Optimizing Electric Vehicle Charging Through a Real-Time Control Mechanism

Jacco Reuling, Bart Nijenhuis, Gerwin Hoogsteen, Johann L. Hurink
dept. of EEMCS, University of Twente, Enschede, The Netherlands
e-mail: j.reuling@utwente.nl; b.nijenhuis-1@utwente.nl; g.hoogsteen@utwente.nl; j.l.hurink@utwente.nl

***Abstract*—This paper explores an integrated approach combining real-time and predictive control mechanisms to manage electric vehicle charging in alignment with solar energy availability. By utilizing predictive control and a Real-Time Control Mechanism (RCM), the challenges posed by the variability of solar power and the increasing demand for EV charging are addressed. Through simulations and field tests, the proposed strategy demonstrates its ability to reduce peak grid loads, enhance self-sufficiency, and improve self-consumption, while maintaining user satisfaction. The findings indicate that integrating real-time adjustments with predictive EV charging scheduling can significantly contribute to a more stable and efficient grid.**

***Index Terms*—energy transition, energy management, electric vehicles, smart charging**

I. Introduction

The shift towards decarbonization and the availability of affordable solar energy are key drivers in the increasing adoption of electric vehicles (EVs). As the adoption of EVs accelerates, the demand for EV charging grows [1]. This increasing charging demand, along with the unpredictable nature of solar power, creates a new opportunity, but also a challenge: aligning the demand for EV charging with the availability of solar energy. Misalignment can lead to high peak loads on the grid, straining infrastructure and potentially causing instability or failure [2].

One solution is to employ Energy Management Systems (EMS) with predictive control based on forecasted solar power and EV charging demand [3], [4]. Such a forecast based approach can utilize available EV flexibility information to optimize charging schedules in alignment with energy availability and cost, while maintaining a high service to the EV user. However, such optimization strategies often struggle to adapt to real-time fluctuations in solar power generation.

Next to predictive control, there is also a range of charging strategies that employ real-time control, focusing solely on immediate responsiveness without leveraging predictions of PV output or EV charging demand [5], [6]. These strategies may overlook EV user requirements, such as ensuring EVs are adequately charged before their departure time.

Research on integrating both predictive and real-time control has been evolving. [7] introduces a novel approach to predicting the optimal charging schedule for a single EV through an online valley-filling algorithm. However, it does not tackle the challenges of managing multiple EVs.

Furthermore, [8] presents a robust smart charging approach for large fleets of EVs, emphasizing the use of offline aggregated planning and online control. While this method demonstrates improvements in energy management, it overlooks specific user charging needs such as energy demand. However, meeting energy demand of EVs before their departure is a crucial element of user satisfaction and system acceptance [9], [10].

This paper proposes an approach that integrates real-time and predictive control to steer multiple EVs in a charging hub equiped with solar panels, while also meeting specific charging needs of EV users.

The approach leverages a existing predictive control component, the Energy Scheduler (ES), which uses Mixed-Integer Linear Programming (MILP) solvers to optimize EV charging schedules based on inputs like PV power forecasts and time-of-use electricity tariffs. Our contribution enhances this setup with a Real-Time Control Mechanism (RCM), adjusting to actual solar power output and EV demand deviations. This resulting approach not only enhances grid stability and utilization of locally produced energy, but also aligns with user acceptance by involving EV user flexibility information.

We test the approach through simulations and real-life field tests, to ensure the practical applicability and robustness of the proposed strategy.

The main contributions of this paper are:

- The proposal of an RCM that enhances adaptability for EV charging to real-time generation fluctuations
- A demonstration of the effectiveness of the combination of the RCM with the ES in reducing peak grid loads.

We start by explaining the RCM in Section II, describe our testing approach in Section III, and present the outcomes in Sections IV. We conclude with a summary in Section V and discuss broader implications and provide recommendations.

II. Real-Time Control Mechanism

This section describes the RCM approach in detail. Section II-A elaborates on the design considerations and Section II-B describes the implementation.

A. Design Considerations

This section outlines the design considerations for developing the RCM.

1) Dynamic Responsiveness: The control mechanism is required to be dynamic, ensuring rapid and effective adjustments to the charging schedules in response to real-time measurements. This characteristic is crucial in addressing the uncertainty and variability associated with energy forecasts.

