A Cost-Optimization Model for EV Charging Stations Utilizing Solar Energy and Variable Pricing

An The Nguyen
College of Engineering and Computer Science, VinUniversity

Hung Tuan Pham
College of Engineering and Computer Science, VinUniversity

Cuong Do
College of Engineering and Computer Science, VinUniversity
Center for Environmental Intelligence (CEI), VinUniversity

Abstract

This paper presents a cost-optimization model for electric vehicle (EV) charging stations that integrates on-site solar energy generation. The model aims to minimize electricity costs and balance supply and demand by considering hourly variations in electricity prices and solar energy availability. We employ a linear programming approach with a robust optimization framework to address uncertainty in electricity prices using the Bertsimas–Sim methodology. The model determines the optimal charging schedule for EVs while satisfying energy requirements, power limits, and grid capacity constraints. It is compared against the traditional First-Come, First-Served (FCFS) strategy. Our results demonstrate over 30% cost savings in the best scenario and reduced grid dependence through the integration of solar energy and risk-aware scheduling, highlighting the potential for sustainable and cost-effective EV charging infrastructure.

I. Introduction

Climate change is one of the greatest challenges of our time, and Vietnam's commitment to achieving net-zero emissions by 2050 [1] underscores the nation's determination to play a leadership role in global sustainability. However, realizing this vision requires tackling significant hurdles—particularly in the transport sector, which currently accounts for about 10.8% of total emissions and is projected to increase its CO_2 output by 6–7% annually [2]. Accelerating the adoption of electric vehicles (EVs) has emerged as a pivotal strategy to curb these emissions and mitigate the impact of a rapidly expanding transport sector [3].

A key indicator of Vietnam's EV momentum is the rise of VinFast, the country's first domestic EV manufacturer. Launched in late 2021, VinFast quickly established its inaugural line of electric cars and, by 2024, had sold over 51,000 vehicles [4, 5]. While this rapid growth reflects strong consumer demand and technological promise, it also exposes critical infrastructure gaps. Insufficient charging stations [6] and an aging urban grid system, already under strain, threaten to stall progress and reduce the overall effectiveness of EVs in cutting emissions. To address these obstacles and sustain EV growth, Vietnam must make substantial investments in renewable energy, especially solar, which can help meet surging electricity demands while advancing the nation's net-zero ambition [7].

Smart Charging is a compelling research topic with numerous subproblems that many researchers are actively addressing. These subproblems include Demand Forecasting, Charging Schedule Optimization, Power Allocation, Charging Infrastructure and Grid Connection, Communication and Payment, and Security and Privacy. Various advanced methodologies have been applied to tackle these challenges.

In [8], a hybrid model combining Deep Reinforcement Learning (DRL) with the Quantum-Inspired Genetic Algorithm (QIGA) was proposed to address the Optimal Power Flow (OPF) problem in hybrid renewable energy systems. In [9], a quadratic programming and convex problem formulation approach was introduced for smart charging in a single household equipped with an electric vehicle and an energy storage system. Linear Programming and Robust Optimization were employed in [10] to handle uncertainties in electricity prices and energy demand. In [11], the mean clustering algorithm and queuing theory were utilized to determine the optimal location and capacity of charging stations.

We propose a cost-optimization model that integrates on-site renewable solar energy at the charging station, incorporating hourly variations in electricity prices and solar energy availability. Our technique is leveraging Linear Programming, a mathematical optimization technique used to achieve the best outcome (in our case is minimizing cost) in a given mathematical model. It involves a linear objective function and a set of linear constraints that define the feasible region. The subsequent sections of this paper include the symbols and parameters, complete optimization model, simulation results and discussion, conclusion and future work.

II. Symbols and Parameters

- T: Number of time steps in a day (e.g., $T = 24$ hours).
- Δt: Length of each time step (hours).
- N: Number of electric vehicles (EVs).
- p_t^{grid}: Electricity price from the grid at time t (Euro/kWh).
- R_t: Solar energy output at time t (kW).
- $\bar{R}_t$: Maximum achievable solar energy output at time t (kW).
- s_i: Maximum charging power provided by the charging station for EV i (kW).
- $A_{t,i}$: Matrix representing the charging time of vehicle i by hour.
- C_{grid}: Grid capacity limit (kW).
- η: Charging efficiency of the EV (in the range $(0, 1]$).
- L_i: Minimum required energy (kWh) that EV i needs when leaving the station.
- $\mathcal{T}_i$: Set of time points when EV i is present at the station (based on $A_{t,i}$).

