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A Cohort-Based Optimization Model for Electric Vehicles Charging

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Abstract: In this paper we propose a novel cohort-based dynamical model for describing the dynamics of charge of electric vehicles (EVs) entering a large EV parking/charge facility. Based on such model, we address the problem of optimally managing the charging and thus allocate power among the EVs so to minimize costs while maintaining customer satisfaction and fulfilling operational constraints. The problem is formulated as a Linear Program (LP), to be solved over a given period of time, on the basis of parameters estimated at the beginning of such period. Our approach is validated through simulations inspired by real electricity price data, demonstrating the potential for relevant cost saving compared to a First-In-First-Served (FIFS) strategy.

Keywords: Modeling for Control Optimization, Electric Vehicles, Linear Programming.

1. INTRODUCTION

The rapid rise in electric vehicle (EV) adoption has introduced significant challenges in energy management. In several countries, as it is shown in Ayoade and Longe (2024), the charging infrastructure remains insufficient in both availability and technological advancement, though its expansion is inevitable. As the number of EVs on the road continues to grow (see IEA (2024)), the demand for intelligent and scalable charging solutions becomes increasingly critical. These systems must navigate real-world complexities such as fluctuating electricity prices, unpredictable user demand, and variations in vehicle arrivals and departures. Implementing smart charging strategies is essential to efficiently manage power distribution, lower operational expenses, and facilitate the seamless integration of renewable energy sources into the electrical grid.

As global interest in smart charging has increased, most research efforts, like Deb et al. (2022), have concentrated on reducing energy demand peaks to prevent the smart grid from being overwhelmed by the expected surge in EV numbers within urban areas (Green Car Congress (2024)). In Crozier et al. (2020), a convex optimization approach for smart charging is introduced, demonstrating that, in a case study of Great Britain, it can eliminate the necessity for additional infrastructure to accommodate a full transition to EVs while also lowering the percentage of distribution networks requiring reinforcement from 28% to 9%. The charging station placement problem has been tackled by some works like Padmanabhan et al. (2022). This study proposes a deep reinforcement learning approach to determine optimal locations for public EV charging stations. By analyzing traffic density, EV registration data, and proximity to public infrastructure, the model predicts charging demand and suggests the best station locations, improving network efficiency.

Other research efforts focus on improving cost efficiency in the management of EV charging within charging stations, enforcing a business point of view. In Ambrosino et al. (2024), the authors formulate a discrete-time optimization problem to efficiently distribute the available power within a charging station while minimizing operational expenses. Their model achieves sizable cost-savings compared to standard algorithms, by intelligently selecting the time interval and EV to charge in order to minimize the operational costs associated with purchasing electricity from the power grid by the charging station. In Tran et al. (2024), the authors present a robust optimization model designed to balance cost efficiency with fast charging demands. Their approach integrates L2-norm uncertainty into the charging cost formulation, ensuring that the optimization framework remains effective even under fluctuating cost conditions. Similarly, Liu et al. (2021) explores intelligent resource allocation and adaptive scheduling adjustments, enhancing efficiency and reducing costs through a bi-level programming (BP) framework. A scheduling model to minimize the cost of charging EVs, while maintaining the satisfaction of the owners, is formulated in Sun et al. (2020), using a linear power flow approximation. By modeling user's behaviors and other factors, the optimization schedule minimizes overall cost but does not guarantee a lowest cost of each individual vehicle.

Among the various uncertain factors in EV charging management, both energy prices and the behavior of vehicles entering and leaving the charging station at different time instances must be considered. There is a branch of literature on forecasting spot energy prices, utilizing methods such as time-series models and neural networks,

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as discussed for example by Lehna et al. (2022). For what concerns EVs behavior, one of the main points is dealing with the EVs arrival times. Poisson processes, including non-stationary variants, are commonly employed to model the arrival patterns of EVs in this context, see, e.g., Li (2022).

