DTU Library

# Online optimization of a workplace electric vehicle charging station under grid constraints

**Malkova, Anna; Zepter, Jan Martin; Marinelli, Mattia**

*Publication date:*
2023

*Document Version*
Publisher's PDF, also known as Version of record

# ONLINE OPTIMIZATION OF A WORKPLACE ELECTRIC VEHICLE CHARGING STATION UNDER GRID CONSTRAINTS

*Anna Malkova[1]* , Jan Martin Zepter[1], Mattia Marinelli[1]*

[1]*Department of Wind and Energy Systems, Technical University of Denmark, Roskilde, Denmark*
**E-mail: anmalk@dtu.dk*

**Keywords:** ELECTRIC VEHICLES, CLUSTER MANAGEMENT, ONLINE OPTIMIZATION, SHRINKING HORIZON, MODEL PREDICTIVE CONTROL

## Abstract

As the number of electric vehicles (EVs) on the roads continues to grow, the implementation of smart charging strategies will be a viable solution to reduce the impact of simultaneous charging of a large number of EVs and assist in mitigating the variability of local renewable energy source (RES) generation. This article presents a control model for a workplace EV charging station, focusing on maximizing the profit of the charging station while considering the presence of local PV generation. The proposed model is an online shrinking horizon optimization model that operates in 5-minute intervals, determining the power reference for the EV cluster at the charging station. In addition, the model incorporates a day-ahead PV forecast which will be updated with actual measurements throughout the day. The model demonstrates responsiveness to changing system conditions. The model is compared to perfect foresight of PV production and only using PV forecast data for the dispatch. The comparative analysis of the proposed model indicates a 5.6 % improvement in profit compared to the initial dispatch of power reference using only PV forecast data.

## 1 Introduction

The increasing awareness of global warming is expediting the adaptation of electric vehicles (EVs). It is anticipated that by 2030, there will be around 200 to 350 million EVs on roads worldwide depending on the development scenario [1]. Despite the numerous positive aspects associated with the propagation of EVs on our roads, such as the minimization of contribution to global warming and the improvement of air quality in urban areas, EVs also introduce challenges to the power system. The expansion of generation capacity, as well as the overloading of lines and transformers, can result in costly equipment replacement procedures and the need for grid expansion [2]. Concurrently, the presence of renewable energy sources (RES) and distributed energy resources (DERs) is increasing in various levels of the electricity networks. This necessitates greater system flexibility to address emerging challenges of a renewable-based system with variability of generation, such as the need for voltage level regulation, peak reduction as well RES power output smoothing [3]. Additionally, many countries are implementing hourly electricity tariffs, which are expected to facilitate load peak reduction and shifting.

However, the utilization of smart charging strategies for EVs can not only mitigate the adverse effects of simultaneous charging of a large number of EVs but also offer grid flexibility services, local DERs enhancement and reduction of electricity costs by shifting charging to off-peak hours [4]. The expansion of charging infrastructure and the aggregation of vehicles based on their location, including workplaces, commercial car depots, and malls, among others, enhance controllability for providing flexibility services [5]. This approach treats them as a unified unit with increased power and energy capacity load. Ref. [6] indicates that the coordinated control of an aggregated EV cluster offers benefits to both the grid and charging infrastructure owner. These advantages include a reduction in energy consumption during peak hours and the ability to shift charging to hours when electricity prices are lower due to hourly tariffs.

A common problem with the coordination of EV charging in parking lot clusters is that the exact availability (arrival time and charging duration) of the cars is unknown. Due to various reasons, EV owners could come to work or company cars might be in transit at different times of the day. However, the total energy charged over the course of a day is more predictable, once some information about typical charging needs is gathered. Previous studies focused on distributed control of individual EVs with a focus on power dispatch. Ref. [7] proposes a two-level charging station management model. Initially, a one-time dispatch of power reference for a day is carried out, taking into account the base load profile of the considered power system and the anticipated EV charging profile. Following this, real-time distributed power control of EV chargers is performed. The method described in the paper does not consider possible DERs in the system that may vary their power output throughout the day and mostly focuses on distributed power control of chargers. Ref. [8] focuses on the modulation of smart chargers' power within the distributed control algorithm. The article does not address the energy system level and leaves the decision-making regarding setting the power reference to the discretion of market needs, system operators, or utilities by means of transformer capacity constraints.

