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Solar charging - lessons learned from field observation

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Executive Summary

Although the combination of solar power and electric vehicles has been suggested to be beneficial, practical application shows a wide variance. A dataset of 725 household energy time series was analyzed to determine the proportion of solar energy used for charging and to identify the main drivers of a high solar share. Furthermore, the degree of self-sufficiency of these households with respect to solar charging has been examined in detail.

Keywords: Consumer behaviour, Smart Charging, Energy Management, Modelling and Simulation

1 Introduction

Solar power (PV) and electric vehicles (EV) are key elements of a fossil-free transition [1].
The combination of solar energy and EVs appears to be beneficial for residential consumers, as solar energy is more cost effective than grid consumption. Homeowners with private driveways are the primary beneficiaries of this trend, due to the ease of implementation. Owners of PV systems often choose to invest in EVs to utilize their surplus energy. Conversely, EV users also show interest in purchasing PV systems, although this interest has slightly lower statistical significance [2].
Nevertheless, the share of PV owners who also operate an EV is growing faster than the rest of the population, e.g., in Germany it is by about 16% [3], [4] compared to 2% for all inhabitants [5]. This is only at first glance an environmental concern, but the motivation shifts to economic considerations. The economic benefits have been investigated in several case studies (e.g. [6], [7], [8]).
While the combination of solar and EV is an accepted concept, there is a lack of detailed analysis based on comprehensive statistical data that demonstrates the practical implications of this combination. Factors such as the mobility patterns of working individuals, PV generator sizing, the integration with battery storage, and solar smart charging are expected to significantly impact the economic and energy benefits of a solar EV household. In order to accurately determine these benefits, it is essential to have a comprehensive statistical data base. Only a few studies have evaluated the use of individual private EVs based on measured data (e.g. [7]). This paper provides a detailed analysis of a whole year of monitoring data from over 3800 EVs paired with PV systems. This study investigates how solar-relevant parameters affect the solar charging of electric vehicles. It aims to bridge the knowledge gap between conceptual studies and the practical use and benefits in the German, Austrian, and Swiss mass markets.

2 Monitoring Data

2.1 Basic description

The data analyzed is provided by Fronius International, an Austrian solar system integrator. Fronius collects energy-related data through a web monitoring portal to provide better service to its customers. This portal provides transparency on operational functions, showing energy consumption types, solar energy shares, power flows, and time series data of load and generation.
An energy system depicted in the data can be illustrated using Figure 1, showcasing all relevant power flows. The system consists of a grid-connected PV generator, which may include a battery system, residential load,

EV charging as a sub-entity, and a grid connection. Both the PV and battery systems can supply power to different loads or feed surplus energy into the grid. The loads are categorized into different sinks, such as households and thermal applications on the one hand and the EV on the other. Note that EV usage is measured separately. In Figure 1, boxes represent the system elements, while arrows indicate the flow of power from a source to a sink. Thus, PV power is represented by a straight arrow, battery power by a dashed arrow, and grid power by a dotted arrow.
It is worth noting that not all quantities within the data are measured by a dedicated meter. For example, EV power is given by the electric vehicle supply equipment (EVSE), while PV and battery power are provided by a calculation from the system integrator. It integrates PV (DC-) converter values, battery (DC-) converter values, and AC values from the PV battery inverter. Only the grid power is measured by a dedicated energy meter. The total load is therefore the value that results when all other values within a certain time step are added together. The power flows between the units were taken from a Fronius International's calculation, however they could be recalculated. Contrary to the original data, this study states that the PV system prioritizes the household demand before powering the EV, rather than powering both by the share on total load. This is crucial when assessing the solar contribution to EV charging.

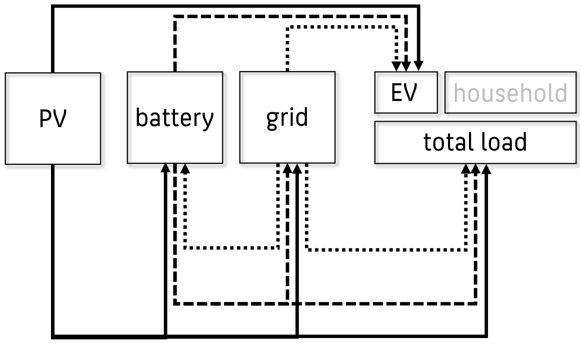

Figure 1: Schematic of the represented home energy Arrows symbolize a power flow from one to another.

Since the system integrator holds more than the provided data of interest (PV+EV+X), export filters were applied. First, only data that includes an EVSE was included. Second, at least one year of monitoring was acquired to ensure accurate solar evaluations; therefore, two years of data per household were provided by Fronius International to meet this requirement. Since one household could have up to two years of usable data, they were analyzed as two separate datasets, even though they may be very similar. Third, data was extracted solely from the "DACH region" (Germany, Austria, Switzerland), assuming a comparable socio-economic environment.
The 3800-household-dataset provided consists of a metadata table and a time series table for each anonymous user. The metadata includes a system description such as installed PV power, presence of a battery system, country, four-digit postal code and Boolean representation of other system elements. Time series are available for PV power and the power to battery, total load, EV and grid. In addition, the power from battery to total load, EV and grid and the state of charge (SOC) can be used for the analysis. At least all power flows from the grid, to the battery, total load and EV can be found in the dataset. Note that the calculated time series are not perfectly balanced. This may be due to the combination of DC and AC values on one side and differences in the time stamp on the other side. Additionally, measurement deviations must be considered. The dataset is suitable for evaluations over one year.