Smart charging will inevitably need to integrate aspects related to clean and renewable energy sources. In Akbari-Dibavar et al. (2021), the authors consider the problem of managing a hybrid charging station integrated with the photovoltaic system, with uncertain parameters such as market price and load demand. Their two-stage stochastic linear programming model, in which the decision-maker adjusts the conservatism level, is risk-constrained. According to the robust optimization, the day-ahead market price uncertainty increases the total expected cost by about 8.9%. In return, the risk of scheduling is reduced significantly with the risk-averse strategy. Chandra Mouli et al. (2016) also explore the integration of photovoltaic (PV) energy into EV charging stations to reduce grid dependency in a case study in Netherlands. Simulations using real-world solar radiation data demonstrate that integrating PV and storage can significantly enhance charging station sustainability. Other interesting innovative solutions have been investigated for example by Leiding (2021), which proposed a decentralized self-organized charging model where semi-autonomous EVs can independently access public or private charging infrastructure, by leveraging blockchain-based smart contracts.

In this paper, we propose a smart charging optimization framework that dynamically allocates power based on real-time conditions. Unlike most existing models that optimize charging schedules at the individual vehicle level, our approach introduces a cohort-based formulation, grouping EVs into classes based on their charging needs. This aggregation enables a more structured and scalable representation of the system, simplifying decision-making while maintaining the fundamental goal of efficiently charging EVs. By grouping EVs into cohorts instead of managing them individually, our model lowers computational complexity and enhances practicality for large-scale charging infrastructures. Unlike prior studies that optimize a single KPI, our multi-objective framework aims to minimize simultaneously costs, ensures customer satisfaction, and safeguards grid stability by mitigating overload risks.

The model setup is defined in Section 2, where we also introduce a state-space representation to capture the evolution of vehicle charging states over time. In Section 3 we introduce out proposed optimization model defining the objective function, variables and constraints. The goal is to minimize the charging cost from the charging station's perspective, while ensuring a satisfying charge is delivered to vehicles. In Section 4 we perform simulations of our optimization model, and to benchmark the effectiveness of our approach we compare it with a First-In-First-Served (FIFS) method, a widely used yet suboptimal charging strategy. Section 5 concludes the paper by giving some key insights on the proposed optimization approach and suggesting research directions that could be explored in the future.

2. MODEL SETUP

2.1 Charging Station Setup

We consider a defined area, such as an EVs parking lot, where vehicles can arrive, park for charging or remain in standby mode, and eventually leave. The system operates over discrete time instants, denoted as $t = 0, 1, 2, \ldots, T$, which are separated by a fixed interval of time Δ, for example, five minutes. Each time interval is represented as $[t\Delta, (t+1)\Delta)$, during which the number of vehicles present in the lot remains unchanged. Vehicles are allowed to enter or exit only at the boundaries of these time intervals, ensuring that the parking lot's state is updated in discrete steps.

The charging infrastructure consists of multiple charging ports, each delivering a constant power level, denoted as P_0, across all available plugs. The total power capacity allocated to the parking lot at time t is represented by $\bar{P}(t)$, which is assumed to remain constant throughout the corresponding time interval $[t\Delta, (t+1)\Delta)$.

2.2 Class Definition

Upon arrival, each vehicle declares its energy requirement based on its state-of-charge (SOC) and the desired final SOC. From this information, the total energy E needed is computed and converted into the corresponding number of charging cycles. This transformation accounts for potential rounding approximations and determines the number of discrete time intervals for which the vehicle should be actively charging. The number of charging cycles required by a vehicle is given by

$$i = \min\left(\lfloor E/(\Delta P_0) \rfloor, n\right),$$

where n represents the maximum allowable charging cycles for any single vehicle. Accordingly, as it is shown for example in Figure 1, each vehicle is categorized into a class, identified by an integer $i = 0, \ldots, n$, that specifies its charging demand. We will look at the EVs in an aggregate way instead of considering them individually.

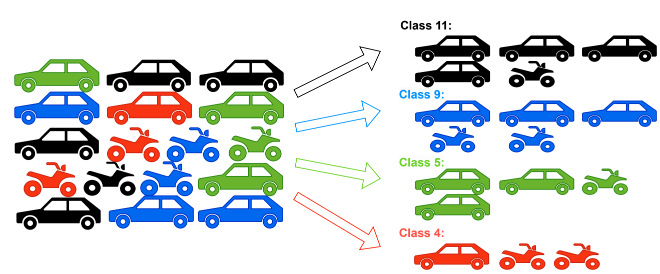

Fig. 1. Example of EVs arrival and suddivision in classes.