2) User Requirements: By incorporating EV user requirements, the mechanism ensures EVs reach the desired charge levels before user-specified departure time.

3) Utilization of Locally Produced Energy: A central goal is to maximize the utilization of locally generated solar energy, thereby reducing grid stress and charging costs.

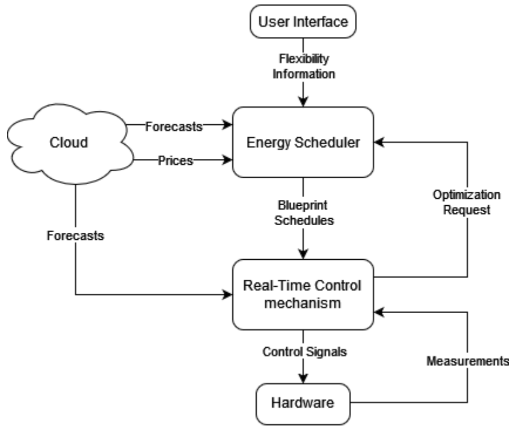

Fig. 1: Flowchart illustrating the functional structure of the RCM.

4) Simplicity and Computational Efficiency: The design of the RCM emphasizes on computational efficiency.

5) Timing Requirements: The RCM operates with a discretized time horizon, where control actions are dictated by the chosen length of time intervals. The system continuously assesses and responds at regular time intervals. The choice of the time interval length directly impacts the responsiveness and accuracy of the system.

A proper choice of time interval length is crucial for system optimization. Shorter time intervals improve control responsiveness to PV variability but can strain computational resources and charger adaptability. Longer time intervals ease computational demands and give chargers more reaction time, but might miss fast PV changes, impacting control accuracy.

B. RCM Implementation

The RCM adjusts EV charging schedules based on discrepancies between forecasted and actual PV power, aiming to optimize grid load and energy usage. Fig. 1 illustrates the structure of the complete EMS, where the RCM operates between the ES and the hardware, adjusting control signals in real-time. Initially, forecasts and flexibility information is processed by the ES to provide blueprint schedules to the RCM. These schedules serve as input for the RCM to apply real-time adjustments based on the evolving power dynamics in the system.

The blueprint schedules form the basis for the feedback control by the RCM. The RCM involves measuring the actual values of PV generation, grid load, and EV charging powers ($P_{\text{actual}}(t)$), and compares these with the forecasted values ($P_{\text{forecast}}(t)$) at every time interval t. Significant discrepancies between the forecasted and actual measured values result in positive (more power available than forecasted) or negative (less power available than forecasted) *Power Discrepancy* ($P_D(t)$).

$$P_D(t) = P_{\text{actual}}(t) - P_{\text{forecast}}(t), \tag{1}$$

The RCM operates on the principle of adjusting the charging rates of active chargers based on the Power Discrepancy. If there is Power Discrepancy, the charging schedule is adjusted by the RCM using its internal algorithm. This leads to deviations from the blueprint schedule. After calculating the adjusted charging rates, the control signals are send to the chargers. These steps are executed at every time tick within the system.

The subsequent sections describe how the RCM calculates the adjustments to the blueprint schedule.

C. Distributing Power Discrepancy Among Chargers

To achieve the aforementioned adjustments, the mechanism in principle aims to divide $P_D(t)$ at time interval t evenly among the number of active chargers $n(t)$ (i.e. occupied chargers) at time interval t. The basic adjustment $A_i(t)$ for charger $i \in I$ at time interval t is computed by:

$$A_i(t) = \frac{P_D(t)}{n(t)}. \tag{2}$$

However, although it might appear straightforward to evenly distribute the Power Discrepancy, additional strategies are required. The next sections discuss the additional strategies employed.

1) Fulfilling EV Requirements: The blueprint schedules are established by the ES considering two parameters: the energy demand of the EVs and their respective estimated or indicated departure times. When the system deviates from these blueprint schedules, it may potentially lead to an inability to meet the energy demand.

A strategy to manage time constraints involves maximizing charging power as a last resort, used only when the remaining time before an EV's departure is insufficient to meet energy needs using the standard settings. However, this approach can lead to undesirable grid load peaks and is therefore employed only when primary mechanisms for compensation fail.

To deal with this challenge we also consider the time until departure in determining the charging powers. For this we prioritize chargers which should receive more energy based on both their remaining energy demand and the remaining time they have to charge.

