Economic impact of PV forecast inaccuracies on a corporate parking charging infrastructure

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Executive Summary

The number of electric vehicles is increasing exponentially and there is a high need for charging infrastructure. Furthermore, climate change motivates for the integration of renewable energy. Therefore, a DC-coupled charging station connected to photovoltaic and a stationary battery system is being researched for a workplace environment. The component sizes are economically optimized for 20 charging points. The influence of a simple photovoltaic persistence forecast on the marginal charging tariff and the self-sufficiency is analysed depending on the component sizes. It is shown, that the positive influence of implementing a self-consumption maximizing charging strategy outweighs the monetary losses of forecasting inaccuracies. The decrease in self-sufficiency compared to a perfect PV forecast for a system without a stationary battery is 1 percentage point versus an increase of 20 percentage points compared to uncontrolled charging. Although systems without a battery are more economic, it is also shown, that systems with a battery can become economic for larger PV sizes.

Keywords: energy storage, infrastructure, load management, photovoltaic, prediction

1 Motivation and literature study

Motivated by climate change, electricity production and mobility are to be restructured worldwide. Increasing sales of electric vehicles (EVs) require the expansion of charging infrastructure. Simultaneously the share of renewable energy sources (RES) increases. The power generation by RES lead to fluctuations on the supply side while uncoordinated charging activities lead to fluctuations on the demand side causing technical and economic issues for the distribution grid [1]. Decentralized energy supply systems with photovoltaic (PV) systems and stationary battery storage (BAT) ensure emission-free electricity production. Together with an energy management system (EMS) which uses PV forecasting, they reduce the impact on the electricity grid while reducing the operational costs (OC) of the system. Depending on the use case, the charging station (CS) needs to be scalable. Dimensioning and operational optimization are thus important economic aspects. Due to the inaccuracy of the PV forecast, there is an economic disadvantage. However, there is only little research on the economic impacts of PV forecasting inaccuracies on costs, charging tariff or self-sufficiency in combination with the sizing of the system.

The influence of PV forecasts on the performance of the system has already been considered in the past in the area of stationary home storage [2, 3]. A smaller residential CS with just one charging point and a large-scale CS with 20 charging points both without a BAT have been analysed. The results for both scenarios show that day-ahead PV power forecasting aid in optimally scheduling the charging and help to reduce the burden on the grid. A system analysis of residential PV systems is carried out over 15 years in [3]. It shows incorporating PV forecast in EMS can increase electricity self-consumption by 70% as well as lower the levelized cost of electricity by around 12-15%. It also shows that forecast-based

operation strategies can enhance battery life. PV and BAT are profitable in the medium term due to high self-consumption rates [4]. It shows a positive net present value (NPV) of a household PV System when analysed over 20 years. However, in [3] and [4] financial analysis is only done for household energy systems and not for a commercial environment.
Due to the long parking durations especially over daytime, the workplace is attractive for the maximization of self-consumption and the use of RES [5]. An EMS based on the variation in the DC link voltage is proposed in [6] for a PV-based CS. [7] demonstrate the influence of PV and BAT sizing on the amortization period in different scenarios over 30 years. However, these studies did not integrate PV forecasts in their EMS.
Seddig et al. investigate the impact of different PV power prediction models on the operation costs and the flexibility of commercial, opportunity and commuter customers [8]. The authors in [9] proposed an intelligent EMS that has increased PV self-consumption from 49% to between 62% and 87% with the help of V2G, persistence PV forecasting and load predictions. [10] and [11] use a forecasting enabled EMS in a mixed-integer linear programming framework for a workplace DC-linked CS. The PV power is forecasted with an ARIMA model. The EMS minimizes the total costs while reducing stress on the grid and increasing PV self-consumption. Consequently, the sustainability of the EV fleet is increased while taking dynamic purchase tariff and feed-in tariff into account. It achieved an increase of around 8% in self-consumption and reduced the exchange with the grid by 20%. The authors of [12] and [13] use PV and load forecasting in their EMS to shift the power demand from the on-peak period to off-peak thus also reducing the exchange with the utility grid by a factor of 2-3. In [14], linear programming is used to reduce the costs of charging EVs from PV based on time of use tariffs and PV forecasting. Cost reductions of 6% and 15.2% compared to the base case are obtained for the simulation of 12 EVs powered by a 50 kWp PV system. The charging rates depend on the predicted PV power, the demand of the EVs, and the energy price from the utility grid. Three different scenarios are discussed in [15]. Wind and solar energy of a chosen day are forecasted using time-series forecasting. Their results show that energy and reserve scheduling obtains reduced daily operation costs compared to no energy and reserve scheduling or V2G by 8.4% and 1.6%, respectively. However, the above research has been done on a smaller scale with a smaller number of EVs, focusing on the EMS development and evaluating only short time periods.

This paper extends the existing literature by analysing the economic impact of PV forecast and sizing on a corporate parking charging infrastructure. The EVCS is connected to the power grid, uses PV and BAT as energy sources, and has both DC and AC charging points. It is coupled by a DC-bus. The objective is to avoid efficiency losses due to DC coupling and to achieve economic benefits by considering the overall concept. Using self-consumption maximized charging, the economic influence of PV forecasting inaccuracies is investigated also concerning a higher number of 20 EVs as well as over a longer time period of 1 year. The interplay with the sizing of the systems is taken into account.
This paper aims to show how PV forecast integrated smart charging strategies impact the costs and self-sufficiency of the workplace EVCS based on implementing a persistence PV forecast (PF) and using real-world EV and electricity price information.