III. Model Formulation

Several straightforward solutions have been considered for managing EV charging, such as the "First Come, First Served" (FCFS) principle, which guarantees equity by servicing vehicles in the sequence of their arrival. However, FCFS lacks consideration of critical factors such as electricity pricing, real-time energy demand, and overall impact on the power grid. This limitation can lead to inefficient energy allocation, increased operational costs, and potential grid instability, especially during peak demand periods.

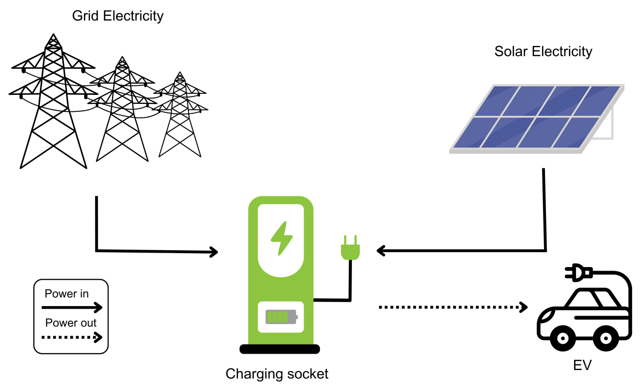

Figure 1: On-Site Solar-Integrated Charging Station Model

Figure 1 illustrates the power flow diagram of charging stations with solar-integrated. The charging socket receives energy from both the solar panel and the grid, and then delivers it to the EVs. In this model, we employ a Linear Programming approach to minimize net electricity consumption costs, which occur only when the charging demand exceeds the available solar renewable energy.

Decision Variables:

- $Y_{i,t} \geq 0$: Charging power (kW) of EV i at time t.
- $S_t^+ \geq 0$: Auxiliary variable representing the positive part of the net load at time t, that is:

$$S_t^+ = \max\Big\{\sum_{i=1}^{N} Y_{i,t} - R_t,\ 0\Big\}.$$

- R_t: The amount of solar energy used at time t.

Objective Function:

$$\min_{Y,\, S^+,\, R} \quad \sum_{t=1}^{T} p_t^{\text{grid}}\, S_t^+\, \Delta t,$$

where S_t^+ is used to linearize the expression $\big(\sum_{i=1}^{N} Y_{i,t} - R_t\big)$.

The solar contribution R_t is computed as follows:

$$R_t = A_{\text{pv}} \frac{G(t)}{1000} \eta_{\text{pv}},$$

where:

- A_{pv} indicates the area of the PV panels in m^2,
- $G(t)$ indicates the solar irradiance in W/m^2,
- η_{pv} is the efficiency of the PV panels.

Constraints:

1. Each EV i must be charged with at least the minimum required energy L_i throughout its available period $\mathcal{T}_i$. Here, η is the charging efficiency, $Y_{i,t}$ is the charging power at time t, and Δt is the length of each time interval. This requirement can be expressed as:

$$\eta \sum_{t \in \mathcal{T}_i} Y_{i,t}\, \Delta t \geq L_i, \quad \forall i.$$

2. The charging power of each EV at time t must not exceed the maximum power limit s_i that the station provides. However, the actual available power is scaled by the fraction of the time interval during which EV i is connected, denoted by $A_{t,i}$. For example, if the EV is connected only for 10 minutes in an hour (i.e., $A_{t,i} = \frac{10}{60}$), then the maximum available charging power becomes $s_i \times \frac{10}{60}$. When the EV is not connected (i.e., $A_{t,i} = 0$), no charging power is provided, ensuring that $Y_{i,t} = 0$. This is modeled by:

$$Y_{i,t} \leq s_i\, A_{t,i}, \quad \forall i, \forall t.$$

3. The total charging power from all EVs at time t must not exceed the maximum grid capacity C_{grid} after subtracting the renewable energy R_t:

$$\sum_{i=1}^{N} Y_{i,t} - R_t \leq C_{\text{grid}}, \quad \forall t.$$

4. The variable S_t^+ represents the additional power to be purchased from the grid if the total charging power exceeds R_t. When renewable energy sufficiently supplies the EVs, S_t^+ may be zero. It is ensured that the power purchased from the grid cannot be negative:

$$S_t^+ \geq 0, \quad \forall t.$$

5. Finally, the solar energy R_t cannot exceed its maximum available limit $\bar{R}_t$ at each time and it must larger or equal than 0

$$0 \leq R_t \leq \bar{R}_t, \quad \forall\, t.$$

Database:

We obtained detailed charging session information from 2018 to 2019 from ACN Data—a public dataset on electric vehicle (EV) charging collected through a collaboration between the PowerFlex System and the California Institute of Technology (Caltech) [12]. This dataset comprises detailed information on EV charging sessions at two distinct locations: the Caltech campus and the Jet Propulsion Laboratory (JPL) campus. The JPL site is representative of workplace charging, whereas Caltech represents a hybrid of workplace and public charging.

We selected hourly electricity price data for Spain corresponding to the same period as the charging data, sourced from Ember—European Wholesale Electricity Price Data [13].

Hourly irradiance data were obtained from the EU Science Hub [14] for the same period. We assume that G_t represents $G(i)$ [W/m^2]—the global in-plane irradiance with a slope of 36° and an azimuth of 0°—with Madrid, Spain, chosen as the representative location.

Table I: Constant values

Parameter	**Value**
C_{grid}	300 kW
η	0.9
η_{pv}	0.2
A_{pv}	80 m^2
s_i (Caltech)	86 kW
s_i (JPL)	37.5 kW

IV. Robust Optimization

To account for uncertainty in the electricity price, we model the grid price at time t as

$$p_t^{\text{grid}} = \hat{p}_t + \Delta p_t,$$

where $\hat{p}_t$ is the nominal electricity price and Δp_t represents the deviation from this nominal value. We assume that the deviation is bounded as

$$|\Delta p_t| \leq \overline{\Delta p}_t, \quad \forall t.$$

To avoid an overly conservative solution—i.e., assuming that every time period experiences the maximum deviation simultaneously—we adopt a budget of uncertainty Γ. The uncertainty set for $\Delta p = (\Delta p_1, \ldots, \Delta p_T)$ is defined as

$$\mathcal{U} = \left\{ \Delta p \in \mathbb{R}^T : |\Delta p_t| \leq \overline{\Delta p}_t, \quad \sum_{t=1}^{T} \frac{|\Delta p_t|}{\overline{\Delta p}_t} \leq \Gamma \right\}.$$

The nominal electricity cost from the grid is given by

$$\sum_{t=1}^{T} p_t^{\text{grid}}\, S_t^+\, \Delta t = \sum_{t=1}^{T} \hat{p}_t\, S_t^+\, \Delta t,$$

where S_t^+ represents the purchased electricity (in kW) from the grid at time t. Under uncertainty, the robust counterpart of the objective becomes a min–max formulation:

$$\min_{Y,\, S^+,\, R}\ \max_{\Delta p \in \mathcal{U}} \sum_{t=1}^{T} \big(\hat{p}_t + \Delta p_t\big)\, S_t^+\, \Delta t.$$

This expression can be decomposed into the nominal cost and the additional cost resulting from the uncertainty:

$$\sum_{t=1}^{T} \hat{p}_t\, S_t^+\, \Delta t \;+\; \max_{\Delta p \in \mathcal{U}} \sum_{t=1}^{T} \Delta p_t\, S_t^+\, \Delta t.$$

A. Bertsimas–Sim Reformulation

We now reformulate the inner maximization problem:

$$\max_{\Delta p \in \mathcal{U}} \sum_{t=1}^{T} \Delta p_t\, S_t^+\, \Delta t,$$

subject to

$$\begin{aligned} |\Delta p_t| &\leq \overline{\Delta p}_t, \quad \forall t, \\ \sum_{t=1}^{T} \frac{|\Delta p_t|}{\overline{\Delta p}_t} &\leq \Gamma. \end{aligned}$$