2.2 Data preparation

In a second step, the data was reviewed and records with poor data quality or implausibility were excluded. Missing values of one week in a row were accepted, but manually revised. Small data tips of less than one hour were interpolated. Additionally, any missing EV loads greater than one month were excluded, as well as PV power above 30 kW and a load without EV greater than 15 MWh/a, as these were assumed to be non-residential. Note: A classification was applied during the review process since some of the data is not applicable to all analyses. This leads to different numbers in various analyses. Table 1 provides an indicative view of the total data set numbers.
A common issue is the disconnection of the EVSE from the internet or an unmonitored secondary EVSE, resulting in unmonitored charging events. As a result, this may lead to an increased household load, as the EV cannot be subtracted from the total load. To address this problem, a detection algorithm has been implemented to identify charging events with steep power edges or solar charging. Detected but unmonitored charging events were reviewed and replaced if deemed acceptable.

Table 1: Data sample statistics

		N	Percent
Total provided data	Households	3808	100 %
	One year	7616	100 %
Applicable to general statistics	Households	734	23 %
	One year	849	11 %
Applicable to all analysis	Households	642	16 %
	One year	725	10 %

In addition, some metadata has been partially manipulated and expanded. According to the provider the metadata sometimes contains manual entries by installers or costumers and is therefore prone to errors. At the same time, some PV systems have been expanded over the course of the year and the metadata only contain the higher value. Especially PV power was adjusted to plausible values where necessary. Means for misleading values were the specific PV energy, maximum power output compared to the noted installed power. Furthermore, Boolean entries of further system element have been set to plausible values. For example, if a battery system is expected from the metadata but no power flow could be found in the time series.

Since the metadata lacks interesting entities like the presence of electrical heating devices such as heat pumps or battery these metadata were derived by an analyzes of the individual time series. Furthermore, quantities for evaluation can be derived from the data. The methodological approach is presented in Table 2.

Table 2: Methods to enhance the metadata

Estimation of the battery capacity	$mean\left(\frac{P_{\mathrm{bat}}(t)\cdot\Delta t}{\Delta SOC(t)}\right)$	The battery capacity $E_{c,\mathrm{bat}}$ was determined by dividing the energy change of a time step change $P_{\mathrm{bat}}(t)\cdot\Delta t$ by the SOC deviation in the same time step $\Delta SOC(t)$. Since the SOC of a lithium battery is typically derived from the voltage, counted ampere-hours [9] some limitations need to be advised. First, there may be non-linear effects at low SOC levels and secondly the granularity of the SOC is low, therefore a higher energy is necessary to get plausible changes in the SOC. In this study only those 30% of time with highest SOC changes have been used for calculation.
Binary decision function if a heat pump is used	$w\begin{pmatrix} E_{\mathrm{load}} \\ \sigma(E_{\mathrm{load}}) \\ \max(E_{\mathrm{load}}) \\ \max(E_{\mathrm{load}})-\min(E_{\mathrm{load}}) \end{pmatrix}$	Detecting the use of a heat pump in a household can be achieved by detailed analysis of energy consumption patterns. Heat pumps typically show lower energy usage when temperatures rise, though other appliances may follow this pattern to a lesser extent. Additional variables such as standard deviation, maximum, and the difference between minimum and maximum energy consumption can help identify households with heat pumps. In this study two conditions need to be satisfied for a binary decision variable. 1. The quadratic balance function of the monthly energy consumption must be opened upwards to fulfill the condition of the annual energy consumption pattern. 2. Monthly energy consumption has been linked though different weight functions. The weight functions have been calibrated by observations of a training dataset, so that the sum is greater than one if the presence of a heat pump is very likely
Rural and urban location analysis	$DoU(id_{\mathrm{post}})$	The degree of urbanization (DoU) is determined for each individual household by attribution to the postal code id_{post} contained in the dataset as proxy for daily commuting distances [10]. It is separated into three categories: cities, towns and suburbs, rural areas.
Solar share on EV charging	$\frac{E_{\mathrm{pv2evse}}}{E_{\mathrm{evse}}}$	To what degree solar energy is used to power the EV is determined by dividing the solar energy preserved by the EVSE E_{pv2evse} by the total energy conducted by the EVSE E_{evse}.
Degree of self-sufficiency	$\frac{E_{\mathrm{pv2loadtotal}}}{E_{\mathrm{loadtotal}}}$	Next to the solar share on EV charging, the degree of self-sufficiency is an important entity to quantify the performance of a solar system with self-consumption. It denotes the share on solar energy that is consumed onside $E_{\mathrm{pv2loadtotal}}$ on the total load $E_{\mathrm{loadtotal}}$.

Note: These extended meta values are calculated with care but in some cases, they are probably wrong due to a very specific load profile. In some households, heat pumps and unmonitored charging events could not be clearly distinguished. These households were also excluded from further analysis. It is worth noting that the PV energy consumed onsite may have been previously stored in a battery system. In this case solar share of EV charging and the level of self-sufficiency had to be adjusted slightly.

3 Data statistics

According to Table 1, the absolute number of analyzed data is more than 725 years within 642 households. All households operate a PV system and an EV. The proportion of households with a stationary battery storage system (BAT) is 48%. The battery capacity is less than 15 kWh in more than 90% of cases. In addition to the battery an electrical heating system is observed frequently. Users who already operate a heat pump or other electric auxiliary heating systems could be evaluated to 44% (HP). This is particularly relevant for the, as households with thermal applications have a higher energy demand, especially in winter. The sample appears to be significant in comparing German households, according to a study by the KfW Institute [4]. Table 3 shows the comparison. Below is a statistical description of the data set, focusing on PV system characteristics and load analysis. Special attention is given to the EV charging analysis.

Table 3: Proportion of household equipment according to KfW and the sample.
(PV: solar system, EV: electric vehicle, HP: heat pump, BAT: battery storage)
Data: KfW [4] and Fronius International.