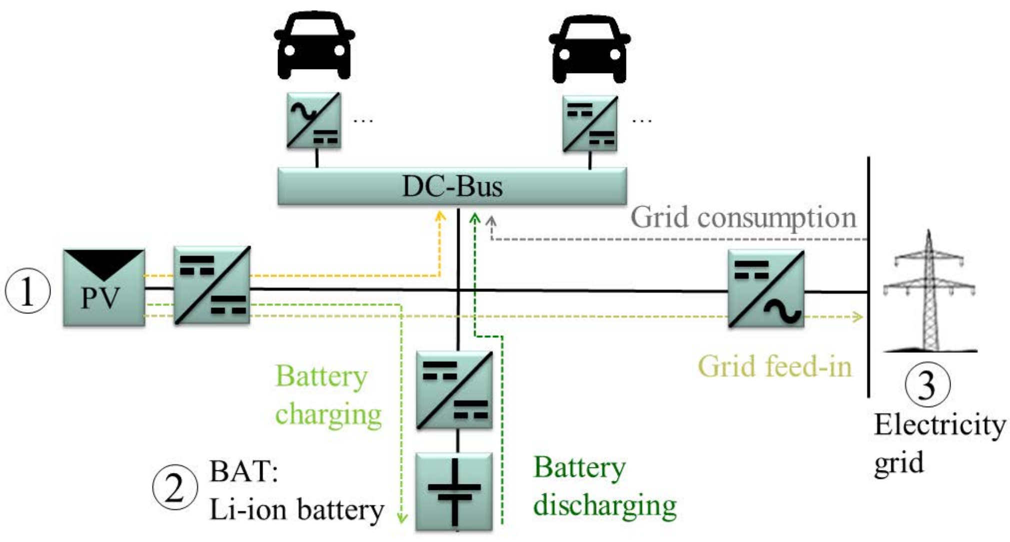


Figure 1: Topology of the DC-coupled EVCS with AC and DC charging points, PV, BAT and grid connection [5]

2 Modelling of charging infrastructure and energy management

The following section gives an overview over the system setup including the most important equations as well as an overview over the EMS. The perspective is that of an EVCS investor and operator who asks how to size the system as well as what impact a self-consumption maximizing charging strategy with a simple PV forecasting model might have.

2.1 System setup

Fig. 1 shows the EVCS's structure. PV, BAT and EV are connected via a DC-bus. The EVCS is connected to the grid. There are DC and AC charging points. As no dynamic grid prices or the feed-in from BAT or EV into the grid are assumed, the basic power flow priorities for covering the EV load are simulated as fixed in the order PV (1), BAT (2) and grid (3) [11]. The exchange of energy between grid and BAT is not considered. The charging station was described in detail in [5, 16]. The simulation was further developed regarding power dependent efficiencies for all converters as well as a more sophisticated EMS.

Regarding the EMS, uncontrolled charging and self-consumption maximizing charging are considered. Perfect knowledge of EV arrival and departure times as well as the EV charging demand is assumed. The self-consumption can either be perfectly maximized (in case the PV prediction is perfect) or imperfectly (in case the PV forecast is not perfect). As a benchmark, the considered PV forecasting model is the offline PF model. A detailed description of the PV prediction model is to be found in [17].

2.2 Basic equations

Eq. 1 describes the annual costs per year a of the system. The costs for grid consumption are calculated using the energy consumed from the grid E_{Grid} and the electricity price p_{Grid}. The costs for the BAT usage and the PV direct usage comprise the energy drawn from the battery E_{BAT}, the energy of the PV direct-use $E_{PV,dir.}$ and the price from Germany's renewable energy's act p_{EEG}.

$$C(a) = E_{Grid} \cdot p_{Grid} + (E_{BAT} + E_{PV,dir.}) \cdot p_{EEG} \tag{1}$$

The annual revenues are calculated using Eq. 2 considering the excess PV energy fed into the power grid $E_{PV,exc.}$, the compensation for feeding into the grid $p_{exc.}$, the energy used for EV charging E_{EV} and the EV charging tariff p_{EV}, as in:

$$R(a) = E_{PV,exc.} \cdot p_{exc.} + E_{EV} \cdot p_{EV} \tag{2}$$

Using the annual costs and revenues calculated above, the net present value NPV is calculated using Eq. 3 with the investment costs I_0 comprising the sum of all component investments depending on the component sizes and the interest rate z.

$$NPV = -I_0 + \sum_{a=1}^{n} \frac{R(a) - C(a)}{(1+z)^a} \tag{3}$$

Finally, the charging station's component sizes are optimized by minimizing the marginal tariff p_{EV} which is the minimum price the EV users would have to pay so that the NPV is zero after the assumed lifetime. Eq. 4a and 4b depict the according objective function and its constraint, as in:

$$\min \quad p_{EV} \tag{4a}$$

$$\text{s. t.} \quad NPV \leq 0 \tag{4b}$$

2.3 Implementation of PV prediction based charging strategy

Considering the assumption, that the load patterns are known, either due to a perfect load forecast or EV user input, for each EV the latest time point for a charging start can be calculated. Until this time point, the EVs can be charged only by PV and BAT energy, maximizing the self-consumption and minimizing the grid impact as well as the charging costs.

