Economic and Environmental Optimization of EV Fleets Charging under MIBEL Day-ahead Spot Prices

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***Abstract*— This paper presents an optimization model for electric vehicle (EV) fleet charging under MIBEL (Iberian Electricity Market). The model integrates EV charging with day-ahead forecasting for grid energy prices, photovoltaic (PV) generation, and local power demand, combined with a battery energy storage system (BESS) to minimize total charging costs, reduce peak demand, and maximize renewable use. Simulations across Baseline, Certainty, and Uncertainty scenarios show that the proposed approach would reduce total charging costs by up to 49%, lower carbon emissions by 73.7%, and improve SOC compliance, while smoothing demand curves to mitigate excessive contracted power charges. The results demonstrate the economic and environmental benefits of predictive and adaptive EV charging strategies, highlighting opportunities for further enhancements through real-time adjustments and vehicle-to-grid (V2G) integration.**

***Index Terms*-- Battery Energy Storage System, Electric Vehicle Charging, Optimization, Peak Demand Management, Renewable Energy Integration.**

I. INTRODUCTION

Electric vehicle (EV) adoption is changing the energy environment and has a strong impact on the power distribution infrastructure. Following the increase in the number of EVs, the demand for effective and smart charging management is rising, aiming to balance grid demands, reduce energy costs, boost the use of renewable energy sources and improve grid stability. With this aim, existing research examined a variety of smart charging solutions with an emphasis on timing EV charging optimally. Many of these methods, however, have drawbacks, such as limited adaptability in handling different car counts or failure to consider the possibility of optimizing self-consumption of locally produced renewable energy [1] [2].

This paper introduces an innovative optimization model for scheduling EV charging, specifically designed to go beyond real-world restrictions like restricted charger availability and grid power constraints. The approach seeks to increase the economic effectiveness of charging operations, give priority to the use of renewable energy (particularly photovoltaic) and lessen reliance on grid electricity by proactively modifying charging schedules. This strategy aligns with the increasing need to integrate renewable energy sources into the power system, offering a sustainable solution for EV fleet management. Furthermore, the model incorporates day-ahead energy forecasts, enabling more accurate and adaptive scheduling that considers both grid energy prices and renewable energy availability and a battery energy storage system (BESS). In the context of the electricity market in Portugal, optimizing EV charging schedules is critical due to the non-domestic pricing structure currently in force. Peak demand fee is a capacity charge based on the maximum average power demand observed over a 15-minute interval. Once reached, this value is kept for one year, unless a higher power is measured. Consequently, unexpected spikes in energy consumption, such as those caused by unplanned EV charging, can lead to elevated annual costs, underscoring the importance of careful load management to avoid these financially burdensome peaks. Additionally, there is a peak-hours energy charge which is calculated based on the average power consumed in peak hours, so there is an additional incentive to move consumption from these periods.

The proposed approach introduces significant benefits, such as the ability to manage more EVs when compared to available chargers, and dynamically modify charging rates to balance grid capacity and economic costs. A number of variables, including contracted power restrictions, charging priority, and the financial trade-offs related to CAPEX investments in charging infrastructure, are integrated to provide this flexibility. This model places more emphasis on economic considerations than conventional scheduling algorithms, with the goal of maximizing energy use and minimizing expenses while taking into account practical limitations [3][4].

Indices and Sets

EVs: $\{\mathbf{1},\ \mathbf{2},\ \dots,\ \mathbf{n}\}$	Set of electric vehicles;
Chargers: $\{\mathbf{1},\ \mathbf{2},\ \dots,\ \mathbf{m}\}$	Set of EV chargers;

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Periods: $\{\mathbf{1},\ \mathbf{2},\ \ldots,\ \mathbf{T}\}$	Set of time periods for charging schedules.