The number of vehicles of class i attempting to enter the lot during the interval $[t\Delta, (t+1)\Delta)$ is denoted as $a_i(t)$. These vehicles officially become part of the lot's occupancy at time $t+1$. Similarly, the number of vehicles of type i intending to leave the lot during the same interval is given by $d_i(t)$. These vehicles will exit the lot at instant $t+1$, regardless of whether they were charging or in standby mode during the interval $[t\Delta, (t+1)\Delta)$.

2.3 Variable Definitions

At any given time t, the total number of vehicles of type i present in the lot is represented by $x_i(t)$. A subset of these vehicles are actively charging, denoted by $c_i(t)$, which clearly must satisfy the condition $0 \le c_i(t) \le x_i(t)$. The remaining idle vehicles (in standby mode), which are parked but not currently charging regardless of their class i, are described by the quantity

$$I_i(t) = x_i(t) - c_i(t).$$

These definitions provide the foundation for the linear programming (LP) model that follows, capturing the system's state evolution, power constraints, and optimal charging strategy. The objective of the optimization model is to determine an efficient power allocation policy that minimizes operational costs while ensuring fairness and high customer satisfaction.

2.4 State-space model dynamics

We next write a discrete time model for the state $x(t)$ of the system:

$$x(t) = \begin{bmatrix} x_0(t) \\ x_1(t) \\ \vdots \\ x_n(t) \end{bmatrix} \tag{1}$$

having $a(t) = (a_0(t), \ldots, a_n(t))$ as input signal and $c(t) = (c_0(t), \ldots, c_n(t))$ as command (decision) signal. Assuming also $d(t) = (d_0(t), \ldots, d_n(t))$ is assigned, the key recursion is written for $i = 0, \ldots, n$ and $t = 0, \ldots, T-1$ as

$$\begin{aligned} x_i(t+1) &= I_i(t) + c_{i+1}(t) + a_i(t) - d_i(t) \\ &= x_i(t) + (c_{i+1}(t) - c_i(t)) + (a_i(t) - d_i(t)) \end{aligned} \tag{2}$$

where $c_0(t) = 0$ for all t, and $0 \le c_i(t) \le x_i(t)$ for all t and all i.

We next express the departures, for each vehicle class, as a fraction of the number of vehicles of that class, that is, we let $d_i(t) = \alpha_i(t)x_i(t), \quad i = 0, \ldots, n, \quad t = 0, 1, \ldots, T-1$, where $\alpha_i(t) \in [0, 1]$ denotes the departure rate for the ith class at t. Plugging $d_i(t)$ into (2), we obtain for $t = 0, 1, \ldots, T-1$:

$$x_i(t+1) = (1 - \alpha_i(t))x_i(t) + (c_{i+1}(t) - c_i(t)) + a_i(t). \tag{3}$$

The evolution of the system is thus governed by the linear time-varying equations:

$$x(t+1) = A(t)x(t) + a(t) + Bc(t), \quad t = 0, 1, \ldots, T-1 \tag{4}$$

where

$$A(t) = I - \mathrm{diag}(\alpha(t)), \quad B = \begin{bmatrix} -1 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 1 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & -1 & 1 \\ 0 & \cdots & \cdots & 0 & -1 \end{bmatrix}. \tag{5}$$