Yet, keeping the cluster coordination on an energy instead of power level has the advantage that almost no information from the cars needs to be communicated to the control system. Moreover, transitioning to the energy system level opens up more opportunities for distributing the flexibility potential across the entire system, considering DERs and other potential loads and devices. Additionally, it is advantageous to apply real-time online control, enabling the system to adapt to incoming inputs, such as signals from the grid operator, and DERs output, among others. The contribution of this paper is an online shrinking horizon optimization model that sets a power reference for the whole EV cluster based on electricity prices, PV measurements and historical EV charging data analysis.

The remainder of this paper is structured as follows: Section 2 introduces the system setup including the control architecture. Section 3 details the methodology of the online shrinking horizon optimization model. Section 4 presents the developed model results of work and comparison analysis with other possible scenarios. Section 5 provides the conclusion and future model development prospects.

## 2 System setup and architecture

This section describes the charging station setup and the proposed control system architecture.

### 2.1 Charging station setup

The proposed model has been developed for the implementation of smart charging at workplace parking lots. It is assumed that the charging station is connected to the main grid through a transformer, as well as to a local renewable energy source, with photovoltaic (PV) being the focus in this study as either the office building or the parking lot canopies could have PV installed. The connection diagram of the considered system is depicted in Figure 1. The chargers are connected to the rest of the system through PCC (Point of Cluster Connection) and power cables.

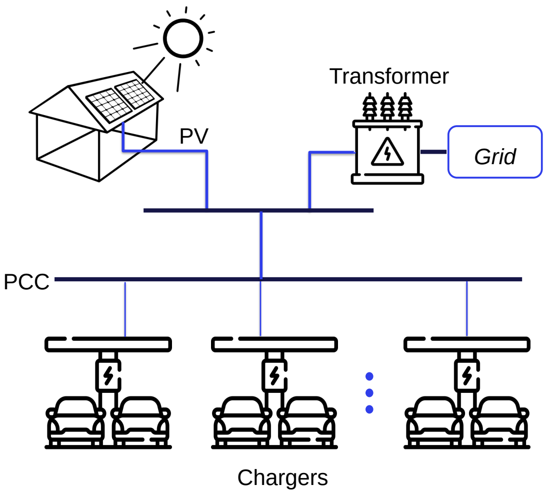



Fig. 1: Electrical connection of the setup.

### 2.2 System architecture

The schematic representation of the proposed upper-level control in a distributed charging station management is illustrated in Figure 2. The essential set of parameters consists of the transformer fuse limit ($P_{\text{fuse}}$), the time window of the EV cluster presence, the target preserved energy, day-ahead electricity prices and day-ahead PV production forecast. The transformer fuse limit is an upper-bound which must not be exceeded in order to prevent damage to the transformer. The presence of the EV cluster ($Z_{\text{clus}}$) is the time interval of the day during which the vehicles are expected to be present at the parking area. It could be a whole day or just several hours which are considered the most likely time window for the presence of EVs. To maintain data privacy given the absence of specific vehicle information, the definition of this time window is essential for more precise energy distribution. The concept of including preserved energy secures that a minimum amount of energy is reserved for charging the EVs, according to the power reference throughout the day. The electricity prices are decoupled into import and export prices.

The model runs every five minutes throughout the whole day with a shrinking optimization horizon. The sequence of model execution is as follows:

1. The update of essential parameters occurs, considering the time elapsed since the start of the day and the energy already charged to the vehicles.
2. The output power of PV is measured, and along with the day-ahead PV power output forecast, it passes through the PV data adaptation block.
3. Then, the optimization problem model is executed, generating the power reference ($\boldsymbol{P_{ref}}$) for the cluster of EVs at the charging station for each remaining time step of the day.