	KfW 2024		Sample
	On PV share 2023	On PV + EV + …share 2023	PV + EV + … share 2022/23
PV+EV	8 %	35 %	28 %
PV+ EV + HP	4 %	17 %	24 %
PV+EV+BAT	7 %	30 %	30 %
PV+EV+BAT+HP	4 %	17 %	18 %

3.1 PV statistics

The distribution of the installed PV power is shown in Figure 2 (left) and compared to the distribution of the PV system power between 1 kW and 30 kW according to the German Federal Grid Agency [11]. Hence, the PV power in the data set is slightly higher on average than it would have been expected based on the Federal Grid Agency. The distribution has its median at 10 kW and the middle 50% range from 7.5 kW to 14.7 kW. The specific yield of PV systems is a key measure of their quality. Figure 2 (right) illustrates the PV power along with the absolute yield on the secondary axis. The median specific annual yield for the PV systems in the dataset is 960 kWh/kW, with the middle 50% ranging from 830 kWh/kW to 1090 kWh/kW. The absolute annual photovoltaic (PV) yield is adjusted based on the installed PV capacity, resulting in a wider range of values. Annual yields vary from 4.5 MWh to 30 MWh, with a median value of 10 kWh. It is noteworthy that 90% of the systems in the sample achieve an annual yield greater than 7000 kWh.

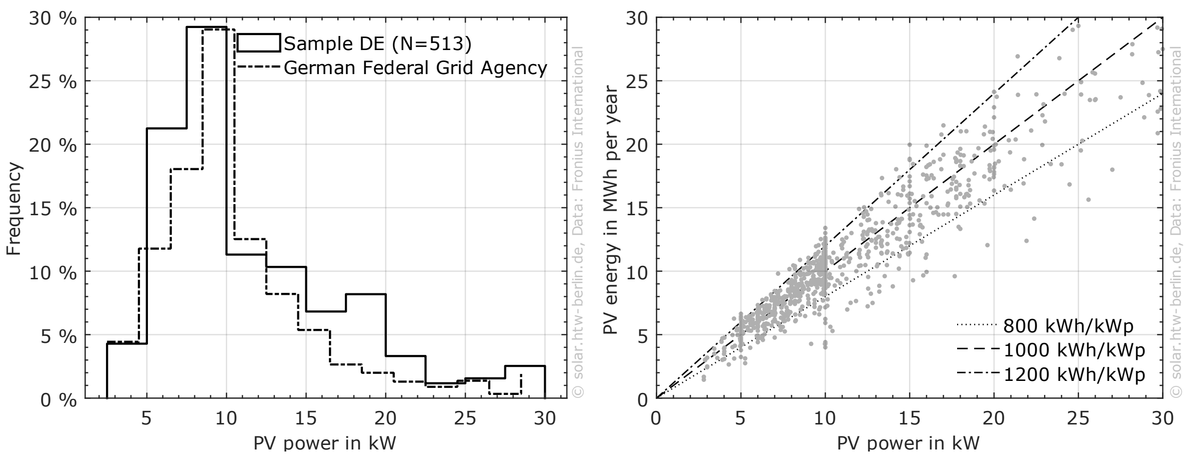

Figure 2: Distribution of the installed PV power (left). Yield and specific yield (right, n=849).
Data: Fronius International, German Federal Grid Agency

3.2 Load statistics

As Figure 1 shows, the load of the considered systems can be divided into three parts: total load, household load and EV load. Figure 3 (left) shows the distribution of the household load and the total load. In the median of the dataset 5.6 MWh per year are consumed by the household and 8.1 MWh if an EV is included.

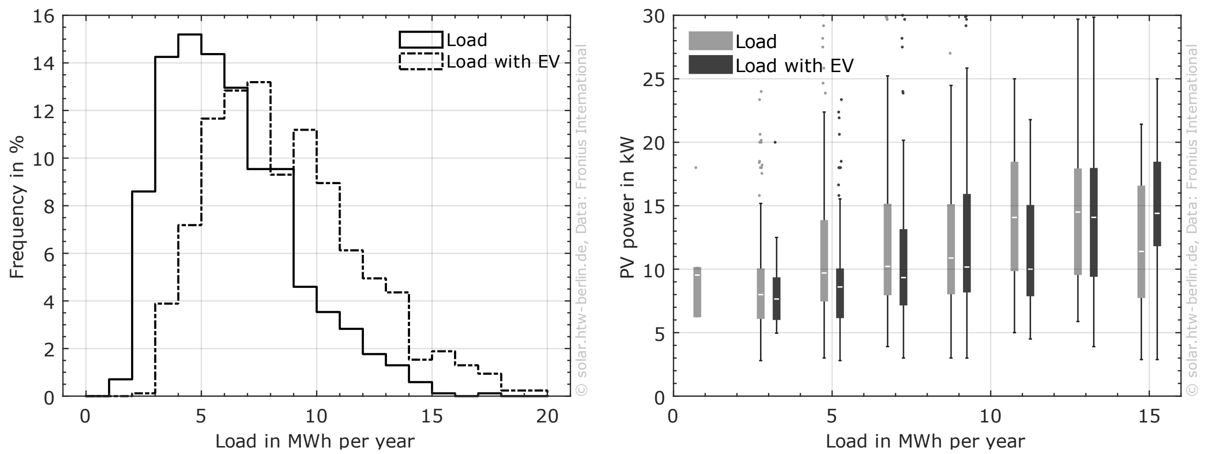

Figure 3: Distribution of the total load and the load excluding EV (left). Correlation of PV power and load (right). n = 849, Data: Fronius International.

Furthermore, the distribution is wide and the middle 50 % of the household loads vary between 3.9 MWh and 7.5 MWh. A similar variation around the median can be seen for the total load. The median energy consumption is summarized in Table 4 for households with different combinations of appliances. On the right side of Figure 3, the energy demand is correlated with the solar power. It can be seen that the installed power increases with the energy demand. The median is 0.5 kW per 1000 kWh. It is worth noting that it is impossible to determine whether high consumption or high production caused this observation. The energy consumption of the households is therefore slightly higher than expected from other questionnaires [12]. This can be explained by the fact that a larger part of the sample already uses electric or partially electric heating. On the one hand, this increases the energy demand; on the other hand, it indicates that the sample is likely to be biased in terms of income, environmental awareness and household equipment compared to the population as a whole.