3. OPTIMIZATION PROBLEM

The total power required for charging at t is

$$P(t) = P_0 \sum_i c_i(t) = P_0 \mathbf{1}^T c(t), \tag{6}$$

The total energy delivered to vehicles during the t-th period is $E(t) = \Delta P(t)$. Letting $\pi_t \ge 0$ denote the price per unit energy drawn from the power network during period t, we have that the overall cost over a horizon from 0 to T is

$$\Upsilon_T = \sum_{t=0}^{T-1} \pi_t E(t). \tag{7}$$

For customer satisfaction, we aim at making the number of vehicles with large needed residual charge as small as possible. Defining

$$\beta_0 \le \beta_1 \le \beta_2 \le \cdots \le \beta_n, \quad \beta = (\beta_0, \ldots, \beta_n),$$

the overall dissatisfaction of customers is assumed to be expressed by

$$S_T \doteq \sum_{t=0}^{T-1} \beta^T x(t). \tag{8}$$

One possibility, for example, is to take simply $\beta = (0, 1, \ldots, 1)$, so to penalize all vehicles who did not receive a full charge. The tuning and choice of proper values for β depends on the specific case of use and tradeoff preferences.

The optimization objective to be minimized is here taken as a tradeoff of energy cost and customer dissatisfaction:

$$J_T \doteq \Upsilon_T + \gamma S_T, \tag{9}$$

where $\gamma \ge 0$ is some tradeoff parameter.

Letting $\mathcal{T} \doteq \{0, \ldots, T-1\}$, and organizing the problem variables in matrix/vector format as

$$\begin{aligned} C &= [c(0) \cdots c(T-1)] \in \mathbb{R}^{(n+1)\times T}, \\ X &= [x(1) \cdots x(T)] \in \mathbb{R}^{(n+1)\times T}. \end{aligned}$$

the smart charging optimization problem can be cast as the following Linear Program (LP)

$$\begin{aligned} \bar{p} = \min_{C,X} & \sum_{t=0}^{T-1} \pi_t \Delta P_0 \mathbf{1}^\top c(t) + \gamma \sum_{t=0}^{T-1} \beta^\top x(t) \\ \text{s.t.} \quad & 0 \le P_0 \mathbf{1}^\top c(t) \le \bar{P}, \quad t \in \mathcal{T}, \\ & 0 \le c(t) \le x(t), \quad t \in \mathcal{T}, \\ & x(t+1) = A(t)x(t) + a(t) + Bc(t), \quad t \in \mathcal{T}. \end{aligned} \tag{10}$$

The objective function minimizes the total energy cost, represented by the weighted sum of energy prices π_t, while also incorporating customer satisfaction through a penalty term weighted by γ. The first constraint ensures that the total charging power does not exceed the available power at the plant, the second ensures that charging does not exceed available vehicles, and the last one describes the system's state evolution based on arrivals, departures, and charging decisions.

The optimal solutions $c^*(t)$ and $x^*(t)$ derived from the optimization problem in Equation (10) are positive due to the imposed constraints. However, they are not necessarily restricted to integer values, even though they represent the number of physical EVs and should ideally be positive integers. Therefore, an appropriate rounding to integer values like

$$\begin{aligned} c_i^r(t) &= \lfloor c_i^*(t) + 0.5 \rfloor, \quad i = 0, 1, \ldots, n, \quad t \in \mathcal{T}, \\ x_i^r(t) &= \lfloor x_i^*(t) + 0.5 \rfloor, \quad i = 0, 1, \ldots, n, \quad t \in \mathcal{T}. \end{aligned} \tag{11}$$

must be applied afterward, ensuring that the constraint $0 \le c^r(t) \le x^r(t)$ remains satisfied by construction.

4. NUMERICAL SIMULATIONS

To evaluate the effectiveness of the proposed smart charging strategy, we implemented a simulation framework in MATLAB. We employed the MOSEK solver (MOSEK ApS (2025)), through the CVX modeling toolbox, to solve the linear programming (LP) problem in Equation (10). MOSEK was selected for its robustness and efficiency in handling large-scale linear programs, especially under dense constraints.

4.1 Parameters Setup

The system models 11 vehicle classes (therefore $n = 10$) depending on the EV's State of Charge (SoC) at their arrival. Class index i goes from 0, meaning fully charged EV, to n, meaning EV with 0% SoC. We simulate a time horizon of $T = 24$ hours with discrete time steps of duration $\Delta = 10$ minutes, resulting in a total of 144 discrete time steps. The charging station delivers a constant power of $P_0 = 22$ kW per socket, with a total station capacity fixed and limited to $\bar{P}(t) = 3300$ kW, $\forall t$. Customer satisfaction is incorporated into the model through the vector $\beta \in \mathbb{R}^{n+1}$, set to $\beta_0 = 0, \beta_i = 1, \forall i = 1, \dots, n$. The trade-off between maximizing revenue and improving customer satisfaction is controlled by the parameter γ, which after a proper calibration is set equal to 9 in our next simulations.

