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How Much Does the Sun Power Your EV?

Simulation Study on Wallbox Efficiency

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Abstract. Solar smart charging of electric vehicles is becoming increasingly important for several reasons. This paper uses a detailed time series simulation to show which are the most important influences on the success for the individual user. More than 100,000 runs were analyzed. A key finding is the influence of charging and driving behavior and the amount of excess solar energy on the degree of solar energy used by the electric vehicle. wallbox related parameters such as dead time and control accuracy have less impact on cost savings. In addition, user behavior and different energy management strategies were analyzed within the simulation.

Keywords: Solar, Electric Vehicle, Energy Management, Simulation

1. Introduction

Electrifying transportation is a key step toward a carbon-free energy system [1]–[3]. While uncontrolled charging of electric vehicles (EV) increases peak demand in distribution grids by only 20%–30% [4]–[7], uncoordinated photovoltaic (PV) feed-in can still cause significant challenges for the distribution grid [8]. Controlled solar charging enables an efficient integration of EVs and PV systems: it allows low-cost, carbon-free EV operation and helps to mitigate PV feed-in peaks. This concept aligns with user preferences: over two-thirds of German EV owners already use solar power, with many others considering retrofitting [9], [10]. Despite the synergies between EVs and PV systems, several questions remain: What if daytime charging is not possible? Does slow charging result in high energy losses? And how can advanced wallboxes with phase switching or energy management systems improve the overall efficiency? Although solar home charging is widely practiced, there is a lack of high-resolution data to evaluate the dynamic interaction between PV and EV [11], especially regarding practical features like phase switching and others. Against this background, the present study investigates solar charging performance under real-world-inspired conditions and provides simulation-based answers to key questions. To situate this contribution within the existing body of research, a brief review of previous studies on residential solar EV charging is provided, with a particular focus on the solar share of charging.

Munkhammar et al. (2013) conducted one of the first simulation studies on the coincidence of PV and EV with uncontrolled charging [12]. Besides that, Samweber et al. (2014) also conducted a simulation study based on 15-minute data. They found that shifting maximum power charging could increase the solar share on charging to 25% to 30% and utilizing a stationary battery could double this share [13], [14]. Their findings were later supported and extended by Wille-Hausmann et al. who included demographic factors on the households' inhabitants and found slightly higher shares for pensioners and home office workers [15]. Furthermore, Hofmann et al. (2017) evaluated the solar share of the mileage based on simulations, focusing systematically on driving patterns and specific EVs. The evaluated scenarios highlight the importance of daytime availability and smart charging. Here a stationary battery was found to be negligible for households with the opportunity to charge during the day [16]. Hofmann et al. further explored the influence of usage patterns, while Martin et al. (2022) emphasized the role of user behavior and charging strategies using high-resolution empirical data. This highly relevant work showed that the charging mode as well as the plug-in behavior significantly impact the amount of charged solar energy. Based on empirical data, they simulated solar-optimal instead of maximum power charging and found solar shares between 20% and 90%, depending on the total demand. The importance of routinized plug-in behavior is highlighted in this contribution and could increase the solar share to above 70% and up to 100%. It is supplemented by a side investigation on the use of a stationary battery that could further increase the solar share ranging from 90% to 100% [17]. Ostermann et al. (2023) presented the results of a limited field trial and calculated solar share of unidirectional controlled charging from bidirectional charging. They found solar shares varying from around 30% to 90% [18]. These studies highlight the potential of smart and user-adapted charging to significantly increase the share of solar energy in EV charging.

2. Theoretical Background

This section provides an overview of the system layout, charging strategies, and relevant loss mechanisms. First, the energy system under consideration is shown schematically in Figure **1**. The elements are the PV system, the uncontrolled loads, such as household loads and possibly a heat pump, the home charger, here wallbox, with EV, a coupled power grid and an energy management system controlling the wallbox. A stationary battery may be added, but it is not the focus of this study.

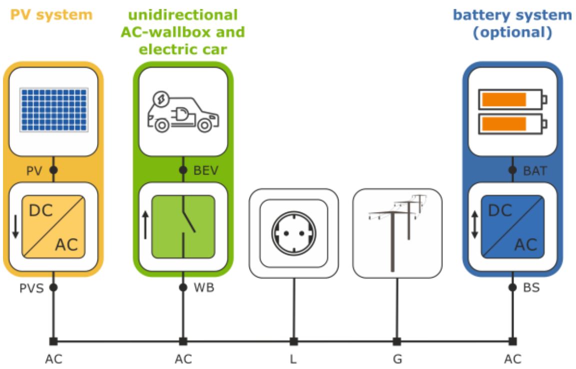

Figure 1. *Schematic system diagram*

Secondly, EV charging can be controlled in different ways. This article focuses only on the use of solar energy, which neglects optimizations that consider dynamic electricity prices. Thus, various charging strategies can be categorized as follows:

- uncontrolled charging (Figure **2** left),
- charging with a release signal, divided into time-controlled charging and threshold-based charging (Figure **2** middle),
- controlled, dynamic excess charging (Figure 2 right).

