POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Integrating EV Fleets and Renewable Sources into Building Energy Management with an Adaptive MPC Approach

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'Automazione e Controllo

Author: Gianluca Piccoli

Advisor: Prof. Luca Ferrarini

Academic year: 2023-2024

1. Abstract

Within the realm of Energy Management Systems (EMS) a novel approach using a Model Predictive Control (MPC) solution is proposed. This approach investigates the practicality of adopting Battery Management System (BMS)-aware techniques to regulate energy flows by utilizing a non-proprietary fleet of Electric Vehicles (EVs) as an optimal method for energy storage and utilization. Instead of considering uncertainty on factors such as varying electricity costs, energy usage, and storage availability, it focuses extensively on methodologies for the efficient employment of EVs while minimizing the impact of BMS limitations. The study first examines strategies to reduce battery wear in vehicles, thereby enhancing the effectiveness of each EV's use. Additionally, it scrutinizes potential responses of the BMS to manage uncertainties concerning power constraints. A novel solution is presented for the online learning of unfamiliar vehicles.

2. Introduction

Following the European Climate Law, enacted on June 30, 2021, aiming for a 55% reduction in greenhouse gas emissions by 2030 and achieving climate neutrality by 2050, there is a pressing need for innovative measures across sectors to improve energy efficiency and alter consumption patterns [1]. The anticipated surge in EV sales to 73 million units by 2040, up from 2 million in 2020, signals a significant shift in the automotive market and presents both challenges and opportunities for electricity providers and energy management. This increase in EVs requires innovative solutions to optimize renewable energy use and address peak-hour electricity demands, emphasizing the importance of smarter energy consumption practices in response to rising energy prices and geopolitical tensions.

The existing body of scientific research presents a variety of strategies aimed at addressing energy management challenges from different perspectives. Many of these strategies emphasize enhancements within organizational operations, such as refining the synchronization between equipment and material handling systems to bolster production efficiency—a key bottleneck highlighted in studies on production throughput [2]. Despite these advancements, the reluctance to invest in energy efficiency improvements remains a significant hurdle for numerous firms, primarily due to the extended periods required

to recover costs, due to uncertain improvements in their energy bills.
This research adopts a recognized strategy of managing energy flows into and out of facilities from an external standpoint, thus providing a comprehensive solution to the abovementioned challenges. The utility of batteries as energy storage solutions is well acknowledged; however, the prohibitive costs of battery systems often dissuade businesses from making such investments.
As a viable alternative, it's proposed to leverage EVs as energy storage vessels, taking advantage of their substantial battery capacities when idle and plugged into the facility charging station.

3. Proposition of the solution

This research introduces an innovative solution to the diverse array of options in energy management, focusing on a critical yet unexplored aspect. Theoretical simulations often describe system behaviors in ideal scenarios that diverge significantly from real-life conditions. A strategy that assumes the unrestricted use of vehicles would likely encounter substantial challenges in practical applications. The main obstacle is the Battery Management System (BMS) of electric vehicles, an electronic framework designed to protect the battery from hazardous conditions. The proposed solution unfolds in a series of steps designed to gradually increase the scenario's complexity and thoroughly examine the significance of each aspect:

1. The initial phase involves a V2B application where an MPC strategy is employed to schedule optimal operations. This stage considers a range of days for testing and a variable vehicle fleet.
2. The next phase addresses the need for a BMS-aware approach, focusing on minimizing actions that could accelerate battery degradation.
3. The final phase aims for a more sophisticated control that simulates the BMS's dynamic limitations, especially concerning the unique current characteristics of the battery. This comprehensive approach seeks to enhance the feasibility and efficiency of employing EVs as energy storage units within an integrated energy management system.