The electricity price data is based on historical values from the Italian market (see EMBER (2025)) and measured in €/kWh, loaded into the simulation as a time-series vector. Historical data were collected on hourly basis for a total of 456 consecutive days, from 1-Jan-2023 to 31-Mar-2024. Given the time resolution of the simulation, the hourly mean prices were interpolated ensuring a smooth time series representation at the defined granularity of 10-minutes time step. The covariance matrix between the 456 different electricity price realizations is also computed, assuming the prices follow a multivariate normal (Gaussian) distribution.

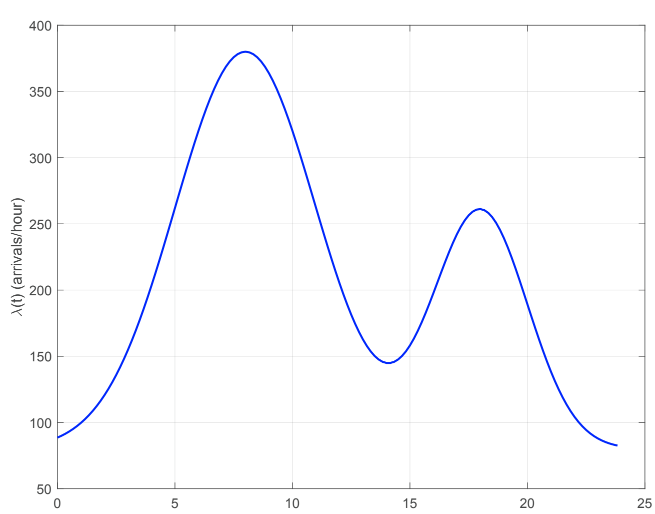

Fig. 2. Time-dependent parameter $\lambda(t)$ of the Poisson arrival process during one day (24 hours).

Vehicle arrivals were assumed to follow a non-stationary Poisson process with a time-dependent rate $\lambda(t)$ per hour as shown in Figure 2. The EVs arrival pattern has basically two peaks: the first one at 8 a.m., representing people who leave the vehicle and go to work in the morning, and the second one at 6 p.m., representing people who get off from work and get to charge before coming back home. The arriving vehicles were classified into the $n = 10$ charging demand classes. The proportions of vehicles in each class were fixed at each time step, and set to increasing values from class 1 to 10, assuming no EVs arrives fully charged (i.e. of class 0). Specifically, the proportions of arriving EVs, denoted as z_i were defined as

$$z_0 = 0, \quad z_i = \frac{i+1}{\sum_{j=1}^{n}(j+1)}, \quad i = 1, \dots, n. \tag{12}$$

The effective number $a_i(t)$ of EVs arriving at each time step and for each class is now computed as:

$$a_i(t) = \lfloor z_i \cdot \Delta \cdot \psi(t) + 0.5 \rfloor, \quad i = 0, 1, \dots, n, \quad t \in \mathcal{T}, \tag{13}$$

where $\psi(t)$ is a realization of a Poisson-distributed random variable with mean $\lambda(t)$, that is $\psi(t) \sim \text{Poisson}(\lambda(t))$.

Departures are computed in a deterministic way, not depending on time, with each vehicle in class i having a class-dependent likelihood α_i of leaving the station at any given discrete time t, following a decreasing sequence that prioritizes longer stays for higher-demand vehicles. Since the optimization model is an aggregate model, there is actually no information about any precise vehicle leaving, but there is the notion about how many vehicles of each class has left. The values used in the simulations were

$$\alpha_i = \frac{n+1-i}{n+2}, \quad i = 0, 1, \dots, n. \tag{14}$$

The system evolution follows the recursive update equation seen in (4) that accounts for arrivals, departures, and vehicles transitioning between classes as they receive charge.

