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Malkova, Anna; Zepter, Jan Martin; Marinelli, Mattia; Amezquita, Herbert; Morais, Hugo

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Receding horizon optimization for distributed control of electric vehicle charging stations

Anna Malkova, Jan Martin Zepter, Mattia Marinelli
Department of Wind and Energy Systems
Technical University of Denmark
Roskilde, Denmark
{anmalk; jmwze; matm}@dtu.dk

Herbert Amezquita, Hugo Morais
Department of Electrical and Computer Engineering
INESC-ID
Instituto Superior Técnico (IST), Universidade de Lisboa
Lisbon, Portugal
{herbert.amezquita; hugo.morais}@tecnico.ulisboa.pt

***Abstract*—With the continuous increase of electric vehicle (EV) adoption, deploying smart charging techniques offer a practical solution to mitigate the impact of grid overloading caused by simultaneous EV charging. At the same time, smart charging can help to stabilize the fluctuations in the production from local renewable energy sources (RES). This article introduces a receding horizon optimization model for the distributed control of EV chargers at charging stations, focusing on maximizing the profit of the charging station, while enhancing the utilization of local PV generation. The proposed model operates in 5-minute intervals, determining the power reference for the EV cluster at the charging station. Results demonstrate that the proposed model effectively lowers electricity cost for charging stations, while ensuring more than 90% energy delivery for charging EVs. Future research will be focused on integrating wind energy and refining the model in controlled lab tests for practical implementation and validation.**

***Index Terms*—electric vehicles, receding horizon, distributed control, EV charging station**

I. Introduction

An increase in the number of electric vehicles (EVs) on the roads leads to higher power loading of grid infrastructure, necessitating costly system hardware upgrades. However, smart charging can postpone these upgrades [1] by providing grid flexibility through methods such as power sharing and charging scheduling, among others. Smart charging can offer grid flexibility services, mitigate fluctuations in local renewable energy sources (RES), and reduce electricity costs by scheduling charging during lower-cost hours [2].

The greater part of smart charging research is focusing on a centralized control architecture, where one global controller dispatches the control signals to the chargers. Such control has advantages in terms of straightforward implementation and optimal operation, however it is exposed to several disadvantages: scalability problems, single-point failure prompting, potential privacy corruption under cyber attacks. A decentralized architecture mitigates all centralized issues, but may be sub-optimal as each charger's controller is stand-alone in taking decisions and not getting any information from other units. Distributed control is a combination of centralized and decentralized architectures and brings advantages of both while also ensuring the optimality and easier implementation compared to decentralized one [3].

At the same time, receding horizon control is considered one of the most successful optimal control strategies for constrained systems [4]. In this approach, the system state is continuously updated, and the computational unit produces decisions for a set time horizon, which rolls forward in real time. However, most receding horizon applications for EV smart charging rely on centralized architectures [5], [6]. Additionally, the majority of research on receding horizon with distributed architecture is done in other fields of power system studies, such as building management [7] and hybrid power plant management [8], among others. This study bridges the gap between receding horizon optimization and distributed control architectures for EV smart charging.

The remainder of this paper is structured as follows. Section II describes the charging station setup. Section III details the general model structure and presents the mathematical formulation of the optimization problem. Section IV outlines the studied scenarios, model inputs, and assessment metrics. Section V presents the results of the developed model for different scenarios. Finally, Section VI provides the conclusion and discusses prospects for future model development.

II. Charging station setup

The researched charging station setup is illustrated in Figure 1. The charging station consists of six slow chargers with a 22 kW power limitation per charger. Each charger has two 11 kW charging plugs. The charging station is connected to the rest of the system through a point of cluster connection (PCC) with an overall power limitation of 43 kW. The system is further connected to the main grid through power transformer. Depending on the investigated scenario, the research is conducted with presence and absence of a 60 kWp rooftop PV system.