With uncontrolled charging, the EV is charged at maximum power as soon as it is plugged in. If excess solar power is available, it is used to charge the EV (Figure 2 left). Depending on the wallbox, an energy management system can not only enable charging at a fixed maximum power, but also continuously change the maximum power level of the wallbox. This allows the wallbox to dynamically track excess power and respond to fluctuations in solar power generation and load (Figure **2** right). Uncontrolled charging is used as a reference in this article, as there is no further control of the wallbox. A comparison to dynamic surplus charging is made to show the range of results and the maximum benefit of a solar system for wallbox charging.

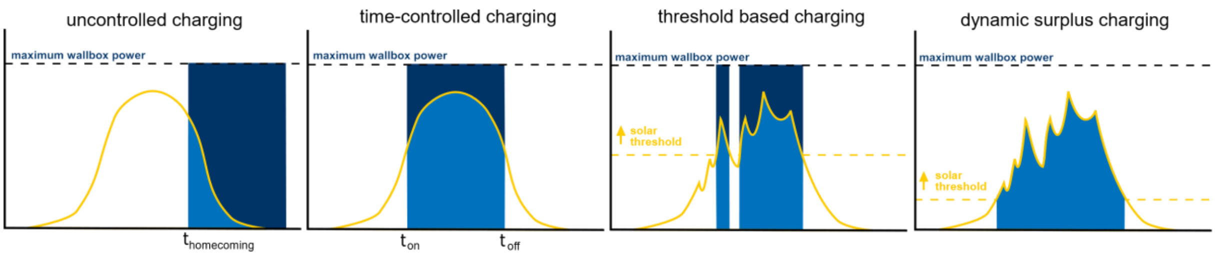

Figure 2. *Charging strategies for wallbox solutions*

Third, in the real application, dynamic surplus charging cannot ideally follow the surplus power. Energy management processing and implementation by the wallbox and EV are prone to errors. Control deviations, delays and dead times are the result. Fluctuations in the household load and changes in PV generation caused by passing clouds occur within seconds. The control delay of the analyzed systems tends to be in the range of minutes to avoid oscillations in the wallbox control. Some observable loss mechanisms are shown in Figure **3**. The first to be mentioned here are stand-by losses. A wallbox is inactive for more than 8000 hours per year, so this is an important parameter. Furthermore, several delays should be mentioned. For example, the delay for phase switching, which is used to ensure a safe switching number of used phases of the onboard charger. Furthermore, the dwell time until charging is started or stopped needs to be mentioned. The charging process is only initiated when the excess power has been above a certain limit for a defined duration. If it falls below the threshold limit, charging continues at minimum power for the dwelling time until charging is stopped. The control dead time is also an important variable as field observation shows diverging delays from instantaneous to a few minutes. The last point to mention is the control accuracy, which is physically limited in addition to the controller. Usually it can only be done 1-A-steps and it is determined by the power limits in single- and three-phase operation.

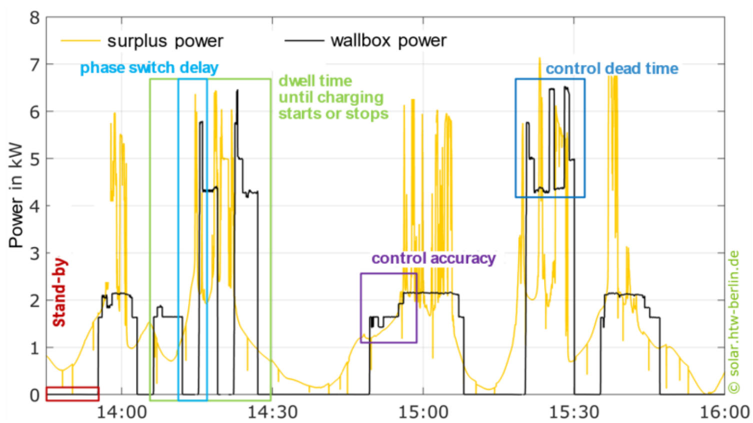

Figure 3. *Wallbox energy management loss mechanisms observed in field measurement.*

3. Methodology and Model Description

A simulation model of a wallbox and a generic EV is used for these investigations. It was developed and parameterized in the context of the research project “Wallbox-Inspektion” [19]. The model represents a 1-minute time series simulation. With over 100,000 annual energy simulations, the wallbox is thoroughly analyzed, and its interaction with the PV system is investigated in detail. The results were checked for plausibility and validated by using monitoring data from real households. The subsequent simulation allows the variation of numerous parameters and the comparison under otherwise identical framework conditions. Among others, the following parameters are considered:

1. Input time series: These include weather and PV generation data [20], household electricity consumption [21] and the mobility behavior of different vehicle users [22].
2. Technical building parameters: Details such as generator orientation, nominal generator power, electrical heat generators or existing battery storage capacity.
3. Wallbox and vehicle parameters: Various technical aspects and regulations, including power limits, phase switching, charging current increments and dead times during charging processes (see Table **2**).
4. Energy management: This includes different charging strategies which can also be found in the wallboxes analyzed in a market overview. For example, uncontrolled charging, threshold-based charging or solar-controlled charging (see Figure **2**).
5. User-specific variations in charging behavior: This includes the circumstances under which charging is initiated. A distinction might be whether this is done in a planned manner, according to routines or with some degree of stochasticity.
6. The simulated systems were compared in terms of both the fraction of annual kilometers covered by the solar system and the absolute savings of an energy management compared to uncontrolled charging.

See Table **1** for a summarizing overview on the input Data

Table 1. *Summarizing table for building parameters and simulation range.*

Parameter	By default	Range
PV power	10 kW	5-20 kW
PV orientation	South	South, East-West
PV inclination	35°	15°, 35°, 45°
PV location	DWD Lindenberg	DE (North, South)
Load profile	HTW 2015 (ADES-IZES #31)	
Mobility	144 SynPro mobility profiles	
Cost energy (Grid)	40 ct / kWh	
Feed-in-tariff	10 ct / kWh	

As this paper focuses on mobility some details need to be pointed out. The mobility behavior is based on the study “Mobility in Germany” [23]. Therefore, a representative sample is asked to document their own mobility behavior. The protocols have been used in numerous studies to generate synthetic households [22], [24]–[26]. In this contribution, synthetic mobility profiles from SynPro by Fraunhofer ISE were used [22]. The mobility profiles include information on arrival and departure times, kilometers driven and vehicle consumption in kilowatt hours. They could be differentiated by household and activity level (e.g. pensioners, workers) and residential environment (e.g. rural, urban). For this study, 144 profiles were selected, considering the demographic and sociological composition of Germany [27].

The EV is modeled as a simplified battery storage system with ideal control behavior (see SimBat [28]). This simplification seems appropriate as it focuses on the influence of the wallbox. The losses of the EV are largely determined by the onboard charger, which has been parameterized with data from Sevdari et al. [29]. The vehicle battery has a usable capacity of 70 kWh, which is less important. Since the wallbox and energy management should be evaluated at this point, the vehicle battery has an ideal efficiency of 100%. Furthermore, the wallbox is characterized by its control behavior. The following properties are considered:

- Dwell time at start or end of charge with solar surplus
- Phase switch delay
- Stand-by power consumption
- Limitations on the minimum and maximum currents, as well as the current increments
- Control dead time

Besides driving, the user has more possibilities to interact with the charging interface. For example, by plugging in the vehicle more often. Plug-in behavior depending on the EVs state of charge and energy for the next trip(s) [9], [30], [31]. Furthermore, the forecasted solar power is considered in this model. By default, the simulation assumed that user’s plug-in and set there EV into waiting mode if:

- The state of charge falls below a certain limit, which is a common charging behavior.
- The EV charge is insufficient for scheduled trips next day, which reflects planning.
- A sunny day is expected, an adjustment to the household's energy resources.

When the EV is plugged in, a target charge level at departure is set up to guarantee mobility requirements. The EV will charge at full power at the latest possible instance of time to reach the target plus an offset. See Table **2** for the default values and range of study. Finally, the monitoring data from a solar integrator is utilized for validation. These cannot be described in detail here, as they are still being published. However, an overview of the data set is provided in Figure **4**.

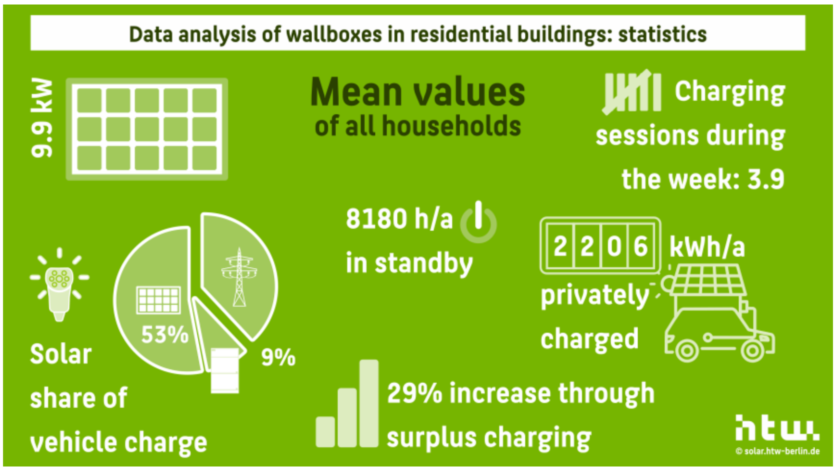

Figure 4. *Data description of the validation data (Data: Fronius International).*