The RCM defines an *Urgency* $U_i(t)$ for each active charger i at time interval t, as the remaining energy demand $E_{\text{rem},i}(t)$ divided by the remaining time intervals $T_i - t$.

$$U_i(t) = \frac{E_{\text{rem},i}(t)}{T_i - t}. \tag{3}$$

A higher Urgency means that the charger has high remaining energy demand and/or little time left to charge, so it gets prioritized when adjusting the charging schedules.

This Urgency metric is then used to distribute the Power Discrepancy among the active chargers. This is done by calculating the Urgency Proportion $U_{\text{prop},i}(t)$ for each charger at each time interval. It is calculated by:

$$U_{\text{prop},i}(t) = \frac{U_i(t)}{\sum_{i=1}^{n(t)} U_i(t)}. \tag{4}$$

Finally, we calculate the evolved new adjustment for each charger at each time interval $A_{\text{new}}, i(t)$, as the product of Power Discrepancy $P_D(t)$ and the Urgency Proportion of the charger $U_{\text{prop},i}(t)$:

$$A_{\text{new}}, i(t) = P_D(t) \cdot U_{\text{prop},i}(t). \tag{5}$$

This way, the chargers with higher Urgency receive a higher proportion of the Power Discrepancy. This avoids that EVs reach a "must charge"-state with severe peak load.

If the Power Discrepancy is negative, the Inverse Urgency $U_{\text{inv},i}(t)$ (i.e. chargers with lower Urgency have higher inverse Urgency) is used in (4) to distribute the reduced energy allocation:

$$U_{\text{inv},i}(t) = \frac{1}{U_i(t)}. \tag{6}$$

2) Cumulative Deviation: To further enhance the control over the charging process, the RCM considers the *Cumulative Deviation* $D_{\text{cum},i}(t)$ of the charging sessions, for a specific charging session. This refers to the aggregated difference between the actual energy delivered to an EV $E_{\text{act},i}(t)$ and the scheduled energy up to the current time interval $E_{\text{sch},i}(t)$:

$$D_{\text{cum},i}(t) = E_{\text{act},i}(t) - E_{\text{sch},i}(t). \tag{7}$$

The Cumulative Deviation is used to determine the adjustments needed to compensate for past deviations of chargers. To achieve this, the Cumulative Deviation is distributed over the remaining time intervals. This distributed deviation is referred to as the *Cumulative Adjustment Ratio* $R_{\text{cum},i}(t)$, and is calculated as the Cumulative Deviation at the current time interval, $D_{\text{cum},i}(t)$, divided by the remaining time intervals:

$$R_{\text{cum},i}(t) = \frac{D_{\text{cum},i}(t)}{T_i - t}. \tag{8}$$

If we integrate this ratio into our original Adjustment of (5), the Total Adjustment for each charger is:

$$A_{\text{tot},i}(t) = P_D(t) \cdot U_{\text{prop},i}(t) - R_{\text{cum},i}(t). \tag{9}$$

As such, if an EV has received more energy than planned in the past (positive Cumulative Deviation), its charging rate will be reduced in the future and vice versa.

3) EV Charging Constraints: The RCM ensures that the adjusted current of the charger stays within acceptable limits, typically 6 to 16 amperes (A) for most EVs. Adjustments outside this range are corrected: below 6 A is rounded to 0 or 6, and above the maximum is is set to 16 A. Additionally, AC chargers adjust in 1 A increments.

4) Recursion: Initially, the discrepancy is allocated based on the Urgency and Cumulative Adjustment Ratios of each charger. However, limits on charging rates of chargers might prevent full allocation in this first step. Also, additions for past over or under-serving might not fully utilize the available Power Discrepancy. The RCM iteratively reassesses, redistributing any remaining Power Discrepancy and adjusting the charging schedule as needed. This process repeats until one of the following three conditions is met: all Power Discrepancy is allocated, no further adjustments are possible (e.g. chargers at maximum capacity or EV energy demands met), or adjustments worsen the Power Discrepancy, avoiding infinite loops.

