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LIGHTWEIGHT SMART CHARGING VS. IMMEDIATE CHARGING WITH BUFFER STORAGE: TOWARDS A SIMULATION STUDY FOR ELECTRIC VEHICLE GRID INTEGRATION AT WORKPLACES

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ABSTRACT

The present study investigates the extension of an existing simulation model combining system dynamics and discrete event simulation by linear optimization for an electric vehicle charging system. The existing simulation framework is extended by a smart charging strategy based on linear programming in order to exploit the flexibility of real charging processes at a workplace parking lot for a better integration of solar photovoltaic electricity generation. Therefore, different smart charging strategies are evaluated. In multiple simulation runs, the strategies are compared with immediate charging using a stationary battery energy storage system for intermediate storage of electricity generated by solar photovoltaic. Results show that smart charging strategies can achieve similarly good results with respect to the self-sufficiency rate and self-consumption rate. In the context of a 100kWp PV system the combination of optimizing charging rates and stationary battery energy storage resulted in self-sufficiency rates of more than 90% in the simulation.

1 INTRODUCTION

In order to mitigate the consequences of climate change, greenhouse gas emissions must be reduced in all sectors. According to the European Union's resolution (Presse- und Informationsamt der Bundesregierung, Germany 2022), savings of 55% in greenhouse gases are planned by 2030 compared to 1990's level. The transition from internal combustion engine vehicles to fully electric vehicles (EV) is one major driver for greenhouse gas reduction. In the EU, newly registered vehicles will no longer be allowed to emit CO_2 from 2035 on. However, the required development in the field of electromobility poses challenges for charging infrastructure and grid capacities (Matanov and Zahov 2020; Moghaddam et al. 2018).

Smart charging strategies could help dealing with these challanges by minimizing peak loads (Powell et al. 2020; Strobel et al. 2022) and thus avoid local power grid overload (Pareek et al. 2020). In addition, the use of electricity from photovoltaic (PV) systems to feed the charging stations is an option at employee parking lots. Vehicles are parked for a great part of the day, especially during hours with high solar radiation rates, offering high potentials for increasing self-consumption (Fachrizal et al. 2022) and by means of this reducing CO_2 emissions. But, while, at phases, several vehicles can be charged in parallel with maximum charging power only with local PV power, the energy must be drawn externally during times the sky is overcast. This, on the one hand, reduces the economic efficiency of PV systems and charging infrastructure, and on the other hand also worsens the ecological footprint of the charging process, since the electricity imported from the grid usually has a worse CO_2 intensity in production than the electricity drawn directly from the PV system. To increase the share of PV energy used for charging, stationary battery energy storage systems (BESS) can be integrated (Jung et al. 2022). In the study by

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Sing et al. (2023), on which the present paper is based, the authors developed a simulation model based on System Dynamics which can be applied to simulate complex energy systems comprising EV charging power demand, solar PV system and BESS. They investigated the potentials of a rule based strategy to maximize the coverage of charging demand by PV electricity generation under consideration of different PV power rates and BESS capacities. Simulation results showed a degree of self-sufficiency of up to 87% and a reduction in CO_2 emissions of over 80%. As an alternative to the intermediate storage of PV electricity production, smart charging management can be considered, so that the flexibility of the charging demand can be optimally exploited. In contrast to immediate charging, which is the standard for EV charging, smart charging does not charge the vehicle at the maximum charging rate as soon as the vehicle is plugged into the charging infrastructure. Instead, an intelligent adjustment of the charging rates takes place. Depending on the optimization goal, this can, for example, improve the use of PV power or reduce peak loads. Many publications (e.g. Kara et al. (2015), Huber et al. (2019), Jian et al. (2018), Fachrizal and Munkhammar (2020), Rücker et al. (2020)) have investigated the potentials of postponing charging operations and thus maximize self-consumption and self-sufficiency. Similarly, systems exist in which precomputed schedules (Frendo et al. 2019) or real-time optimization of charging operations are used (Jiang and Zhen 2019). The present paper contrasts the two approaches of BESS and charging rate optimization and gives an estimate for the improvements in grid integration resulting from smart charging. This paper examines the following questions:

- To what extent, regarding self-consumption and self-sufficiency, can a BESS be replaced by smart charging via charging rate optimization?
- Are BESSs still necessary to achieve a comparable self-consumption?
- Can an even greater self-sufficiency be achieved through a combination of BESS and charging rate optimization?