Parameters

$\mathbf{P}_{\text{max},\,\mathbf{c}}$	Maximum charging power of charger $\boldsymbol{c}$ [kW];
$\mathrm{SOC}_{\mathrm{EV},\boldsymbol{e}}^{\mathrm{Initial}}$	Initial SOC (State of Charge) of EV e [%];
$\mathrm{SOC}_{\mathrm{EV},\boldsymbol{e}}^{\mathrm{Required}}$	Required SOC of EV e [%];
$\mathbf{C}_{\mathbf{e}}$	Battery capacity of EV e [kWh];
$\boldsymbol{r}_{\boldsymbol{e}}^{\max}$	Maximum charge rate for EV e [kW];
$\boldsymbol{\lambda}_{\boldsymbol{t}}$	Cost of energy from the grid at time period t [€/kWh];
$\mathbf{P}_{\text{Grid},\,\mathbf{t}}^{\max}$	Grid capacity limit at time t [kW];
$\mathbf{P}_{\mathrm{PV},\,\mathbf{t}}$	Power generated from PV at time t [kW];
$\boldsymbol{F}_{\boldsymbol{t}}$	Factory demand at time t [kW];
$\boldsymbol{\eta}$	BESS efficiency (%)
$\mathrm{Priority}_{\boldsymbol{e}}$	Priority of EV e
$\mathbf{B}_{\max}$	Maximum capacity of the BESS [kWh];
$\boldsymbol{C}_{\boldsymbol{pen\_unmet}}$	Penalty for unmet SOC
$\boldsymbol{C}_{\boldsymbol{pen\_low}}$	Penalty for Low Charge Rate

Decision Variables

$\mathbf{x}_{\mathbf{e},\,\mathbf{c},\,\mathbf{t}}$	Binary variable: 1 if EV $\boldsymbol{e}$ is charging at charger $\boldsymbol{c}$ at time $\boldsymbol{t}$ (binary);
$\boldsymbol{P}_{\boldsymbol{e},\,\boldsymbol{c},\,\boldsymbol{t}}$	Power allocated to EV e at charger c during time t [kW];
$\mathrm{SOC}_{\mathbf{e},\,\mathbf{t}}$	State of charge of EV e at time t [kWh];
$\mathbf{U}_{\mathbf{e}}$	Binary variable: penalty for unmet SOC for EV e (binary);
$\mathbf{O}_{\mathbf{e}}$	Binary variable: penalty for charging EV e over the required SOC (binary);
$\mathrm{P}_{\boldsymbol{BESS\ ch},\,\mathbf{t}}$	Charging power of BESS in period t (kW);
$\mathrm{P}_{\boldsymbol{BESS\ dis},\,\mathbf{t}}$	Discharging power of BESS in period t (kW)
$\boldsymbol{SOC}_{\boldsymbol{BESS}\,,\,\mathbf{t}}$	SOC of BESS in period t (%)

II. LITERATURE REVIEW

Several studies propose optimization frameworks to schedule EV charging effectively. It has been suggested that dynamic pricing schemes be used to encourage grid-friendly and economical charging practices. For example, Zhou et al. created a scheduling model that takes customer annoyance and fluctuating electricity prices into account to reduce expenses. The model provides EV owners with a thorough framework for decision-making by taking battery deterioration costs into consideration [5]. In another study, Khan and Aziz designed a dynamic pricing framework for Bangladesh, incorporating real-time pricing and time-of-use tariffs. Their results demonstrated a 31% to 48% cost reduction for EV owners who adhered to the proposed charging schedule [6].

It has been demonstrated that including PV and BESS into charging schedules can lessen reliance on grid power during peak hours. By investigating the effects of integrating PV systems with BESS, Aguilar-Dominguez et al. were able to significantly lower peak demand and electricity prices. According to their analysis, time-of-use pricing during periods of high demand might result in savings of up to 30% and additional reductions of up to 85% [7].

Uncoordinated EV charging can lead to significant challenges, including voltage instability and grid congestion. et al. developed a pricing strategy to address these issues by coordinating fast-charging stations. Their approach improved voltage profiles without reducing the revenue of charging station operators, demonstrating the dual benefits of operational stability and economic feasibility [8].

Jawale et al. present a priority-based EV charging strategy aimed at minimizing grid peak loads and enhancing the integration of renewable energy. Their approach categorizes EV users into priority levels based on charging requirements, enabling optimized scheduling and efficient use of charging infrastructure [9].

While previous studies, such as those cited, have explored smart charging strategies, the model presented in this paper introduces several novel features that enhance economic efficiency and grid integration. Firstly, it dynamically prioritizes EVs based on predefined urgency levels, ensuring that high-priority vehicles achieve their required state of charge without unnecessary delays. Secondly, the model incorporates both real-time and day-ahead electricity pricing, allowing for adaptive scheduling that minimizes energy costs while also avoiding peak demand charges. Thirdly, it integrates photovoltaic generation forecasts and BESS dynamics, optimizing self-consumption and reducing reliance on grid electricity, while accounting for grid power constraints and contracted capacity limits. The model also enhances scalability by managing multiple EVs with limited charging infrastructure efficiently, making it suitable for large fleet applications in real-world industrial settings.