Eq. 5 shows the criterion for each charging session. The energy demand at each charging point cp $E_{\text{LOAD,EV}}$ needs to be covered between arrival and departure time, t_{arr} and t_{dep}, through meeting the charging power $P_{\text{LOAD,EV}}$ on EV side. This charging power can be shifted in the limits of the arrival time, departure time and maximum charging power while considering the power dependent efficiencies.

$$E_{\text{LOAD,EV}}(cp) = \int_{t_{\text{arr}}}^{t_{\text{dep}}} P_{\text{LOAD,EV}}\, dt \qquad \forall cp \tag{5}$$

Considering the power dependent converter efficiencies, there are different levels for the balance equations. While meeting the energy demand of each EV has to be calculated on the specific side of each EV (Eq. 5), the balance equations with power from PV, BAT and grid have to be calculated on the DC-bus level. Therefore, Eq. 6 a to f show the required conversions from the different levels including the respective efficiency η.

$$P_{\text{LOAD,EV}}(cp,t) = P_{\text{LOAD,DC-BUS}}(cp,t) \cdot \eta_{\text{EV2DCBUS}}(P_{\text{LOAD,EV}}(cp,t)) \qquad \forall t \tag{6a}$$

$$P_{\text{PV,DC-BUS}}(t) = P_{\text{PV,DC}}(t) \cdot \eta_{\text{PV2DCBUS}}(P_{\text{PV,DC}}(t)) \qquad \forall t \tag{6b}$$

$$P_{\text{BAT,dischg.,DC-BUS}} = P_{\text{BAT,dischg.,DC}} \cdot \eta_{\text{BAT2DCBUS}}(P_{\text{BAT,dischg.,DC}}) \qquad \forall t \tag{6c}$$

$$P_{\text{BAT,chg.,DC}} = P_{\text{BAT,chg.,DC-BUS}} \cdot \eta_{\text{DCBUS2BAT}}(P_{\text{BAT,chg.,DC-BUS}}) \qquad \forall t \tag{6d}$$

$$P_{\text{GRID,from,DC-BUS}} = P_{\text{GRID,from,AC}} \cdot \eta_{\text{GRID2DCBUS}}(P_{\text{GRID,from,AC}}) \qquad \forall t \tag{6e}$$

$$P_{\text{GRID,to,AC}} = P_{\text{GRID,to,DC-BUS}} \cdot \eta_{\text{DCBUS2GRID}}(P_{\text{GRID,to,DC-BUS}}) \qquad \forall t \tag{6f}$$

Eq. 7 shows the limitation that needs to be considered when calculating the latest time point for each charging session. In every time point t, the sum of required load per charging point cp on the DC-bus level has to be in the limits of the power from the grid $P_{\text{GRID,from,DC-BUS}}$ and the predicted PV power $P_{\text{PV,pred.,DC-BUS}}$ on DC-bus level, calculated backwards in time between latest departure t_{dep} and earliest arrival t_{arr}.

$$\sum_{cp=1}^{n_{cp}} P_{\text{LOAD,DC-BUS}}(cp,t) = P_{\text{GRID,from,DC-BUS}}(t) + P_{\text{PV,pred.,DC-BUS}}(t) \qquad \forall t \tag{7}$$

Eq. 7 is used repeatedly over the day to recalculate the latest charging time per charging session, as EVs are arriving and the already covered energy changes due to the actual PV power. As long as P_{GRID} is lower than the maximum peak load, an actual PV power less than predicted means the latest charging start is too late and EV demand cannot be covered. An actual PV power higher than predicted means that EV demand is covered too early from the grid instead of the PV, so the self-sufficiency decreases. A time resolution of $7.5\,\text{min}$ showed to be sufficient for calculating the latest charging start per charging session.

Besides the consideration of a self-consumption maximizing charging strategy, uncontrolled charging was considered as a benchmark. Uncontrolled charging means that every EV immediately starts charging after arrival. In case not all load can be covered directly, the EV power is proportionally shifted to the future. A perfect self-consumption maximizing charging strategy means that the PV power throughout the day is known. For a more in-depth explanation of the uncontrolled and the perfect charging strategy see [5].

2.4 Evaluation metrics

In addition to the marginal EV charging tariff p_{EV}, the self-sufficiency of the system r_{SS} and the share of energy demand that could not be covered until EV departure r_{U} are used as metrics to evaluate the performance of the system.

Eq. 8 depicts the self-sufficiency, calculated using the directly used PV energy $E_{\text{PV,dir.}}$, the energy discharged from the BAT to cover the load $E_{\text{BAT,dischg.}}$ and the covered load $E_{\text{LOAD,cov.}}$ on the DC-bus level.

$$r_{\text{SS}} = \frac{E_{\text{PV,dir.,DC-BUS}} + E_{\text{BAT,dischg.,DC-BUS}}}{E_{\text{LOAD,cov.,DC-BUS}}} \tag{8}$$

Eq. 9 depicts the uncovered energy $E_{\text{LOAD,uncov.}}$ per energy demand E_{LOAD} on the EV level. The energy demand E_{LOAD} is the sum of covered and uncovered load.

$$r_{\text{U}} = \frac{E_{\text{LOAD,uncov.,EV}}}{E_{\text{LOAD,EV}}} \tag{9}$$

3 Results and analysis

The calculations were performed using Matlab. The following section shortly introduces the used data and assumed values. Subsequently, the system component sizes' influence on the uncovered energy, marginal charging tariff and self-sufficiency are evaluated. Finally, the impact of PV prediction inaccuracies on the performance of an example system is evaluated regarding marginal charging tariff and self-sufficiency.

3.1 Data and assumed values

The PV power data are from the KIT Campus North $1\,\mathrm{MW}$ PV field located at 49.1°N and 8.44°E. The measurement data from the year 2016 correspond with the solar output from a $9\,\mathrm{kWp}$ PV array with southerly orientation and a $15°$ tilt. The temporal resolution is $5\,\mathrm{min}$.
The efficiency data for power conversion are from in-house measurements [19] and from manufacturers. The data provide power level related efficiencies as evaluated in [20] and are depicted in Fig. 2.
The charging data were provided by the project partner [18]. Probability distributions of arrival and departure times as well as the energy demand of the EVs were derived from over 5800 charging sessions and used as a basis for generating a fictive dataset over one year for $10 \cdot 5\,\mathrm{kW}$ DC and $10 \cdot 3.7\,\mathrm{kW}$ AC charging points.