To answer these questions, the existing simulation framework of Sing et al. (2023) is extended by a smart charging algorithm. Therefore, we utilize linear programming and the Gurobi solver (Gurobi Optimization, LLC, Beaverton, OR 97008). Additionally, we compare the results with those of the rule-based approach of the previous study.

The remainder of the paper is organized as follows: Section 2 presents the related work. In Section 3, the optimization model as well as the interface for its integration into the simulation framework of Sing et al. (2023) are discussed. An evaluation of the comparison of the charging strategies takes place in the Section 4. Section 5 gives a summary and an outlook on future questions.

2 RELATED WORKS

2.1 Ecological and Economic Potential and Relevance of Smart Charging using BESS and / or Optimized Charging Rates

Reducing CO_2 emissions and costs for installation and oparation by optimizing self-consumption and self-sufficiency of PV systems and EV charging operations is one direction of literature in the area of vehicle grid integration. To this end, several approaches are available.

In a case study considering the dynamic generation of wind and PV power Heredia et al. (2020) reduced installation costs by up to 15% implementing load management technology. Savings of 37% were achieved in operating costs. The paper is focused on minimizing peak loads. The idea of maximizing PV power usage is not addressed. Calearo et al. (2021) compare the self-consumption of PV electricity using a BESS versus that of a smart charging system in the context of a Danish household. The latter attempts to minimize the import of external power by using simple logic to postpone the charging of an EV to time slots when PV power is available. The case study considered, delivered an increase in self-consumption of PV electricity from 29% to 54% using smart charging. An 8kWh/2kW BESS provided comparable savings but a 20 times higher payback time, demonstrating the potential of charging rate optimization for single household.

The view on a larger scale is given by Lee et al. (2021). They investigate the profit increase of a flexible adaptive scheduling algorithm based on convex optimization and model predictive control under real-world challenges such as unbalanced three-phase infrastructure, non-ideal battery charging behavior and quantized control signals in real-time deployment. Using the Adaptive Charging Network (ACN) released by Lee et al. (2019), the implemented comparison of this approach with the baseline algorithms shows a profit increase for the operator of 340%. This is achieved by using intelligent scheduling of charging operations, reaching up to 98.1% of the offline optimum, but under consideration of dynamic electricity prices and adaptions in tariffs and less with regard to available PV power. Bhatti and Salam (2018) also underline the financial advantages of smart charging aside from emission reduction by proposing a rule-based energy management scheme for charging EVs via PV power grid systems with fluctuating underlying grid electricity prices, which was able to reduce the costs of charging by 16.1% in addition to reducing the grid load by 93.7%. This is done by using periods for charging when the electricity demand is generally lower. The impact on self-sufficiency and self-consumption is not given. These studies already highlight the clear benefits of smart charging approaches. However, the focus is not on saving emissions, but primarily on the general reduction of costs and maximizing financial profit. Also, the results are often based on real data and do only conditionally allow a transfer to other configurations, like the simulation tool of the present work was originally designed for.

Analysing the improvements through smart charging for the environment, Spitzer et al. (2019) determined a reduction in greenhouse gas emissions of approximately 40%. This was done in the context of studying power supply stability as EV charging energy demand increases. Roselli and Sasso (2016) show the potentials of reducing CO_2 emissions of an office building in southern Italy by maximizing the self-consumption of its PV power supply. The study reports energy savings by switching from natural gas fired boiler, an electric chiller and a diesel car to all-electric heating, air conditioning and mobility with a CO_2 equivalent of 40%. The impact of a smart charging strategy is not addressed in this work.

For an optimal usage of PV power, a good prediction of the PV power production is necessary. While Abronzini et al. (2016) present an optimal power flow management for a smart charging micro-grid minimizing costs for day-ahead prediction of the energy flow, Jiang and Zhen (2019) use a Support Vector Machine model (Shi et al. 2012) to maximize the solar energy self-consumption. They are engaged in real-time optimization of a smart charging management system consisting of EV charging stations, PV system and BESS by using the Improved Binary Grey Wolf Optimizer with the goal of minimizing the costs of charging operations. Weather forecasts are made for each charging operation. The authors achieved up to 55% cost reduction compared to an immediate charging strategy.

While there exist many works focusing on the benefits of smart charging in combination with renewable energy sources, how smart charging compares to a conventional approach with BESS and immediate charging still needs to be quantified.