III. METHODOLOGY

A. Objective Function

$$\begin{aligned} \min \sum_{e\, \in \mathrm{EVs}} \sum_{c\, \in \mathrm{Chargers}} \sum_{t\, \in \mathrm{Periods}} & \lambda_t \left(P_{e,\,c,\,t} + F_t + \mathrm{P}_{BESS\,ch,\,\mathrm{t}} - \mathrm{P}_{\mathrm{PV},\,\mathrm{t}}\right. \\ & \left. -\ P_{BESSdis,t}\right) + \sum_{e\, \in \mathrm{EVs}} \mathrm{Priority}_e \cdot p_{\mathrm{penalty}}^{\mathrm{unmet}} \cdot U_e \\ & + \sum_{e\, \in \mathrm{EVs}} \sum_{c\, \in \mathrm{Chargers}} \sum_{t\, \in \mathrm{Periods}} p_{\mathrm{penalty}}^{\text{low charge}} \\ & \cdot \left(r_e^{\max} -\ P_{e,\,c,\,t}\right) + \sum_{e\, \in \mathrm{EVs}} p_{\mathrm{penalty}}^{\mathrm{overcharge}} \cdot O_e \end{aligned} \tag{1}$$

B. Constraints

Charger Exclusivity - Ensures that a single EV is connected to a charger at all times:

$$\sum_{e \in \mathrm{EVs}} x_{e,c,t} \le 1\,, \quad \forall c \in \mathrm{Chargers}, t \in \mathrm{Periods} \tag{2}$$

EV Exclusivity - Ensures that each EV can charge at only one charger at a time:

$$\sum_{c \in \mathrm{Chargers}} x_{e,c,t} \le 1 \qquad \forall e \in \mathrm{EVs}, t \in \mathrm{Periods} \tag{3}$$

Charging Power Limits - Charging power must respect the charger's maximum power as well as the vehicle's maximum charging power:

$$\mathrm{P}_{\mathrm{e,\,c,\,t}} \le \mathrm{r}_{\mathrm{e}}^{\max} \cdot \mathrm{x}_{\mathrm{e,\,c,\,t}} \quad , \quad \forall \mathrm{e} \in \mathrm{EVs}, \mathrm{c} \in \mathrm{Chargers}, \mathrm{t} \in \mathrm{Periods} \tag{4}$$

$$\mathrm{P}_{\mathrm{e,\,c,\,t}} \le \mathrm{P}_{\max,\,\mathrm{c}} \cdot \mathrm{x}_{\mathrm{e,\,c,\,t}} \quad , \quad \forall \mathrm{e} \in \mathrm{EVs}, \mathrm{c} \in \mathrm{Chargers}, \mathrm{t} \in \mathrm{Periods} \tag{5}$$

SOC Progression for EVs - Updates the SOC of each EV based on the charging power

$$\mathrm{SOC}_{\mathrm{e},\,1} = \frac{\mathrm{SOC}_{\mathrm{EV,\,e}}^{\mathrm{Initial}} \cdot \mathrm{C}_{\mathrm{e}}}{100} \qquad \forall \mathrm{e} \in \mathrm{EVs} \tag{6}$$

$$\mathrm{SOC}_{\mathrm{e,\,t}} = \mathrm{SOC}_{\mathrm{e,\,t-1}} + \sum_{\mathrm{c}\, \in\, \mathrm{Chargers}} \mathrm{P}_{\mathrm{e,\,c,\,t-1}} \cdot \Delta\,\mathrm{t} \quad , \quad \forall \mathrm{e} \in \mathrm{EVs}, \mathrm{t} > 1 \tag{7}$$

$$\frac{\mathrm{SOC}_{e,T} \cdot\ \mathrm{C}_{\mathrm{e}}}{100} \le C_e \quad , \quad \forall e \in \mathrm{EVs} \tag{8}$$

BESS Charging and Discharging - BESS charging power is limited by its capacity, and its SOC progresses over time:

$$0 \le \mathrm{P}_{BESS\,ch,\,\mathrm{t}}\ \le \mathbf{B}_{\max}, \qquad \forall t \in T \tag{9}$$

$$\mathrm{SOC}_{BESS,\,\mathrm{t}} = \begin{cases} \mathrm{SOC}_{BESS,\,0}, & t = 0 \\ \mathrm{SOC}_{BESS,\,\mathrm{t-1}} +\ \mathrm{P}_{BESS\,ch,\,\mathrm{t-1}}, & t > 0 \end{cases} \tag{10}$$