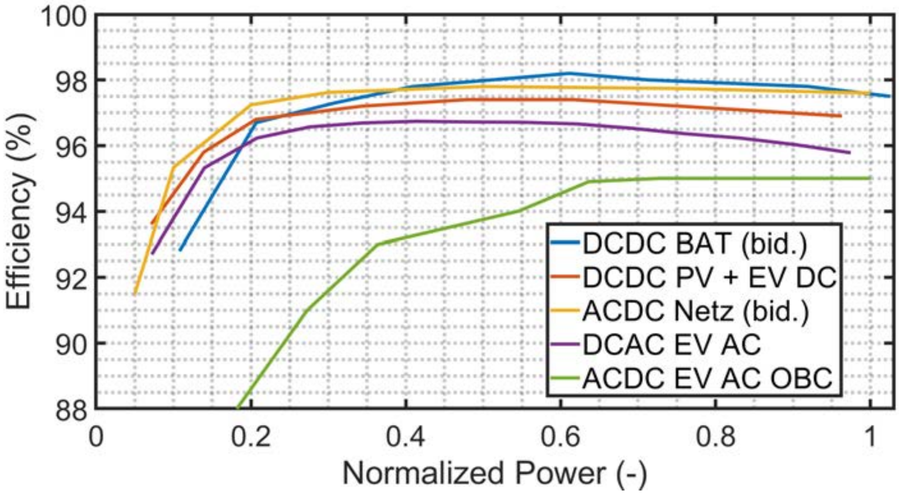
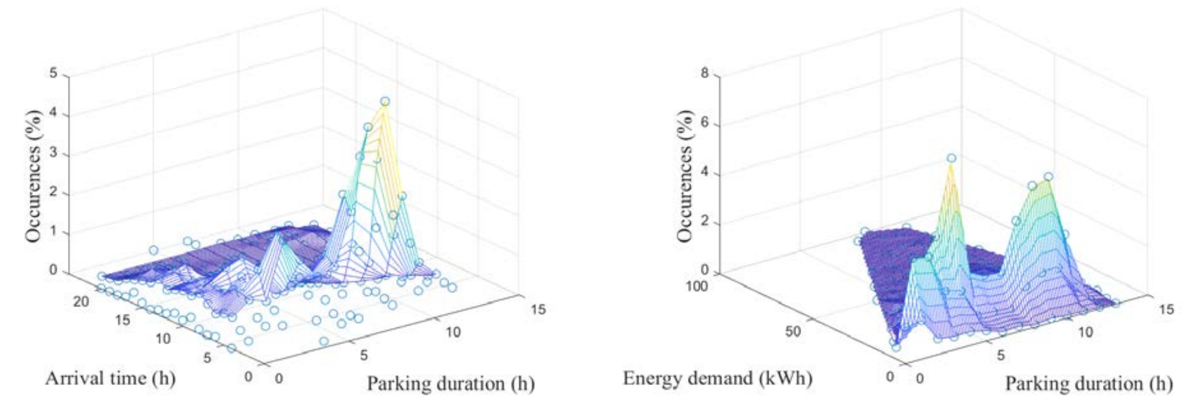


Figure 2: Power dependent conversion efficiencies for the different converters as well as the onboard-charger (OBC) for AC charging. Bidirectional converters are labelled with (bid.).

Table 1: Values assumed for the simulation

	Unit	Value	Source
Electricity grid price p_{Grid}	$\frac{\mathrm{Ct}}{\mathrm{kWh}}$	18.5652	[21]
EEG apportionment p_{EEG}	$\frac{\mathrm{C}}{\mathrm{kWh}}$	0	[22]
Feed-in tariff $p_{exc.}$	$\frac{\mathrm{C}}{\mathrm{kWh}}$	4.74 / 6.06 / 6.24	[22]
Interest rate z	$\%$	0	
Converter costs c_{conv}	$\frac{\mathrm{C}}{\mathrm{kW}}$	150	[23]
PV costs c_{PV}	$\frac{\mathrm{C}}{\mathrm{kW}}$		[24]
BAT costs c_{BAT}	$\frac{\mathrm{C}}{\mathrm{kW}}$		[25]
Observation period n	year	20	

Fig. 3a shows the occurrences of arrival times and parking durations from dataset analysis. Most EVs arrive in the morning and stay for longer times. A smaller number of EVs arrive throughout the day and stay for a shorter time period. Fig. 3b shows the occurrences of energy demand and parking duration from dataset analysis. Patterns show that the energy demand is less when parking for a shorter time



(a) (b)

Figure 3: Occurrences of the combination of arrival time (3a) as well as energy demand (3b) and parking duration.

period. Higher energy demands mostly occur with longer parking durations. The analysis furthermore revealed an average energy demand of $13.88\,\mathrm{kWh}$ per charging session with an average arrival time of 7 o'clock and an average parking duration of $7.1\,\mathrm{h}$. After generating a fictive dataset based on the real charging data, a yearly energy demand of about $100\,000\,\mathrm{kWh}$ in total was calculated.

The electricity grid price, interest rate, component costs and similar values were either assumed to be fixed or derived as an equation. The values and sources are listed in Table 1 for the German market in July 2022. The assumed costs for components are derived from source and calculated without VAT due to the company environment. The observation period is 20 years, the simulation is performed with data from one year.