2.2 Simulation of Energy Systems and EV Charging

Infrastructure and real-world charging events are not always available on site to conduct meaningful research on smart charging. The tool of simulation represents a valid alternative for this purpose. It offers the posibility of making adjustments to the environmental conditions and thus investigating the potentials of different scenarios without extensive construction measures and high time expenditure.

For example, Lützenberger et al. (2014) investigated the maximization of renewable energy use through smart charging in a simulation. An agent-based approach was chosen and an optimization algorithm was embedded. An increase in the share of renewable energy in the simulated charging operations of 15.5% was achieved and the potential for CO_2 savings via optimization was highlighted. However, an option for the user to easily adjust external conditions as input to the optimization is not available. The same applies to Kam and van Sark (2015) who showed the potentials for increasing the self-consumption of PV power by smart charging and vehicle-to-grid technology of a microgrid in the Netherlands using real-time charging control algorithms or linear optimization. Instead, they try to improve PV grid integration using vehicle-to-grid solutions and use the batteries of the vehicles for intermediate storage of PV electricity.

Due to the often limited access to real charging infrastructure systems for meaningful research and the decision support potential of simulations in planning charging hubs on different locations, this paper aims to extend the simulation model of Sing et al. (2023) with a smart charging algorithm. The focus herein lies on comparing the potentials of buffering PV energy in BESS versus optimizing the charging rate and using the full charging flexibility provided by parked EVs at workplaces. The previously shown increases in self-consumption and self-sufficiency are based on the integration of large BESS. Whether smart charging can achieve the same promised gains for increasing self-consumption of locally generated PV electricity and the associated reduction of CO_2 emissions, maybe even with a lightweight optimization model, is the subject of the subsequent sections.

3 METHODOLOGY

3.1 Existing Model and Objective

The underlying rule-based simulation model of Sing et al. (2023) was implemented using the commercial software AnyLogic 8 (AnyLogic, Oakbrook Terrace, IL, USA). It combines system dynamics to model energy flows with discrete-event simulation to model incoming charging events.

The model represents the basic energy flows between grid import, PV power generation, BESS charging and discharging, EV charging and grid export. Efficiencies of EV charging and BESS (dis-)charging are also considered. It contains a parameterizable BESS for intermediate storage of the locally generated PV electricity in order to increase the target values of self-consumption and self-sufficiency. There was no intelligent adaptation of the charging rates to external conditions. Real data from the ACN framework of Lee et al. (2016) is used as input for the charging processes. To model the generation of PV electricity, real data on local solar radiation was obtained from the National Solar Radiation Data Base (National Renewable Energy Laboratory 2021). This data can also be used as a parameter for forecasting PV electricity generation for the optimization. The present model does not include uncertainties in forecasting solar radiation or connection times. Instead it offers an estimation of the potential benefits given the necessary accuracy of the data. A brief analysis of the sensitivity of the model to uncertainties is given in Section 4.4.

The performance metrics used were the relationships presented by Quaschning (2019) to determine self-consumption and self-sufficiency. The self-consumption e is calculated as the fraction of locally generated PV electricity E_{PV} that is directly used by charging electric vehicles on site. This is derived from the determined exported PV electricity E_e as given by equation (1):

$$e = \frac{E_{PV} - E_e}{E_{PV}} \tag{1}$$

The degree of self-sufficiency a determines how much of the energy demand E_B can be covered by the self-generated PV electricity. For this, the amount of electricity E_i imported from the grid is considered.

$$a = \frac{E_B - E_i}{E_B} \tag{2}$$

An extension of the underlying simulation model of Sing et al. (2023), as provided in this work, allows the evaluation of different smart charging strategies as well as a comparison with previous results using a stationary BESS for intermediate storage of PV electricity.

3.2 Extension of the Simulation Model by a Linear Program Optimizer

The approach of this paper is adapting the charging rates to the available PV power, whereas the sum of energy delivered for each charging request remains unchanged. For this purpose, the charging processes of vehicles connected to the charging infrastructure are scheduled by a software optimizer. The existing Java-based simulation model (Sing et al. 2023) is extended by a linear program based on the API of Gurobi. Therefore, in the simulation model, the optimization algorithm has access to the charging rates of all charging stations, as well as central access to the forecast data for PV electricity generation. The concept for the integration of the linear optimizer into the simulation framework is shown in Figure 1.

