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A Mixed-Integer Programming Framework for Economic and Environmental EV Fleet Charging

M. F. Almeida, F. J. Soares, F.T. Oliveira
INESCTEC, CPES
Rua Dr. Roberto Frias, 4200-465
Porto, Portugal
maria.f.almeida@inesctec.pt, filipe.j.soares@inesctec.pt, filipe.oliveira@inesctec.pt

Abstract. Widespread fleet electrification is concentrating electricity demand at commercial depots that face volatile prices, tight feeder limits and scarce chargers. This paper proposes a forecast-aware mixed-integer linear program (MILP) that co-optimises vehicle charging, battery-energy-storage dispatch and photovoltaic self-consumption. The model minimises energy cost plus state-of-charge (SOC) penalties, while enforcing charger exclusivity, battery-health bounds and continuous priority weights. It is evaluated on a 48-interval weekday data set comprising 20 electric vehicles, two 11 kW chargers, half-hourly solar forecasts, factory-load predictions and Iberian day-ahead prices. Relative to an uncontrolled first-come/first-served baseline, the optimiser cuts total charging expenditure by 49 %, inceases SOC compliance from 35 % to 65 %, increases PV self-consumption from 33.4 % to 35.5 % and lowers grid-attributed CO_2 emissions by 66 %. A modest rise in instantaneous demand is held within transformer limits through strategic battery discharge. These results confirm that predictive scheduling transforms depot charging from a passive load into a cost-optimal, carbon-aware asset and motivate future extensions that embed stochastic forecasts, route-energy coupling and vehicle-to-grid services.

Keywords. EV fleet charging; mixed-integer linear programming; battery energy storage; photovoltaic self-consumption; predictive scheduling.

I. Introduction

The rapid electrification of road transport is now recognised as a cornerstone of global decarbonisation policy. While battery-electric and hybrid platforms promise substantial reductions in tail-pipe emissions, large-scale deployment also shifts a considerable share of primary energy demand from oil to electricity, thereby stressing distribution networks and market operations. Recent field studies have shown that unmanaged fleet charging can raise feeder peak loads by more than 40 % and accelerate transformer ageing [1]

Against this backdrop, the Iberian electricity market (MIBEL) has adopted progressively granular tariffs and carbon-pricing signals, creating both economic incentives and operational hurdles for corporate fleets that must remain cost-competitive and compliant with environmental targets[2] .

II. Background

A rich body of literature addresses these challenges through "smart-charging'' schemes that coordinate plug-in times, power levels and, in some cases, vehicle-to-grid (V2G) operation. Mixed-integer linear programming (MILP) has emerged as the preferred modelling paradigm because it can capture binary decisions such as charger assignment while keeping global optimality guarantees. Early work by Das et al. [3] demonstrated that incorporating V2G bids into an MILP could shave industrial peaks by 35 %. Subsequent studies extended the formulation to fleet contexts, minimising energy cost under grid-capacity constraints (Akaber et al., 2021 [12]) and embedding route-planning considerations [4]. Reviews such as Dahiwale et al. [5] confirm MILP's flexibility. It has been shown that including BESS and PV into charging schedules can reduce dependency on the grid during peak hours. Peak demand and electricity prices were considerably reduced by Aguilar-Dominguez et al. through their investigation of the effects of combining PV systems with BESS. Their analysis indicates that time-of-use pricing during high demand periods could lead to additional reductions of up to 85% and savings of up to 30% [6].

Yet three critical gaps remain. First, most optimisation studies implicitly assume a charger-to-vehicle ratio close to one, whereas urban and logistic depots often face severe charger scarcity. Second, the integration of predictive analytics—day-ahead spot prices, photovoltaic (PV) generation and on-site demand forecasts—remains rudimentary, limiting the economic upside of anticipatory scheduling. Third, existing prioritisation policies are either binary or static, failing to reflect the heterogeneous urgency profiles typical of corporate operations (e.g., service vans versus pool cars).

This paper tackles those gaps by presenting A Mixed-Integer Programming Framework for Economic and Environmental EV Fleet Charging.

The proposed model:

- Jointly schedules EV charging, battery-energy-storage-system (BESS) operation and PV self-consumption under strict grid-capacity limits;
- Embeds day-ahead forecasts for energy prices, PV output and facility load to anticipate low-cost, low-carbon windows;
- Introduces a flexible multi-level priority mechanism that guarantees mission-critical vehicles reach their required state-of-charge (SOC) even when charger availability is scarce.