III. Methodology

A. General model structure

The structure of the model is shown in Figure 2. All scripts within the light green frame are running with the receding horizon method and are updated continuously. The initial parameters and settings such as simulation time horizon, optimization horizon, scenarios setups, and other auxiliary

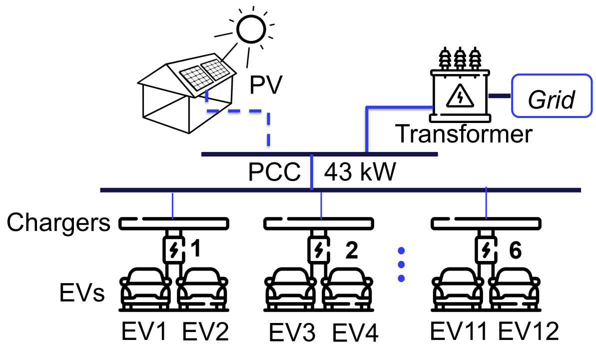

Fig. 1. The illustration of the charging station setup.

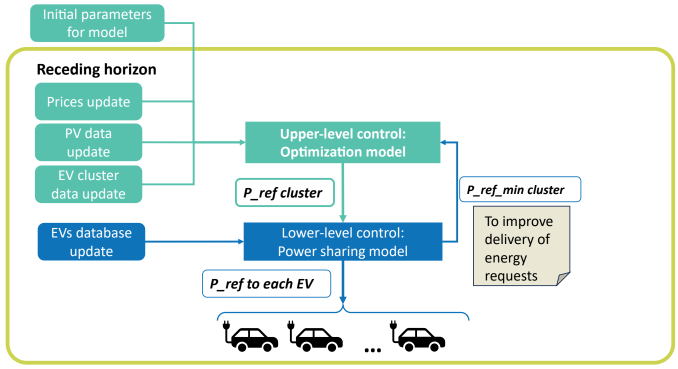

Fig. 2. General model structure scheme.

variables are set before the model run and thus lay outside of the receding horizon light green frame. The model consists of two sub-models: an upper-level and a lower-level model. This corresponds to distributed control algorithms, where the upper-level decides on a charging station level and the lower-level on a chargers and plugs level. The model is structured for running continuously, ready for further field test validations.

The sequential order of the model run is following: the inputs (electricity prices, PV data, EV cluster data) are updated and communicated to the upper-level model, which is a mixed-integer linear programming (MILP) optimization model with the objective to minimize costs. The upper-level optimization allocates P_{ref} (power reference) as a maximum limit of power consumption for the whole charging station and communicates it to the lower-level. The lower-level model dispatches allowed P_{ref} equally among the connected EVs in a power-sharing fashion. It receives information about EVs from the EV database which is updated on an event basis and checked every model run (EV is connected, disconnected). An EV will always comply with its maximum power limitations, and therefore if dispatched power to this EV is higher than its capability it will stick to its power limits.

To comply with EV energy requests, an anonymous feed-back loop is introduced. In every model run, the lower-level model calculates the minimum power necessary for each EV to deliver 100% of the requested energy to the EV. The sum of these power minima is sent to the upper-level model as a minimum power floor for P_{ref} allocation. The summed power requirement is the only information flowing from the lower-level model (and thus the EVs) into the upper-level decision. The upper-level has no access to any inputs from EVs, helping to ensure information security and avoid single-point failures, which are key features of distributed control algorithms.

The receding horizon method is shown in Figure 3. From the set dates of the simulation and the periodicity of runs (Δt), the number of model run steps τ is calculated. This formulates the simulation time horizon ($t \in \tau$). The optimization horizon ($h \in H$) is the number of time steps the model foresees into the future. The prices are considered 100% certain for the model's observation horizon as they are published on the previous day [9]. Other model inputs are uncertain and therefore formulated with forecasts and measurements (PV data, EV cluster data). Every Δt minutes in simulation time the upper-level model optimizes P_{ref} for the charging station for the current and future H steps. However, the model implements only the first value of this vector, which is the decision for the current step. Then, the horizon moves further. The remainder of the P_{ref} vector values are not needed as long as the model runs without any issues. However, for future considerations in the field model implementation of this setup, if an error occurs, e.g. due to communication failure, the last produced P_{ref} decisions will be considered for the next H time steps.