***Table 2**. Parameters of the wallbox model and simulation range.*

Parameter	By default	Range
Target charge level	As late as possible	-
Plug-in behavior	Normal distributed	Every time and randomly
dwell time: start/end charging	5 min	0 min to 10 min
Control dead time	0 min	0 min to 4 min
Minimum current	6 A	-
Maximum current	16 A	-
Current step size	1 A	1 mA to 1 A
Number of used phases	1 & 3 ph.	1 ph., 3 ph., 1 & 3 ph.
Phase switch delay	3 min	0 min bis 6 min
Stand-by power	4 W	0 W bis 15 W
Deep-Standby power	2 W after 10 min	-
On-board-charger efficiency	Median	Min. to max. Efficiency

4. Findings

The use of solar energy is significantly influenced by the energy demand and the timing between load and PV generation. Therefore, the presentation of the results is structured as follows: in the first step a detailed look at the load profiles is taken. In the second step, the influence of a change in PV generation on the solar share is examined. In the third part of the results analysis, the other wallbox parameters are investigated.

4.1 Driving and User Behavior

This section takes a closer look at the driving profiles on which the study is based. First, the availability of the vehicle battery over time and its annual energy demand are considered. The second step is to show what proportion of vehicle charging can be expected from solar charging with a 10 kW PV system. The simulation parameters are taken from Table **2**.

As mentioned above, the travel profiles are based on a survey. Among other things, the trip destinations are specified so that the arrival and departure time at the place of residence are included in the trip profile. The average daily travel profiles can be divided into three groups (see Figure **5** left). The profiles in green represent the group of full-time employees. They typically leave home between 5 and 8 a.m. and return by 6 p.m. According to the survey, the data shows that, on average, 45% of the working population is at home during the day. Part-time workers are more likely to be home at noon (blue curve). In the afternoon, they are more likely to be home than full-time workers. The driving profiles of the third cluster in orange can be assigned to retired people, people who work from home, and families with a division of labor. They have a less pronounced daily traffic pattern and are more likely to be at home during the day. Looking at the weekly mobility profiles, it is not surprising that the daily travel profile of working people is mainly attributable to the working days Monday to Friday. Over the weekend, the vehicles of these two clusters are often at home, which increases the average value over the course of the day.

Figure **5** (right) shows the relationship between the average amount of time a vehicle spends at home between 8 a.m. and 4 p.m. and the kilometers driven by each vehicle. The colors correspond to the average driving profile clusters depict in Figure **5** (left). Not surprisingly, vehicles with high annual mileage tend to be on the road more often. Based on the clusters, it can be seen that working people drive more kilometers with EVs than people with a higher daytime share. On the other hand, there is a wide range of annual mileage for a given proportion of daytime presence. For example, the driving profiles with an average daytime presence of 40% have annual mileages between 8000 km and 28000 km, a discrepancy that can be partially explained by rural or urban residence.

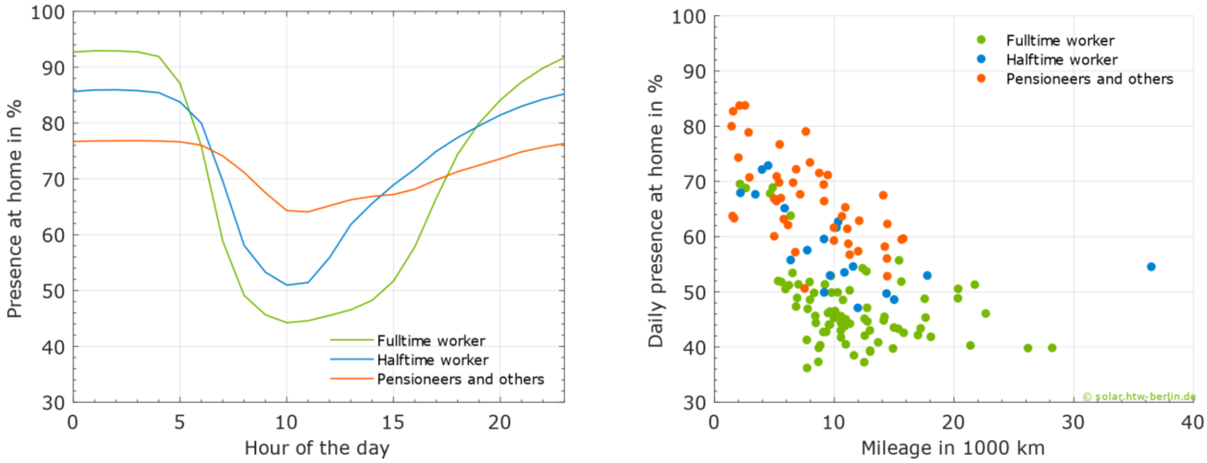

Figure 5. *General and daily presence at home over the course of the day (left) and mileage (right).*

The annual mileage correlates to the energy consumption of an electric vehicle. On average the vehicles in the simulation consume 1790 kWh per year and drive 10000 km. Since driving behavior is also represented by the model, a range is given for the same mileage. Between 1300 kWh and 2300 kWh are consumed for 10000 km and between 2500 kWh and 4000 kWh for 20000 km respectively. To cover a high proportion of this energy, the PV system must generate a significant proportion of the energy while the vehicle is at home.