Grid Capacity Constraint - Ensures total energy consumption does not exceed available grid and PV capacity:

$$\begin{aligned} \sum_{\mathrm{e}\, \in\, \mathrm{EVs}} \sum_{\mathrm{c}\, \in\, \mathrm{Chargers}} & \mathrm{P}_{\mathrm{e,\,c,\,t}} + \mathrm{P}_{\mathrm{BESS}}^{\mathrm{charge,\,t}} \\ & \le\ \mathrm{P}_{\mathrm{Grid,\,t}}^{\max} + \mathrm{P}_{\mathrm{PV,\,t}} + \mathrm{P}_{\mathrm{BESS}}^{\mathrm{discharge,\,t}} \\ & - \mathrm{F}_{\mathrm{t}}, \qquad \forall \mathrm{t} \in \mathrm{Periods} \end{aligned} \tag{11}$$

Penalty for Unmet SOC - Applies a penalty if the SOC at the end of the time period is less than the required SOC:

$$M =\ \mathrm{C}_{\mathrm{e}} \quad \cdot r_e^{\max}\,, \qquad \forall\ \mathrm{e} \in \mathrm{EVs} \tag{12}$$

$$\mathrm{SOC}_{\mathrm{e,\,T}} \ge \frac{\mathrm{SOC}_{\mathrm{EV,\,e}}^{\mathrm{Required}} \cdot \mathrm{C}_{\mathrm{e}}}{100} - M \cdot \qquad , \quad \forall\ \mathrm{e} \in \mathrm{EVs} \tag{13}$$

Overcharge Constraint - Prevents charging the battery beyond the required SOC:

$$\mathrm{SOC}_{\mathrm{e,\,T}} \ge \frac{\mathrm{SOC}_{\mathrm{EV,\,e}}^{\mathrm{Required}} \cdot \mathrm{C}_{\mathrm{e}}}{100}\ +\ M \cdot \mathrm{O}_{\mathrm{e}} \quad , \quad \forall\ \mathrm{e} \in \mathrm{EVs} \tag{14}$$

The capital M present in the last two constraints works dynamically. If U_{e} in constraint (13) is 1, it activates the penalty for unmet SOC, reducing the lower bound of the SOC constraint. For equation (14), if O_{e} is 1 t activates the penalty for overcharging, increasing the upper bound of the SOC constraint.

This allows the penalties to only be enforced when required to do so.

IV. CASE STUDIES AND SIMULATIONS

The use case is illustrated in Figure 1 and consists of an optimized EV fleet charging system operating within the MIBEL. The diagram outlines the flow of energy, data and optimization decisions, integrating PV generation, grid prices, on-site power demand and user-specific inputs to determine cost-effective charging schedules in a generic EV fleet of a company. The previously described optimization model, positioned centrally in the diagram, processes multiple data sources, including energy supply from PV or external providers, real-time electricity prices, load forecasts, and user-defined parameters such as charging availability and route planning. The model then generates an adaptive charging schedule that balances cost, grid stability and energy availability. Additionally, a BESS, depicted as part of the energy management system, enhances flexibility by storing excess renewable energy and discharging during peak price periods. The output of the optimization model includes charging schedules, route suggestions and charging station recommendations, ensuring that EVs meet their required SOC while minimizing costs.

To test the model using this use case, three distinct scenarios were created:

- Baseline Scenario: A non-optimized, first-come first-served charging strategy, in which EVs charge whenever a charger is available, without considering energy price variations, renewable generation forecasts, or grid constraints. This scenario serves as a benchmark for comparison, representing how the system operates prior to optimization.
- Perfect Forecast Scenario: An idealized case in which all relevant parameters, including PV generation, grid energy prices and local energy demand are perfectly known in advance. This scenario establishes an upper bound on the achievable cost savings and energy efficiency improvements.
- Uncertainty Scenario: This scenario represents a realistic evaluation framework incorporating stochastic variations in PV generation, grid demand, energy prices and EV initial SOC to account for forecasting inaccuracies and the latter being user-provided and inherently uncertain. 1000-iteration Monte Carlo simulations are employed to assess the model's resilience and quantify the impact of input uncertainty on the scheduling performance.