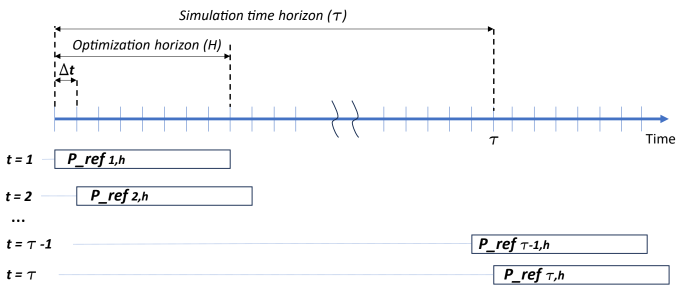

Fig. 3. Receding horizon method scheme.

B. Mathematical formulation of optimization problem

The simulation time horizon and optimization horizon are set to a week and six hours, respectively, with a five-minute time resolution. Thus, the simulation steps are $t = 1, 2 \ldots \tau = 1, 2 \ldots 2016$; and optimization horizon steps are $h = 1, 2 \ldots H = 1, 2 \ldots 73$.

1) Constraints: Equations (1)–(4) represent transformer power throughput variable $P^{\text{grid}}_{t,h}$ decomposition into the import $P^{\text{import}}_{t,h}$ and export $P^{\text{export}}_{t,h}$ power variables as the system import power from the main grid or exports excessive production into it. These constraints also determine that import and export can not happen simultaneously by introducing binary variables $f^{\text{import}}_{t,h}$ and $f^{\text{export}}_{t,h}$, and should not exceed the fuse limit of the transformer in absolute values.

$$P_{t,h}^{\text{grid}} = P_{t,h}^{\text{import}} + P_{t,h}^{\text{export}} \quad \forall\, t \in T,\ h \in H \tag{1}$$

$$0 \leq P_{t,h}^{\text{import}} \leq f_{t,h}^{\text{import}} \cdot P_{\text{trafo}}^{\max} \quad \forall\, t \in T,\ h \in H \tag{2}$$

$$-f_{t,h}^{\text{export}} \cdot P_{\text{trafo}}^{\max} \leq P_{t,h}^{\text{export}} \leq 0 \quad \forall\, t \in T,\ h \in H \tag{3}$$

$$f_{t,h}^{\text{import}} + f_{t,h}^{\text{export}} \leq 1 \quad \forall\, t \in T,\ h \in H \tag{4}$$

Constraint (5) is the power balance constraint of the system, where $P_{t,h}^{\text{ref}}$ is a main output variable of the optimization, $P_{t,h}^{\text{PV}}$ is PV data input, $P_{t,h}^{\text{grid}}$ is transformer throughput. Equation (6) constrains the decision variable within the permissible power limits, where the lower limit is set by the lower level control as power request from chargers to comply with energy delivery for the cars and upper limit is the same as transformer limit of 43 kW. The constraints (7) and (8) 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. Formula (9) calculates the energy requirement by summing forecasted power profiles of the charging station $P_{t,h}^{\text{forecast}}$ over the optimization horizon.

$$P_{t,h}^{\text{ref}} = P_{t,h}^{\text{PV}} + P_{t,h}^{\text{grid}} \quad \forall\, t \in T,\ h \in H \tag{5}$$

$$P_{t,h}^{\min} \leq P_{t,h}^{\text{ref}} \leq P_{t}^{\max} \quad \forall\, t \in T,\ h \in H \tag{6}$$

$$E_{t}^{\text{cluster}} = \sum_{H} P_{t,h}^{\text{ref}} \cdot \Delta t \quad \forall\, t \in T,\ h \in H \tag{7}$$

$$E_{t}^{\text{required}} \leq E_{t}^{\text{cluster}} \quad \forall\, t \in T \tag{8}$$

$$E_{t}^{\text{required}} = \sum_{H} P_{t,h}^{\text{forecast}} \cdot \Delta t \quad \forall\, t \in T,\ h \in H \tag{9}$$