Table 4: Median energy demand with and without EV

	Energy demand without EV in MWh/a	Energy demand with EV in MWh/a
Median whole sample	5.6	8.1
Median without heat pump or battery	4.1	6.2
Median with heat pump	7.3	10.1
Median with heat pump and battery	8.2	10.5
Median with battery	4.8	6.9

3.3 EV statistics

The following analysis focuses on vehicle use. It should be noted that complete data on vehicle use is not available in this study, and that only the proportion of energy charged at home is considered. Several studies have shown that, on average, this accounts for about 70% to 75% of the energy charged [13], [14], [15]. However, as the NOW company states in its survey on EV users: "There is some variation in the proportion of private charging. While half of the respondents said that more than 90% of the charging was done at home, 10% said that only up to a quarter of the total charging volume was done at home" [14].

The energy charged by electric vehicles at home within the sample ranges from 500 kWh to 6000 kWh per year. The median is around 2000 kWh and 50% of the households surveyed charge between 1400 kWh and 2800 kWh per year at home. It's worth noting: Locations with lower population density have on average 10% more charged energy than densely populated locations. This is plausible because daily commuting times are longer in rural areas than in urban centers.

For better comparability between fossil and electric mobility, the amount of energy can be roughly converted into annual kilometers driven (mileage). This study assumes a consumption of 20 kWh per 100 km. Therefore, Figure 4 (left) shows the distribution of kilometers driven for the sample, a survey on EV users conducted by the consulting firm uscale [13], and a survey of all drivers conducted by the German automobile trust [16]. The uscale survey sample covers an average mileage of 12670 km per year. This is slightly lower than the value of 12320 km per year stated by the Germany’s Federal Motor Transport Authority [17]. Even lower is the median mileage of the sample of this article with 11032 km per year. This can be explained by the fact that only home charging is included in the monitoring data. The 70% to 75% of

home-charged energy mentioned above would fit quite well for this the distribution to resample uscales distribution. On the other hand, the automobile trust survey gives a lower mileage distribution, which indicates that EV users drive more than their fossil equivalents [16].
Besides driving, the charging behavior has a huge impact on the energy used in the car. If the charging process is started in the morning or during the day it is likely that a greater proportion will come from solar energy. On the other hand, dynamic tariffs, with low prices at night and midday are obliged to encourage grid-friendly charging behavior by shifting loads from the morning and evening to lower-priced times.
One measure to gain insight into the individual charging behavior is a mean day profile, which contains the energy portion of each time step. A kmeans cluster analysis was performed on these mean daily profiles and the resulting typical charging profiles are shown in Figure 4 (right). The average daily pattern could be clustered into four groups:

1. 70%, most of the households, charge in a solar charging pattern, (n=587). They can be divided into two groups, those who charge as soon as possible and those who charge during the day.
2. 15% of the sample tend to charge in the afternoon but partially charge solar whenever it is possible (n=123).
3. 7% charge in the evening hours, often charging at maximum power on arrival (n=61), this is a typical behavior of users without a PV system [14].
4. 8% shift their charging to midday or night hours, off-peak to grid load. These households are assumed to use dynamic tariffs (n=71).

The charging frequency of the 849 datasets examined is distributed as shown in Figure 5: 18% of households, plug in the electric vehicle every day or at least 5 days a week. Exactly half of the households charge their vehicle 3 to 5 days per week. For 10% and 1% of the households, respectively, charging 4 times a month or less is the exception rather than the rule. There is a tendency for higher charging frequencies to be associated with higher energy demand. Even if the charged energy is distributed within an individual household the median of the charging events of each household could be compared. 75% of the households consume less than 12 kWh of energy per charge and the median is 9 kWh.
The question is, what are the reasons for those households with spare charging frequency, e.g. less than twice a week, to shift their charging? These households are found to charge more frequently on the weekends, have slightly smaller PV installations, and charge more energy at once. The median of this subsample increases by about 30% to 11.5 kWh, which is close to the upper interquartile of the full sample. The distribution within the individual household is more spread out compared to the full sample. The 75% charge less than 18.5 kWh per charge.

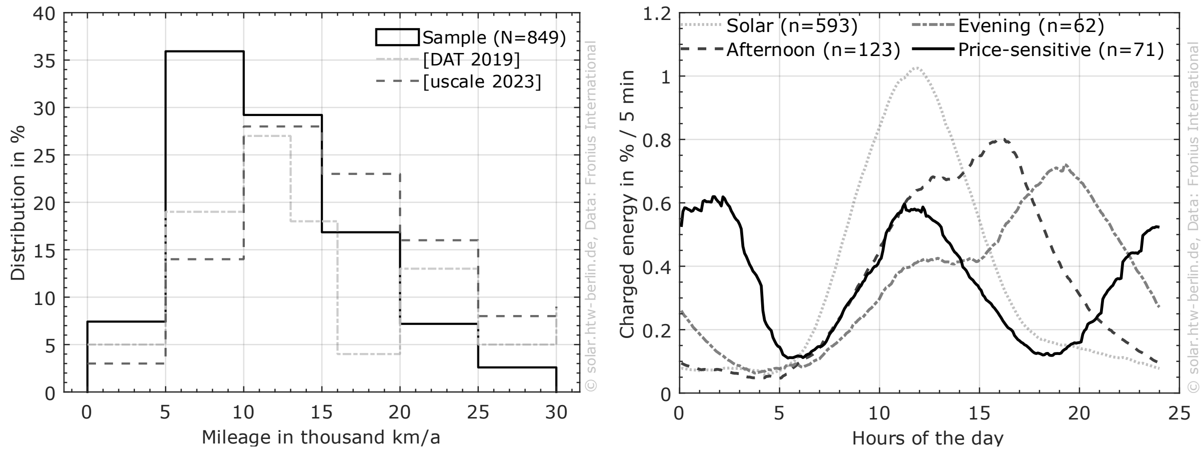

Figure 4: Distribution of the mileage in comparison to different studies (left). Clustered distribution of charged energy over the day (right). Data: Fronius International