4. V2B Energy Optimization with MPC

Initial analyses focus on utilizing these batteries for cost savings, disregarding any internal constraints. Here, MPC targets the power equilibrium, incorporating all input and output powers for each vehicle throughout the day. The MPC assesses the full day's horizon to determine the optimal sequences for charging and discharging operations:

$$c_t(P_t^{i+}, P_t^{i-}) = (P_t^{\text{load}} - P_t^{\text{PV}} + P_t^{+}(P_t^{i+}) - P_t^{-}(P_t^{i-}))\frac{\Delta t}{60}$$

With input P_t^{i+} and P_t^{i-} and state SOC_t^i for $i \in$ fleet and for $t \in$ horizon. c_t denotes the energy consumption at time t of the day whereas P_t^+ and P_t^- total energy given or taken by the fleet. The optimization tool, GUROBI, is set to optimize the following objective function:

$$\underset{P_t^{i+}, P_t^{i-}}{\text{argmin}}\, J, \quad J = \sum_t^T C_t(P_t^{i+}, P_t^{i-})$$

where C_t denotes the total energy cost at time t and T contains step of the planning horizon.
Upon evaluating the data over 30 days, it was observed that the potential for savings was significantly influenced by tariff factors and industrial load consumption (Figure 1).

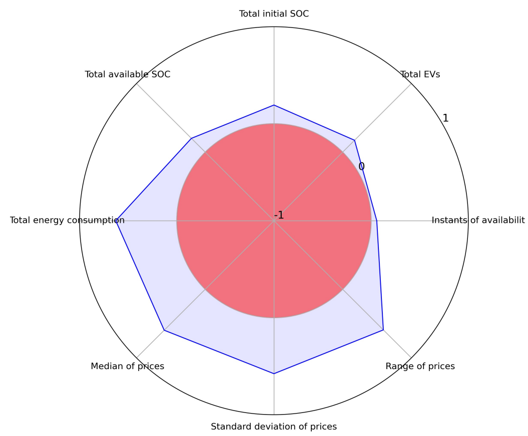


Figure 1: This radar chart represents the correlation between electricity tariffs and household consumption with the recorded cost savings. If a characteristic has mostly a direct influence on savings, its position on the radar is between 0 and 1. Conversely, data points fall within the inner red circle.

This overshadowed the impact of the EV fleet's characteristics, which is the primary focus of this thesis. To isolate and examine the variability associated with the EV fleet more closely, a consistent profile for both load and energy cost was selected and applied across the 30 days. Subsequent testing yielded predictable outcomes regarding how changes in fleet characteristics such as the number of vehicles, the initial SOC, available empty SOC, and duration of presence can influence positively energy savings.

5. Decay minimization

The initial concept centering on a BMS-aware control strategy focuses on the degradation of the battery following external operations. This degradation has been quantified using an empirical model, which was developed through the fitting of measured values derived from numerous experiments conducted in a laboratory setting. The model effectively captures the alteration in the State of Health (SOH) percentage resulting from a cycle of charging and discharging operations.

$$\Delta\mathrm{SOH}\% = e^{\left(k_T \cdot \frac{(T_t - T_{\mathrm{ref}})}{T_t} \cdot k_{DOD} \cdot DOD_t + k_{C_{ch}} \cdot Cch_t + k_{C_{dch}} \cdot Cdch_t\right)} \cdot \left[1 + b_{\mathrm{mSOC}} \cdot \mathrm{mSOC}_t \cdot \left(1 - \frac{\mathrm{mSOC}_t}{2 \cdot \mathrm{mSOC}_{\mathrm{ref}}}\right)\right] \cdot \beta\,(FEC_t)^{a_{\mathrm{opt}}}$$

This equation is composed of three parts denoting the dependency of the decay concerning variables in different proportions. Considering the exponential, part of major influence, there are:

- **Charging C-rate (C_{ch}), discharging C-rate (C_{dsch}):** Reflects the charging/discharging rate with the battery's total capacity.
- **Depth-Of-Discharge (DOD):** Indicates the extent of battery use by comparing initial and final SOC.
- **Operating temperature (T_t):** A critical factor with a significant impact on degradation, modeled using the lumped capacitance method for temperature analysis. Despite its utility, this approach lacks temperature regulation considerations essential for maintaining optimal conditions, leading to the introduction of a scaling factor k to adjust for temperature variations, though this increases the error margin.