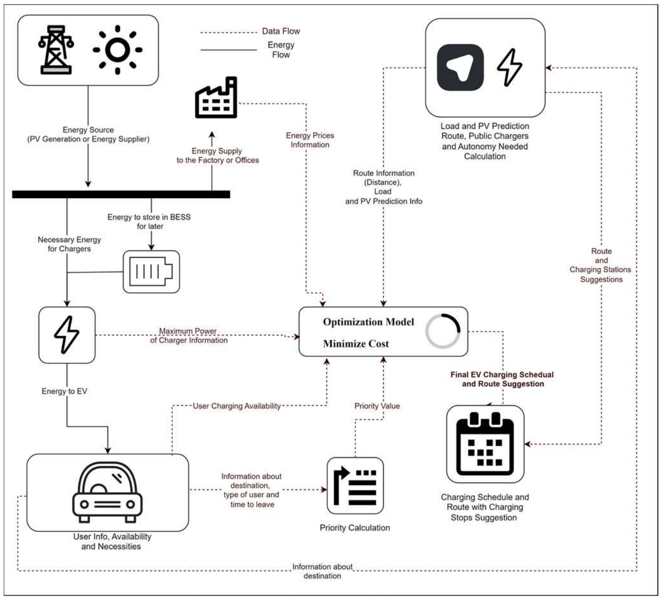

Figure 1 - Diagram of the Use Case

A. *Dataset*

In terms of data used and to ensure the model's applicability to real-world industrial settings, a dataset representing a fleet of 20 vehicles (EVs and Plug-in hybrid EVs) operating within an non-domestic facility in Portugal is utilized. Each EV is characterized by distinct parameters, including battery capacity, initial SOC, required SOC and maximum charging rate. The charging infrastructure consists of four chargers, each with a maximum charging power of 11 kW, and an availability schedule aligned with operational constraints.

The model leverages day-ahead forecasts for key energy parameters to enhance scheduling accuracy. PV generation forecasts are obtained from the Quartz Solar Forecast API, which provides site-specific, hourly solar generation estimates. On-site energy demand is predicted using an XGBoost-based machine learning model, trained on historical consumption data from the same facility and the data used to test the model is a real anonymized Portuguese factory data. Day-ahead grid electricity prices are forecasted using a supervised learning approach, specifically an XGBoost regression model, replacing the historical average method employed in previous studies. This enables the model to dynamically adjust charging schedules based on projected price fluctuations. The data used was obtained from the MIBEL which is the entity responsible for integrating the Portuguese and Spanish energy markets [10].

As for the BESS, it is integrated into the optimization framework to enhance grid flexibility and cost efficiency. The BESS has a total capacity of 193.5 kWh, and a maximum charge and discharge rate of 100 kW. The present study allows BESS charging from both PV and the grid, enabling further reductions in peak demand and energy costs.

The dataset is structured to support a 24-hour simulation period, ensuring temporal alignment of EV availability, PV generation, on-site demand and grid prices. Model performance is evaluated based on cost reduction, peak demand mitigation, renewable energy self-consumption and SOC compliance, providing a comprehensive assessment of the benefits of optimized charging strategies compared to conventional uncoordinated charging.

B. *Performance Metrics and Results*

The performance of the proposed optimization model is evaluated using key indicators that assess cost effectiveness, renewable energy utilization, and charging reliability:

- Total Charging Cost (€) – Represents the total expenditure on electricity for EV charging, minimized by optimizing charging schedules based on day-ahead energy prices and renewable generation availability.
- Peak Power Demand (kW) – Measures the highest power drawn from the grid within the scheduling period, directly impacting grid-sourced electricity costs.
- Renewable Energy Self-Consumption (%) – Indicates the proportion of EV charging energy supplied by on-site PV generation, reducing reliance on grid electricity.
- SOC Compliance (%) – Reflects the percentage of EVs that reach their required charge level by the end of the scheduling horizon, ensuring operational feasibility.
- BESS Utilization (%) – Quantifies the extent to which the BESS is used to manage charging demand and enhance grid flexibility.

V. SIMULATION RESULTS

The simulations were conducted, and the key performance metrics were computed, yielding the results summarized in Table I. Analyzing the results it is patent that the total charging cost is reduced by 49.0% in the Certainty Scenario (194.57€) and 33.0% in the Uncertainty Scenario (255.76€) when compared to the Baseline (€381.8€). This confirms that the predictive scheduling effectively minimizes energy expenses, even under forecast uncertainty. In terms of peak power demand, it increased slightly in optimized scenarios (252.77 kW in Certainty and 292.20 kW in Uncertainty, vs. 242.83 kW in Baseline) due to cost-driven scheduling. However, the model significantly improved SOC compliance, ensuring 75% of EVs met charging requirements in the Certainty scenario and 55% in the Uncertainty scenario, compared to 35% in the Baseline scenario.