Here, the terms S_t^+ and Δt are treated as fixed parameters. Following the approach of Bertsimas and Sim, we introduce an auxiliary scalar variable $\lambda \geq 0$ and auxiliary variables $\mu_t \geq 0$ for all $t = 1, \ldots, T$. The worst-case additional cost due to price deviation is then equivalently expressed as

$$\Gamma\, \lambda + \sum_{t=1}^{T} \mu_t,$$

subject to the dual feasibility constraints

$$\mu_t \geq \overline{\Delta p}_t\, S_t^+\, \Delta t - \lambda, \quad \forall t.$$

B. Final Robust Optimization Model

Incorporating the Bertsimas–Sim reformulation into the full model, the robust optimization problem is given by:

$$
\begin{array}{lll}
\min\limits_{Y,\,S^+,\,R,\lambda,\mu} & \sum\limits_{t=1}^{T} \hat{p}_t\, S_t^+\, \Delta t \;+\; \Gamma\,\lambda + \sum\limits_{t=1}^{T} \mu_t & \\
\text{s.t.} & \mu_t \geq \overline{\Delta p}_t\, S_t^+\, \Delta t - \lambda, & \forall\, t, \\
 & \lambda \geq 0, \quad \mu_t \geq 0, & \forall\, t, \\
 & \eta \sum\limits_{t \in T_i} Y_{i,t}\, \Delta t \geq L_i, & \forall\, i, \\
 & Y_{i,t} \leq s_i\, A_{t,i}, & \forall\, i,\, \forall\, t, \\
 & \sum\limits_{i=1}^{N} Y_{i,t} - R_t \leq C_{\text{grid}}, & \forall\, t, \\
 & S_t^+ \geq \sum\limits_{i=1}^{N} Y_{i,t} - R_t, & \forall\, t, \\
 & S_t^+ \geq 0, & \forall\, t, \\
 & 0 \leq R_t \leq \bar{R}_t, & \forall\, t, \\
 & Y_{i,t} \geq 0, & \forall\, i,\, \forall\, t.
\end{array}
$$

Here, the term $\sum_{t=1}^{T} \hat{p}_t\, S_t^+\, \Delta t$ represents the nominal electricity cost from the grid, while $\Gamma\,\lambda + \sum_{t=1}^{T} \mu_t$ captures the worst-case additional cost under bounded price uncertainty. The budget parameter Γ offers a flexible trade-off between protection against extreme scenarios and conservatism in scheduling decisions.

V. Simulation and Discussion

We compare our method with the traditional First Come, First Served (FCFS) charging approach, which is commonly adopted by many EV charging stations in Vietnam. The FCFS policy allocates available power to vehicles based on arrival order, without considering real-time electricity price fluctuations. Specifically, the power X_{ti} allocated to an electric vehicle at time t is determined by the following formula:

$$X_{ti} = \min\left(s_i,\, L_i^{\text{res}},\, C_t^{\text{res}}\right)$$

where s_i represents the available power of the station for EV i, L_i^{res} denotes the remaining energy required by vehicle i, and C_t^{res} is the remaining energy that the station can supply. When the station has fully allocated its capacity to other vehicles, i.e., $C_t^{\text{res}} = 0$, newly arriving vehicles must wait until power becomes available.