$$T_t = T_{t-1} + (P_{\mathrm{th},t-1} + Q_{\mathrm{gen},t-1} - h \cdot A \cdot (T_{t-1} - T_{\mathrm{atm}})) \cdot C_{\mathrm{th}} \cdot \Delta t \cdot k$$

To provide concrete examples, the battery's degradation after 8 years of operation was analyzed, reflecting the minimum warranty period for EVs, where the SOH percentage is not expected to drop below 80%, a commonly accepted threshold for the end of life. The findings (Figure 2) reveal that not addressing this aspect significantly compromises battery health due to unregulated vehicle operations:

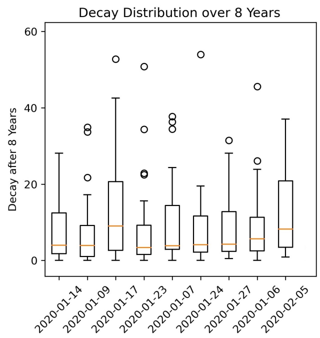


Figure 2: Box plot showing the distribution of vehicle battery decay over several days of testing. The x-axis lists the specific days tested, and the y-axis indicates the percentage difference in the SOH of the battery. The median value is marked by the orange line within each box. The main body of each box represents 50% of the data points, while the extended lines, or 'whiskers', capture the range excluding outliers, which are denoted by circles.

To address battery degradation during optimization, a novel "price of service" for battery usage was developed. The service fee for each battery is pegged to its current market value and the extent of SOH impact incurred. This financial valuation is then converted into an equivalent amount of energy, which is reimbursed to the vehicle at the end of the day, thereby aiming to reduce overall industrial costs and, consequently, the expenses related to battery usage. The formula given below illustrates this concept:

$$SOC^i_{end} = SOC^{EV_i}_{in} + \frac{\Delta SOH^i \cdot Price^i}{\pi^+}$$

Here $Price^i$ denotes the assigned cost for each battery, which, after calculating the price due to SOH degradation (by multiplying the SOH difference), is divided by π^+, a predetermined energy price (€/kWh), to calculate the compensatory energy amount. Despite the positive effects on decay mitigation (Figure 3), overall savings remained largely unaffected when compared to the baseline scenario without such measures (Table 1).

Min Δ (%)	Max Δ (%)	Med Δ (%)
-0.00012	-1.74207	-0.00403

Table 1: Summary of differences in savings.

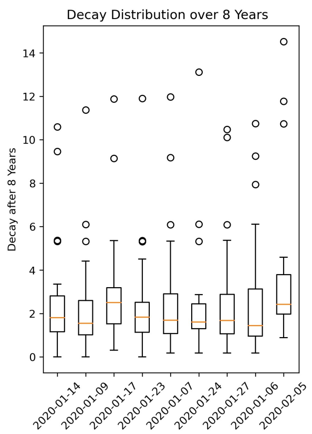


Figure 3: By reducing the operational frequency, each EV exhibits at least a 50% reduction in battery decay rates, although some outliers persist, which may be attributed to vehicles with less expensive batteries being used more extensively.

This finding underscores the potential of preventing harmful battery practices by adopting a BMS-aware optimization strategy, which could have significant implications for long-term battery health and operational sustainability.

6. Power limits

When considering the limitations imposed by the BMS on battery usage, it is important to take into account various factors. Due to the limited number of measurements available, the focus has been placed on the power limits' relationship with the current SOC. Before moving on to more intricate models, which are more suitable for real-world situations, simulations were conducted to assess the impact of power limits on the objective function. The simulations were based on a simple pre-defined knowledge of the system, where power limits remain constant while SOC changes and the MPC knows a value different from the actual one. By incorporating feedback from the system, the MPC collects information to refine its state knowledge, ensuring closer alignment between the simulation and potential real-world applications.