2) Objective function: The objective function aims to minimize electricity costs for charging station:

$$\min \sum_{H} (C_{t,h}^{\text{import}} \cdot P_{t,h}^{\text{import}} + C_{t,h}^{\text{export}} \cdot P_{t,h}^{\text{export}}), \tag{10}$$

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

IV. Scenarios and Metrics

A. Model inputs

In Figure 2, the inputs depicted inside the receding horizon frame are continuously updated: electricity prices, PV data, EV cluster data and EVs database. Electricity prices are based on spot prices from the Danish bidding zone DK2 (Eastern Denmark) [9] and dynamic grid tariffs [10]. The data on solar PV comprise a daily persistence forecast and actual PV measurements. Within the model optimization horizon, the current PV measurement is fixed for next thirty minutes of model observation as the most probable power output value. A description on the PV data composition is detailed in a previous work [11]. The EV database is a summary of recorded charging sessions at a charging station at DTU Lyngby Campus. The EV database includes arrival and departure times, maximum power consumption capability of individual EVs, and their energy requests. The EV cluster power consumption forecasts (provided by INESC-ID, Portugal) are obtained for one week in summer (August) and one week in winter (January), using the recorded charging sessions of the DTU charging station. The machine learning algorithm used for the obtaining the forecasts is a Light Gradient Boosting Machine (LightGBM) algorithm and the metric used for its performance evaluation is the Normalized Root Mean Square Error (NRMSE). A detailed explanation of the forecasting and the results is presented in [12].

B. Investigated scenarios

The introduced model is tested with the three scenarios presented in Table I. All scenarios have been run for a simulation horizon of one week in both summer (August 1st – 8th 2023) and winter (January 1st – 8th 2023) and hence allow for a performance evaluation with different levels of PV production, prices and EVs presence. The scenarios are applied to the upper-level model as a key research component of this study, while the lower-level model always remains a power sharing model.

TABLE I
SCENARIOS OVERVIEW COMPARISON

	Cost minimization	**Cluster power limit**	**RES integration**
Scenario 0: Uncontrolled charging	×	✓	×
Scenario 1: Cluster limit	✓	✓	×
Scenario 2: RES integration	✓	✓	✓

Scenario 0: Uncontrolled charging serves as a reference case for the model assessment. In this scenario the cost optimization is excluded and P_{ref} is fixed to the cluster limit of 43 kW. In *Scenario 1: Cluster limit*, the cost optimization is introduced, and therefore P_{ref} is constantly updating throughout the model run. *Scenario 2: RES integration* is directed at the optimal operation of the charging station connected not only to the main grid but also local RES, specifically solar PV in this study.

C. Metrics

The metrics along which the model performance is assessed are:

- Energy delivery fulfilment to individual EVs (in %)
- Electricity cost of cluster operation (includes expenses of purchasing from the grid and revenues from selling to the grid, in €)
- Total profit of charging station (EVs payments for delivered energy with 0.34 €/kWh minus electricity cost, in €)
- Self-sufficiency and self-consumption of the EV cluster (in %). Self-sufficiency defines the share of energy delivered to EVs from local PV production, while self-consumption defines the share of PV production consumed locally by EVs [13].

V. Results and discussion

The simulations were performed for both summer and winter weeks. However, due to space limitations, only the summer results are presented graphically. Specifically, two days from each week were selected for illustration: the 2nd and 3rd of August, 2023. Additionally, *Scenario 0: Uncontrolled Charging* is only included in the metrics since no price or PV dependency is observed in this case. Nevertheless, the final metrics comparison encompasses all four scenarios for the entire weeks in both summer and winter.

A. Scenario 1: Cluster limit

Figure 4 shows the results for P_{ref} allocation of the model for the two selected days of the summer week. The figure structure is the same for all scenarios: the top plot shows P_{ref} with $P_{ref}^{\min}$ ($P_{t,h}^{\min}$ in optimization formulation terms) and cluster limit; the middle plot illustrates P_{ref} together with electricity prices and aggregated power consumption of the EVs; and the bottom plot provides the power consumption of each EV charging on a specific day. The model fully follows the price signals considering the minimum power request from the EVs ($P_{ref}^{\min}$) and power consumption forecasts. Thus, the model allocates most power for EV charging during the cheapest hours, with a foresight of prices for the next six hours. When EVs are present at the charging station, the upper-level model receives the $P_{ref}^{\min}$ signals, forcing it to allocate at least $P_{ref}^{\min}$ for EVs to fulfill their charging needs in the connection time, despite prices being higher. The spikes of $P_{ref}^{\min}$ are due to the approaching departure time of the individual EVs and their respective charging power needs to increase with shrinking remaining charging time. Finally, the model never sets P_{ref} above the cluster limit of 43 kW, and therefore fully complies with the set grid connection limit.