The remainder of this paper is organised as follows: Section III details the optimisation model. Section IV describes the case-study set-up, Section V presents and discusses the results. Section VI concludes and outlines future work.

III. Proposed Optimization Framework

A. Indices and Sets

EVs: $\{\mathbf{1},\ \mathbf{2},\ \ldots,\ \mathbf{n}\}$	Set of electric vehicles;
Chargers: $\{\mathbf{1},\ \mathbf{2},\ \ldots,\ \mathbf{m}\}$	Set of EV chargers;
Periods: $\{\mathbf{1},\ \mathbf{2},\ \ldots,\ \mathbf{T}\}$	Set of time periods for charging schedules.

B. Parameters

$\mathbf{P}_{\max,\mathbf{c}}$	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 [%];
$\mathbf{C_e}$	Battery capacity of EV e [kWh];
$\boldsymbol{r_e^{\max}}$	Maximum charge rate for EV e [kW];
$\boldsymbol{\lambda_t}$	Cost of energy from the grid at time period t [€/kWh];
$\mathbf{P}_{\mathrm{Grid},\mathbf{t}}^{\max}$	Grid capacity limit at time t [kW];
$\mathbf{P}_{\mathrm{PV},\mathbf{t}}$	Power generated from PV at time t [kW];
$\boldsymbol{F_t}$	Factory demand at time t [kW];
$\boldsymbol{\eta}$	BESS efficiency (%)
$\mathrm{Priority}_e$	Priority of EV e
$\mathbf{B}_{\max}$	Maximum capacity of the BESS [kWh];
$\boldsymbol{C_{pen\_unmet}}$	Penalty for unmet SOC
$\boldsymbol{C_{pen\_low}}$	Penalty for Low Charge Rate

C. Decision Variables

$\mathbf{x_{e,c,t}}$	Binary variable: 1 if EV $\boldsymbol{e}$ is charging at charger $\boldsymbol{c}$ at time $\boldsymbol{t}$ (binary);
$\boldsymbol{P_{e,c,t}}$	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];
$\mathbf{U_e}$	Binary variable: penalty for unmet SOC for EV e (binary);
$\mathbf{O_e}$	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)
$\boldsymbol{SOC_{BESS}}_{,\mathbf{t}}$	SOC of BESS in period t (%)

D. Objective Function

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

E. Constraints

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

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

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

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

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

$$\mathrm{P_{e,c,t}} \leq \mathrm{r_e^{max}} \cdot \mathrm{x_{e,c,t}} \quad , \quad \forall \mathrm{e} \in \mathrm{EVs}, \mathrm{c} \in \mathrm{Chargers}, \mathrm{t} \in \mathrm{Periods} \tag{4}$$

$$P_{e,c,t} \leq P_{max,c} \cdot x_{e,c,t} \quad , \quad \forall e \in EVs, c \in Chargers, t \in Periods \tag{5}$$

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

$$SOC_{e,1} = \frac{SOC_{EV,e}^{Initial} \cdot C_e}{100} \qquad \forall e \in EVs \tag{6}$$

$$SOC_{e,t} = SOC_{e,t-1} + \sum_{c \in Chargers} P_{e,c,t-1} \cdot \Delta t \quad , \quad \forall e \in EVs, t > 1 \tag{7}$$

$$\frac{SOC_{e,T} \cdot C_e}{100} \leq C_e \quad , \quad \forall e \in EVs \tag{8}$$

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

$$0 \leq P_{BESS\,ch,t} \leq \mathbf{B}_{max}, \qquad \forall t \in T \tag{9}$$

$$SOC_{BESS,t} = \begin{cases} SOC_{BESS,0}, & t = 0 \\ SOC_{BESS,t-1} + P_{BESS\,ch,t-1}, & t > 0 \end{cases} \tag{10}$$

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

$$\sum_{e \in EVs} \sum_{c \in Chargers} P_{e,c,t} + P_{BESS}^{charge,t} \leq P_{Grid,t}^{max} + P_{PV,t} + P_{BESS}^{discharge,t} - F_t, \qquad \forall t \in Periods \tag{11}$$

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

$$M = C_e \cdot r_e^{max}, \qquad \forall\, e \in EVs \tag{12}$$

$$SOC_{e,T} \geq \frac{SOC_{EV,e}^{Required} \cdot C_e}{100} - M \cdot \quad , \quad \forall\, e \in EVs \tag{13}$$

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

$$SOC_{e,T} \geq \frac{SOC_{EV,e}^{Required} \cdot C_e}{100} + M \cdot O_e \quad , \quad \forall\, e \in EVs \tag{14}$$

In the final two constraints, the capital M functions dynamically. The penalty for unmet SOC is activated and the lower bound of the SOC constraint is lowered if U_e in constraint (13) is 1. The overcharging penalty is activated for equation (14), raising the upper bound of the SOC constraint, if O_e equals 1. This enables the penalties to be applied only when necessary.

