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A Weighted Index Model for Electric Vehicle Charging Behavior Incorporating Driver Preferences

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Abstract

Accurately modeling Electric Vehicle (EV) charging behavior is crucial for the design and operation of charging stations that offer drivers multiple charging options. A realistic representation of driver decision-making enables better planning, load management, and energy efficiency. This paper proposes a weighted index-based model that captures the heterogeneous preferences of EV drivers, incorporating four key factors: battery state of charge (SoC), time sensitivity, price sensitivity, and environmental impact. Each factor is assigned a weight and combined into separate indices for slow and rapid charging options. The final charging decision for each EV is determined by selecting the option with the lower weighted index, reflecting the drivers' priorities and real-world behavior. Randomized input within predefined ranges allows the model to replicate variability among drivers. The proposed methodology captures both deterministic tendencies, such as preference for fast charging when the battery is low, and stochastic variations reflecting human behavior. Simulation results demonstrate that the model produces consistent, interpretable, and realistic charging patterns, with the distribution of slow and fast charging choices closely aligning with expected driver behavior across multiple scenarios. The simulation results indicate that the model converges well under stochastic input variables. Specifically, running 20 simulations for five EVs showed that, in most cases, either three EVs chose fast charging and two chose slow charging, or vice versa. A sensitivity analysis of the parameter weights further revealed that changing the weights of the environmental, price, and time indices led to respective increases of 12%, 30%, and 54% in the probability of choosing slow charging.

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1. Introduction

Electric vehicles (EVs) are emerging as key components in contemporary power systems and microgrids [1]. With the concurrent development of smart grids [2, 3], smart homes [4, 5], and intelligent energy networks [6], EVs are increasingly integrated into these infrastructures, necessitating sophisticated charging management. EVs are available in various forms, including fully electric, hybrid, and hydrogen-based vehicles [7], all of which require charging systems capable of providing appropriate power and speed. Consequently, EV charging stations have been developed both at residential levels with low power and at commercial levels with high power and fast charging capabilities, promoting broader acceptance and adoption among users [8]. Battery-swapping station deployment is also an innovative and effective strategy for enhancing user acceptance and accelerating adoption [9].

In various modeling studies, EVs are analyzed both within grid-connected scenarios [10] and in off-grid environments [11], considering factors such as optimal charging, the impact of charging on the power network, and vehicle battery capacity [12]. Complementary technologies, including renewable energy sources and large-scale energy storage systems, are often incorporated with charging stations to facilitate optimal charging strategies [13].

User satisfaction studies have also been conducted, examining metrics such as driving range, waiting time, and overall charging experience to identify and mitigate barriers to EV adoption [14, 15]. Numerous charging stations provide multiple charging alternatives with varying speed and cost [16, 17]. Drivers typically make decisions based on charging cost, waiting time, duration of charge, and battery longevity. Fast charging incurs higher costs, but minimizes charging duration , whereas slow charging is more economical yet requires longer waiting periods and is suitable for prolonged intervals such as nighttime [18].

Given these considerations, accurately modeling driver behavior in selecting charging options is crucial. Inaccurate modeling can affect subsequent evaluations of grid or microgrid performance connected to charging stations, perhaps resulting in unrealistic outcome. Therefore, a model capable of predicting the probability of selecting a specific charging type for each vehicle is essential. Historical data, artificial intelligence, neural networks, and machine learning can support the development and training of such models [19, 20].

This paper presents a simplified yet comprehensive model for identifying and simulating driver behavior at EV charging stations, emphasizing the critical role of accurate behavioral modeling in EV charging studies. The proposed weighted-index framework incorporates four key input indices that denote the primary factors influencing driver decisions: the vehicle's State of Charge (SoC) upon arrival at the station, the duration required for charging, the cost of charging, and environmental considerations such as renewable energy availability and local emissions. Each index is generated within specified ranges to reflect the diversity of driver preferences and is assigned separate weights for slow and fast charging options. For each EV, the model calculates a final weighted score for both slow and fast charging by combining these indices, with the option associated with the lower score being designated as the preferred alternative. The SoC index serves as a multiplier reflecting the urgency of charging, ensuring that vehicles with low battery levels have a higher probability of selecting fast charging, while price-sensitive or time-flexible drivers may prefer slower charging options. Numerical simulations demonstrate that the model accurately replicates authentic driver behavior patterns: for example, alterations in index weights for price, time, or environmental factors result in predictable shifts in charging preference. Most EVs opt for fast charging when batteries are low and drivers are time-constrained, while a more balanced or slow-charging preference arises when costs or waiting times are predominant. The results confirm that this methodology captures both the stochastic nature of individual driver decisions and the aggregated trends at the station level, providing a reliable tool for evaluating charging infrastructure, demand management, and the integration of renewable energy in EV charging networks.