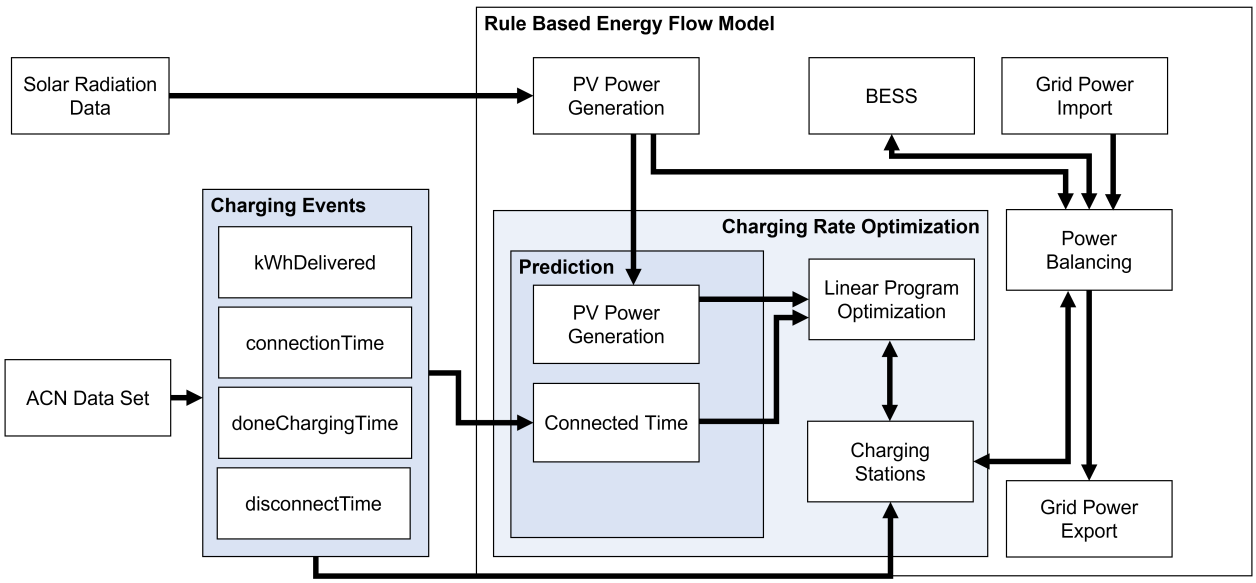

Figure 1: The concept for the integration of the Linear Program Optimizer into the simulation framework.

The optimization is invoked with each arrival of an EV at the parking lot. The time period available for the charging process is delimited by the times of plugging into the charging infrastructure and unplugging from it. These times are available as `connectionTime` and `disconnectTime` via the ACN data from Lee et al. (2016). Also available for each charging process is the amount of energy delivered `kWhDelivered`, which is used as the amount of energy to be charged in the simulation. No constraints are placed on the number of charging points. Please note that the charging and discharging of the BESS is not part of the optimization process.

We implemented two optimization strategies. For option A, the charging profile is optimized only for the vehicle just arriving, so that the charging rates of previously arrived and already scheduled vehicles remain unchanged in the further course of their charging processes. For option B, in addition to the charging process of the newly arriving vehicle, the charging processes of all vehicles already connected are optimized again, taking into account the newly arriving vehicle.

Option A seems to be a reasonable lightweight approach for the use of the optimization in reality, since it avoids that already scheduled processes are interrupted by a later optimization. Also, the computational effort remains calculable, since it does not depend on the number of already planned vehicles in the local optimization, which is the basis for scalability. In simulation runs, the average time for the optimization using option A was not significantly affected by the number of arriving vehicles, while for option B an increase of simulated charging events by factor five ended up in a five time higher average computing time of the optimization part.

3.3 Optimization Model

3.3.1 Parameters and Variables

For the optimization of the charging process of an observed arriving EV, the underlying conditions result in the input sets given in Table 1. Table 2 shows all input parameters which are needed for the optimization. The optimization variables are shown in Table 3.

Table 1: Input sets for the optimization of the charging process of an arriving EV.