4.2 Results

To benchmark the optimization model, we implemented a First-In-First-Served (FIFS) strategy. In this approach, vehicles are charged in the order they arrive and remain in charge until they either reach full capacity or depart. In the event of simultaneous arrivals, higher classes are prioritized. If the total available power is insufficient, newly arriving vehicles must wait until charging slots become available. The arrivals for the FIFS model are the same as the ones for the optimal model, and vehicle in class i has the same probability α_i of leaving the charging station at any given time t. Here, there will be information about which specific vehicle has left the charging station, and furthermore the presence matrix X_{fifs} may be slightly different with respect to X of the optimal model, because they depend respectively on the (probably different) charging strategies C_{fifs} and C.

Figure 3 presents the (rounded) model outputs obtained by simulating the electricity cost as the average over 456 days from the Italian dataset introduced earlier (see the top panel in Figure 4). The shape and total number of EVs charging depend on both the electricity price and the number of EVs inside the charging station.

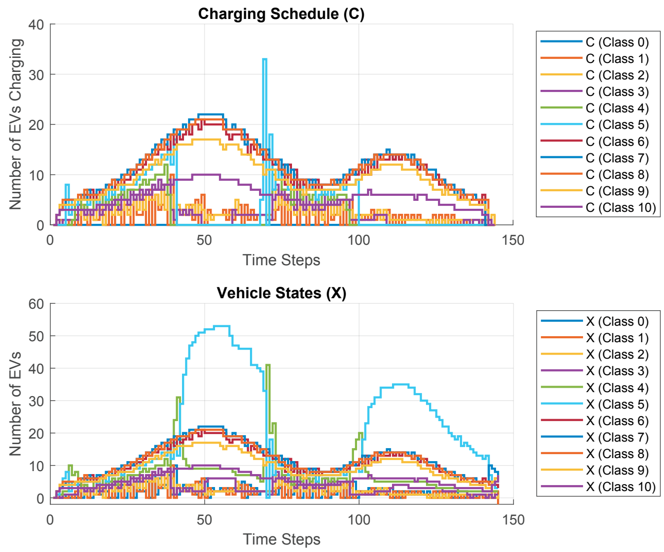

Fig. 3. Top panel: stairs plot of $c_i^r(t)$. Bottom panel: stairs plot of $x_i^r(t)$

The algorithm promotes vehicles to transition from higher to lower classes (which happens by charging them), and tends to optimally delay charge so that it happens more intensely in the periods where the electricity cost is lower. This becomes particularly clear when considering the percentage of EVs being charged at each time step. Given that we have fixed $P_0 = 22$ kW, having around 50 EVs during low-cost energy periods (see top panel in Figure 4) means that the charging station, operating at full capacity, reaches 1100 kW, as shown in the bottom panel of Figure 4, by putting all present vehicles in charge. Conversely, during high-cost periods, which also coincide with a higher number of EVs in the station (see mid panel always in Figure 4), the optimal model significantly reduces the number of vehicles being charged compared to the FIFS approach, thus protecting the smart grid and substantially lowering costs.

The main objective of the optimization model in (10) is to minimize charging costs, which it achieves by smoothing out power consumption, avoiding unnecessary peaks, and shifting charging loads to more cost-effective periods. The optimal model effectively reduces power peaks and follows a cost-aware allocation, making it more efficient and economically viable compared to the FIFS model, which allocates power more aggressively without considering price variations. In this specific simulation, the average electricity price among all the 456 days in the dataset is used, as well as the mean Poisson value $\lambda(t)$ for the total number of EVs arrival at time t. The optimization model achieves a cost saving of 19.55% compared to the FIFS strategy in this setting.