Two distinct scenarios have been tested:

1. **Overestimation of limits by 50%:** In this case, the MPC scheduled operations based on limits significantly higher than actual system capabilities. While one might anticipate such assumptions to lead to truncated actions, the critical question is whether the system can still enhance its scheduling despite these inaccuracies. Below is a summary of the findings from a 30-day evaluation, detailing the minimum, maximum, and median variations in savings compared to a perfect optimization scenario (Table 2).

Min Δ (%)	Max Δ (%)	Med Δ (%)
-0.65606	-22.87135	-13.51953

Table 2: Summary of changes when limits are overestimated.

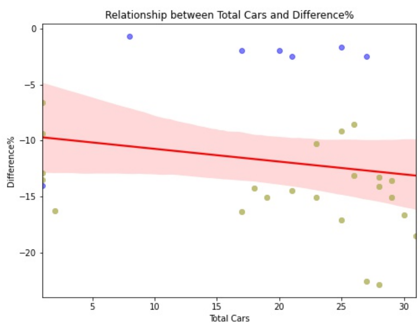


Figure 4: The scatter plot illustrates the variation in percentage differences across the number of vehicles. Yellow markers represent the group of vehicles with maximum power exceeding a specific threshold (p), while blue markers indicate those with maximum power below this threshold.

The analysis of these results uncovers a complex relationship. Initially, it might appear that a larger fleet could more effectively correct discrepancies from previous failed outcomes due to having more vehicles at disposal. Contrary to expectations, the findings (Figure 4) suggest a negative impact, potentially due to the limited windows for optimal operation. Therefore, inaccurate scheduled operations within these critical periods can drastically affect savings.

2. **Underestimation of limits by 50%:** Here, the MPC's scheduled operations were within the actual system's capabilities, negating the need for adjustments.

Min Δ (%)	Max Δ (%)	Med Δ (%)
-1.61164	-20.50290	-6.07872

Table 3: Summary of changes when limits are overestimated.

This scenario (Table 4) suggests that operations not limited by truncated responses generally yield better results, as the system can still schedule effective operations with fewer resources. The results highlight a dependency on available power, where an increase in power availability generally reduces losses against the optimal scenario.

In the absence of empirical data to accurately depict real-world behavior, this study utilizes simulations to replicate response curves similar to those observed in experiments by P3 Group [3]. These models include simple linear and nonlinear behaviors, as well as complex step curves, with parameters randomly assigned to each vehicle to simulate a scenario of high variability. The methodology assumes a fixed understanding by the MPC of the maximum and minimum power levels, set at the median value of the entire curve. Comparing the results with the optimal result knowing perfectly the curve is obtained:

Min Δ (%)	Max Δ (%)	Med Δ (%)
-0.03344	-6.60936	-2.41649

Table 4: Summary of changes when limits are overestimated.

These outcomes suggest that complete knowledge of the BMS behavior regarding maximum and minimum power across the SOC spectrum is not essential for achieving favorable results. A median value provides sufficient information for effectively utilizing the vehicle as a BESS.

7. Online scheduling

To accommodate the real variable nature of these operational limits, the proposition of an adaptive corrective strategy using Online Kernel Regression technique has been proposed . This approach allows for the real-time optimization of charging and discharging operations, constantly adjusting to the most recent data regarding operational limits. Such a strategy is pivotal for ensuring that the energy management system remains efficient and responsive to the fluctuating conditions of battery performance. Considering dynamic boundary conditions for the inputs:

$$\begin{cases} 0 \leq P_t^{i+} \leq P_{\hat{MAX}}(SOC) & (1) \\ 0 \geq P_t^{i-} \geq P_{\hat{MIN}}(SOC) & (2) \end{cases}$$

Where curve $P_{\hat{MAX}}(SOC)$ comes from the estimation $\sum_{j=1}^{n} \alpha_j K(SOC, SOC_j)$ using as kernel function the Laplace Kernel and α are the learned weights. The final stage of the simulations includes running the MPC to determine the optimal scheduling every 15 minutes, complemented by the application of Online Kernel Regression at one-minute intervals to refine the system's understanding of the operational limits. This dual approach ensures that the controller adapts to the system and schedules better operations (Figure 5).