The relationship between presence and solar share for a 10 kW PV system is shown in Figure **6** (left). If the wallbox charging can follow the solar excess power, the solar share could be between 30% and 90%, with an average of 54%. There is a clear correlation between the solar share and the daily presence, as shown by the equalization line in the figure. The scatter of the data can be partially explained by the different energy requirements of the vehicles, as indicated by the color of the dots. For the same daytime presence, the proportion of solar energy is higher for lower wallbox energy requirements and lower for higher energy requirements.

However, the absolute amount of energy from the PV system in the EV increases in this case. A larger PV system causes a shift of the data points and the equalization curve, which indicates that the energy at 10 kW is not sufficient to fully charge the vehicles with solar energy. This means that for a high share of solar energy, a high daytime presence is advantageous, but not mandatory. In addition, the PV energy produced should correspond to a multiple of the vehicle demand multiplied by the daytime presence to have sufficient energy available for charging especially in winter times.

Figure **6** (right) shows the effect of plugging in the vehicle more frequently. If the vehicle is plugged in whenever possible, solar charging can be increased. However, this requires some routine and may require some effort. The benefits are shown in blue for a 10 kW PV system. On the one hand, the solar share has increased by approximately 17%, while on the other hand, the variance has decreased marginally, indicating that the solar share is becoming less dependent on EVs usage. The measured data from the monitoring portal are highlighted in gray. It can be seen that the bandwidth can be mapped quite well. Note: Gray data points with low solar shares in the monitoring can often be associated with households charging at evening and night hours.

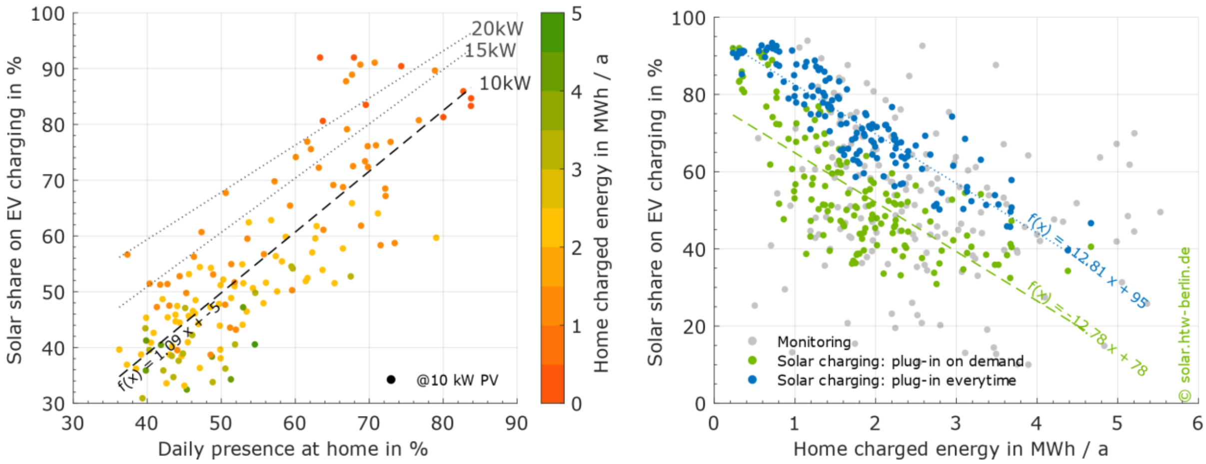

Figure 6. *Solar share on EV charging versus daily presence (left) and home charged energy with different plug-in behavior (right). (Data Fronius)*

4.2 PV Power

In addition to user behavior, the size of the PV generator plays an important role. For smaller PV systems in particular, the question arises whether a minimum charging power of 4.2 kW for three-phase charging is appropriate or whether single-phase charging is more promising. Figure **7** shows the average value of the solar fraction of the 144 EV driving profiles versus the PV power. The colors indicate whether the wallbox is charging single-phase, three-phase or with phase switching. In addition, the uncontrolled charging on arrival with maximum power is shown in blue. It serves as a reference. The gray dots represent the median solar fraction from all monitoring data under comparable conditions. Note: the monitoring data does not distinguish between charging modes or phases in use, therefore the data cannot be separated as clearly as in the simulation, The graph thus illustrates several things:

1. The solar share increases as the PV surplus increases.
2. Uncontrolled charging of an electric vehicle on arrival is not very compatible with the use of solar energy, as most households tend to arrive in the late afternoon hours.
3. If a solar-only charging mode is desired, this cannot be reasonably achieved with three-phase charging for small solar systems. An offset should be used here so that even lower PV power can be used sensibly.
4. Systems with a PV output of less than 15 kW can also achieve a high proportion of solar energy with a single-phase wallbox. The disadvantage is a lag of flexibility for faster charging and higher conversion losses.
5. Highest solar shares can be achieved with a wallbox with phase switching capability.
6. The monitoring data show that the simulations are, on average, a good representation of reality.

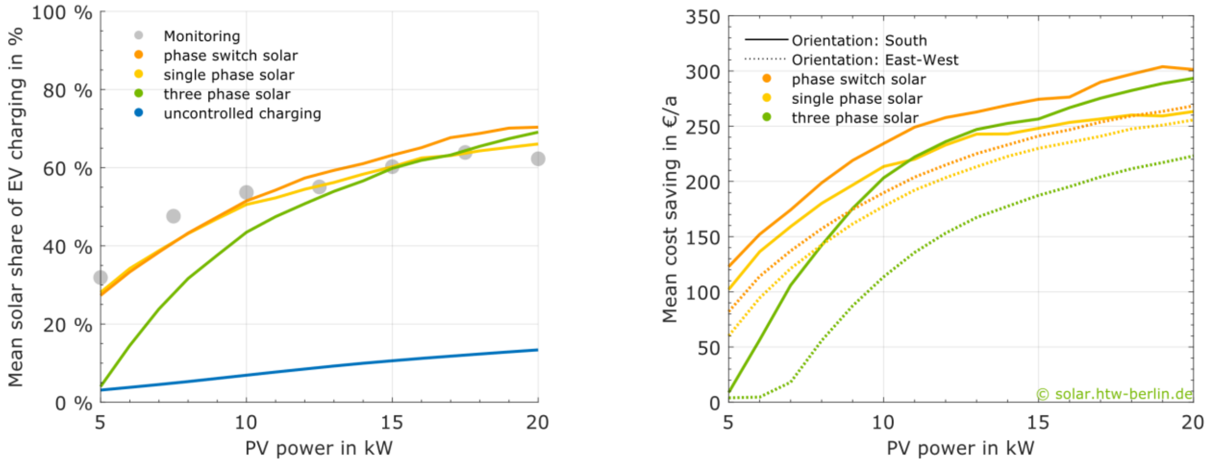

Figure 7. *Solar share of wallbox charging (left) and energy management savings (right) versus PV power. Line colors indicate single-, three-phase and phase-switching wallboxes. Data: Fronius*

It may be misleading to consider the solar share only. This is because high conversion losses in the on-board charger [29] make charging over a longer period less attractive [32]. Figure **7** (right) shows the average operating cost savings due to energy management compared to uncontrolled charging, in terms of PV power. It is worth noting that the differences between single-phase and three-phase wallboxes are relevant at low PV power levels but become significantly less relevant at power levels above 10 kW. Wallboxes with the ability to switch phases are particularly advantageous between 8 kW and 15 kW compared to the fixed number of phases. A different inclination and orientation of the PV generator has a surprisingly small effect. Thus, a higher solar production in the morning and evening times could be used disproportionately better than the midday solar energy. It is important to note that a three-phase only wallbox works much worse in this case. Besides the EV load profile, it has been shown that the PV generation is a key factor influencing the benefits of solar charging. Hence, it seems appropriate to adapt the used phases and therefore the maximum wallbox power under consideration of the available PV power.

In addition to the economic assessment, the efficiency of the energy system also deserves attention. Analyses show that the charging losses of single-phase wallboxes can sometimes exceed 30%. This is due to the low partial load efficiency of the on-board charger. In contrast, using the full power of the on-board charger can reduce losses to less than 20% on average. However, since solar power is much cheaper than grid power, higher losses can still be economically advantageous. The efficiency of the on-board charger can also be varied in the simulation model and is closely related to the number of phases used. A summary of the savings from a low, medium and high efficiency on-board charger derived by [29] is shown in Figure **8** for a 10-kW-PV-system on the left side.