4.3 Multiple Scenarios Results

To better evaluate the effectiveness of our optimization model and assess its robustness against different realizations of electricity prices, we performed the simulation $N = 100$ times, solving problem (10) 100 times, each time using a different realization of the price vector π. Each price vector was simulated according to a multivariate

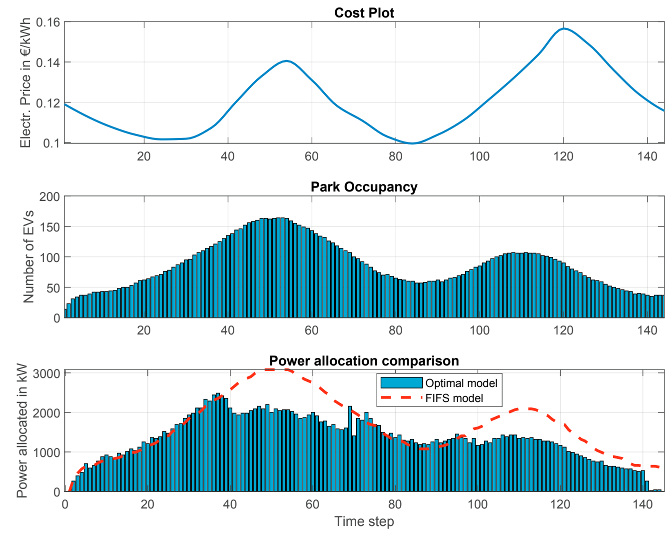

Fig. 4. Top panel: mean value of electricity price in time. Mid panel: EVs presence in time. Bottom panel: power allocation comparison.

Gaussian distribution, with mean vector and covariance matrix computed from the 456 data vectors available in the Italian electricity price database introduced before. The average cost-saving achieved by applying our smart charging model is 19.29% compared to the FIFS approach, and the daily results obtained are reported in Table 1.

	Optimal Model	FIFS Model
Average Daily Cost	22277€	28746€
Standard Dev Daily Cost	1800.5€	6696.8€
Average Leaving Class	4.99	4.62
Standard Dev Leaving Class	0.31	0.01

Table 1. Simulations results across 100 different simulations.

Customer satisfaction is evaluated by computing the average class of vehicles leaving the charging station, as this metric indirectly represents somehow the distance from maximum satisfaction. In our simulation settings, the FIFS approach results in an average leaving class of 4.62 with a standard deviation of 0.01 (since FIFS is not affected by energy price variations). In contrast, the optimization model achieves an average leaving class of 4.99 with a standard deviation of 0.31, while significantly reducing daily costs. Indeed, the FIFS model results in an average daily cost of 28,746 €, whereas our optimization model reduces this to 22,277 €, demonstrating the economic efficiency of this smarter approach.

5. CONCLUSIONS

This paper presents an optimization framework for smart EV charging, addressing the dual objectives of cost minimization and customer satisfaction. By formulating the scheduling problem as a Linear Program (LP), our cohort-based approach dynamically allocates power to vehicles while adapting to electricity price variations and naturally mitigating energy demand peaks.

Simulation results demonstrate that our optimization model achieves a cost reduction of 19.29% compared to a standard First-In-First-Served (FIFS) approach, keeping a customer satisfaction very close to the FIFS. Another key advantage of our approach is its ability to reduce peak-hour energy consumption, making the proposed strategy well-suited for real-world applications where electricity prices fluctuate over time and are difficult to predict.

Future research on this topic includes the integration of renewable energy sources, such as photovoltaic (PV) panels, as an additional resource for the charging station to power EVs. Such an approach would further emphasize the transition towards a green economy, aligning with the core objective of smart charging.

In the simulations conducted for this paper, we considered different electricity price scenarios. The proposed optimization model could be further improved by incorporating robust optimization techniques to account for additional uncertain factors, such as uncertainties in vehicle arrivals and departures, which are typically among the most challenging aspects to predict in real-world applications. Also, in practice, the approach described here shall be deployed in a dynamic way based on a sliding-horizon approach in which the optimization problem is repeatedly solved at each time step over a forward.sliding horizon. Such a robust dynamic approach is the subject of ongoing research.

REFERENCES

Akbari-Dibavar, A., Tabar, V.S., Zadeh, S.G., and Nourollahi, R. (2021). Two-stage robust energy management of a hybrid charging station integrated with the photovoltaic system. *International Journal of Hydrogen Energy*, 46(24), 12701–12714.