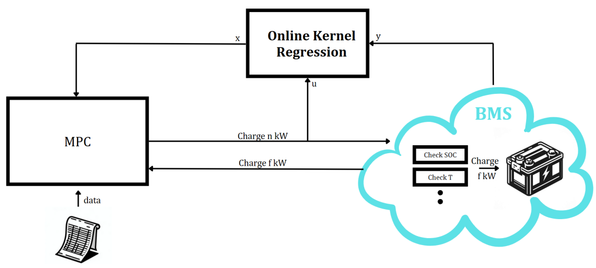


Figure 5: Online control scheme with OKR.

The concluding results underscore the efficacy of an online approach in grasping the nuanced dynamics of the SOC (Table 5).

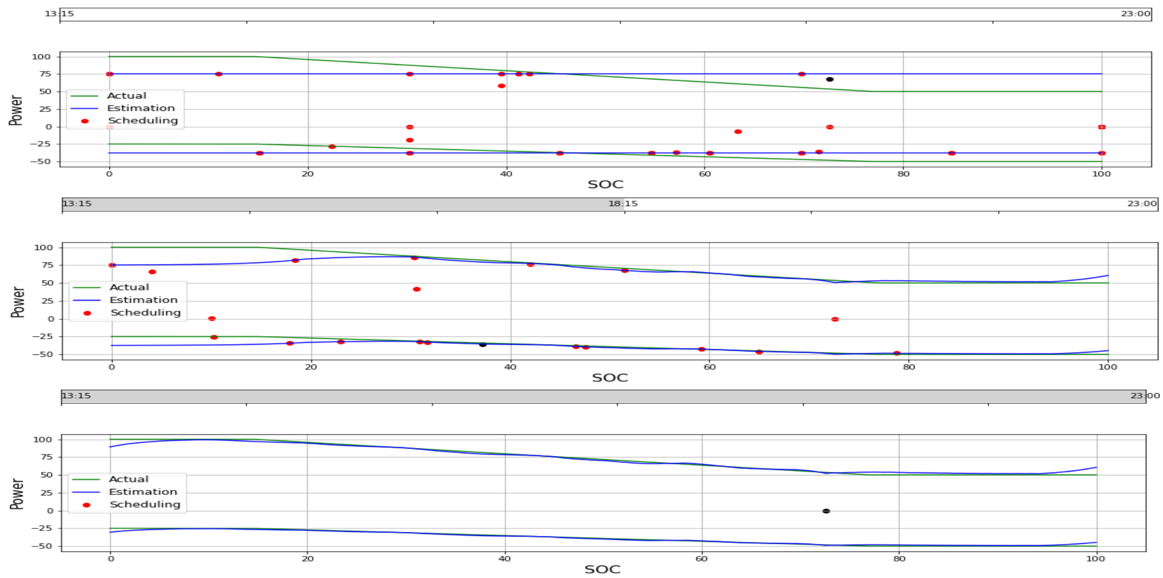


Figure 6: Progression of the learning phase from start to midpoint, and through to the conclusion. Green lines represent actual power thresholds, blue lines depict estimated values, and red dots denote operations planned for an unspecified time within the horizon (black one at the current moment).

Approach	Online Opt	Fixed Opt
Max Δ (%)	-6.240	-6.609
Min Δ (%)	-0.029	-0.033
Med Δ (%)	-2.196	-2.416

Table 5: Comparison of results with the last two approaches.

Regarding the learning curve, the online algorithm demonstrates effective and timely performance when dealing with curves that exhibit mild non-linear characteristics (Figure 6), but its accuracy diminishes with more pronounced non-linearities.

8. Comprehensive Testing

This section outlines all the tests conducted during the analysis, leading to the decisions and considerations previously highlighted.