5) Re-optimizations: A reoptimization is initiated when the actual energy delivery deviates significantly from the scheduled profile. This process involves sending a request to the ES to create a revised blueprint schedule, accounting for the updated energy demands. This realigns actual energy delivery with planned schedules. This re-optimization is triggered when the Cumulative Adjustment Ratio, which assesses the magnitude of deviation from the original schedule relative to the remaining correction time, exceeds a certain threshold. Setting the threshold for this trigger requires carefully balancing the computational resources used and the quality of the solution.

III. Testing Setup

To evaluate and analyze different performance evaluation metrics, simulations and a field test are employed. The simulations allow for systematic and controlled testing, while the field test provides insights in real-world conditions.

A. Performance Evaluation Metrics

Five performance evaluation metrics are used to assess the performance of the different scheduling techniques:

- **Total Electricity Costs:** This metric represents the overall expense incurred by the charging hub in importing and exporting electricity from the grid. We consider the dutch EPEX day-ahead prices [11].
- **Peak Grid Loads:** This metric focuses on the highest power peaks imported or exported from the grid. We express the peak grid load as the mean of the top 1% of the highest grid loads during a certain period.
- **Self-Sufficiency:** This metric is defined as the average percentage of the energy needs of the EV charging station met by on-site solar power on a day:

$$SS_{\text{mean}} = \frac{1}{N} \sum_{d=1}^{N} \left(1 - \frac{\sum_{t \in t_{\text{day}}} E_{\text{imp}}(t)}{\sum_{t \in t_{\text{day}}} E_{\text{cons}}(t)} \right) \cdot 100. \tag{10}$$

  Here, N is the total number of days considered, t_{day} is the set of time intervals in a day d, $E_{\text{cons}}(t)$ is the energy consumed at time t, and $E_{\text{imp}}(t)$ is the energy imported from the grid at time t. A higher SS_{mean} indicates reduced grid dependence.
- **Self-Consumption:** This metric quantifies the proportion of solar energy produced on-site that is directly used by the charging hub instead of being exported to the grid:

$$SC_{\text{mean}} = \frac{1}{N} \sum_{d=1}^{N} \left(\frac{\sum_{t \in t_{\text{day}}} (E_{\text{cons}}(t) - E_{\text{imp}}(t))}{\sum_{t \in t_{\text{day}}} E_{\text{gen}}(t)} \right) \cdot 100. \tag{11}$$

  Hereby, $E_{\text{gen}}(t)$ is the energy generated by the PV panels at time t. A higher SC_{mean} indicates better utilization of the locally produced solar energy.

B. Test Setting

The test site is a charging hub at an office in Rijssen, the Netherlands. The site is equipped with 24 controllable AC charging stations (22 kW each) and a 73 kWp PV system. The historical EV arrival and departure data of the testing site is used as input for simulations. Historic data can be used for personalized scheduling when user specified departure times or energy demands are unavailable. The system operates with a 10-second time interval, balancing real-time control with computational efficiency and response times for both the ES and EVs.

C. Simulations

For the simulations the aforementioned office location is used. These simulations cover distinct periods (A week in summer and a week in winter) to analyze the effects of seasonal changes on PV production. Five key scenarios are simulated:

1) Business As Usual (BAU): This scenario serves as the baseline, simulating conditions without EMS where EVs are charged using a greedy strategy without predictive and/or real-time control. This provides a reference scenario for comparing.

2) Cost Optimization Mode (CO): The ES is used with cost minimization as objective where EVs are scheduled upon arrival (i.e. first-come-first-serve).

3) Cost Optimization with Real-Time Control (CO+RCM): This scenario combines Cost Optimization with RCM. It provides insights into their joint impact on performance.

4) Peak Shaving Mode (PS): This scenario employs the ES in Peak Shaving mode.

5) Peak Shaving with Real-Time Control (PS+RCM): The final scenario merges Peak Shaving with RCM. Its goal is to gauge the efficiency of the system in lowering peak grid loads when incorporating the RCM.

D. Simulation Data and Assumptions

The following section provides an overview of the data sources, assumptions, and key elements used in the simulations. The EV arrival and departure patterns are derived from real-world data collected at the testing site during April 3-9, 2023. This data is used to simulate typical EV patterns at an office location for both summer and winter weeks.

User inputs for simulations include offsets in actual and indicated departure times and energy demands. These reflect real-world inaccuracies and are modeled using a normal distribution as detailed in [12].

For PV power data, we utilize forecasted data from a nearby weather station alongside historic measured data from the testing location.