2. Weighted index approach for realistic EV charging behavior

In the proposed EV charging decision model, four key indices are considered to represent the driving and charging preferences: the SoC index, the Time index, the Price index, and the Environmental index. Each index reflects a distinct aspect of the driver's behavior and charging priorities, and the combination of these indices determines the optimal charging option for each vehicle. Figure 1 illustrates the comprehensive workflow of the proposed model, including its major components and the sequence of operations.

The SoC index reflects the battery level of the EV upon arrival at the charging station. A lower SoC indicates that the battery is nearly depleted, prompting drivers to favor fast charging to reduce waiting time and expedite the charging process. Consequently, in such cases, the fast-charging index is assigned a lower weight, increasing the likelihood that fast charging will be selected. Conversely, when the battery has a higher initial charge, the urgency to charge rapidly is reduced. This enhances the relative appeal of slow charging by assigning it a lower index, thereby encouraging drivers to choose for the slower, less energy-intensive alternative.

The Time index signifies the importance of charging duration from the driver's perspective. A higher value indicates that the driver is time-sensitive and values reduced charge durations. In these cases, the model reduces the index for fast charging and increases the index for slow charging, reflecting a higher probability that fast charging will be chosen. Drivers who are less concerned about time exhibit smaller differences between the indices, allowing other factors, such as price and SoC, to have greater influence.

The Price index captures the driver's sensitivity to charging expenses. When drivers prioritize price, the model decreases the index for the cheaper charging options, typically slow charging, and increases the index for the more costly alternative, typically fast charging. Consequently, a higher price sensitivity directs driver preference toward the cost-effective option, whereas lower sensitivity allows other factors, such as SoC or charging time, to play a dominant role in the decision.

The Environmental index measures the driver's concern for environmental effects, including carbon emissions and renewable energy usage. Higher environmental sensitivity favors charging options with lower environmental footprints. In most cases, slow charging correlates with reduced emissions or improved compatibility with renewable energy supply, leading to a lower index for slow charging when environmental concerns are paramount. Nevertheless, the influence of the Environmental Index is generally weaker than that of SoC, Time, and Price indices, indicating that drivers often prioritize personal convenience and cost over environmental impacts in many practical scenarios.

For each EV, the final decision is determined by calculating the weighted sum of these indices for slow and fast charging, with each multiplied by the SoC index. This produces two numerical values, one for slow charging and one for fast charging, with the choice corresponding to the lower value being chosen. This methodology ensures that the model aligns with real-world driver behavior: vehicles with low battery levels and time-sensitive drivers tend to choose fast charging, whereas vehicles with higher initial charge or greater price sensitivity generally favor slow charging. Environmental considerations can influence the decision but rarely override the dominant effects of battery level, time, and cost.

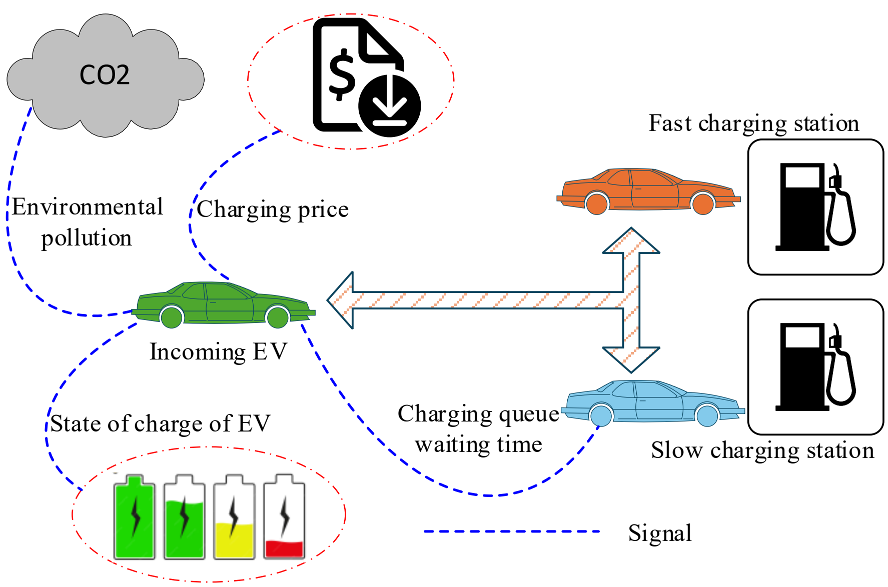

Fig. 1. Selection of fast or slow charging based on price, charging time, SoC, and environmental indicators. The figure illustrates how different factors influence a driver's charging choice, highlighting the trade-offs between cost, waiting time, battery level, and environmental impact.