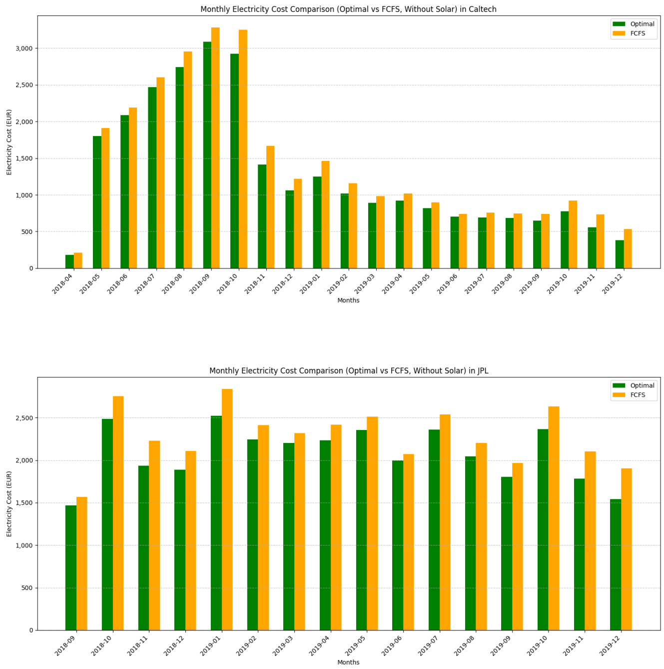

Figure 2: Comparison of Total Payment Between Two Methods, Solar Energy Not Included

We evaluated the efficiency of our optimized charging method compared to the FCFS (First Come, First Served) approach by analyzing electricity consumption data from two charging stations: the Caltech station, which recorded 25,981 charging sessions between late April 2018 and early November 2019, and the JPL station, with 22,185 charging sessions from early September 2018 to Dece 2019.

The data indicates a significant cost reduction when using our proposed optimal solution compared to the traditional FCFS approach. For example, at the Caltech station, the lowest cost under FCFS was 211.90 EUR in April 2018, while our solution achieved a cost of 182.00 EUR—a reduction of approximately 14.1%. In October 2018, the difference was even more pronounced, with FCFS costing about 3252.41 EUR versus 2925.64 EUR for our method, amounting to a reduction of 326.77 EUR or roughly 10.0%. At the JPL station, the cost savings ranged from a modest reduction of about 6.2% in September 2018 to a maximum of around 19.2% in December 2019. On average, our optimal approach reduced costs by approximately 12% at Caltech and about 12.7% at JPL.

These results underscore the economic benefits of our method, demonstrating its potential to lower charging expenses significantly while enhancing energy management efficiency for electric vehicle users. A noticeable decline in charging activity can be observed starting from November 1, 2018, at the Caltech campus. This is due to the discontinuation of free charging and the introduction of a fee of $0.12 per kWh.

Figure 3: Charging Cost Comparison: Baseline First-Come-First-Served without Solar Energy versus Optimized Solar Integration Strategy

Our optimization model integrates solar renewable energy to minimize electric vehicle charging costs. To demonstrate the effectiveness of this approach, Figure 3 presents a comparative analysis of electricity consumption at the Caltech and JPL stations under two scenarios: the baseline First-Come-First-Served (FCFS) model without solar energy integration, and our proposed optimization model incorporating solar energy. The results clearly show that integrating solar energy via our optimization model (depicted by the green line) significantly reduces grid electricity consumption compared to the FCFS baseline without solar (depicted by the black line) at both locations.

Specifically, at Caltech (excluding April 2018 due to data collection commencing on April 25), the minimum observed cost reduction occurred in September 2018, with costs decreasing from 3278.50 EUR to 2651.15 EUR, a saving of 627.35 EUR ($\approx$ 19.15%). The maximum reduction at Caltech was observed in December 2019, where costs fell from 531.01 EUR to 362.16 EUR, representing a saving of 168.85 EUR ($\approx$ 31.80%).

At the JPL station, the smallest cost reduction was recorded in June 2019, decreasing from 2069.44 EUR to 1846.06 EUR, yielding savings of 223.38 EUR ($\approx$ 10.80%). Conversely, the largest saving at JPL occurred in December 2019, with costs reduced from 1904.11 EUR to 1488.18 EUR, achieving savings of 415.93 EUR ($\approx$ 21.85%).

Therefore, applying our optimized model with solar renewable energy integration leads to substantial reductions in grid electricity procurement costs, ranging from approximately 19.15% to 31.80% at Caltech and 10.80% to 21.85% at JPL. These findings underscore the significant potential for cost savings and reduced environmental impact when optimized electric vehicle charging management is synergistic with renewable energy integration.