Electricity pricing is based on EPEX day-ahead prices [11] for both importing and exporting electricity.

E. Field Test

The system is validated through a real-world field test. During the field test only the scenario with the ES in PS+RCM was tested. In this setup, energy scheduling was based on historical transaction data of each respective EV user. This historical data included average parking times and energy demands per EV user. The EMS was created charging schedules for known users and integrating a greedy schedule for unknown users.

To assess the impact of control strategies and the influence of real-world uncertainties on system performance, additional simulations using the exact data from the field test period were conducted. Results of these can be compared with the field test results.

IV. Results

In the following sections the results from the tests are analyzed.

A. RCM Under Varied Simulation Conditions

Performance of the RCM in a charging hub is investigated to three cases: Days with high fluctuations in PV production, underestimated forecasts, and overestimated forecasts. A charging schedule is exemplified.

1) High Fluctuations in PV Production: Fig. 2 depicts the adaptability of the RCM during a day with significant fluctuations in PV production. The RCM dynamically adjusts the charging rate in response to actual PV production, deviating from the forecast. For instance, the RCM initiated charging during high production periods, contrary to the plan of the ES (e.g. 9:00-12:00), and reduced the charging rate during low production periods, deviating from the scheduled maximum rate (e.g. 12:00-15:00).

The efficiency of the RCM follows from an increased self-sufficiency, rising from 70.15% to 81.91%, and a reduction in mean top 1% grid load from 57.6 kW to 30.5 kW on this day. These metrics underscore the capacity of the RCM to enhance system performance and manage grid load amidst PV production variability.

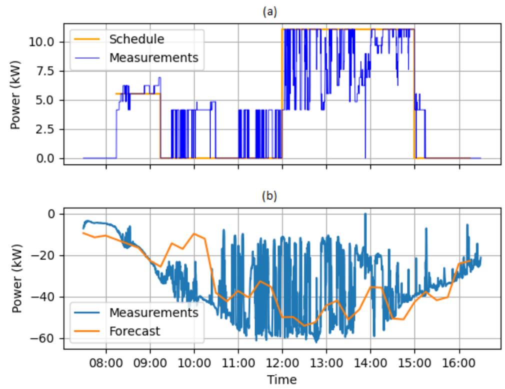

Fig. 2: Adaptability of RCM during high PV fluctuations: (a) ES charging profiles and adjustments. (b) Forecasted vs. actual PV power.

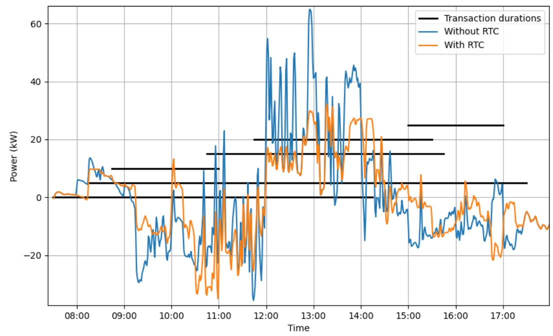

Fig. 3: The impact of RCM on grid load during a day with high PV production fluctuations.

a) Fluctuations in Charging Rate: The RCM displays a rapid oscillation in charge power, especially noticeable between 0 and 4 kW, during peak PV fluctuations. While chargers can respond swiftly to control signals within 10-second intervals at rates between 4 and 11 kW, the on (4 kW) or off (0 kW) oscillations at lower kW levels posed challenges. These oscillations necessitate chargers to exit standby mode rapidly, which can lead to problems. This emphasizes the need for refined control strategies that integrate charger constraints in real-time management.

b) Impact on Grid Load: Fig. 3 demonstrates the effect of the RCM on grid load during high PV production fluctuation. The RCM notably reduces grid load during peak production and high EV charging demand, effectively using available PV power. However, it also leads to transient increases in grid load just before EV departures, compensating for prior deviations to meet energy requirements. This is particularly pronounced during short-duration transactions, resulting in some higher peak loads.

2) Overestimated PV Power Forecasts: Fig. 4 shows the RCM on a day with overestimated PV power forecasts. The working of RCM reduced the charging rate between 11:30 and 12:30 to compensate for the forecast overestimation. However, it adhered to the original schedule at 14:00 despite a negative power discrepancy, as part of its compensation strategy. From 17:00 onwards, the RCM increased the charging rate to 4 kW, ensuring the energy demand of the EV user is met by the time of departure, despite the absence of PV power, leading to potential increases in power peaks.