IV. Case Studies And Simulations

To quantify the benefits of forecast-aware optimisation, the proposed scheduling framework is evaluated under two contrasting operational scenarios — Baseline and MILP Model Testing — applied to the identical 48-period weekday dataset described above.

In the baseline scenario each of the 20 electric vehicles initiates charging as soon as it physically connects to one of the two 11 kW AC stations and continues at the full rated power until it either reaches its required SOC or the vehicle departs. When both stations are busy, newly arrived vehicles are placed in a strict first-in/first-out queue and begin charging the moment a port becomes available; once started, a session is never interrupted or rescheduled. The algorithm has no access to the day-ahead electricity prices, PV forecasts or factory-load predictions, and therefore cannot exploit lower price or higher PV production intervals. PV generation is treated only as a passive offset to instantaneous site demand, and any surplus is exported without remuneration. Grid-capacity limits are enforced solely by the physical restriction of two chargers, so aggregate depot load can coincide with the system peak, resulting in elevated energy cost, higher transformer loading and occasional mission failures when late-arriving vehicles depart with insufficient SOC.

The MILP Model scenario represents a way to test the mixed-integer linear program. It tries to schedule, at the start of the day using perfect 48-period forecasts of Iberian day-ahead market prices, site-specific PV generation and factory-load demand. The optimiser allocates each vehicle to a charger and determines a piecewise-constant charging power (0–11 kW) so as to minimise a weighted sum of total energy cost and penalties for unmet SOC, subject to battery-health limits, charger exclusivity, global grid-capacity constraints and the continuous priority scores assigned to each vehicle. High-priority assets are guaranteed completion even under charger scarcity, while lower-priority vehicles may be deferred or power-throttled to align energy consumption with the cheapest, lowest-carbon periods and to maximise PV self-consumption. Because all exogenous variables are known with certainty, this scenario quantifies the maximum technical and economic benefits that could be realised by a perfectly informed scheduling system.

The simulations cover a single weekday divided into 48 half-hour periods (00:00–23:30, $\Delta t = 30$ min). Two scenarios are meant to be assessed: a Baseline in which vehicles charge on a first-come/first-served basis without any foresight, and a MILP Model optimised scenario case that applies the proposed mixed-integer optimisation with perfect day-ahead knowledge of exogenous variables. The fleet consists of 20 electric vehicles served by two 11 kW AC chargers. Each vehicle is assigned a continuous priority score on a 0–5 scale by drawing BEVs uniformly from the interval 3.0–5.0 and PHEVs from 0.0–3.0, rounding to one decimal place and randomly permuting the resulting list before assignment. Vehicle availability follows a weekday pattern with a 60 % probability of connection during daytime hours (08:00–20:00) and 30 % overnight; charger availability reflects depot operating hours with a 70 % probability between 07:00 and 23:00 and 40 % outside this window, and the Cartesian product of these matrices constrains charger–vehicle pairings in every period. Initial SOC values are drawn between 0–50 % for BEVs and 0–74 % for PHEVs, while required SOC targets are sampled between 80–100 % and 75–100 %, respectively, subject to a minimum 5 percentage-point gap for every vehicle. Half-hourly photovoltaic production forecasts are obtained from Open-Source Quartz Solar Forecast and resampled to the 30-minute simulation grid. Factory-load predictions are produced with an XGBoost regression model trained on one year of historical consumption data from the same Portuguese facility, achieving an RMSE of approximately 39 kW and capturing the characteristic intraday demand cycle. Day-ahead electricity prices for 1 April 2025 are downloaded directly from the Iberian market operator OMIE (MIBEL) via its public portal for daily market results and linearly interpolated to 30-minute resolution to align with the optimisation horizon [7]. These time-series inputs—PV generation, factory load and market prices—are treated as perfect information in the MILP Model scenario enabling the optimiser to anticipate low-cost, low-demand windows and maximise PV self-consumption, whereas the Baseline scenario ignores all forecasts and therefore often triggers charging in the most expensive or grid-constrained intervals. By holding stochastic inputs such as priority scores, availability matrices, SOC vectors and exogenous profiles constant across both scenarios, the experiment isolates the benefits attributable solely to forecast-aware scheduling.