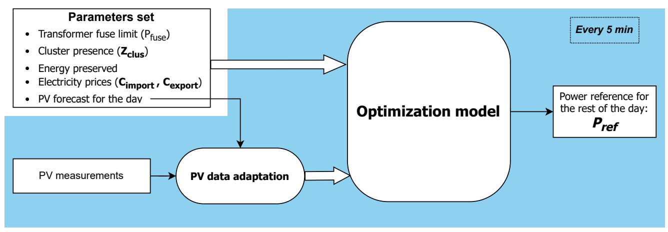



Fig. 2: Online optimization control system architecture.

The PV adaptation block processes measurements and forecasts, providing the processed PV data to the optimization model. Even though modern forecasts of PV power production are somewhat accurate, already one day ahead, the situation may change throughout the day [9]. To achieve a more precise understanding of the ongoing dynamics, it becomes essential to incorporate PV measurements. Figure 3 details the functioning of the PV adaptation block. The graph illustrates PV adaptation at 6:00 AM. The predicted PV output for that time is approximately 10 kW, but the actual measured value is 15 kW. The

PV adaptation block utilizes the current measured value at this timestamp and maintains this value for the subsequent 30 minutes (indicated by the green shaded segment in Figure 3). This approach assumes that during the next thirty minutes, the PV output remains consistent with the measured value, and afterwards, it follows the PV forecast. This adaptation occurs at every five-minute time step.

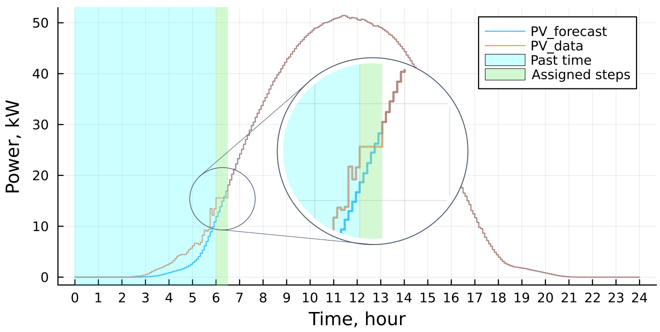



Fig. 3: PV data adaptation at 6:00 AM.

## 3 Methodology

The model proposed in this paper is an online shrinking horizon model predictive control mixed-integer linear optimization problem (according to [10]). The model was developed using the Julia programming language, using the JuMP optimization formulation package, and solved with the Gurobi commercial solver. For convenience, the developed model is from now on in this article abbreviated as *OSH* (Online Shrinking Horizon). The considered horizon is one day with 288 steps of five minutes: $24\,\text{hours} \times 60\,\text{min} \div 5\,\text{min} = 288\,\text{steps}$. The horizon shrinks every five minutes, and as a result, the dimension of the optimization model diminishes by 1 at each step.

$$S = \tau - (t - 1) \tag{1}$$

Equation (1) determines the dimension $S$ of the optimization problem (controlled horizon), where $\tau = 288$ is the total number of steps (whole horizon) and $t$ is the current time step.

### 3.1 Variables

The decision variable, referred to as $P^s_{\text{cluster}} \geq 0$, represents the output solution of the optimization problem. It is the overall power reference for the cluster of EVs at the parking lot. Additional variables necessary for optimization formulation are $E_{\text{cluster}}$ detailing the energy charged within the time horizon $S$, and $P^s_{\text{grid}}$ representing power throughput at the transformer. Also, $P^s_{\text{grid}}$ is further decomposed into $P^s_{\text{import}}$ and $P^s_{\text{export}}$ for applying distinct import and export prices. The auxiliary binary variables $f^s_{\text{import}}$ and $f^s_{\text{export}}$ are used to prevent the model from simultaneously importing and exporting.

### 3.2 Objective Function

The objective function aims to minimize costs (maximize own benefit):

$$\min \sum_S (C^s_{\text{import}} \times P^s_{\text{import}} + C^s_{\text{export}} \times P^s_{\text{export}}), \tag{2}$$

where $C^s_{\text{import}}$ is a total import price including spot price, grid tariffs, and taxes, while $C^s_{\text{export}}$ is only the spot price. Thus, local renewable excess production is sold at a lower price than drawing energy from the grid.