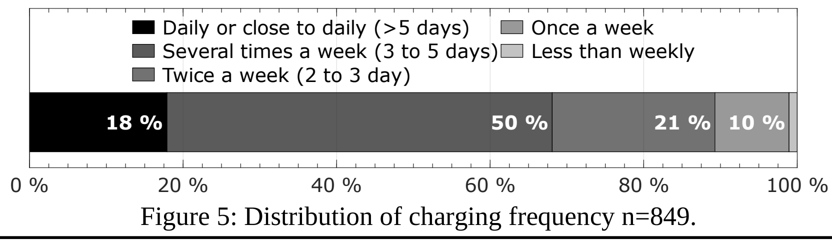

Figure 5: Distribution of charging frequency n=849.

4 Solar share

Solar power has a strong diurnal and seasonal progression; car use is dominated by daily or weekly usage patterns. As shown in Figure 4 (right), the majority of the sample shows a charging behavior adapted to the solar generation. Most of them adapt the charging power to the solar surplus power, that would otherwise be fed into the grid. But the question is, to what extent can a solar system power an electric vehicle? And what are the most important factors for a high solar share?

4.1 PV power

Figure 6 shows the amount of energy charged at home in relation to the share of solar energy charged. The color and style of the marker indicate the installed PV power. The share of solar energy is highly dispersed and varying by about ± 40% around the median of about 60%, decreasing with higher energy and kilometers driven. It is clear that the available solar energy is one reason for the distribution of the solar share, as darker data points, indicating larger PV installations, are mainly in the upper region and lighter data points tend to be in the lower left corner. This could also be described by the median shown on the right side of Figure 6. It can be seen that 75% of the smaller PV systems could use one third of solar energy in their EV, while 50% have more than 48% and 25% even more than 63% of solar share. A typical PV system of just over 10 kW will power the EV for half of its journey, and for more than 25% of the households 2/3 of their EV mobility comes from the sun. PV systems larger than 15 kW have a big advantage in terms of solar energy availability during winter and transitional periods. More than 75% reach the 50% and the top 25% will have more than 70%-80% sun on the road. The median for the largest PV systems is not shown because there are only a few systems.

Across all power classes, an increase of 5 kW to the next power class was found to increase the total solar share by about 2-10%. Within the sample, this is associated with an increase in energy consumption, as the median user with 5-10 kW consumes 2 MWh per year, while households with larger PV systems consume on average around 2.5 MWh per year. The increase in the solar share is therefore slightly higher in a comparable setting. Note: On the one hand, an increase in PV power increases the solar share; on the other hand, the decrease with higher demand tends to be less pronounced with a larger PV system. It can be seen that the highest solar shares above 80% require a PV system of more than 10 kW. A smaller PV system can only achieve comparable results at very low annual mileage. Even if the availability of solar energy is a reasonable explanation, it cannot explain all the diversity.

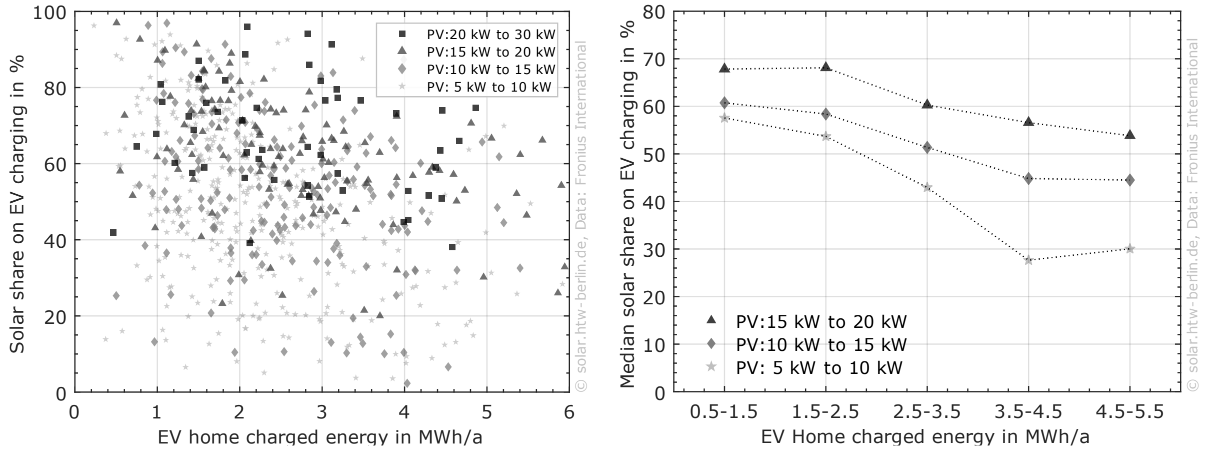

Figure 6: Solar share of charging over the energy that is charged at home by the EV (left, n=725). Colors and Size indicate PV power and PV yield. Median of the solar share of charging over classified home charged energy and PV power (right, n=632). Data: Fronius International