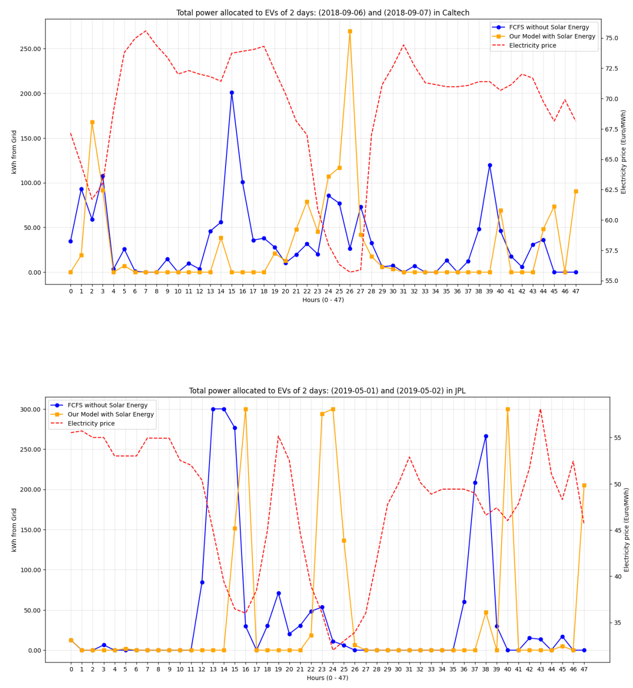

Figure 4: Comparing Total Power Allocation Based on Price Fluctuation

The figures distinctly demonstrate the substantial disparities in cost and net electricity consumption between our ideal model and the FCFS model, as seen in Figures 2 and 3. Our method strategically identifies the time intervals when electricity rates are minimized to commence car charging. An exemplary instance transpired around 2:00 AM on September 7 at Caltech, when electricity rates fell to roughly 55.0 EUR/MWh. Currently, our model has obtained the maximum daily electricity supply from the grid, surpassing 250 kWh. Conversely, the FCFS model acquired approximately 25 kWh—tenfold less than our proposed model. A similar occurrence was noted at JPL on May 1 and 2, particularly about 12:00 AM on May 2. The electrical shortfall was then offset during other periods of the day when electricity prices were markedly elevated, leading to superfluous expenses. Utilizing our method—especially during overnight charging sessions—optimizes the charging schedule to save expenses, so benefiting consumers and alleviating strain on the grid.

Additionally, by utilizing solar energy, there are extended periods during the day when the electricity generated from solar panels exceeds the charging demand from EVs, resulting in net electricity consumption being zero at those times. It is important to note that the selected days are representative—featuring 198 charging sessions at Caltech and 143 charging sessions at JPL across the chosen days—and similar results would likely be observed on other days as well.

VI. Conclusion and Future Work

Our study demonstrates that integrating on-site solar energy with a cost-optimization model for EV charging can significantly reduce electricity expenses and grid dependency compared to traditional FCFS methods. By employing a linear programming approach, our model dynamically determines optimal charging schedules based on hourly variations in electricity prices, vehicle energy requirements, maximum power limits, and grid capacity constraints. The results reveal that this optimized scheduling not only achieves substantial cost savings but also leverages solar energy to further decrease the reliance on grid power—especially beneficial for overnight charging where electricity is cheapest.

Building on these promising outcomes, future research should aim to extend our framework by incorporating advanced optimization algorithms that integrate machine learning techniques. We intend to incorporate a Battery Energy Storage System (BESS) alongside supplementary renewable energy sources, like wind power. Furthermore, sophisticated machine learning algorithms will be utilized to predict solar and wind energy production, consequently optimizing energy management, decreasing operational expenses, and enhancing overall system efficiency for electric vehicle users. For example, hybrid approaches combining deep reinforcement learning, genetic algorithms, or particle swarm optimization could be explored to address multiple objectives simultaneously. These objectives might include not only cost minimization but also reductions in CO emissions and charging times, as well as improvements in demand forecasting accuracy. Such multi-objective, adaptive strategies would further enhance the sustainability and efficiency of EV charging infrastructures, ultimately supporting the transition toward greener energy systems and smarter grid management.

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