3.2 Evaluation of the economically optimal system

Before determining the economically optimal system, an evaluation of the uncovered load depending on the grid converter size helps to narrow down the sizing problem. As was shown in [5], the load cannot fully be covered by PV power especially in winter due to the geographical conditions as well as the tilt of the PV array.
Fig. 4 shows a heat map of the uncovered energy in % depending on the grid converter size and the PV size. Only from a grid converter with $75\,\mathrm{kW}$ rated power the uncovered energy is below $1\,\%$ of the total energy demand. Therefore, although there are way cheaper options available with less grid power, the economically optimal system is determined for a grid converter $\geq 75\,\mathrm{kW}$ rated power.
Evaluating the same heat map for a system with a self-consumption maximizing charging strategy using the PV prediction, the uncovered load was only slightly higher than using uncontrolled charging. The seasonal difference, especially concerning winter, was less than 0.03 percentage points (pp). The most significant difference were the rather constant energy losses in winter over PV size, while the energy losses decreased with the PV size in all other seasons.
Applying Eq. 3 for the uncontrolled charging strategy explained in Sect. 2.3, the charging infrastructure was optimized with a grid converter size $\geq 75\,\mathrm{kW}$. A PV size of $120\,\mathrm{kW}$ peak showed to be optimal, no BAT and a grid converter with $75\,\mathrm{kW}$, see Table 2. The investment costs turned out to be $149\,750$ € for an assumed lifetime of 20 years. The grid converter with a rated power of $75\,\mathrm{kW}$ is sized rather small compared to the 10 AC and 10 DC charging points with a maximum peak load of $87\,\mathrm{kW}$. This indicates longer parking durations which do not need a larger grid connection. The marginal charging price p_{EV} of $16.99\,\frac{\mathrm{Ct}}{\mathrm{kWh}}\mathrm{withoutVATisabout2}\,\frac{\mathrm{Ct}}{\mathrm{kWh}}\mathrm{lowerthantheassumedindustrialelectricitygridpricewithoutVAT}.$
This indicates that the charging station is overall more economic than only charging from the grid without PV. The marginal charging price is $20.02\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ with VAT for the EV users. An analysis of the impact of a BAT is done later on in the paper.

3.3 Evaluation of the influence of different component sizes

Fig. 5a and Fig. 5b show scatter plots of the marginal charging tariff p_{EV} (Eq. 4a) over the PV size. The values with application of the self-consumption maximizing charging strategy are shown. The colour

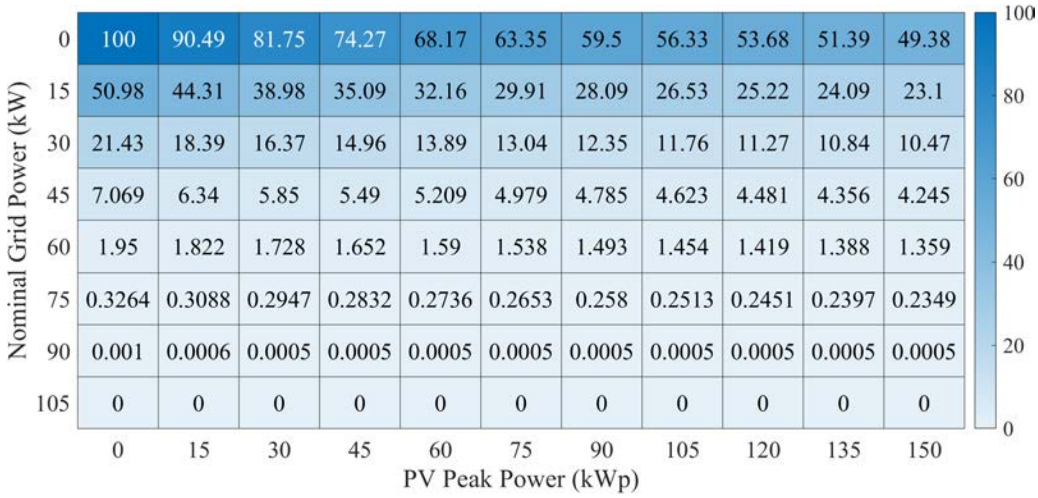
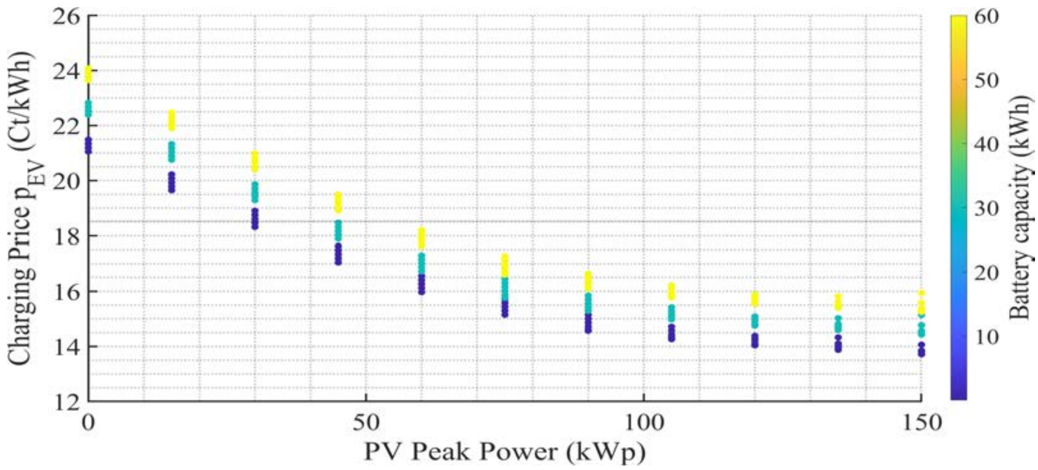
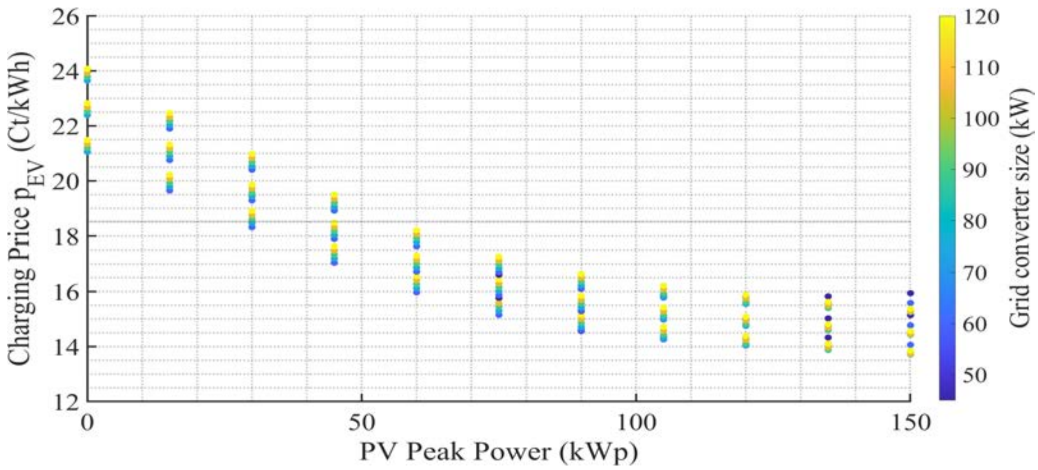