Set	Description
I	Vehicles with indices $i \in I$ denoting all EVs connected to the charging infrastructure at the moment just after the arriving vehicle is connected and whose charging rates are to be optimized. For optimization option A this is only the just arriving vehicle.
T_i^{con}	Connection time of vehicle i to the charging infrastructure $\forall i \in I$
T_i^{dis}	Disconnection time of vehicle i from the charging infrastructure $\forall i \in I$
T	Considered time period with time step indices $t \in T$ from connection of the just arriving EV $\min\{T_i^{con}\}\ i \in I$ to the latest disconnection of all the currently connected EVs $\max\{T_i^{dis}\}\ i \in I$
Δt	Time step length as 1/60 of an hour
A_{it}	Indicators of the fractions of time the vehicle i can actually be charged in time step t $\forall t \in T$, $\forall i \in I$, $A_{it} \in [0,1]$

Table 2: Optimization parameters.

Parameter	Description
P_t^{PV}	Remaining PV power available at time step t $\forall t \in T$.
$P_{i,max}^{C}$	Maximum charging power of vehicle i $\forall i \in I$
E_i^{req}	Amount of energy required to fully charge vehicle i $\forall i \in I$
P_{max}^{G}	Maximum total grid import of the charging hub

Table 3: Optimization variables.

Variable	Description
$P_{i,t}^{C}$	Charging power of vehicle i at time step t $\forall i \in I, \forall t \in T$
P_t^{G}	Grid import at time step t $\forall t \in T$
$P_{out,t}^{PV}$	Grid export of excess PV power at time step t $\forall t \in T$

3.3.2 Objective function

The objective function is set up to maximize the degree of self-sufficiency as described in equation (2) by minimizing the imported grid power P_t^G:

$$\min \sum_{t \in T} P_t^G \cdot \Delta t$$

3.3.3 Constraints

The constraints described below must be met:

The total charging energy amount for vehicle i over its availability A_{it} corresponds to the given energy demand E_i^{req} of the vehicle for all time steps t.

$$\sum_{t \in T} (P_{i,t}^C \cdot A_{it} \cdot \Delta t) = E_i^{req} \qquad \forall i \in I$$

The maximum grid import is limited for all time steps.

$$P_t^G \leq P_{max}^G \qquad \forall t \in T$$

The charging power $P_{i,t}^C$ per vehicle i is bounded for all time steps t by the vehicle's given maximum charging power. Moreover, feeding power from vehicle into grid is not allowed so that the charging power must be greater than or equal to zero at any time step.

$$0 \leq P_{i,t}^C \leq P_{i,max}^C \qquad \forall t \in T, \forall i \in I$$

The total energy flow must be balanced for all time steps t. This means that for all time steps t the amount of exported PV electricity $P_{out,t}^{PV}$ equals the remainder from the sum of PV generation P_t^{PV} and imported electricity P_t^G minus the current total charging power $\sum_{i \in I}(P_{i,t}^C)$, or the total charging power is exactly covered by imported electricity P_t^G and PV electricity P_t^{PV}.

$$\sum_{i \in I} P_{i,t}^C = P_t^{PV} + P_t^G - P_{out,t}^{PV} \qquad \forall t \in T$$

3.3.4 Validation

Test runs were performed for minimal data sets as well as for the entire date, in order to validate the optimization model. Apart from the functional criterion of reducing grid power import after scheduling the charging processes by the optimization, we also take care of the consistency and comparability of the scenarios examined. This includes, in particular, the sum of the charged energy quantities, the maximum charging rates for infrastructure and vehicles, and the energy balance of the overall system under consideration. In addition, we evaluate and confirm that the charging runs occur exclusively during the time windows when the vehicles are plugged in. For this purpose, the quantities to be validated were output and analyzed in the time resolution of the model. Deviations of less than 0.1% for the energy amounts in comparable setups in the original model of Sing et al. (2023) and ours exist which are negligible in the context under study.

4 RESULTS

In the following, for reasons of comparison, we use a quite similar setup to Sing et al. (2023) meaning that we consider the same charging events of the year 2019 with a total annual charging demand of about 95 MWh and the same solar radiation data is used. The model provides 54 parallel usable charging stations each providing a maximum charging rate of 6.7 kW (Lee et al. 2021).

4.1 Shift of Charging Rates

The influence of the smart charging algorithm on the charging rates over time can be seen in detail in Figure 2 and Figure 3 for one single day. In the comparison of the figures, it can be seen that the optimization has a higher influence on the shift of the charging processes when the PV electricity production is increased. The impact of this shift in charging rates on grid integration for a whole year is analyzed below under different scenarios.