This adjustment resulted in a marginal reduction in self-sufficiency from 11.66% without RCM to 11.42% with

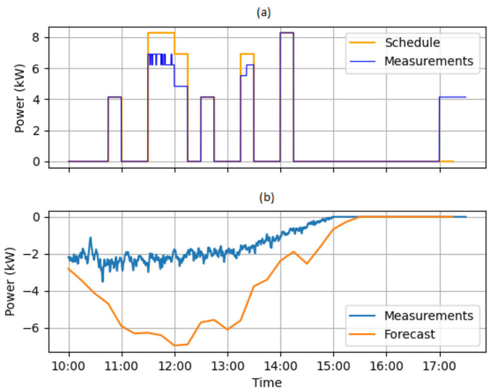

Fig. 4: Differences in planned vs. actual charging with overestimated PV forecasts: (a) ES charging profiles and adjustments. (b) Forecasted vs. measured PV power.

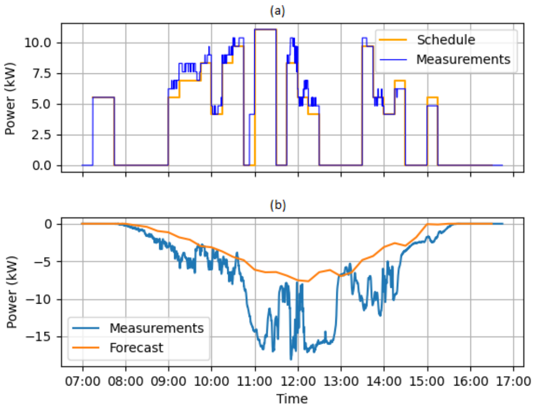

Fig. 5: RCM adjustments to charging under underestimated PV forecasts: (a) Planned vs. actual charging post-RCM. (b) Forecasted vs. actual PV power.

TABLE I: Simulation results for summer (S) and winter (W) weeks.

Scenario	Cost [€]		TG [kW]		SS [%]		SC [%]	
	S	W	S	W	S	W	S	W
BAU	95.4	340.3	80.7	84.6	49.3	7.9	45.9	70.5
CO	31.0	302.2	81.9	78.6	51.3	8.1	47.8	69.1
CO+RCM	34.5	301.2	72.2	77.5	56.7	8.1	51.6	68.7
PS	44.8	296.6	47.7	42.2	57.4	9.1	51.4	71.4
PS+RCM	46.9	297.2	35.9	43.3	64.6	9.1	56.8	71.4

RCM. The mean top 1% grid load remained unchanged. The simulation highlights that compensation occurring at times with low PV power could potentially be mitigated by early re-optimizations by the ES, potentially redistributing energy demand to periods with available PV power.

3) Underestimated PV Power Forecasts: On days with underestimated PV forecasts, the RCM adapts differently. Initially, as observed in Fig. 5, the RCM increases the charging power when the actual PV exceeds forecasts, capitalizing on the unanticipated surplus in PV production.

However, towards the end of the day, specifically around 14:15 and 16:00, the RCM reduces the charging power despite ongoing positive PV discrepancies. This adjustment aims to compensate for the deviations in the past.

The addition of the RCM increased self-sufficiency from 50.48% to 52.28% and there was a minor decrease in the mean top 1% grid load, from 43.3 kW to 42.2 kW.

B. Simulation Results

Table I summarizes the performance for the scenarios for summer and winter periods. It provides a comparative

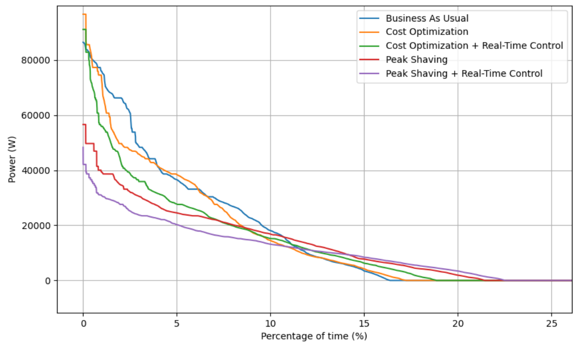

Fig. 6: LDCs for the simulated summer week.