Figure 4: Share of uncovered load r_{U} in % over PV size in kWp and grid converter size in kW.



(a) BAT size shown in the colour bar.



(b) Grid converter size shown in the colour bar.

Figure 5: Marginal charging tariff p_{EV} in Ct/kWh without VAT over PV size in kWp with application of the self-consumption maximizing charging strategy and PV forecasting inaccuracies.

Table 2: Dimensioning of the DC-coupled EVCS based on the uncontrolled charging strategy.

	Unit	Value
PV size	kWp	120
BAT capacity	kWh	0
Grid converter size	kW	75
Marginal charging tariff p_{EV}	$\frac{\mathrm{Ct}}{\mathrm{kWh}}$	16.99
Invest costs I_0	€	149 750

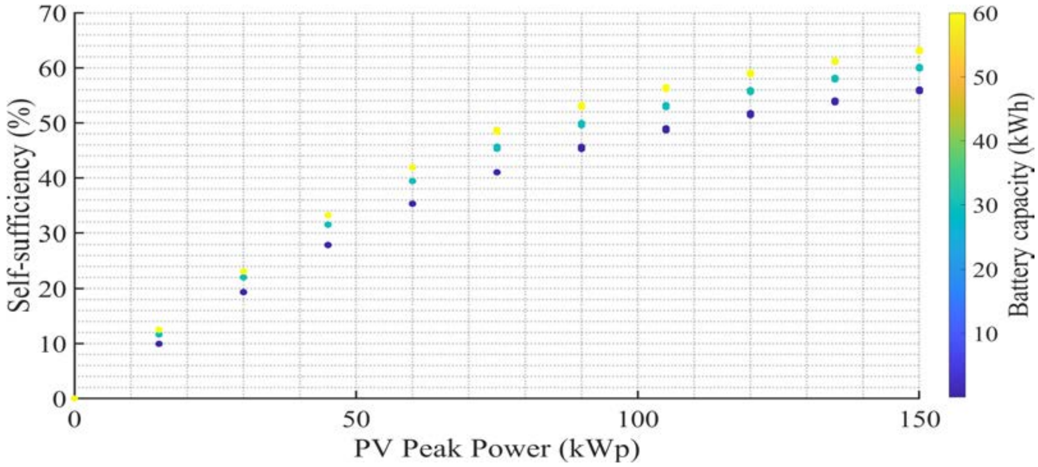
indicates the BAT capacity and grid converter size respectively. The horizontal line represents the grid price p_{GRID}. Marginal charging tariffs below the grid price mean that charging the EVs with PV power in addition costs less than charging from the grid only. Therefore, the system is more economic than a system with only a grid connection. From both graphics it becomes clear that from a PV size of about $60\,\mathrm{kWp}$ on even the systems with a BAT capacity up to $60\,\mathrm{kWh}$ become economical. The systems without BAT are the most economical. However, a system with a smaller grid converter and with a BAT can be more economical than a system with a larger grid converter and without BAT. This turns around from a PV size of about $135\,\mathrm{kWp}$. The minimum marginal charging tariff is reached for PV sizes larger than $120\,\mathrm{kWp}$, initially for the smallest grid converter of $75\,\mathrm{kW}$. Both BAT and grid converter sizes initially have a negative impact on the marginal charging tariff with increasing size. The prices reach down to $4.5\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ less than the assumed industrial grid price without VAT.

Fig. 6a and Fig. 6b display the same form of scatter plots as above for the self-sufficiency r_{SS} (Eq. 8) of the system. The self-sufficiency indicates how much of the EV demand can be covered by the PV and BAT. Therefore, the metric is especially helpful to evaluate the impact of a BAT. It becomes clear that systems with larger BAT are more self-sufficient than other systems. The maximum self-sufficiency of $65\,\%$ is reached for a PV size of $150\,\mathrm{kWp}$. This makes up a difference of over 10 pp for the same PV size and no BAT. Regarding the grid converter size, its impact is reciprocal to the impact of the BAT size. The smaller the grid converter, the higher the self-sufficiency. However, the impact is less than 1 pp. Later on, the impact of the self-consumption maximizing charging strategy is shown and therefore, the comparatively lower marginal charging tariffs as well as a higher self-sufficiency are shown.