Table I - Results Summarizing Table

Scenario / Metrics	Baseline Scenario	Certainty Scenario	Uncertainty Scenario
Total Charging Cost (€)	381.8	194.57	255.76
Peak Demand (kW)	242.83	252.77	292.20
Renewable Energy - Self Consumption (%)	22.96	33.43	22.63
SOC Compliance (%)	35	75	55
Carbon Emissions (kg CO2)	1427.07	375.33	480.59
BESS Utilization (%)	1.84	10.36	10.56

Renewable energy self-consumption increased by 45.5% (33.43%) in Certainty but remained close to Baseline levels (22.63%) in Uncertainty, highlighting the importance of accurate PV forecasting. The BESS utilization rate increased from 1.84% (Baseline) to around 10.5% in optimized scenarios, helping to balance grid consumption and store excess PV energy.

Lastly, carbon emissions were reduced by 73.7% (Certainty) and 66.3% (Uncertainty), confirming that optimized scheduling enhances sustainability.

VI. CONCLUSION

This study presented an optimization model for EV fleet charging that minimizes total electricity costs and carbon emissions, while improving renewable energy integration and SOC compliance. The results demonstrate that predictive scheduling can reduce total charging costs by up to 49%, while increasing PV self-consumption and SOC compliance. Despite achieving overall cost reductions, peak power demand slightly increased due to scheduling concentration in lower-cost periods. The integration of BESS proved effective in offsetting peak demand and optimizing energy costs, while carbon emissions were reduced by over 66%, confirming the environmental benefits of the approach.

Future work could focus on enhancing forecasting accuracy, real-time adaptive control, and vehicle-to-grid (V2G) integration to further improve flexibility and economic efficiency in EV fleet management.

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REFERENCES

[1] S. Das, P. Acharjee, and A. Bhattacharya, "Charging Scheduling of Electric Vehicle Incorporating Grid-to-Vehicle and Vehicle-to-Grid Technology Considering in Smart Grid," *IEEE Trans Ind Appl*, vol. 57, no. 2, pp. 1688–1702, Mar. 2021, doi: 10.1109/TIA.2020.3041808.

[2] M. Francisca *et al.*, "Modelling and Optimizing the Charging of an Electric Vehicles Fleet," Minho University, Braga, Portugal, 2024.

[3] K. Sheng, M. Dibaj, and M. Akrami, "Analysing the Cost-Effectiveness of Charging Stations for Electric Vehicles in the U.K.'s Rural Areas," *World Electric Vehicle Journal*, vol. 12, no. 4, p. 232, Nov. 2021, doi: 10.3390/wevj12040232.

[4] E. Dimanchev, S.-E. Fleten, D. MacKenzie, and M. Korpås, "Accelerating electric vehicle charging investments: A real options approach to policy design," *Energy Policy*, vol. 181, p. 113703, Oct. 2023, doi: 10.1016/j.enpol.2023.113703.

[5] K. Zhou, L. Cheng, X. Lu, and L. Wen, "Scheduling model of electric vehicles charging considering inconvenience and dynamic electricity prices," *Appl Energy*, vol. 276, Oct. 2020, doi: 10.1016/j.apenergy.2020.115455.

[6] T. A. Khan and T. Aziz, "Developing A Day-Ahead Dynamic Pricing Scheme for Charging Electric Vehicles in Bangladesh," in *2022 International Conference on Green Energy, Computing and Sustainable Technology, GECOST 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 440–445. doi: 10.1109/GECOST55694.2022.10010568.

[7] D. Aguilar-Dominguez, A. Dunbar, and S. Brown, "The electricity demand of an EV providing power via vehicle-to-home and its potential impact on the grid with different electricity price tariffs," in *Energy Reports*, Elsevier Ltd, May 2020, pp. 132–141. doi: 10.1016/j.egyr.2020.03.007.

[8] X. Dong *et al.*, "A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks," *Appl Energy*, vol. 225, pp. 857–868, Sep. 2018, doi: 10.1016/j.apenergy.2018.05.042.

[9] S. A. Jawale, S. K. Singh, P. Singh, and M. L. Kolhe, "Priority Wise Electric Vehicle Charging for Grid Load Minimization," *Processes*, vol. 10, no. 9, Sep. 2022, doi: 10.3390/pr10091898.

[10] OMIE, "Preço Horário do Mercado Diário." Accessed: Feb. 01, 2025. [Online]. Available: https://www.omie.es/pt/market-results/daily/daily-market/daily-hourly-price