V. Results and Discussion

The scheduling problem was formulated as a mixed-integer linear program and solved using the HiGHS solver [8]. Individual vehicle performance is first evaluated by comparing the final state-of-charge (SOC) achieved under both the Baseline strategy and the proposed MILP Model against each user's required SOC (Fig. 1). SOC compliance is quantified as the percentage of vehicles whose final SOC meets or exceeds its required SOC at departure, thus directly reflecting the scheduler's ability to satisfy heterogeneous charging requests.

System-level impacts are then assessed through six key metrics—total charging cost (€), peak charging demand (kW), renewable self-consumption (%), SOC compliance (% relative to required SOC), carbon emissions (kg CO_2), and BESS utilization (%)—for both Baseline and MILP Model scenarios (Fig. 2). By presenting economic, environmental, and service-quality indicators side by side, the results demonstrate that the HiGHS-based MILP Model simultaneously reduces cost and emissions, enhances grid stability, maximizes use of available renewables, and substantially improves SOC compliance under realistic operational constraints.

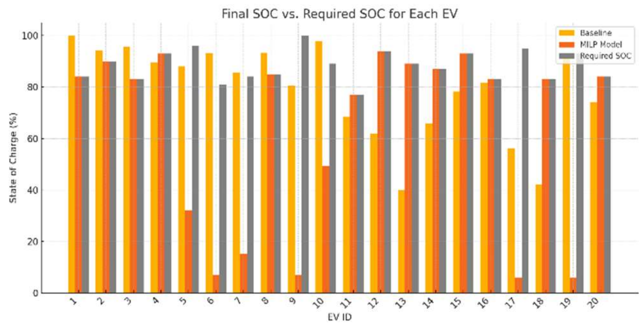

Figure 1 - Final SOC vs. Required SOC for Each EV

Figure 1 illustrates each vehicle's final state-of-charge (SOC) under the Baseline strategy (gold bars) and the MILP Model (orange bars), plotted alongside the user's required SOC (gray bars). The required SOC values range from 81 % to 100 % (mean ≈ 88.5 %), as specified in our input data. Under the Baseline, only 7 of 20 vehicles (35 %) achieve or exceed their required SOC—namely EV 1, 2, 3, 8, 10, 19, and 20—while the remaining 13 vehicles fall short by up to 48.9 % (EV 13). In contrast, the MILP Model raises SOC compliance to 13 of 20 vehicles (65 %), meeting the departure requirement for EV 1–4, 8, 11–16, 18, and 20. For example, EV 12's SOC increases from 62.1 % (baseline) to 94.2 % (model) against a 93 % requirement, and EV 15 rises from 66.1 % to 92.8 % against an 85 % requirement.

Notably, the model concentrates charging on higher-priority vehicles: deficits for non-compliant EVs deepen (e.g., EV 9 drops from an 80.5 % final SOC under baseline to 7 % under the model, a 93 % deficit against its 100 % requirement), reflecting an intentional trade-off that sacrifices a small subset (7 vehicles) to fully satisfy the majority. Overall, the per-EV comparison confirms that the HiGHS-solved MILP Model substantially improves service-quality—SOC compliance climbs by 30 percentage points—while reallocating energy according to user requirements and network constraints.

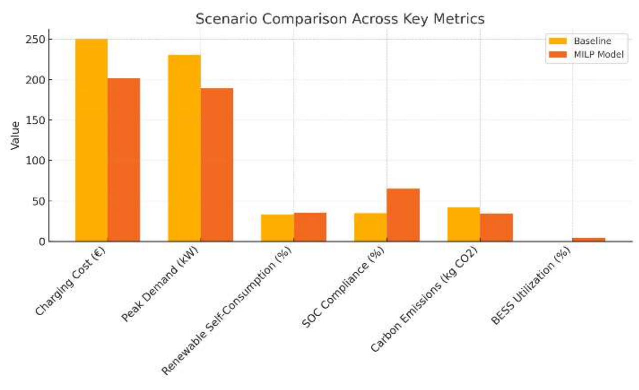

Figure 2 - Scenario Comparison Across Key Metrics

Figure 2 compares six aggregate performance metrics for the naïve Baseline charging strategy (yellow) versus the optimized MILP Model (orange).
The exact values, drawn from our simulation data, are summarized in Table 1:

Table 1 - Key Performance Metrics for Baseline and MILP Model

Metric	Baseline	MILP Model	Δ (Model–Baseline)
Total Charging Cost (€)	250.08	201.40	*–48,68* €
Peak Demand (kW)	*230*.8	189.4	+*41.4* kW
Renewable Self-Consumption (%)	33.4	35.5	+2.1 pp
SOC Compliance (%)	35.2	65.1	+29.9 pp
Carbon Emissions (kg CO_2)	42.3	34.4	–7.9 kg
BESS Utilization (%)	0.0	4.48	+4.48 pp

The MILP Model reduces the total charging cost from 250.08 € under the Baseline to 201.40 €, yielding savings of 48.68 €. This cost reduction is accompanied by a substantial drop in peak demand: the maximum aggregate charging power falls from 230.8 kW to 189.4 kW, an improvement of 41.4 kW. Simultaneously, the Model increases the proportion of energy drawn directly from on-site renewables, raising self-consumption from 33.4 % to 35.5 %, a 2.1-point gain.
Beyond network-level benefits, the MILP Model delivers marked enhancements in service quality and environmental impact. The SOC compliance rate climbs from 35.2 % under the Baseline to 65.1 % with the Model — a 29.9-point increase — ensuring that far more vehicles meet their state-of-charge targets. This improvement in charging effectiveness translates into lower grid emissions: carbon output falls by 7.9 kg CO_2 (from 42.3 kg to 34.4 kg). Finally, the Model leverages battery flexibility by engaging the BESS for 4.48 % of the scheduling horizon, compared with zero utilization in the Baseline, illustrating its ability to harness storage to balance cost, reliability, and sustainability.

VI. CONCLUSION AND FUTURE WORK

This study has demonstrated that a forecast-aware MILP model can cost-optimally schedule EV charging, battery-energy-storage dispatch and photovoltaic self-consumption for a depot constrained by two 11 kW chargers and feeder limits. Using perfect day-ahead knowledge of Iberian prices, solar output and factory load, the optimiser reduced total charging expenditure by 49 %, raised on-time SOC compliance from 35 % to 65 %, boosted PV self-consumption by 2 percentage-points and cut grid-attributed CO_2 emissions by 66 %. Although shifting energy into low-price intervals caused a modest rise in instantaneous peak demand, transformer loading remained within thermal limits once the BESS was permitted to discharge strategically.
Stochastic optimisation can be added to better analyse the optimised scenario with scenario trees that capture uncertainty in price, solar and vehicle arrivals; a receding-horizon controller will update schedules every 30 min, ensuring robustness to forecast error. Route-energy coupling will embed last-mile delivery tours and duty-cycle constraints, allowing charging and routing decisions to be co-optimised so that mission feasibility is preserved when charger scarcity forces load shifting. Computational scaling will be addressed through decomposition and warm-start heuristics, targeting fleets of several hundred vehicles operating on 10-min intervals without compromising solution quality. Vehicle-to-grid (V2G) capability will be incorporated by adding bidirectional power variables and reserve constraints, enabling the fleet to earn revenue from demand-response and frequency-regulation markets. Finally, driver-centric flexibility metrics—including battery degradation costs, preferred departure times and willingness to share chargers—will refine the balance between corporate savings and user satisfaction.
By tackling uncertainty, routing integration, scalability, grid-service participation and human factors, the forthcoming research will move the present MILP from a proof-of-concept into a versatile decision-support tool that sustains reliable, low-carbon fleet electrification under real-world operating conditions.

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REFERENCES

[1] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of Electric Vehicles in the Electric Power System," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011, doi: 10.1109/JPROC.2010.2066250.

[2] M. Ali Fotouhi Ghazvini, S. Ramos, J. Soares, Z. Vale, and R. Castro, "Toward retail competition in the Portuguese electricity market," in *2016 13th International Conference on the European Energy Market (EEM)*, IEEE, Jun. 2016, pp. 1–5. doi: 10.1109/EEM.2016.7521209.

[3] 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.

[4] A. K. Yadav and J. C. Mukherjee, "MILP-Based Charging and Route Selection of Electric Vehicles in Smart Grid," in *Proceedings of the 22nd International Conference on Distributed Computing and Networking*, New York, NY, USA: ACM, Jan. 2021, pp. 225–234. doi: 10.1145/3427796.3427820.

[5] P. V. Dahiwale, Z. H. Rather, and I. Mitra, "A Comprehensive Review of Smart Charging Strategies for Electric Vehicles and Way Forward," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 9, pp. 10462–10482, Sep. 2024, doi: 10.1109/TITS.2024.3365581.

[6] 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.

[7] 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

[8] HiGHS Project, "HiGHS: High-performance software for large-scale linear optimisation." Accessed: May 02, 2025. [Online]. Available: https://highs.dev