### 3.3 Constraints

Equations (3) – (6) represent transformer power decomposition into the import and export power. These constraints also determine that import and export can not happen simultaneously and should not exceed the fuse limit of the transformer in absolute values.

$$P^s_{\text{grid}} = P^s_{\text{import}} + P^s_{\text{export}} \tag{3}$$

$$0 \leq P^s_{\text{import}} \leq f^s_{\text{import}} \times P_{\text{fuse}} \tag{4}$$

$$-f^s_{\text{export}} \times P_{\text{fuse}} \leq P^s_{\text{export}} \leq 0 \tag{5}$$

$$f^s_{\text{import}} + f^s_{\text{export}} \leq 1 \tag{6}$$

Constraint (7) is the power balance constraint of the system. Equation (8) constrains the decision variable within the permissible power limit and the established time limit for the presence of the cluster of vehicles at the charging station. The last constraints (9) and (10) compute the energy that will be charged into the vehicles with the power distribution of power reference decided at the current time step and implemented within the remaining time, and enforces the satisfaction of the energy requirement.

$$P^s_{\text{cluster}} = P^s_{\text{PV}} + P^s_{\text{grid}} \tag{7}$$

$$P_{\text{min}} \times Z^s_{\text{clus}} \leq P^s_{\text{cluster}} \leq P_{\text{fuse}} \times Z^s_{\text{clus}} \tag{8}$$

$$E_{\text{cluster}} = \sum_S P^s_{\text{cluster}} \times \Delta t \tag{9}$$

$$E_{\text{required}} \leq E_{\text{cluster}} \tag{10}$$

The value of $E_{\text{required}}$ is updated every time step by subtracting the already charged energy from the initially preserved energy:

$$E_{\text{required}} = E_{\text{preserved}} - E_{\text{charged}} \tag{11}$$

### 3.4 Model inputs

The developed model has been adapted to the evolving charging station system of Campus Bornholm, Denmark, as part of the ACDC and EV4EU projects. The campus setup corresponds to the charging station setup depicted in Figure 1. The

PV production data of the roof-top PV panel with an installed capacity of 180 kW is diminished by a factor of 2 in order to match the charging station power load. The PV data are taken from two weeks of measurements from June 2021 with one of the days taken as PV forecast and another one as PV measurements for the model (Figure 4).

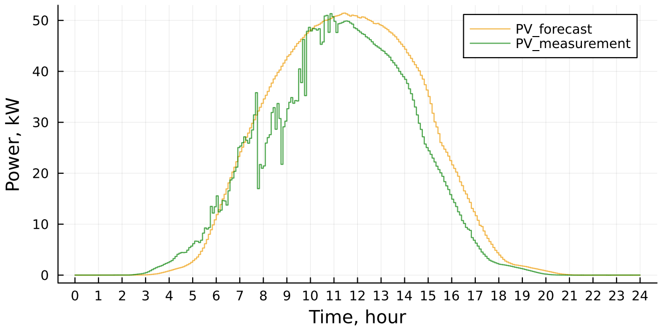



Fig. 4: PV forecast and measurements for one day.

The charging station at the parking lot consists of six smart chargers with two outlets each. Consequently, up to 12 EVs can charge simultaneously. The transformer fuse limit is 43 kW. The prices are taken from the website of Bornholm's energy supplier and account for spot prices, variable tariffs, transmission costs and taxes [11] (Figure 5).

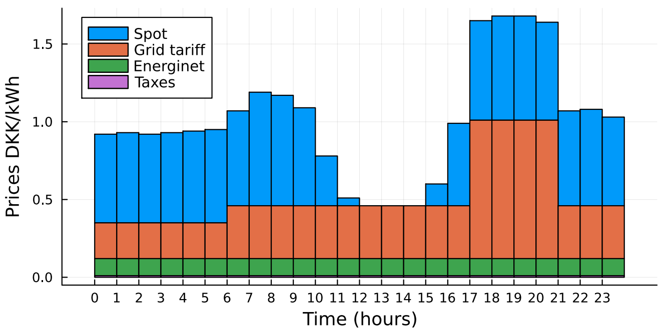



Fig. 5: Bornholm electricity prices.