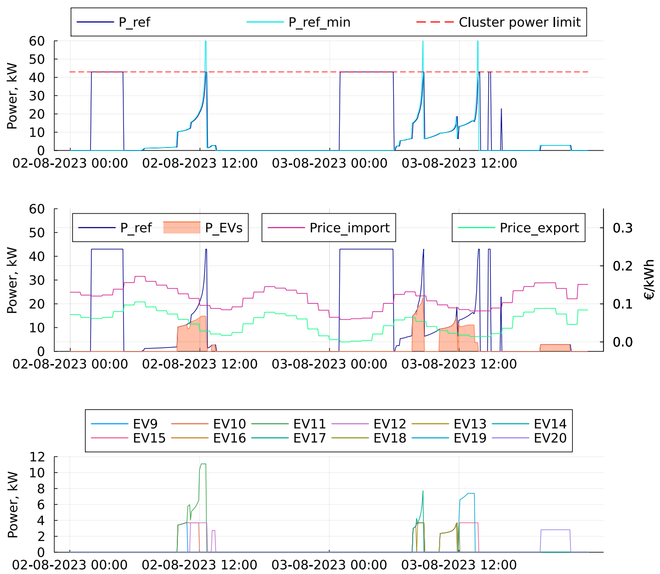

Fig. 4. Simulation results of *Scenario 1: Cluster limit*. Summer week case: 2nd and 3rd of August, 2023

B. Scenario 2: RES integration

The results of *Scenario 3* are shown in Figure 5. This scenario introduces the possibility to use a local PV system in the power reference allocation algorithm. The PV production is in this scenario considered without cost for local consumption, and the production measurements are displayed in orange in the top plot of Figure 5. The power reference follows the measured PV production where economically reasonable. During the day, a large part of the PV production is exported to the grid whenever it exceeds the consumption of the EV cluster to generate revenue for the charging cluster operator. As the considered workplace charging processes tend to coincide with the bell curve of PV production, most of the charging is covered by local generation, leading to a self-sufficiency of up to 76.9% in the summer week.

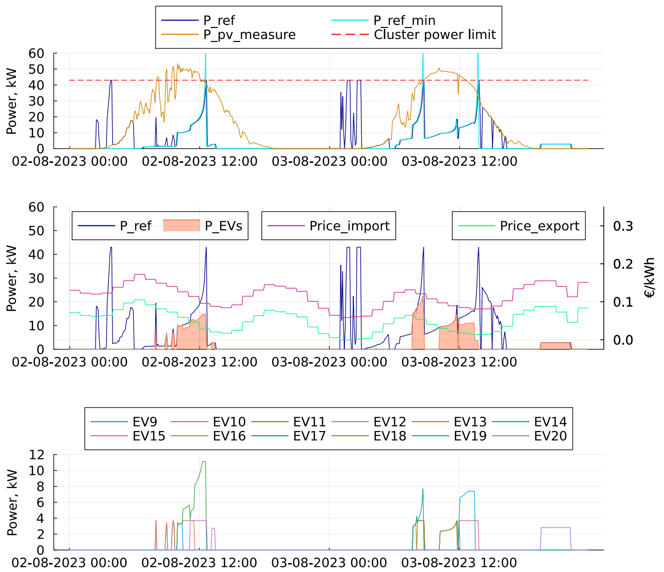

Fig. 5. Simulation results of *Scenario 3: RES integration*. Summer week case: 2nd and 3rd of August, 2023

C. Scenario comparison

Table II provides the full assessment of scenarios for both summer and winter weeks. First, the control model performed well in all scenarios with regards to the fulfillment of energy requests from EVs, considering that the allowed cluster power at 43 kW is only one-third of the sum of the total installed charger power (132 kW). Both *Scenario 1: Cluster limit* and *Scenario 2: RES integration* deliver more than 90% of EVs requested energy, which is quite close to full delivery and to the reference case of *Scenario 0: Uncontrolled charging*.

