact of Socio-Demographic Characteristics on the Peak-Load Impact and the Peak-Load Reduction Potential of Electric Vehicles

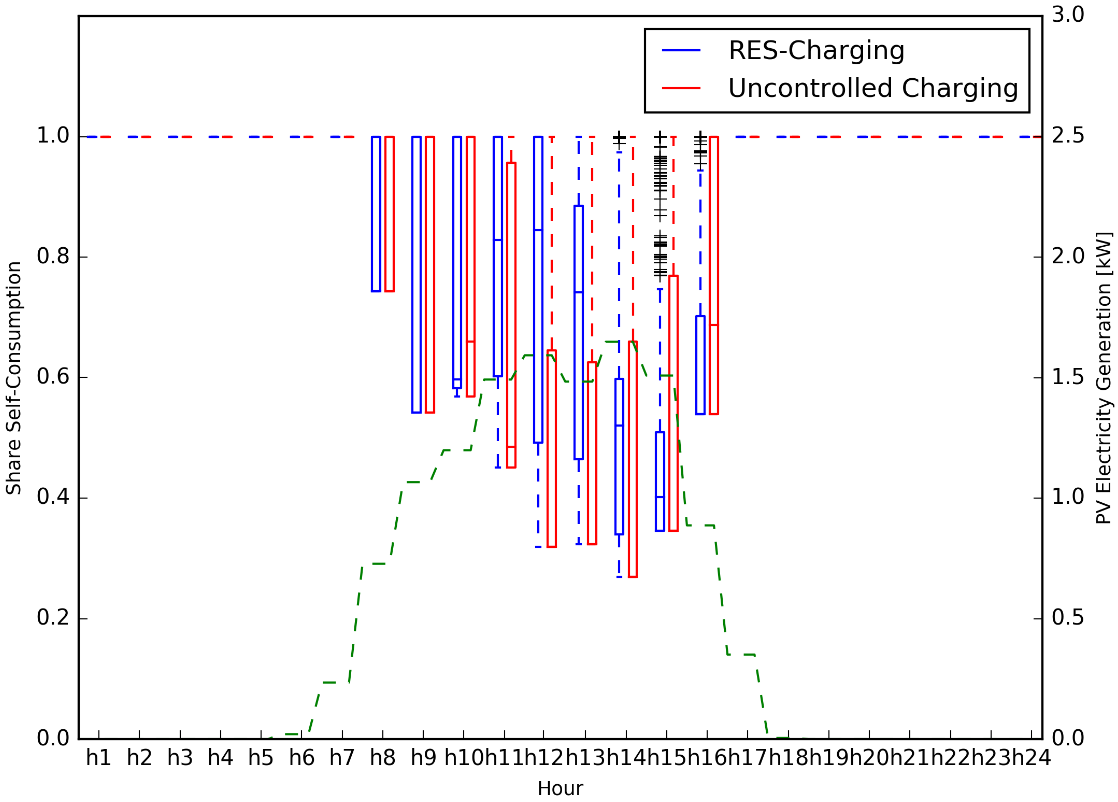

Figure .5: Coincidence index of photovoltaic electricity generation and electric vehicle charging demand in an exemplary summer week (weekdays)

Simulation Results

Case	No EV	Min	5% Percentile	Median	95% Percentile	Max	Mean	STDEV
Case1	8.31	8.31	8.31	8.31	9.6	11.2	8.5	0.58
Case2	4.99	5.85	7.2	7.4	7.4	8.6	7.4	0.3
Case3	5.2	5.3	5.75	7.3	7.4	7.4	6.97	.64
Case4	6.53	6.53	6.82	7.37	8.73	9.21	7.44	0.48
Case5	7.71	7.71	7.71	7.71	7.71	7.71	7.71	0.0
Case6	8.87	8.87	8.87	8.87	8.87	8.87	8.87	0.0

Table .15: Results peak load reduction potential for different socio-economic Specifications

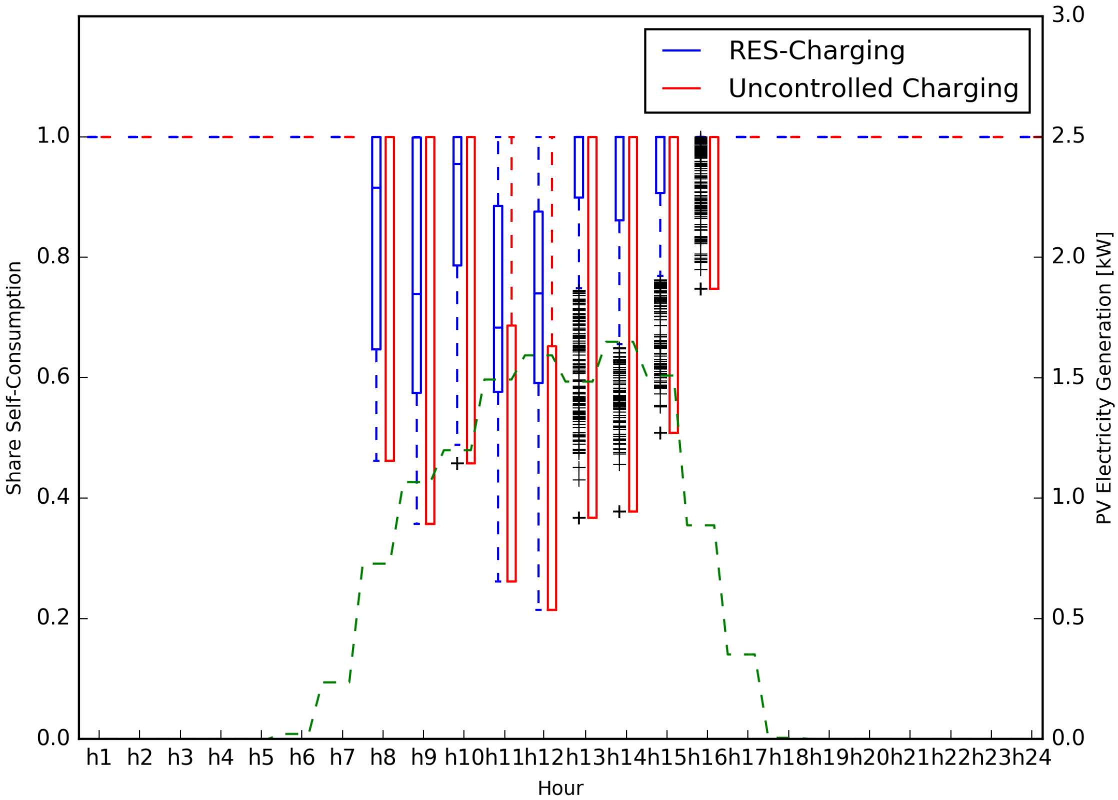

Figure .6: Coincidence index of photovoltaic electricity generation and electric vehicle charging demand in an exemplary summer week (weekend)