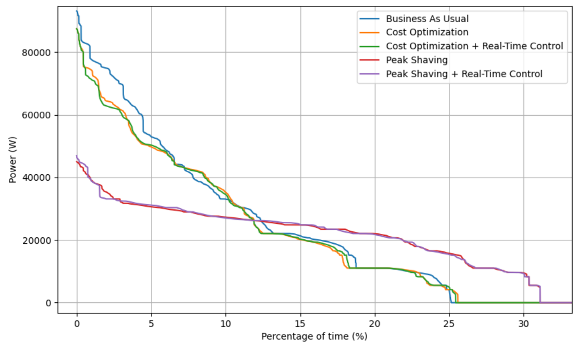

Fig. 7: LDCs for the simulated winter week.

analysis for the performance metrics. Each performance metric is examined in the following subsections.

1) Total Electricity Costs: Implementing CO or PS strategies significantly reduced electricity costs in all scenarios, compared to the BAU scenario.

In summer, the CO mode of the ES reduced costs with 68%. This reduction shows the efficiency of the ES in exploiting lower electricity tariffs and high solar generation. In contrast, in winter with its lower solar generation, saw a smaller reduction in costs (11%) using the same strategy. Under the PS strategy, the total cost was reduced with 53% in summer and 13% in winter. With the integration of the RCM, the costs are similar to using PS alone.

The inclusion of the RCM consistently led to a marginal increase in total costs for both seasons. As costs are due to day ahead prices, we can perfectly plan for it a day upfront. The changes by the RCM imply that the realized schedules are not optimally reducing costs anymore, whereas the schedules without RCM would be optimal in reducing costs.

2) Grid Loads: The PS strategy, particularly when combined with the RCM, shows significant grid load reductions, indicating improved energy management and potential benefits for grid stability.

In summer, the PS strategy reduced the mean top 1% grid load by 41% compared to BAU. Incorporating PS+RCM further reduced this to 56% compared to BAU. Winter results similarly show a substantial 50% reduction in grid load with PS, though the addition of RCM slightly increased the load. The LDCs in Fig. 6 and 7 underscore this. They show that the PS strategies, especially when combined with RCM, effectively reduce time spent in high load zones, thus reducing the strain on the grid.

3) Self-Sufficiency: Implementing the CO strategy yielded a marginal increase in self-sufficiency. However, integrating the RCM with ES under CO significantly

TABLE II: Overview of field test results and corresponding simulations

Scenario	SS [%]	SC [%]	TG [kW]	Cost [€]
BAU Sim.	69.40	33.03	52.98	-0.12
Field Test	78.76	43.97	31.12	-0.24
PS Sim.	83.01	35.32	25.28	-0.27
PS+RCM Sim.	88.99	41.21	22.86	-0.26

TABLE III: Differences in compared to BAU simulation

Scenario	SS [%]	SC [%]	TG [kW]	Cost [€]
Field Test	+13.5	+33.1	-21.86	-0.12
PS Sim.	+19.6	+6.9	-27.70	-0.15
PS+RCM Sim.	+28.3	+24.8	-30.13	-0.14

increased summer self-sufficiency. In winter no improvement was observed.

The PS strategy alone achieved notable self-sufficiency in both summer and winter. Its combination with RCM resulted in an even further increase in summer self-sufficiency but a slight decrease in winter.

4) Self-Consumption: All scenarios involving the ES improved self-consumption rates compared to BAU, particularly during the summer. This improvement implies a more efficient use of locally generated solar energy, contributing to sustainability and cost-efficiency. The combination of PS+RCM resulted in the highest self-consumption rate in the summer, highlighting the potential of these strategies to complement each other for optimal utilization of solar energy.

C. Field Test Results

Table II gives an overview of the results from the field test compared to corresponding simulations across the performance metrics and Table III highlights the differences from the BAU simulation, illustrating the impact on performance by real-world complexities.

The field test surpassed the results of the BAU simulation in terms of self-sufficiency and self-consumption. It had slightly lower performance than the PS+RCM simulation, showing the influence of real-world complexities. The control strategies effectively reduced the grid load in the field test compared to the BAU scenario. However, also here this load was higher than the load in the PS+RCM simulation, indicating the impact of real-world unpredictabilities. Furthermore, the field test leads to a total electricity cost of -0.24 EUR, showing more favorable results than the BAU simulation but marginally less favorable compared to the PS+RCM simulation.