The right side of Figure **8** shows the average solar share for four different charging strategies as a function of PV system size. All strategies exhibit a rising solar share with increasing PV power, as already shown in Figure 6. New here are the two trigger-based strategies and the consideration of variability across individual driving profiles. At the lower end, uncontrolled charging shows a broad variation due to the strong mismatch between arrival times and PV generation. The solar share typically ranges from around –25% to +48% relative to the median, depending on the driving profile. For instance, with a 10 kW PV system, some profiles achieve less than 18% solar share, and for over 75% of profiles, the value remains below 11%. A clock-based trigger charging introduces a fixed daytime charging window, reducing variation somewhat. However, this strategy performs slightly better on average particularly with larger PV systems. The solar share here depends only weakly on driving behavior. A PV-power-based trigger charging activates charging once a predefined PV output (e.g., 50%) is exceeded. This yields in higher average solar shares than clock-based control and already approaches the performance of dynamic control for larger PV systems. However, the variation increases with

PV size, typically ranging around ±12% from the median, depending on user availability. With a 15 kW PV system more than 75% of the households reach solar shares above 50% and 25% of the households more than 65%. At the top, surplus-based charging results in the highest median values and a spread, around ±10 percentage points (absolute). Since charging directly follows excess generation, it adapts well to different PV sizes and driving behaviors. Overall, the effect of the driving profile increases with more advanced control strategies. Certain driving profiles benefit more from simple trigger-based control than others do from dynamic control. Nevertheless, the combination of driving patterns and PV size remains the key determinant of solar charging performance.

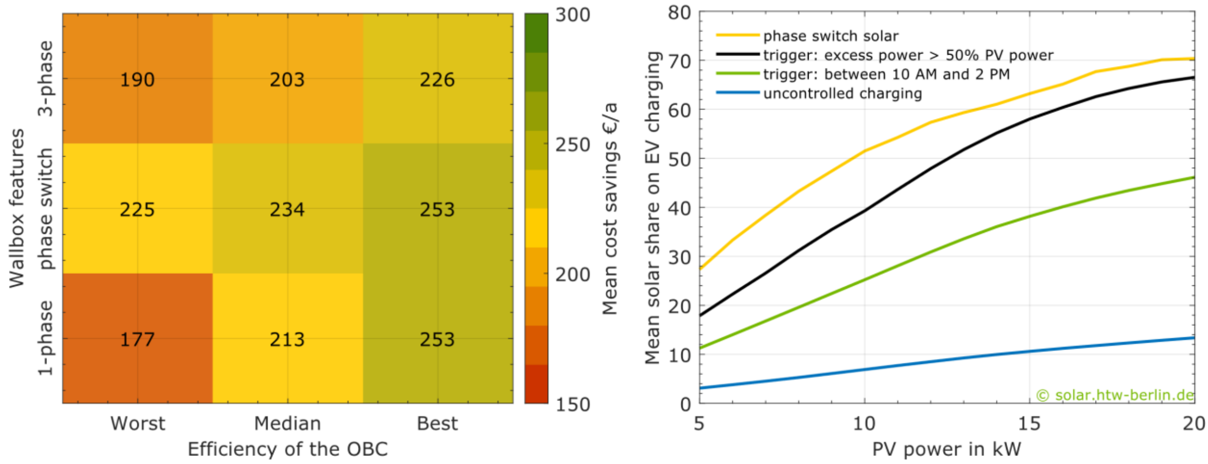

Figure 8. *Energy management savings for on-board chargers with different conversion efficiencies (left). Average solar fraction over PV power as a function of energy management strategy (right).*

4.3 Wallbox Parameters

Finally, the above-mentioned wallbox parameters and the corresponding loss mechanisms shall be investigated (see Figure **3**). As in the previous reference setup, a 10-kW-PV-system and all 144 mobility profiles and a stochastic plug-in behavior are considered. The average cost savings of this setup when using solar charging instead of uncontrolled charging is 234 € per year. The technical parameters of the wallbox seem to have a small but not negligible influence. To determine the influence of each technical parameter, all parameters were varied separately within a reasonable range, while the other parameters were kept at the reference values. Figure **9** shows the difference in energy management savings from the baseline simulation's 234 €/a, with varying the wallbox parameters.

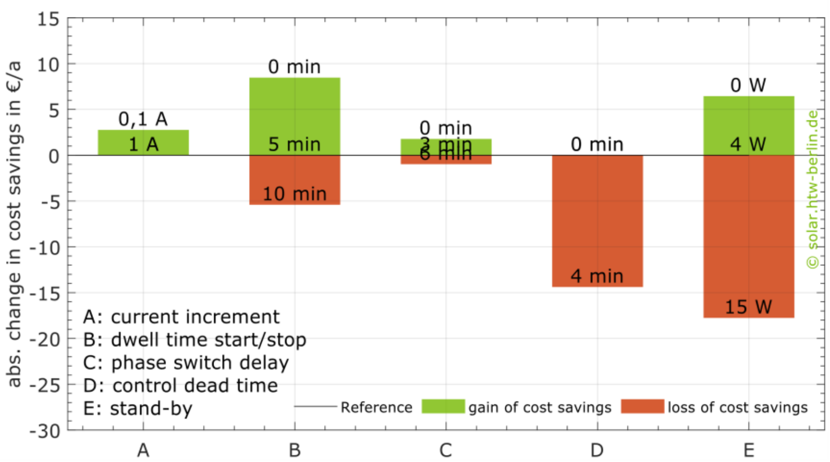

Figure 9. *Average solar fraction over PV power as a function of energy management strategy.*