4.2 Charging cluster

The charge patterns are therefore analyzed in the same way in Figure 7. In addition to the above mentioned, colors and marker styles indicate the different clusters identified in Section 3.3. Not surprisingly, a solar-adapted charging pattern is the main driver for the highest solar shares of EV charging. Even if some households tend to charge in the afternoon or charge price-sensitive might have higher solar shares, the majority can be found below 50%. The median (right) shows that solar chargers could easily drive more than 2/3 just by using their PV system. Even though the share decreases, the absolute solar kilometers increase with higher mileage. The median solar share decreases by about 25%, when charging is often shifted to the afternoon. Nevertheless, 75% of this cluster could cover more than 30% of their daily trips with cheap solar energy and the top 25% even more than 50%. In addition, 62 households that charge primarily in the evening use the grid in median for more than 80% of the energy charged. Not surprisingly, these households charge more energy within a charging session and charge less frequently. The middle 50% can reach solar shares between 10% and 25%. In between these clusters lies the price-sensitive cluster. Even if their charging takes place mainly during the night hours, solar-intensive charging sessions can also be observed on weekends. At the same time, their energy demand drops dramatically on Mondays and Tuesdays. It is worth noting that the median solar share sorted by cluster shows a very low dependence on the charged energy. Finally, it can be stated that solar shares of around 30% can be achieved by most of the charging profiles in the sample. It is assumed that it doesn't matter what the restrictions are regarding the availability of the car. Only a small adjustment of the charging behavior is required, e.g. plug in more often or charge only what is needed from the grid, e.g. target SOC. For the highest solar shares, a solar-adapted behavior is required.

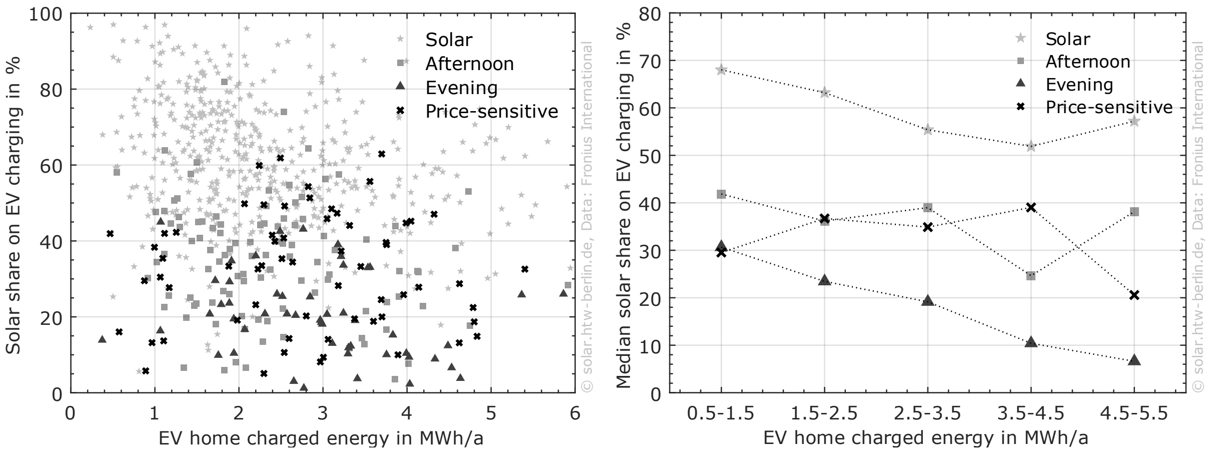

Figure 7: Solar share of charging over the energy that is charged at home by the EV for different charging cluster (left, n=725). Median of the solar share of charging over classified home charged energy as sensitivity of charging cluster (right, n=715). Data: Fronius International

4.3 Explanations for highest solar share

In order to identify those households with a high solar share for EV charging, three groups of the sample were examined in more detail:

1. Household with a solar share more than 50% (n=382)
2. Household with solar share more than 75% (n=108)
3. Household with solar share more than 85% (n=78)

As a result, these main drivers can be identified: Households with high and highest solar shares produced more solar energy on average and charged less energy. Surprisingly, even if the absolute energy charged is significantly lower for higher shares, the number of charging events in all three groups ranges from two to four days per week, with only with a slightly decreasing tendency for the highest solar shares. The charged energy of these charging sessions does not vary. On the other hand, households with the highest solar share charge only during the day. In addition, the charged energy is higher in summer than in winter. The solar energy produced between November and February is twice as high as the charged energy in all households with high solar shares and four times as high in households with the highest solar shares. In addition, there are significantly fewer heat pumps in this group. Households with the highest solar share have half as many heat pumps as the reference group. Correlation analyses show that the season and time of the day (winter and day) and the absolute amount of charged and produced energy have the highest explanatory potential.

4.4 Benefits of dynamic charging and a battery

Since most users use solar charging, the use of surplus charging can be determined from the dataset. A methodological approach is shown in Figure 8. An artificial charging profile is set up. The artificial charge starts at the same time as the original profile (2) and charges the same amount of energy (3), but at the maximum power of the individual charging profile (1). For example, if a household charges dynamically but limits charging to 7.5 kW, this is taken into account. Adjustments have been made concerning small charging events as trickle charge. Therefore, charges of less than 3 kWh were ignored in the first step but added together in the second step to allocate them to a longer charge. It must be mentioned, that not all households charge dynamically even if they have a solar adopted charging pattern.

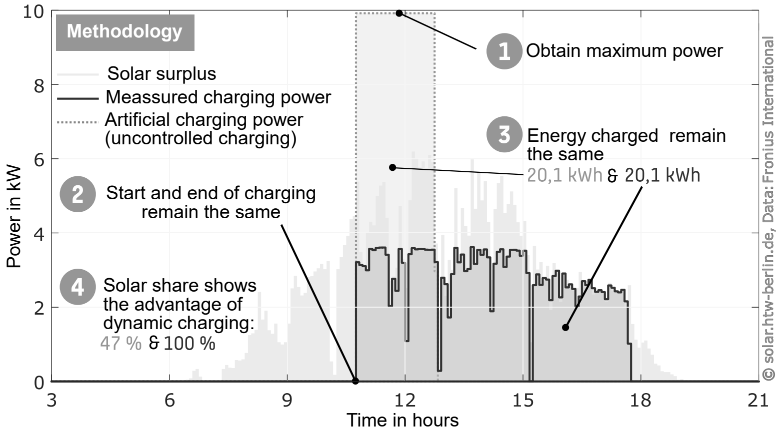

Figure 8: Methodology to evaluate the value of dynamic surplus charging. Data: Fronius International

Figure 9 (left) shows the results of the analysis. Whether or not dynamic charging makes sense depends heavily on the charging pattern. A solar-adapted charging pattern could have increased the median solar share of EV charging by about 30% if the EVSE dynamically followed the surplus instead of charging at maximum power. The households that charge mainly in the afternoon and price-sensitive benefit from an increased median solar share of about 17% to 21%. On the other hand, the median solar share increases by only 9% for households in the evening charging cluster. It should be noted, however, that the variation within a cluster could be greater than the increase in the median.