Understanding low consumption use

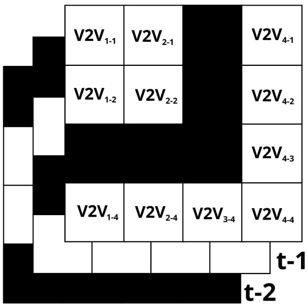
The initial tests focused on the actual household consumption data from the dataset. These tests revealed a distinct pattern of decay analysis (showed some of the 30 days tested):

	Tot_cars	Int_t	Median_Dec_8y%
2020-01-23	27.0	05:45 - 21:00	4.47%
2020-01-31	17.0	06:30 - 21:15	4.32%
2020-01-30	26.0	06:30 - 20:30	1.96%
2020-01-28	27.0	06:15 - 19:00	2.17%
2020-01-27	28.0	06:30 - 19:45	1.45%
2020-01-04	1.0	13:15 - 23:00	10.76%
2020-01-20	1.0	07:00 - 15:15	8.65%
2020-01-29	21.0	06:15 - 18:30	2.73%
2020-01-07	29.0	06:15 - 21:00	2.33%
2020-01-22	25.0	06:00 - 23:00	3.01%
2020-02-04	8.0	09:00 - 21:15	4.98%

Given that the energy transferred to each vehicle was lower, both decay and battery utilization were minimal even without decay minimization. As the primary goal of this study is to examine fleet utilization against various limits and constraints, we increased the consumption by a factor of 50. This adjustment made the consumption profile more similar to that of a metallurgical factory. To avoid expanding the scenario to an even more energy-intensive facility, which would be particularly unique, the consumption level was maintained at this adjusted level.

V2V development

Before adopting the streamlined methodology, an evaluation was conducted considering the financial savings from each vehicle singularly, alongside a comprehensive set of constraints designed to facilitate energy exchange between vehicles:



The framework for energy exchanges was conceptualized using an antisymmetric matrix. Diagonal elements represented power exchanges with the industry, while off-diagonal elements, with their indices, swapped, denoted power exchanges between vehicles. For example, if $V2V_{1-2}$ indicates the power transferred from vehicle 1 to vehicle 2, then $V2V_{2-1}$ would be its negative counterpart, representing power flow from vehicle 2 to vehicle 1.

	V2B_Savings%	V2V_Savings%	V2V_Solutions	V2B_Solutions
2020-01-23	81.39%	81.39%	1	2
2020-01-31	78.12%	78.12%	1	3
2020-01-30	54.31%	54.3%	1	2
2020-01-28	50.74%	50.74%	1	3
2020-01-27	37.97%	37.97%	1	3
2020-01-04	36.13%	36.13%	1	2
2020-01-20	33.67%	33.67%	1	2
2020-01-29	28.94%	28.94%	1	4
2020-01-07	26.59%	26.59%	1	3
2020-01-22	25.33%	25.33%	1	2
2020-02-04	20.55%	20.55%	1	2

The noticeable improvement in solutions across different days highlighted the effectiveness of the more simplified strategy, which enhanced the algorithm's efficiency. A comparison between the V2B method, which included the final formula and thus aggregated all power exchanged by vehicles, and the V2V strategy utilizing the antisymmetric matrix illustrated that the former's simplicity consistently enabled the optimizer to discover more solutions. Considering the intended increase in algorithm complexity due to factors such as decay and power limits, the final simplified approach was considered appropriate.

Strategic Decay Minimization Negotiation

A negotiation proposal was formulated by tackling a multi-objective problem, which aimed at identifying a solution by focusing on minimizing vehicle decay and adjusting the decay weights in the optimization process. The outcomes for a single vehicle were illustrated as follows:

Weight	Decay %	Savings %
+ 0%	0.0004397357	50.74%
+ 10%	0.0003738347	50.73%
+ 20%	0.0003189172	50.69%
+ 30%	0.0002724485	50.63%
+ 40%	0.0002326182	50.55%
+ 50%	0.0001980987	50.46%
+ 60%	0.000167894	50.35%
+ 70%	0.0001414229	50.22%
+ 80%	0.000117553	50.17%
+ 90%	9.63568e-05	50.08%
+ 100%	7.72801e-05	49.94%

A challenge encountered with this approach was the complexity involved in accurately representing each owner's interests. While the method successfully reduced decay, it simultaneously decreased the costs associated with full damage energy payment. Furthermore, incorporating a decision-making layer, which required each owner to select their preferred decay level, prompted a shift towards a more company-focused strategy, leaving the aspect of negotiations to be explored further in studies with a keen interest in negotiation dynamics.