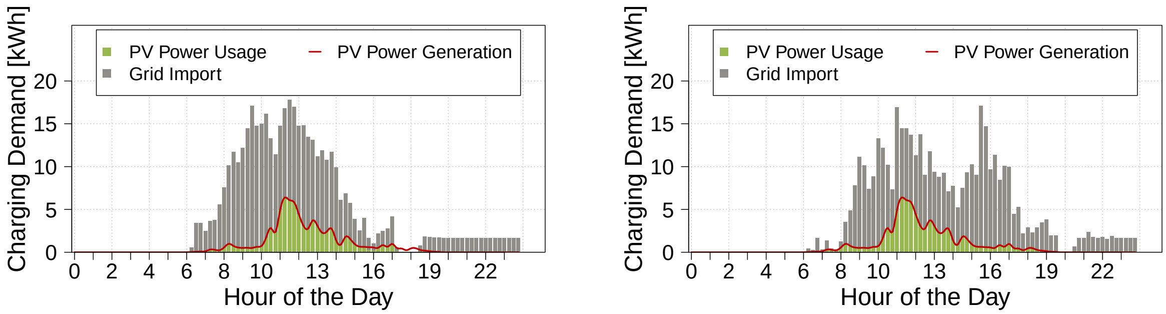

Figure 2: Charging power demand for a day with low PV power generation with Immediate Charging (left) and after optimizing the charging rates (right).

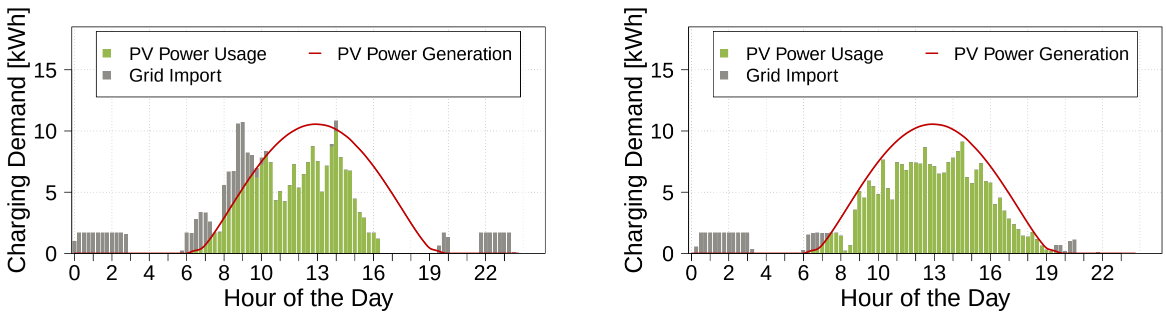

Figure 3: Charging power demand for a day with high PV power generation with Immediate Charging (left) and after optimizing the charging rates (right).

4.2 Self-sufficiency and Self-consumption

In the following, scenarios with immediate charging with and without BESS are used as the baseline. Subsequently, smart charging options A and B are simulated with and without 60 kWh BESS. A list of the scenarios including their identifiers and respective configurations can be found in Table 4.

Table 4: Scenario definition.

Identifier	Charging Rate Scheduling	BESS size [kWh]
IC-0	Immediate Charging	0
IC-60	Immediate Charging	60
A-0	Smart Charging Option A	0
A-60	Smart Charging Option A	60
B-0	Smart Charging Option B	0
B-60	Smart Charging Option B	60

Figures 4 and 5 show the dependency of self-consumption and self-sufficiency from the PV size which is varied from 0 kWp to 100 kWp in 20 kWp steps. For the self-consumption, all the curves decrease steadily with increasing PV system size. The self-sufficiency, on the other hand, increases steadily but flattens out with increasing PV system size. With increasing PV power production, energy is increasingly generated, which cannot be directly consumed by EV charging. At the same time, the need to import external power to cover the charging energy demand decreases. The scenarios can be divided into the groups with and without BESS, each showing similar behavior. In both groups, the advantages of smart charging over immediate charging can be seen, whereby option B always outperforms option A in the target values. In general, all scenarios with BESS deliver better results than those without BESS. The selected battery size of 60 kWh can therefore not be compensated by simply integrating smart charging.