3. Data description and model formulation

The first component of the proposed model determines the SoC Index for each EV arriving at the charging station, as delineated in Eq. (1). This index is defined as the inverse of the EV's actual SoC and reflects the charging urgency of the vehicle. A higher value of the SoC Index indicates that the EV requires more energy. The index is normalized within the range [0,1], with a value of 1 indicating the maximum charging need. In Eq. (1), I_i^{SoC} denotes the SoC Index of EV i, $\mathrm{SoC}_i^{\mathrm{real}}$ is its actual SoC, and Ω denotes the set of all EVs arriving at the station.

$$I_i^{SoC} = \left\{ 1\text{-}\mathrm{SoC}_i^{real} \right\}, i \in \Omega \tag{1}$$

To depict the natural variability of the SoC (SoC_i^{real}) of incoming EVs, a beta distribution is employed. The beta distribution is flexible and can model skewed behavior, rendering it appropriate for capturing the realistic tendency that many EVs arrive with medium or low SoC rather than being uniformly distributed. Vehicles typically visit charging stations when their battery is low, usually below half capacity. To model this behavior, the SoC of incoming vehicles is represented by a skewed Beta distribution, favoring lower battery levels. This better reflects real driver behavior than a uniform or normal distribution. For each EV i, a random value is generated from a Beta distribution with parameters $\left(\alpha_{SoC}, \beta_{SoC}\right)$, as expressed in Eq. (2).

$$x_i = Beta\left(\alpha_{SoC}, \beta_{SoC}\right), i \in \Omega \tag{2}$$

The actual SoC of the EV is then scaled by the maximum allowed SoC level, as expressed in Eq. (3).

$$\mathrm{SoC}_i^{real} = x_i \times \mathrm{SoC}_i^{\max}, i \in \Omega \tag{3}$$

The values used in the model are $\alpha_{SoC} = 2,\ \beta_{SoC} = 5,\ \mathrm{SoC}_i^{\max} = 0.8.$

For each arriving EV, three decision-related indices (i.e., time sensitivity, price sensitivity, and environmental sensitivity) are generated within predefined ranges. These indices reflect the behavioral variability among EV drivers and are sampled randomly to mimic realistic and heterogeneous decision patterns.

Each index is assigned separately for the slow-charging and fast-charging options. For example, the time-sensitivity index for slow charging ($time_i^{slow}$) is drawn uniformly from the interval $[low\_time_i^{slow}, up\_time_i^{slow}]$ as formulated in Eq. (4). Similar relationships are also defined for the price-sensitivity and environmental-sensitivity indices.

$$\begin{cases} time_i^{slow} = low\_time_i^{slow} + (up\_time_i^{slow} - low\_time_i^{slow}) \times rand \\ price_i^{slow} = low\_price_i^{slow} + (up\_price_i^{slow} - low\_price_i^{slow}) \times rand \\ env_i^{slow} = low\_env_i^{slow} + (up\_env_i^{slow} - low\_env_i^{slow}) \times rand \end{cases} \quad (4)$$

Here, *rand* generates a random number in the range [0,1], ensuring that the final value of each index falls uniformly within its specified interval. The predefined ranges used in the model are:

- Time Sensitivity
  - Slow charging: [0.4, 0.9] and Fast charging: [0.1, 0.3]
- Price Sensitivity
  - Slow charging: [0.1, 0.4] and Fast charging: [0.4, 0.9]
- Environmental Sensitivity
  - Slow charging: [0.1, 0.2] and Fast charging: [0.2, 0.3]

In the above ranges, smaller values are assigned to environmental sensitivity, as individuals generally prioritize immediate personal benefits. Price and waiting time directly affect user decisions, while environmental effects are indirect and long-term. This assignment reflects realistic human behavior by giving environmental impact a relatively smaller weight.

These intervals reflect the behavioral assumption that drivers generally value time and convenience more when opting for fast charging, while price considerations play a more dominant role for slow charging. The small environmental-sensitivity values indicate that environmental awareness exerts a relatively minor impact on short-term charging decisions, aligning with real-world observations.