In addition, the timing of charging could be partially compensated by storage capacity. For example, stationary batteries typically range from only a few kilowatt-hours to less than 20 kWh, while EV batteries range from 50 kWh to 80 kWh, so it is not expected that solar charging can be fully replaced. On the other hand, stationary batteries are capable of fast, watt-precise control that EVSE lag sometimes. Therefore, looking at the power flows shows that stationary batteries can buffer control errors and therefore maximize direct solar use. Figure 9 (right) shows how a stationary battery affects the solar share of EV charging for the clustered households. Note that only households with a stationary battery were considered for these analyses. The highest use of a stationary battery is seen when charging occurs frequently in the evening hours. When a stationary battery is considered, the median solar share of EV charging increases by 20% to about 40%. There is an increase of about 15% for afternoon charging. As expected for solar and price-sensitive charging households, a stationary battery has the least impact. It increases the median solar share of EV charging by about 8% to 10%. Note that battery capacity is evenly distributed across all clusters with a median capacity of roughly 10 kWh. The distribution of installed PV capacity is also almost the same for all clusters, except for solar, which tends to have a higher installed capacity. Not shown here: When charging at maximum power, the battery performance in all clusters is about 3% worse than in the dynamic case.

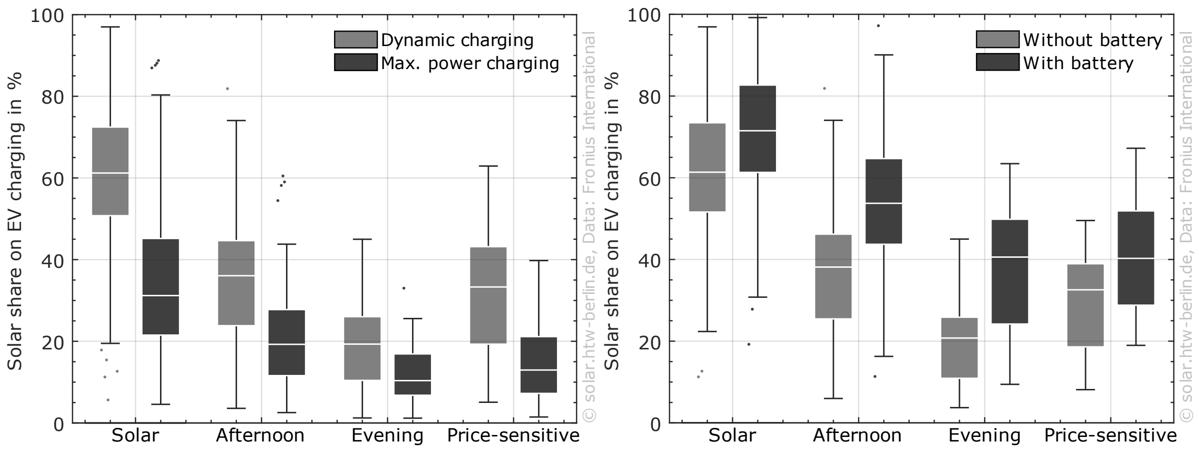

Figure 9: Solar share on EV charging for clustered households comparing dynamic and maximum power charging (left, n=725). On the right side it is highlighted what are the advantages of a stationary battery. Solar n=242, Afternoon n=67, Evening n=27, Price sensitive n=21. Data: Fronius International

A conclusion from this section is that dynamic charging is a very useful feature, especially for those who charge frequently during the day. On the other hand, a stationary battery can compensate for a lack of flexibility if charging is often done in the evening hours. The maximum charge power should therefore consider the limitations of the battery. However, even for late-charging households, it is worth adapting to the available solar power to save costs, e.g. on weekends, so it can be concluded that dynamic charging is a must.

5 Degree of self-sufficiency

Section 4 provides a detailed analysis of the solar contribution to EV charging. In this section, a more detailed look is taken at the household load as well as at the total load by analyzing the degree of self-sufficiency. For better comparability of different households, it has been targeting to normalize the solar output on the load (e.g. [18]). A value of one indicates net-zero consumption, i.e. the annual solar production is equal to the consumption of the household. A value of two indicates that the energy produced is twice the amount consumed. Note: Because consumption and solar production do not always coincide, the household still be using power from the grid.

Figure 10 shows the degree of self-sufficiency as a function of net household energy production. Light gray indicates the base case without EV and dark gray with EV. Since few households exceed a net household energy production of 5, the above values are neglected. As the available PV energy increases, the degree of self-sufficiency increases until a saturation point is reached, which is determined by the temporal overlap of load and generation. This can be seen for the boxes without EV between 4 kWh/kWh and 5 kWh/kWh. The electric vehicle increases the load by about one third on average. Thus, the additional supply of the electric vehicle reduces the surplus of solar energy, but this additional load can be managed to potentially increase the time overlap of load and generation. Consequently, the charging behavior can either reduce or increase the degree of self-sufficiency. On average, it decreases with net energy consumption, e.g., values below 1, and increases with net energy production, e.g., values above 2. A closer look at the data shows that the increase strongly depends on the load profile, here analyzed by looking at the clusters mentioned in 3.3, see Figure 4 (right). Four bars are shown for each cluster. The first bar shows the degree of self-sufficiency for the household load only. Second, the light gray bar represents the change with an EV. The third bar therefore shows the increase in self-sufficiency with stationary battery storage, while the dark gray bar sums up the previous bars.