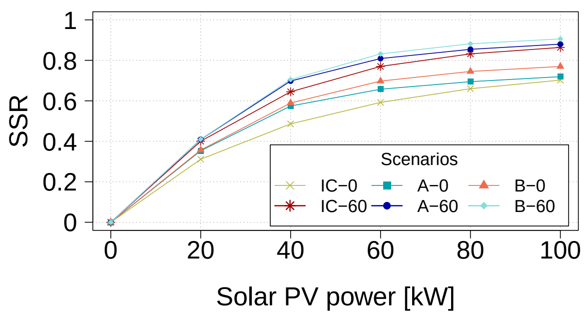

Figure 4: The self-sufficiency of the charging infrastructure depending from PV-system size.

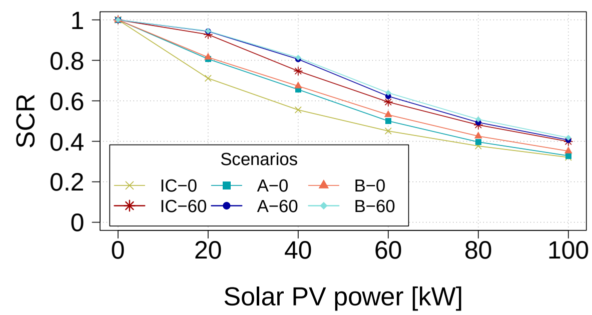

Figure 5: The self-consumption rate of the charging infrastructure depending from PV-system size.

Table 5: Simulation results for the investigated scenarios with 40 kWp PV system size.

Scenario	Grid Import [kWh]	Grid Export [kWh]	Self-Sufficiency	Self-Consumption
IC-0	48,638	36,864	0.486	0.555
IC-60	33,626	20,963	0.645	0.747
A-0	40,287	28,514	0.574	0.656
A-60	28,594	16,111	0.698	0.806
B-0	38,868	27,094	0.589	0.673
B-60	27,907	15,462	0.705	0.813

The subsequent results were determined by simulation over a one year period. Table 5 shows the collected values for a PV size of 40 kWp producing 82,861 kWh throughout the observed year. For all investigated scenarios the total power demand is 94,635 kWh. Here, the scenario IC-60 shows the improvement in self-sufficiency versus IC-0 through integrating a BESS. Applying optimization option B does lead to a better grid integration compared to immediate charging but falls short of the potential of just using a 60 kWh BESS. The obtained improvements correspond to those of a BESS with about 30 kWh capacity without smart charging. Or in other words: For 40 kWp PV systems smart charging can replace a 30 kWh BESS. Further investigations show that this potential depends on the PV system size: For bigger PV systems, the benefit of smart charging decreases, since here poor PV power usage of immediate charging is relevated by a higher PV power generation. Nevertheless, the combination of the implemented smart charging algorithm and a BESS can achieve better values for grid integration. B-60 increases self-sufficiency by 9.3% over IC-60. To achieve an equal rate of grid integration without charging rate optimization at this PV system size, increasing the size of the BESS to about 115 kWh capacity is necessary. Likewise, B-60 already achieved grid integration with a PV system of 80kWp, which was only achieved by IC-60 with a 120 kWp PV system.

Optimization of individual charging requests (Option A) can cause delayed charging as long as the optimization outputs are not impaired. These delayed charging processes lead to the effect that PV power produced earlier would not be used in the current charging request or by later arriving vehicles. Again, the later arriving vehicles might not find enough remaining PV power to fulfill their charging demand since it was used up by the delayed charging processes and need to draw power from grid instead. This impairs the total grid integration.

4.3 Greenhouse Gas Savings

The shown results for the 40 kWp PV setting underline the high deployment value of BESS and smart charging. A summary of the emissions for the different scenarios studied can be found in Figure 6, taking the electricity mix of the U.S. of 2021 with 379g CO_2-equivalents per kWh (Global Change Data Lab 2022) as a basis. The comparisons refer to the total charging energy demand of 94,635 kWh with resulting emissions of 35,867 kg CO_2. IC-60 has already reduced the grid import to 33,626 kWh in the simulation, resulting in CO_2 savings of 23,122 kg. Implementing smart-charging resulted in further reductions of emissions of 1,907 kg CO_2 (15.0%) for A-60 over IC-60 and 2,168 kg CO_2 (17.0%) for B-60 over IC-60.

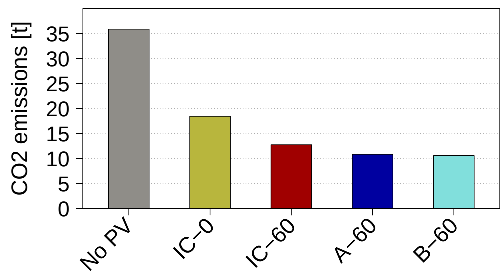

Figure 6: Comparison of CO_2 emissions from different system configurations.