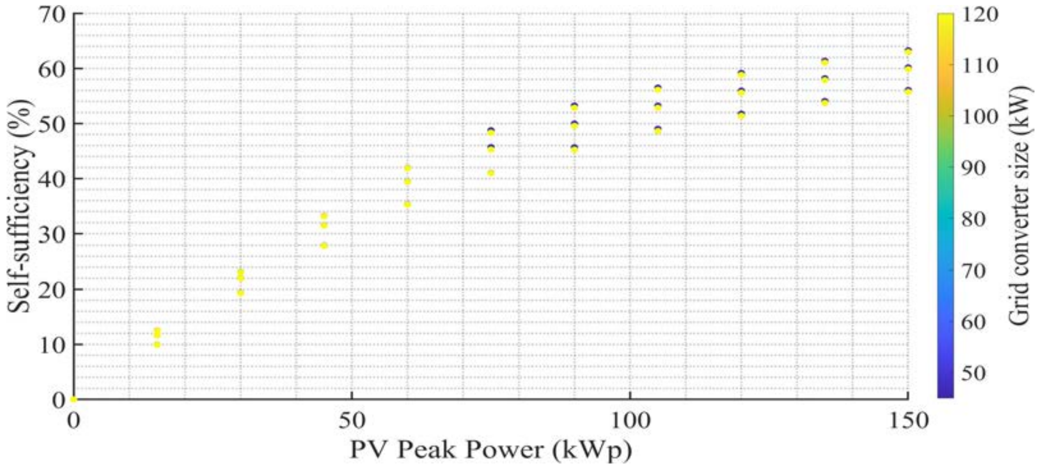
3.4 Evaluation of BAT and PV prediction influence

After the identification of an economically optimal system in the boundaries of uncovered load less than $1\,\%$, the impact of the different charging strategies as introduced in Sect. 2.3 on the marginal charging tariff p_{EV} (Eq. 4a) as well as the self-sufficiency r_{SS} (Eq. 4a) are analysed. The grid converter size impact showed to be far smaller than the impact of the BAT size. Therefore, the grid converter size is fixed with $75\,\mathrm{kW}$ while the PV size is varied between 0 and $150\,\mathrm{kWp}$. The different curves display the three charging strategies and the BAT sizes of 0, 30 and $60\,\mathrm{kWh}$. Accordingly the economically optimal system can be derived as analysed on the basis of Table 2 as well as the surrounding component sizing impact can be seen.
The PV prediction that is chosen for this specific analysis is the so called persistence forecast (PF) as explained and analysed in [17]. The PF is often used as a benchmark for evaluating different forecasting methods. Its advantages are its simplicity, low computational costs as well as offline capability.
Fig. 7 shows the influence of the PV prediction on the marginal charging tariff p_{EV}. Without a PV, the different curves start at a similar price depending on the BAT size with the lowest charging price of about $21\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ without VAT for systems without a BAT and the highest price of about $23.7\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ without VAT for a system with a BAT of $60\,\mathrm{kWh}$. With increasing PV size, the curves divert. In case of an (unrealistic) perfect PV forecast, the price is lowest with down to about $13.9\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ without VAT with a PV size of $150\,\mathrm{kWp}$. The system with the uncontrolled charging strategy and with a $60\,\mathrm{kWh}$ BAT is most expensive with a minimum at about $125\,\mathrm{kWp}$ PV size and about $17.9\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ without VAT.
From the beginning on the prediction based charging strategy is less expensive than uncontrolled charging. The difference between the perfect and the prediction based charging strategy stays at about $0.1\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$. Calculated with the yearly energy demand of $100\,000\,\mathrm{kWh}$, this sums up to a monetary loss of about $100\,€$ per year. At the same time the gain of about $4\,\frac{\mathrm{Ct}}{\mathrm{kWh}}$ in comparison to the uncontrolled charging strategy means a surplus of $4000\,€$ per year for implementing a charging strategy.

It is interesting, that systems with a BAT and with perfect charging yield a similar marginal charging tariff to systems without BAT and with application of imperfect prediction especially at bigger PV sizes.



(a) BAT size shown in the colour bar.



(b) Grid converter size shown in the colour bar.

Figure 6: Self-sufficiency r_{SS} in % over PV size in kWp with application of the self-consumption maximizing charging strategy and PV forecasting inaccuracies.

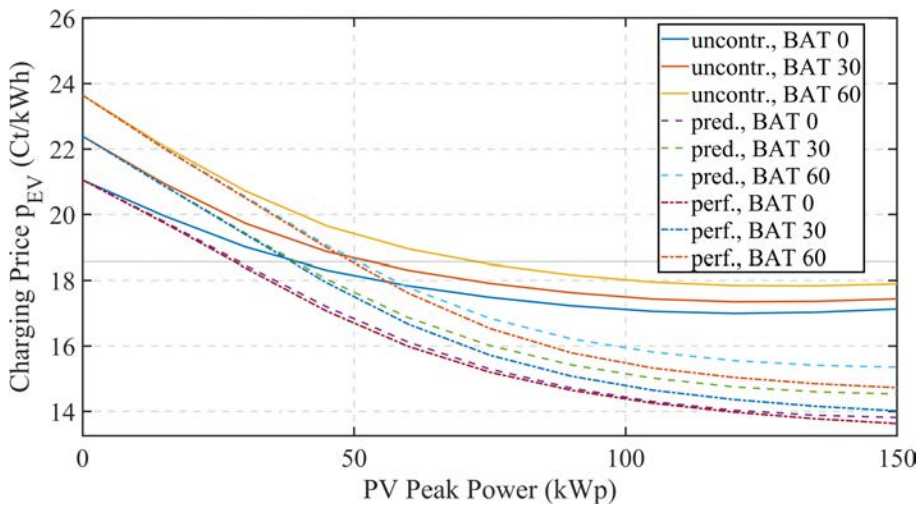


Figure 7: Marginal charging tariff in Ct/kWh for a grid converter of 75 kW and different BAT sizes comparing the cases of uncontrolled, prediction based and perfect charging.