V. Conclusions

While our study revealed that the Energy Scheduler performs efficiently in managing EV charging schedules based on PV forecasts and EV flexibility to reduce electricity costs and peak grid loads, its performance varies seasonally and is challenged by real-time adjustments and insufficient EV flexibility information.

The introduction of the Real-Time Control Mechanism marks a substantial improvement. It effectively handled unforeseen fluctuations in solar power, maintaining service quality to EV users while enhancing grid stability even further. Hereby, electricity costs are not reduced. Incorporating the RCM with the ES led to additional reductions in peak grid loads and further improvements in self-sufficiency and self-consumption rates. This shows that combining real-time and predictive control is beneficial in solving the problem of grid instability and inefficiency due to the unpredictable nature of solar energy and the growing EV charging demand.

To further improve robustness, we recommend enhancing the RCM to adjust not only for discrepancies in PV power predictions but also for unexpected changes in grid load and EV charging demands. Extensive field tests across different seasonal conditions are also suggested to validate the performance of the system over a broader range of operational scenarios and to confirm the practicality and effectiveness of these recommended enhancements.

Acknowledgements

This research is conducted within the *SmoothEMS met GridShield* project (MOOI32005) and *Energy Control Businesspark – Ecofactorij* project (MOOI622007) subsidised by the Dutch ministries EZK and BZK.

References

[1] N. Refa, D. Hammer, and J. van Rookhuijzen, "Elektrisch rijden in stroomversnelling," in *ElaadNL Outlooks*, 2021.

[2] G. Hoogsteen, A. Molderink, G. J. Smit, J. L. Hurink, B. Kootstra, and F. Schuring, "Charging electric vehicles, baking pizzas, and melting a fuse in lochem," *CIRED: Open Access Proceedings Journal*, vol. 2017, no. 1, pp. 1629–1633, 2017.

[3] B. Nijenhuis, L. Winschermann, N. B. Arias, G. Hoogsteen, and J. L. Hurink, "Protecting the distribution grid while maximizing ev energy flexibility with transparency and active user engagement," in *CIRED Porto Workshop 2022: E-mobility and power distribution systems*. IET, 2022, pp. 209–213.

[4] D. van der Meer, G. R. C. Mouli, G. Morales-Espana, L. R. Elizondo, and P. Bauer, "Energy management system with pv power forecast to optimally charge evs at the workplace," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 311–320, 2016.

[5] N. Liu, Q. Chen, J. Liu, X. Lu, P. Li, J. Lei, and J. Zhang, "A heuristic operation strategy for commercial building microgrids containing evs and pv system," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 4, pp. 2560–2570, 2015.

[6] O. Ardakanian, S. Keshav, and C. Rosenberg, "Real-time distributed control for smart electric vehicle chargers: From a static to a dynamic study," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2295–2305, 2014.

[7] M. H. S. Uiterkamp, M. E. Gerards, and J. L. Hurink, "Fill-level prediction in online valley-filling algorithms for electric vehicle charging," in *Proceedings - 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe, ISGT-Europe 2018*. Institute of Electrical and Electronics Engineers Inc., 2018, pp. 1–6.

[8] G. Hoogsteen, L. Winschermann, B. Nijenhuis, N. B. Arias, and J. L. Hurink, "Robust and predictive charging of large electric vehicle fleets in grid constrained parking lots," in *2023 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 2023, pp. 1–6.

[9] E. Delmonte, N. Kinnear, B. Jenkins, and S. Skippon, "What do consumers think of smart charging? perceptions among actual and potential plug-in electric vehicle adopters in the united kingdom," *Energy Research & Social Science*, vol. 60, p. 101318, 2020.

[10] A. Hoekstra and N. Refa, "Characteristics of dutch ev drivers," in *Proceedings of the 30th International Electric Vehicle Symposium & Exhibition*, 2017.

[11] "Epex spot," https://www.epexspot.com/en, accessed: July 28, 2023.

[12] B. Nijenhuis, J. Reuling, G. Hoogsteen, and J. L. Hurink, "The potential of indicating energy flexibility information by ev users for application in energy management systems: a dutch case study," in *2023 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 2023, pp. 1–6.