The EV cluster data is derived from the analysis of real-world charging session data collected over one year by the charger operator SPIRII in Denmark. According to the research findings, it was determined that, on average, a vehicle is charged with 9 kWh of electricity. Also, it is assumed that for the workplace parking lot with 12 outlets, a total number of 15 cars arrive to charge during the working hours of the day. Furthermore, the charging efficiency coefficient of 90 % is accounted for energy preservation for EV cluster. Thus, the preserved energy for EV cluster is $E_{\text{preserved}} = 9\,\text{kWh} \times 15 \div 0.9 = 150\,\text{kWh}$. The presence of the EV cluster ($Z_{clus}$) is established within the time interval from 6:00 to 20:00 during the day, aligning with the average working hours in Denmark, which typically span from 8:00 to 17:00, with the inclusion of some additional buffer time. The minimum power reference for the EV cluster during its presence is established at 2.3 kW. This value is chosen to guarantee that the minimum charging current for a single car is maintained at 10 Amps, which equals 2.3 kW at 230 V. When the cluster is not present, the power reference is kept at 0 kW.

To assess how real-world EVs respond to the model's output reference power in a practical scenario, an additional test model has been developed. This auxiliary model directly manages the charging of each individual EV with the aim of maximizing EV owner satisfaction. Data regarding the EVs in this auxiliary model is once again derived from real-world data, as discussed earlier. It is important to note that this additional model operates independently and does not interfere with the main model presented in this article; it is solely used for testing purposes. The input EV data for the auxiliary model is presented in Table 1. The data for each EV contains arriving and departure time, maximum power of charging, and energy demanded.

Table 1 EVs data for the auxiliary model

| EV | Arriving | Departure | $P_{\text{max}}$, kW | $E_{\text{dem}}$, kWh |
|---|---|---|---|---|
| 1 | 06:20 | 10:40 | 3.7 | 8.46 |
| 2 | 06:45 | 13:25 | 3.7 | 10.74 |
| 3 | 07:00 | 15:10 | 3.7 | 12.90 |
| 4 | 07:15 | 15:00 | 3.7 | 2.68 |
| 5 | 07:30 | 15:30 | 7.4 | 5.43 |
| 6 | 08:05 | 16:05 | 3.7 | 7.76 |
| 7 | 08:10 | 18:05 | 3.7 | 32.34 |
| 8 | 08:30 | 17:00 | 3.7 | 26.17 |
| 9 | 09:05 | 16:30 | 3.7 | 9.76 |
| 10 | 11:10 | 17:00 | 11.1 | 12.91 |
| 11 | 11:50 | 14:40 | 3.7 | 7.91 |
| 12 | 13:25 | 19:25 | 11.1 | 10.47 |
| 13 | 15:10 | 18:15 | 11.1 | 14.67 |
| 14 | 16:35 | 18:50 | 11.1 | 6.56 |
| 15 | 18:30 | 19:10 | 11.1 | 3.78 |

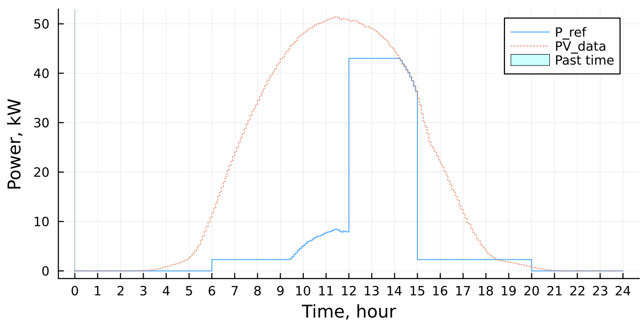
## 4 Results

In this section, the results of the *OSH* model are presented first, followed by a comparative analysis of the proposed model with two other working scenarios: *Oracle* and *Forecast*. The first scenario involves perfect knowledge of PV production. In the second scenario, only the PV forecast data is used.