From $75\,\mathrm{kWp}$ on all displayed curves are below the industrial grid price. Also, from about that point on the price difference between the systems that apply a charging strategy with those that do not become most distinctive.

Fig. 8 shows the influence of the PV prediction on the self-sufficiency r_{SS}. Different to the marginal charging tariff, the impact of charging strategy and BAT size on the self-sufficiency clearly separates the different curves from small PV sizes on. The highest self-sufficiency of about $65\,\%$ is achieved for a system with perfect PV forecast, $60\,\mathrm{kWh}$ BAT and $150\,\mathrm{kWp}$ PV. It is 30 pp higher than the self-sufficiency of the system without BAT using uncontrolled charging. The difference between imperfect and perfect prediction amounts to a self-sufficiency decrease of about 1 pp in case of a system without BAT. In comparison to uncontrolled charging the self-sufficiency increase is 20 pp. Although the imperfect PV forecast introduces losses in the self-sufficiency, even the system without BAT has an about 10 pp higher self-sufficiency compared to a system with uncontrolled charging with a $60\,\mathrm{kWh}$ BAT. This shows, that applying a self-consumption maximizing charging strategy nevertheless lessens the grid impact. The increase of self-sufficiency of about 5 pp due to a BAT in comparison of the different systems with prediction based charging still can speak for the choice of a BAT, as more than $5000\,\mathrm{kWh}$ less grid consumption per year can be achieved. Although a BAT is more expensive, the prices below the grid price for higher PV sizes as well as the self-sufficiency increase with BAT can argue for the choice for a BAT.

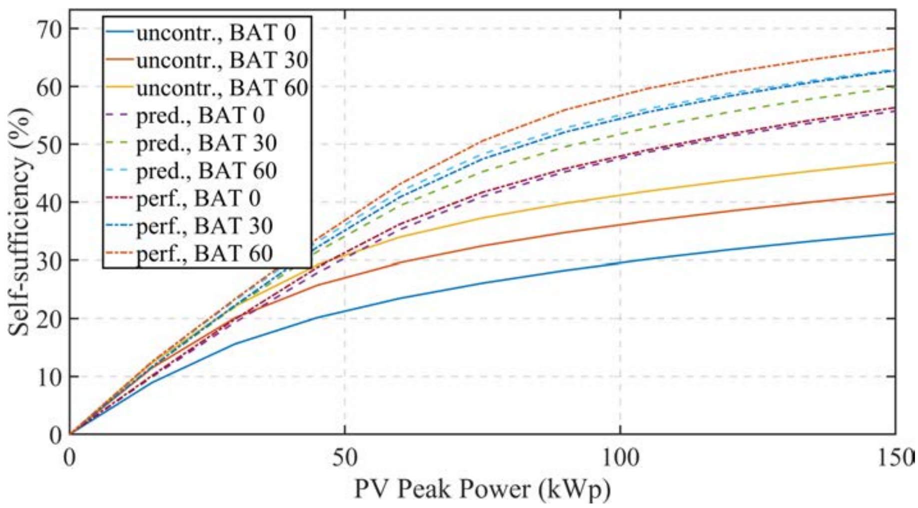


Figure 8: Self-sufficiency in $\%$ for a grid converter of $75\,\mathrm{kW}$ and different BAT sizes comparing the cases of uncontrolled (uncontr.), prediction based (pred.) and perfect (perf.) charging.

4 Conclusion and outlook

A DC-coupled EVCS with PV, BAT and connection to the power grid was sized and simulated for the demand of 10 AC and 10 DC charging points. Different to existing literature, a long time period of over one year and the impact of component sizing were considered. The approach supports companies with the conditions for installing a profitable EVCS.

The impact of forecast accuracy is evaluated by comparing a system with perfect PV forecast, persistence PV forecast and uncontrolled charging. It is shown that implementing a self-consumption maximizing charging strategy outweighs the losses due to prediction. A minimum marginal charging tariff of about 4.5 Ct/kWh less than the industrial grid price without VAT was calculated for a PV of $120\,\mathrm{kWp}$ and a grid converter of $75\,\mathrm{kW}$. These optimal values apply as long as the EV load forecast is perfect. Calculated with the yearly energy demand of about $100\,000\,\mathrm{kWh}$ derived from real workplace charging data, the monetary loss compared to a perfect PV forecast amounted to $100\,€$ per year. In comparison to uncontrolled charging a surplus of $4000\,€$ per year was achieved. The decrease in self-sufficiency compared to a perfect PV forecast was only about 1 pp and outweighed the increase of more than 20 pp compared to uncontrolled charging in case of a system without BAT. Systems with BAT with a PV larger than $80\,\mathrm{kWp}$ become economic. However, systems without BAT are most economic. At the same time, a BAT of $60\,\mathrm{kWh}$ could increase the self-sufficiency up to 10 pp.

The system was sized with the criterion that less than 1 % of the EV demand was allowed to remain uncovered. This criterion might have been too strict and needs to be analysed regarding the distribution of the load losses' uniformity and socio-economic aspects. Furthermore the approach showed that if the grid connection offers more power than the load peak power, the load prediction is more important than the PV prediction. Therefore a comparison of the influence of load and PV forecasting shall be analysed in the future. Regarding the workplace environment and the long parking durations, the load uncertainty is not as striking as in other scenarios such as public charging. This motivates for a more in-depth analysis regarding different use cases, also including battery ageing and vehicle-to-grid.

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Presenter Biography

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