The economic assessment is conducted using several metrics. The electricity cost is the sum of electricity import expenses and export income. The export income only applies to the RES integration scenario as the EV chargers are unidirectional and cannot export power. Compared to *Scenario 0* electricity cost is reduced by 12% in summer and 7.5% in

TABLE II
SUMMER AND WINTER ASSESSMENT OF ALL SCENARIOS.

		Summer	
	Uncontrolled charging	**Cluster limit**	**RES integration**
Delivery, %	99.1	91.3	91.9
Electricity cost (positive: income), €	-70.9	-62.4	36.2
Import expenses, €	-70.9	-62.4	-18.1
Export income, €	0.0	0.0	54.2
EVs payments income, €	232.2	214.0	215.3
Total profit, €	161.3	151.6	251.5
Self-sufficiency, %	-	-	76.9
Self-consumption, %	-	-	27.3
		Winter	
	Uncontrolled charging	**Cluster limit**	**RES integration**
Delivery, %	99.5	91.7	91.7
Electricity cost (positive: income), €	-196.6	-181.8	-156.0
Import expenses, €	-196.6	-181.8	-157.8
Export income, €	0.0	0.0	1.8
EVs payments income, €	359.8	331.4	331.4
Total profit, €	163.2	149.6	175.4
Self-sufficiency, %	-	-	13.0
Self-consumption, %	-	-	84.3

winter for *Scenario 1*, and by 151% in summer and 21% in winter for *Scenario 2*. The reduction of electricity cost more than 100% means that the export income is larger than import expenses in summer week for *Scenario 2*. Electricity costs are higher in the winter week compared to the summer week due to higher electricity prices during this period and increased EV consumption, as more EVs are charged. The electricity export income from the PV system is significantly higher in the summer than in the winter week, as there is more excessive PV power. Despite the reduced electricity costs, the total profit for *Scenario 1* is lower than that for *Scenario 0* in both seasons. This is related to the reduced energy delivery for EVs (91.3% instead of 99.1% for the summer week and 91.7% instead of 99.5% for the winter week), leading to a decrease in EV payment income. While *Scenario 2* shows greater total profit than *Scenario 0*, the initial capital cost of PV installation must be considered. Based on [14], the cost for a 60 kWp rooftop PV system is €800 per kWp. Extrapolating annual profits from the summer and winter weeks, the payback period is around 4.32 years. This does not account for potential savings from the PV system's contribution to the building's electricity, which is beyond the scope of this study but would further improve the economics of *Scenario 2*. The high summer PV production allows the system to have self-sufficiency of 77% meaning that most of the charged energy is coming from PV system. The 27% of self-consumption indicate that the system has extensive potential for consuming generation locally and allowing to have more consumption. However, the situation is flipped for the winter week as there is almost no excessive PV generation present in the system. Therefore, most of the energy charged to the EVs is coming from grid import power which is indicated by self-sufficiency of 13%. The majority of PV is consumed locally, with a self-consumption of 84%.

VI. CONCLUSION

This paper introduces a receding horizon optimization approach for the distributed control architecture of electric vehicle chargers at charging stations. This method unlocks the potential for continuous deployment of smart charging with an economic objective while ensuring scalability, optimality, and robustness compared to other control architectures. Hence, despite limited and anonymous information from EVs, the model ensures more than 90% fulfillment of EVs' energy requests. Additionally, it reduces electricity costs for charging stations, especially unlocking economic potential for those connected to local RES. Nevertheless, total profits need to be addressed and improved further by integrating EV payments into the objective function of the model. Further research will focus on exploring flexibility services for the grid, integrating wind power as a local generation source, and field test validation of the model.

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