Ambrosino, L., Calafiore, G., Nguyen, K.M., Zorgati, R., Nguyen-Ngoc, D., and El Ghaoui, L. (2024). Optimizing electric vehicles charging through smart energy allocation and cost-saving. In *Book of Proceedings ESCC 2024*, 59–64. URL `http://escc.uth.gr/wp-content/uploads/2025/01/ESCC_2024-Book-of-Proceedings.pdf`.

Ayoade, I.A. and Longe, O.M. (2024). A comprehensive review on smart electromobility charging infrastructure. *World Electric Vehicle Journal*, 15(7). doi:10.3390/wevj15070286. URL `https://www.mdpi.com/2032-6653/15/7/286`.

Chandra Mouli, G.R., Bauer, P., and Zeman, M. (2016). System design for a solar powered electric vehicle charging station for workplaces. *Applied Energy*, 168, 434–443. doi:10.1016/j.apenergy.2016.01.110.

Crozier, C., Morstyn, T., and McCulloch, M. (2020). The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems. *Applied Energy*, 268, 114973. doi:https://doi.org/10.1016/j.apenergy.2020.114973. URL `https://www.sciencedirect.com/science/article/pii/S0306261920304852`.

Deb, S., Pihlatie, M., and Al-Saadi, M. (2022). Smart charging: A comprehensive review. *IEEE Access*, 10, 134690–134703. doi:10.1109/ACCESS.2022.3227630.

EMBER (2025). European wholesale electricity price data. URL `https://ember-climate.org/data-catalogue/european-wholesale-electricity-price-data/`.

Green Car Congress (2024). Rho motion: Europe slowest growing region for ev sales in 1h; global battery demand increases 23 URL `https://www.greencarcongress.com/2024/07/20240712-rho.html`.

IEA (2024). Global ev outlook 2024. URL `https://www.iea.org/reports/global-ev-outlook-2024`.

Lehna, M., Scheller, F., and Herwartz, H. (2022). Forecasting day-ahead electricity prices: A comparison of time series and neural network models taking external regressors into account. *Energy Economics*, 106, 105742. doi:10.1016/j.eneco.2021.105742. URL `http://dx.doi.org/10.1016/j.eneco.2021.105742`.

Leiding, B. (2021). Come back when you are charged! self-organized charging for electric vehicles. URL `https://arxiv.org/abs/2106.11025`.

Li, B. (2022). Stochastic modeling and adaptive forecasting for parking space availability with drivers' time-varying arrival/departure behavior. *Transportation Research Part B: Methodological*, 166, 313–332. doi:https://doi.org/10.1016/j.trb.2022.10.014. URL `https://www.sciencedirect.com/science/article/pii/S0191261522001801`.

Liu, J., Lin, G., Huang, S., Zhou, Y., Li, Y., and Rehtanz, C. (2021). Optimal ev charging scheduling by considering the limited number of chargers. *IEEE Transactions on Transportation Electrification*, 7(3), 1112–1122. doi:10.1109/tte.2020.3033995. URL `http://dx.doi.org/10.1109/TTE.2020.3033995`.

MOSEK ApS (2025). Mosek optimization toolbox. `https://www.mosek.com/`. Accessed: April 2025.

Padmanabhan, S., Petratos, A., Ting, A., Zhou, K., Hageman, D., Pisel, J.R., and Pyrcz, M.J. (2022). Optimal placement of public electric vehicle charging stations using deep reinforcement learning. URL `https://arxiv.org/abs/2108.07772`.

Sun, W., Neumann, F., and Harrison, G.P. (2020). Robust scheduling of electric vehicle charging in LV distribution networks under uncertainty. *IEEE Transactions on Industry Applications*, 56(5), 5785–5795.

Tran, T.D., Nguyen, N.D., Chu, H.T.M., Ghaoui, L.E., Calafiore, G., and Ambrosino, L. (2024). A robust optimization model for cost-efficient and fast electric vehicle charging with l2-norm uncertainty. In *Book of Proceedings OIC 2024*, 208–216. URL `https://drive.google.com/file/d/18Ji52b5LiX9ITvm5r5q4xsol0s8im9AU/view`.