4.4 Sensitivity Analysis

4.4.1 Power Prediction

In order to estimate the influence of the real world PV power forecasting error, we scale the actual solar radiation data to create synthetic erroneus forecasts. Varying the prediction scaling factor from 50% (half of the true radiation) to 200% (twice the true radiation), led to the values for self-sufficiency and self-consumption shown in Figure 7. One can see a maximum when the prediction is correct. Furthermore, there is a higher sensitivity to an underestimation of the PV electricity generation than to an overestimation.

4.4.2 Impairment of the Fulfillment of the Charging Energy Demand due to Early Disconnecting.

By optimizing charging operations to minimize grid power import, unlike immediate charging, charging operations are delayed. Therefore, for charging operations that are disconnected from the charging infrastructure earlier than anticipated, the desired charging energy may not be received. The extent to which this reduced fulfillment of the charging energy requirement depends on the shortened connection time is shown in Figure 8, comparing scenarios IC-0 and B-0 for a single month. For the latter, a linear relationship can be seen. The charging fulfillment for the scenario with immediate charging on the other hand remains almost unimpaired until the plugged-in time is reduced to less than half of the original value and than rises exponentially.

5 CONCLUSION

To answer the key questions of this paper, it can be concluded as follows: Lightweight optimization of EV charging rates provides limited opportunities to replace BESS. For small PV systems it is more important to utilize the generated power intelligently to achive good values for grid integration which is exactly where smart charging is aiming at. In the investigated scenarios, in a setup with 40 kWp PV system, smart charging could replace a BESS with 30 kWh to reach similiar self-sufficiencies. This advantage decreases with growing PV systems for which the resulting higher solar power production compensates the drawbacks of immediate charging. However, a combination of BESS and even simple smart charging can achieve further improvements for which in some scenarios a doubling of the BESS size would be necessary

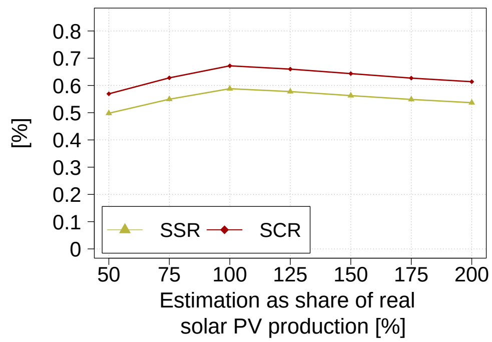

Figure 7: Influence of inaccurate predictions of PV power generation.

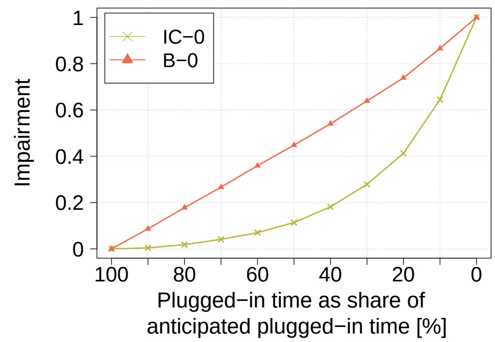

Figure 8: Impairment of the demand fulfillment due to the optimization.

without smart charging. A combination of 60 kWh BESS and smart charging achieved a self-sufficiency level of 70.5% for the given setup and thus an increase of 45.1% compared to the system without BESS or optimization. The corresponding gain of 9.3% in self-sufficiency compared to the system with BESS could achieve savings of CO_2 emissions by over two tons based on the electricity mix of the U.S. of the year 2021. With a higher dimensioned PV system of 100 kWp, more than 90% self-sufficiency could be achieved. Sensitivity analyses were performed regarding the underlying PV power prediction and the extent to which early plugging out affects the fulfillment of the charging energy requirement. Moreover, it was shown that the used lightweight optimization model applied on seperatly viewed individual incoming charging events can lead to reductions in grid integration.

For future work on this topic, improvements to the optimization model are planned. These could, for example, take into account the charging processes and the charging status of the BESS. Avoiding peak loads through optimized charging could also be investigated. Likewise, the charging rates used for the baseline scenarios could be modeled more accurately. The cost reductions that can be achieved by means of smart charging through reduced grid import and a reduction in peak loads could also be investigated.

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