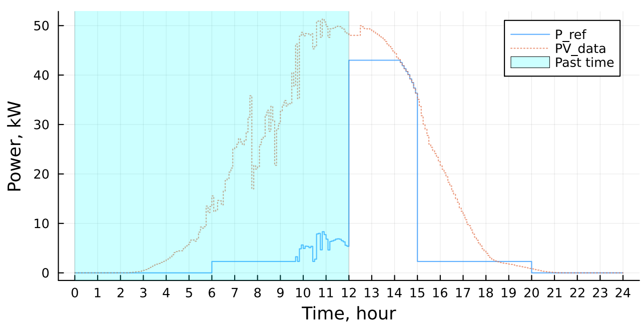
### *4.1 OSH model workflow*

Figure 6 illustrates the *OSH* model performance. Figure 6a displays the optimization outcome for the initial step at 00:00. During this step, the PV data utilized in the optimization model largely aligns with the PV forecast for the day. Taking into account electricity prices, the model sets the highest power reference during the most cost-effective hours, from 12:00 to 15:00. Additionally, the model strives to maintain the power reference below the PV data curve to maximize financial benefits. Consequently, wherever feasible, the power reference remains at a minimum value and aligns with the shape of the

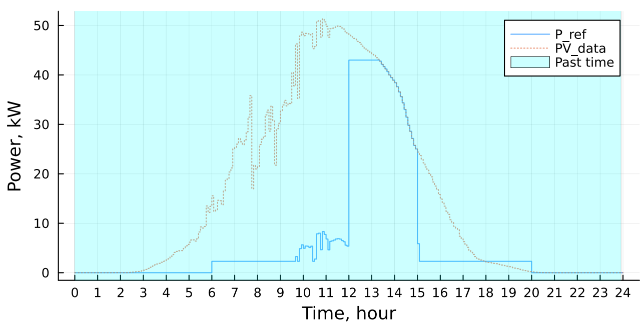
PV data. By 12:00 (Figure 6b), the shape of the PV data curve has undergone a significant change, noticeably adapting to the PV measurements. It is important to note that the measurement value obtained at 12:00 is set as a constant value for the following half-hour. Additionally, it can be observed that the power reference values between 9:30 and 12:00 changed, mirroring the shape of the PV data curve. Figure 6c illustrates the final step of the model's operation at 23:55, encompassing all the preceding steps conducted up to that point in time. There is a distinct change in the power reference that happened between 13:25 and 15:00 compared to the model run at 12:00. The power reference is set to maximize the utilization of PV-generated power and prevent the sale of PV power at a lower price during those hours. Also, at 15:00 the power reference is around 6 kW and not the minimum power of 2.3 kW as was previously dispatched. This happens to ensure a minimum required preserved energy supply.




(a)



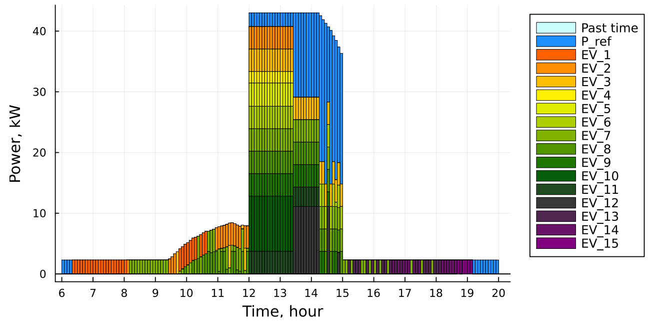

(b)



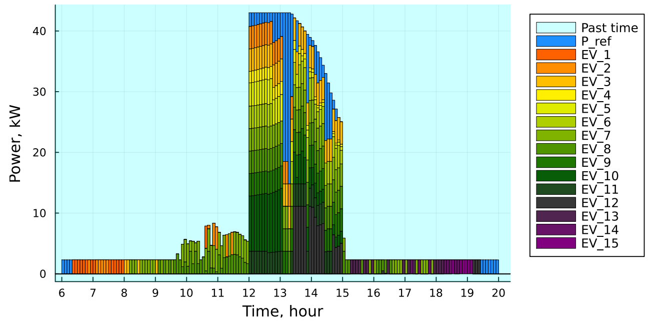

(c)

Fig. 6: EV cluster power reference output of the *OSH* model with PV data at (a) 00:00, (b) 12:00, (c) 23:55 time of the day.

The direct dispatch of EVs by auxiliary model can be observed from Figure 7.The contrast between the dispatch at 00:00 (Figure 7a) and 23:55 (Figure 7b) is significant. EVs rearrange their charging adapting to the power reference set. For instance, EV 1 is no longer capable of charging the same amount of energy it was dispatched initially due to the limitation of power reference before noon. This occurs because the auxiliary model does not prioritize individual EVs but focuses solely on maximizing the overall energy satisfaction of the entire EV cluster.