Therefore, households that charge their vehicles using primarily solar energy increase their self-sufficiency by about 5% on average due to the controlled charging of the electric vehicle. In particular, households that produce more than twice as much electricity as they consume benefit the most. By adjusting the charging behavior, the total load demand shifts by about 6% more to the daytime and 1.5% more to the summer, resulting in an average 12% higher utilization of on-site PV energy.

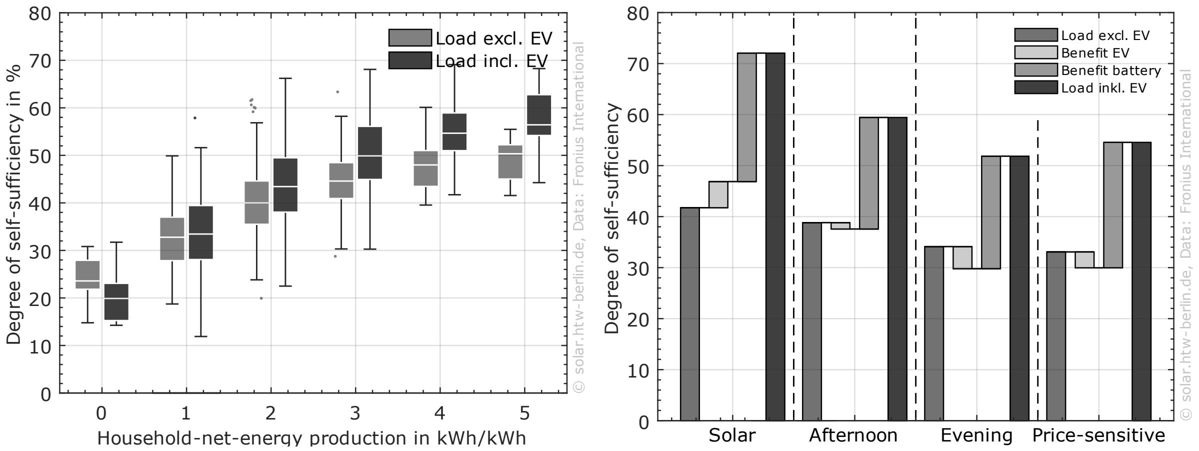

Figure 10: Degree of self-sufficiency correlated with household net energy production incl. and excl. EV (left, n=357). Median change in degree of self-sufficiency by an EV and a stationary battery sorted by clustered households. Solar n=242, Afternoon n=67, Evening n=27, Price sensitive n=21. Data: Fronius International

There is only a small decrease in the degree of self-sufficiency for households that charge mainly in the afternoon and those that are price-sensitive. Afternoon charging households shift their load by 3% to the daytime, but not seasonally. Conversely, price-sensitive households increase their energy consumption at night when considering an EV. The load shifts by 1.5% to the summer, indicating that these households are likely to charge more externally in winter. The on-site-consumed solar energy increases by about 8% to 10% due to controlled charging. Households that charge in the evening and at night experience a net loss of about 5% in self-sufficiency due to the EV. The load does not shift significantly, but this still results in a 6% increase in on-site solar energy consumption. A battery increases the degree of self-sufficiency by decoupling generation and consumption over time. On average, a battery increases the level of self-sufficiency by about 24%. Not all households benefit equally from the battery. 90% of households increase their self-sufficiency by more than 16%, but only 10% by more than 32%. It also depends on the appliances used. Households with heat pumps increase their self-sufficiency by 19% on average, while households without heat pumps increase their self-sufficiency by 26%. Furthermore, households that charge in the evening and at night get less benefit from the battery than those that charge at midday or in the afternoon. This can be explained by the overcompensation of the negative impact of the EV. The sample shows that a household with PV battery and EV can be supplied by its own PV system by more than 56% on average. If solar-adapted charging is used, median values of more than 77% are possible. If a heat pump is used on site, the self-sufficiency decreases but can still reach median values above 45% up to 61% for optimized households.

6 Summary

The sensible combination of PV and EV is analyzed in this study by taking a closer look at a monitoring dataset. First, the dataset is described. In a second step the data was assessed by an introducing analysis on data statistics. The first view on this promising dataset shows expectable biases that are typically found in EV surveys. On the one hand, for example, a high energy demand and a higher presence of heat pumps as proxy for higher income. On the other hand, high energy mobility patterns. Here 4 main charging clusters were identified. On a second view the dataset shows that the share of solar energy for charging and load contribution (degree of self-sufficiency) varies within a certain range. The main factors contributing to high solar energy shares have been identified through different perspectives on the same image. Both seasonal and diurnal adjustments were found to have a significant influence. While a stationary battery can increase the flexibility of diurnal adaptation, seasonal adaptation has been found in two ways: first, by increasing the production of solar energy even in the darkest month, and second, by suspended charges at home during the winter months. It was also found that solar charging is a must, as it easily increases the solar share by about 25% compared to uncontrolled charging. This is obviously advantageous since the degree of self-sufficiency is directly influenced by the solar share of the charged energy: it decreases if proportion of solar energy in the EV is comparable low to the household load. As the data shows, a stationary battery can overcompensate this to a certain degree but reduces the possible degree of self-sufficiency significantly.

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Presenter Biography

Joseph Bergner studied renewable energy (M. Sc.) at the University of Applied Sciences Berlin. Since 2016 he works as a Researcher in the research group "Solar Storage Systems" in different research projects. Since 2022 he simulates and analyzes the efficiency of solar powered charging within the research project "Wallbox Inspektion".