Pricing Effects on Vehicle Utilization

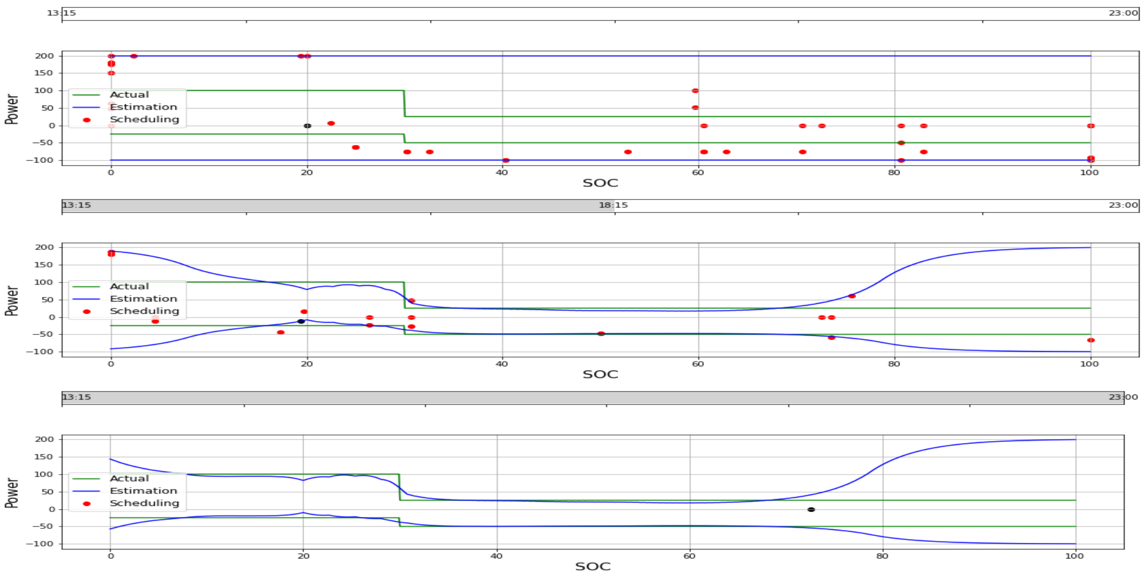
To derive insights related to battery utilization, further analyses were conducted with varying assumptions about vehicle pricing. The initial experiment involved setting a uniformly low price for all vehicles:

	Tot_cars	Int_t	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	1.644e-18%	81.39%	81.39%
2020-01-31	17.0	06:30 - 21:15	1.593e-18%	78.12%	78.12%
2020-01-30	26.0	06:30 - 20:30	1.593e-18%	54.31%	54.3%
2020-01-28	27.0	06:15 - 19:00	1.542e-18%	50.74%	50.74%
2020-01-27	28.0	06:30 - 19:45	1.593e-18%	37.97%	37.97%
2020-01-04	1.0	13:15 - 23:00	2.055e-18%	36.13%	36.13%
2020-01-20	1.0	07:00 - 15:15	1.747e-18%	33.67%	33.67%
2020-01-29	21.0	06:15 - 18:30	1.542e-18%	28.94%	28.94%
2020-01-07	29.0	06:15 - 21:00	1.387e-18%	26.59%	26.59%
2020-01-22	25.0	06:00 - 23:00	1.490e-18%	25.33%	25.33%
2020-02-04	8.0	09:00 - 21:15	1.799e-18%	20.55%	20.55%

In this scenario, results indicated uniform utilization across all vehicles, albeit to a lesser extent compared to the baseline scenario. In another experiment, the vehicle price was fixed at a significantly higher rate:

	Tot_cars	Int_t	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	7.9%	81.39%	81.09%
2020-01-31	17.0	06:30 - 21:15	8.4%	78.12%	78.11%
2020-01-30	26.0	06:30 - 20:30	4.59%	54.31%	54.13%
2020-01-28	27.0	06:15 - 19:00	4.39%	50.74%	47.21%
2020-01-27	28.0	06:30 - 19:45	4.65%	37.97%	30.47%
2020-01-04	1.0	13:15 - 23:00	13.11%	36.13%	36.12%
2020-01-20	1.0	07:00 - 15:15	11.59%	33.67%	32.45%
2020-01-29	21.0	06:15 - 18:30	5.37%	28.94%	28.2%
2020-01-07	29.0	06:15 - 21:00	4.9%	26.59%	20.58%
2020-01-22	25.0	06:00 - 23:00	5.47%	25.33%	24.57%
2020-02-04	8.0	09:00 - 21:15	8.54%	20.55%	19.73%

This demonstrated a clear influence of vehicle pricing on battery utilization, which could, in turn, affect cost savings due to varying vehicle prices. A final experiment was conducted to ensure equal decay across all vehicles:



	Tot_cars	Int_t	Median_Dec_8y%	Savings%	Decay_Savings%
2020-01-23	27.0	05:45 - 21:00	0.0%	81.39%	0.0%
2020-01-31	17.0	06:30 - 21:15	0.0%	78.12%	0.0%
2020-01-30	26.0	06:30 - 20:30	0.0%	54.31%	0.0%
2020-01-28	27.0	06:15 - 19:00	0.0%	50.74%	0.0%
2020-01-27	28.0	06:30 - 19:45	0.0%	37.97%	0.0%
2020-01-04	1.0	13:15 - 23:00	11.6%	36.13%	36.12%
2020-01-20	1.0	07:00 - 15:15	8.71%	33.67%	33.09%
2020-01-29	21.0	06:15 - 18:30	0.0%	28.94%	0.0%
2020-01-07	29.0	06:15 - 21:00	0.0%	26.59%	0.0%
2020-01-22	25.0	06:00 - 23:00	0.0%	25.33%	0.0%
2020-02-04	8.0	09:00 - 21:15	5.02%	20.55%	19.99%

This test illustrated the complexity of the issue, showing that finding a viable solution becomes increasingly challenging in scenarios with more than one vehicle involved.

Impact of Initial Conditions on OKR Efficacy

To evaluate the proposed online approach's robustness, tests were conducted with initial maximum and minimum power levels set 200% higher than actual values, affecting savings as follows:

Min Δ (%)	Max Δ (%)	Med Δ (%)
-0.039	-10.840	-2.596

This highlights the significance of accurate initial conditions. Even though the algorithm adapts quickly, incorrect initial settings can significantly impact savings, emphasizing the need for precise initial data for optimal performance.

9. Conclusions

The findings underscore the importance of understanding the characteristics of vehicles for effective management in EV-smart systems. They show that accounting for aspects like decay and power constraints is essential for accurately simulating vehicle behaviors. The research indicates that controlled use of vehicles can significantly enhance performance with minimal impact on savings, regardless of the mix of vehicles, while unchecked usage can lead to substantial battery degradation. Simulations of BMS reveal that power limitations have a major impact on the cost, highlighting the need to consider the dynamic changes caused by factors such as the SOC. The study suggests adopting adaptive learning methods for adjusting dynamic control due to the variability within vehicle BMS, which can enhance operation schedules through a deeper understanding of the system. Furthermore, possessing a thorough understanding of power limitations can greatly enhance the learning process.

References

[1] REGULATION (EU) 2021/1119 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 30 June 2021 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 ('European Climate Law'), 2021.

[2] P. Renna and S. Materi. A literature review of energy efficiency and sustainability in manufacturing systems. *Applied Sciences*, 11:7366, 2021.

[3] P3. P3 charging index update. P3, 2022.