(a)




(b)

Fig. 7: EVs dispatch of the auxiliary model at (a) 00:00 and (b) 23:55 of the day.

### 4.2 *Comparison analysis*

The developed *OSH* model is compared with two different cases: *Oracle* and *Forecast*. This comparison is essential for an objective evaluation of the developed model in terms of cost-benefit and delivered energy to the EVs. The *Oracle* case is considered an ideal non-realistic scenario where the PV output is perfectly known in advance. In this case, the optimization model runs once, using the actual PV measurements as the PV input, and generates the power reference setpoints for the cluster. In the more realistic *Forecast* scenario, the model dispatches the power reference for the entire day using the PV forecast data. Then, this dispatched power reference remains constant and is taken into account in the power balance equation with the actual PV output measured on that day.

Table 2 displays the performance results of all three models. As can be observed, the revenue generated by the *OSH* model is remarkably close to that of the ideal *Oracle* model. Furthermore, when the *OSH* model is used by the charging station operator instead of the *Forecast* model, the increased income amounts to 5.11 DKK per day or 5.6 %. This is undeniably a positive outcome, and when extrapolated over a year, it would result in a revenue increase of 1865.15 DKK solely by changing the station's energy management strategy. Nevertheless, it is important to highlight that both the ideal case *Oracle* and the *OSH* model deliver slightly less energy compared to the *Forecast* model. This is because the *Forecast* model incorporates a higher power reference during the morning hours. In the case of *Oracle*, it is known in advance that PV production will be lower during these hours, so it restricts the power reference to have the opportunity to sell more PV output at a higher price. In the case of the *OSH* model, the charging performance for the first two EVs is the poorest among all other models. This is primarily due to the reduction in power reference during the morning hours and the limited time the cars spend at the charging station. Furthermore, the *OSH* model will be enhanced to improve the delivered energy to EVs by incorporating measurements at the PCC. This will enable feedback and the adaptation of preserved energy based on these measurements without compromising the privacy of the charging profiles of individual EVs. It is important to note that the auxiliary model does not prioritize the charging of earlier-arriving EVs; instead, it aims to increase the charged energy for the entire cluster. This will not pose an issue when *OSH* is tested with distributed control of chargers, where prioritization is considered.

Table 2 Comparison results of *Oracle*, *OSH*, *Forecast* models

| | *Oracle* | *OSH* | *Forecast* |
|---|---|---|---|
| Delivered energy, % | | | |
| EV 1 | 45.9 | 31.8 | 84.0 |
| EV 2 | 99.9 | 64.3 | 91.7 |
| EV 3 | 85.4 | 82.2 | 92.9 |
| EV 4 | 100.0 | 99.9 | 100.0 |
| EV 5 | 100.0 | 99.9 | 100.0 |
| EV 6 | 100.0 | 97.8 | 100.0 |
| EV 7 | 62.4 | 62.1 | 62.6 |
| EV 8 | 61.7 | 65.0 | 58.8 |
| EV 9 | 100.0 | 98.1 | 100.0 |
| EV 10 | 100.0 | 99.9 | 100.0 |
| EV 11 | 100.0 | 99.0 | 100.0 |
| EV 12 | 100.0 | 99.5 | 100.0 |
| EV 13 | 24.8 | 17.6 | 24.8 |
| EV 14 | 40.9 | 21.0 | 40.9 |
| EV 15 | 25.4 | 27.4 | 25.4 |
| Average energy delivery, % | 76.4 | 71.0 | 78.7 |
| Cost (negative - income), DKK | -96.33 | -96.31 | -91.20 |

## 5 Conclusion

This paper describes the performance of an online shrinking horizon optimization model for an EV charging station. This model aims to maximize the benefit of the charging station. The analyzed electrical configuration incorporates local PV generation, a connection to the main grid through a transformer, and six smart chargers, each equipped with two outlets, enabling the simultaneous charging of up to twelve EVs. The proposed model runs every 5 minutes within 24 hours of a day, generating a power reference for the EV cluster at the charging station. It incorporates a PV adaptation logic that utilises both the day-ahead PV forecast and the measured PV data at each step. This adaptation logic establishes the measured PV values for the subsequent 30 minutes within the current model run before returning to the forecasted progression. The results from running the model indicate that it operates effectively and adapts to real-time system signals, such as changing PV power, by adjusting power references to maximize the station's benefits. The model allocates the maximum power reference during the most cost-effective hours of the day, specifically between 12:00 and 15:00.