First, it should be noted that stand-by losses have the most significant impact on energy management savings and should be managed carefully. As the wallbox is in idle mode for an average of more than 8000 hours per year, designers and engineers are asked to work on appropriate solutions to recover most of the up to 7% potential losses. A large optimization potential seems to be a well implemented deep stand-by. Secondly the dwell time until charging starts or stops and control dead time should be mentioned. On average, up to 6% of the cost savings could have been lost if this parameter is not chosen appropriately. Surprisingly, the step size of the charging current, and thus the watt-precision control of the charging power, as well as the phase switch delay have little impact on the savings. Note that the simulation always negatively offsets the excess PV power, so that the wallbox control signal does never exceed the excess power.

The simulation analysis also reveals that the choice of "cloud hysteresis", the delay until the wallbox is turned off or initializes a phase switch, and the phase switch delay have a significant impact on the number of switching operations. This is of particular interest as it could have an impact on the lifetime of the wallbox, which should be considered when choosing these parameters.

5. Discussion

The detailed modeling of wallbox control behavior presented in this study closely reflects real-world operation. The developed model tends to be calibrated with laboratory measurements from an efficiency guide developed within the research project "Wallbox Inspection". As seen before, the simulations fall in line with the observations in the field data if the plug-in behavior is parameterized well (see Figure **6**) and confirms findings from previous simulation studies [17], [33], [34]. On the other hand, it is obvious that a generic plug-in algorithm could not represent the variation of the real behavior. A plausible approach has been presented, using a three-dimensional distribution function that reflects plug-in behavior, trip energy demand, and expected solar generation. It should be noted, however, the interpretation of the results is more ambiguous than the summary figures may suggest. This is due to the wide distribution of the results depending on the input. Here, explanations were found in EV energy demand and daytime presence at home. Nevertheless, the results are within ±15% of the averages shown in most of the figures. This makes it difficult to draw clear conclusions from the given picture, as the different categories largely overlap.

In addition, the available energy has a major influence on the results as section0shows. On the other hand, the variation of the time series of the uncontrollable load and PV input data could not be sufficiently presented within this contribution. The site dependent solar energy may have influenced the simulation in the same way as the uncontrollable load, since both determine the excess power. To illustrate the effect of geographic variation, a classification for the 10 kW reference system is provided. If the location of the simulation is moved for example to Hamburg, the solar fraction could be reduced by 5% on average and rise by 4% if located in Munich.

In addition, neither heat pumps nor batteries were included in the simulation, although there are common among PV and EV users [35]. For heat pumps monitoring data shows that their operation can reduce the solar share by 6% at median, primarily due to increased daytime consumption during darker months. Furthermore, stationary batteries contribute little to the solar fraction of EV charging. This is due to the often relatively small capacity of a stationary battery compared to an EV battery. On the other hand, field observations have shown that stationary batteries could help eliminate most of the control-related losses shown in Figure 3. This reduces grid energy and disproportionately increases cost savings. However, this strongly depends on the energy management system of the battery, whether it can meet the demand of the EVs and thus improve the control. However, an indication is the median shift of +10% in the solar fraction found in the validation data. A deeper analysis of battery-EV coordination via energy management systems remains a key area for future work, as it could unlock further efficiency gains.

6. Conclusion and outlook

The results show that solar controlled charging offers significant advantages in terms of operational cost savings. Charging and driving behavior, as well as the available solar energy, emerge as the primary determinants of solar utilization. In contrast, wallbox-specific parameters such as dead time or control precision play a secondary role. To analyze all parameters in detail, a wallbox simulation model is presented, which could be parameterized by the results of the efficiency guideline also developed in the research project "Wallbox Inspection”.

While the presented model provides a solid basis for understanding solar-controlled charging, further research is required to address open questions regarding integrated energy management — including the interaction with heat pumps, batteries, and dynamic electricity tariffs. In addition, the high-resolution validation dataset collected during monitoring warrants a more detailed analysis in a dedicated future publication.

Data availability statement

The underlying third-party data can’t be provided as it is protected by copyright. The simulation results will be published with the model but is available earlier on request.

Underlying and related material

The simulation model is currently undergoing publication and will be made available for the evaluation of laboratory measurements of the efficiency guideline once it is publicly available.

Competing interests

The authors declare that they have no competing interests.

Author contributions

Bergner wrote the draft of the manuscript (Writing – Original Draft). Bergner and Orth carried out the investigation (Investigation). Quaschning supervised the research (Supervision).

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