A comparative analysis was also conducted, comparing the developed *OSH* model with two other cases: *Oracle* and *Forecast*. The *Oracle* model is considered an ideal model with complete information about future PV generation. On the other hand, the *Forecast* model is a more practical model in which the power reference for the entire day is set directly using the PV forecast. The comparison revealed that the cost-benefit of the developed *OSH* model is nearly equivalent to that of the ideal *Oracle* case and is 5.6 % more favourable money-wise than using the *Forecast* model. However, the amount of energy delivered by the *OSH* model, as derived from the auxiliary model, is lower than that in the comparative models. This can be attributed to the shorter presence of vehicles at the station in the early morning and the reduction in power reference during those hours due to PV measurement adaptation.

Future developments will focus on incorporating PCC measurements to improve the updating of preserved energy and increase the delivered energy to the vehicles. Work will also be carried out to enhance PV adaptation by integrating more accurate PV forecasts and conducting time-series analysis of PV measurements into the model.

## 6 Acknowledgment

The work in this paper has been supported by the research project ACDC (EUDP grant nr: 64019-0541) www.acdc-bornholm.eu and by the research project EV4EU (Horizon Europe grant no. 101056765) https://ev4eu.eu/

## 7 References

[1] "Global EV Outlook 2022 – Analysis - IEA." [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2022

[2] S. Tirunagari, M. Gu, and L. Meegahapola, "Reaping the Benefits of Smart Electric Vehicle Charging and Vehicle-to-Grid Technologies: Regulatory, Policy and Technical Aspects," *IEEE Access*, vol. 10, pp. 114 657–114 672, nov 2022.

[3] I. Energy Agency, "Unlocking the Potential of Distributed Energy Resources Power system opportunities and best practices." [Online]. Available: www.iea.org/tc/

[4] S. Striani, K. Sevdari, L. Calearo, P. B. Andersen, and M. Marinelli, "Barriers and Solutions for EVs Integration in the Distribution Grid," *2021 56th International Universities Power Engineering Conference: Powering Net Zero Emissions, UPEC 2021 - Proceedings*, aug 2021. [Online]. Available: https://orbit.dtu.dk/en/publications/barriers-and-solutions-for-evs-integration-in-the-distribution-gr

[5] K. Sevdari, L. Calearo, P. B. Andersen, and M. Marinelli, "Ancillary services and electric vehicles: An overview from charging clusters and chargers technology perspectives," *Renewable and Sustainable Energy Reviews*, vol. 167, p. 112666, oct 2022.

[6] E. C. Kara, J. S. Macdonald, D. Black, M. Bérges, G. Hug, and S. Kiliccote, "Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach," 2015. [Online]. Available: http://dx.doi.org/10.1016/j.apenergy.2015.05.072

[7] M. C. Kisacikoglu, F. Erden, and N. Erdogan, "Distributed Control of PEV Charging Based on Energy Demand Forecast," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 332–341, jan 2018.

[8] K. Sevdari, L. Calearo, S. Striani, P. B. Andersen, M. Marinelli, and L. Ronnow, "Autonomously Distributed Control of Electric Vehicle Chargers for Grid Services," *Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021*, 2021.

[9] J. M. Zepter and J. Weibezahn, "Unit commitment under imperfect foresight – The impact of stochastic photovoltaic generation," *Applied Energy*, vol. 243, pp. 336–349, jun 2019.

[10] C. V. Caldwell, E. G. Collins, and S. Palanki, "Integrated guidance and control of AUVs using shrinking horizon model predictive control," *OCEANS 2006*, 2006.

[11] "Bornholms engiforsyning," https://www.beof.dk/privat, 2023.