The slow charging index for each EV is calculated as a weighted sum of time, price, and environmental impact. The SoC index acts as a multiplier, reflecting the EV's urgency for charging. The slow charging index is calculated as modeled in Eq. (5). In this equation, $\left(\omega_{\text{time}}^{\text{slow}}, \omega_{\text{price}}^{\text{slow}}, \omega_{\text{env}}^{\text{slow}}\right)$ show the weightings for time, price, and environmental values. In the proposed model, the weight coefficients for time, price, and environmental factors are chosen through trial-and-error. Historical data could help refine these weights, but exact values cannot be assured due to potential future behavioral and economic fluctuations.

$$\mathrm{I}_i^{slow} = I_i^{SoC} \times \left(\omega_{\text{time}}^{\text{slow}} \cdot time_i^{slow} + \omega_{\text{price}}^{\text{slow}} \cdot price_i^{slow} + \omega_{\text{env}}^{\text{slow}} \cdot env_i^{slow}\right), i \in \Omega \quad (5)$$

The fast-charging index is computed similarly to the slow charging index, but with potentially different weights for time, price, and environmental factors, as modeled in Eq. (6). A lower index indicates a more preferred option.

$$\mathrm{I}_i^{fast} = I_i^{SoC} \times \left(\omega_{\text{time}}^{fast} \cdot time_i^{fast} + \omega_{\text{price}}^{fast} \cdot price_i^{fast} + \omega_{\text{env}}^{fast} \cdot env_i^{fast}\right), i \in \Omega \quad (6)$$

The final charging decision for each EV is determined based on the computed weighted indices. An EV selects the charging option associated with the lower overall index value, reflecting the more favorable choice according to its charging need, time sensitivity, price preference, and environmental considerations. This decision rule is expressed as Eq. (7). For each simulation run t (where, τ represents set of simulation runs), the percentage of EVs choosing slow or fast charging is calculated based on Eq. (8) and Eq. (9).

$$\text{Chosen\_Charger}_i = \begin{cases} Slow\,, & \text{if} \quad \left\{ \mathrm{I}_i^{slow} \leq \mathrm{I}_i^{fast} \right\} \\ Fast\,, & \text{if} \quad \left\{ \mathrm{I}_i^{slow} > \mathrm{I}_i^{fast} \right\} \end{cases} \tag{7}$$

$$\text{Percentage}_{\text{slow}}^{t} = \frac{\text{slow}_t}{\text{slow}_t + \text{fast}_t} \times 100, t \in \tau \tag{8}$$

$$\text{Percentage}_{\text{fast}}^{t} = \frac{\text{fast}_t}{\text{slow}_t + \text{fast}_t} \times 100, t \in \tau \tag{9}$$

4. Results, analysis and discussion

To demonstrate the effectiveness of the proposed methodology, a case study with five EVs arriving at the charging station is considered. For each EV, the corresponding indices are computed according to the proposed weighted-index framework, and the results are summarized in Table 1. The table reports all contributing factors—including the SoC index, time index, price index, and environmental index—for both slow and fast charging alternatives. Additionally, the total weighted index for each charging option is provided. The final column specifies the selected charging type for each EV, determined by comparing the total indices and choosing the option with the lower value, indicative of the more favorable charging strategy based on the modeled driver behavior.

Table 1. Charging decision indices and selected charging type for 5 incoming EVs.

EV No.	Charging Type	SOC Index	Time Index	Price Index	Environmental Index	Total Index	Chosen Charging Type
1	Slow	0.973	0.760	0.363	0.158	1.247	Fast
	Fast	0.973	0.114	0.861	0.280	1.221	
2	Slow	0.790	0.819	0.229	0.147	0.945	Fast
	Fast	0.790	0.212	0.534	0.274	0.807	
3	Slow	0.599	0.637	0.208	0.178	0.614	Slow
	Fast	0.599	0.256	0.734	0.213	0.721	
4	Slow	0.844	0.890	0.185	0.180	1.061	Slow
	Fast	0.844	0.279	0.698	0.288	1.069	
5	Slow	0.777	0.412	0.233	0.164	0.631	Slow
	Fast	0.777	0.204	0.586	0.293	0.843	

To further validate the robustness and consistency of the proposed model, the simulation is executed 20 times under identical conditions. The decision-making system is partially stochastic, mirroring natural variability in driver behavior; thus, the outputs are anticipated to remain consistent between iterations, exhibiting only minor changes. Figure 2 presents the number of EVs selecting slow and fast charging in each of the 20 simulation runs.

The results demonstrate that the model produces highly consistent patterns. In most simulation runs, either two EVs (40% of the five EVs) choose fast charging and three (60%) choose slow charging, or the reverse ratio transpires. This behavior indicates that the proposed methodology converges around a nearly steady operating point, showing stable performance across repeated simulations under identical conditions. Moreover, these subtle variations realistically reflect actual driver behavior, since real-world EV users do not make identical decisions even under similar circumstances. The model therefore captures both the dominant decision trend and the natural randomness inherent in human charging preferences.

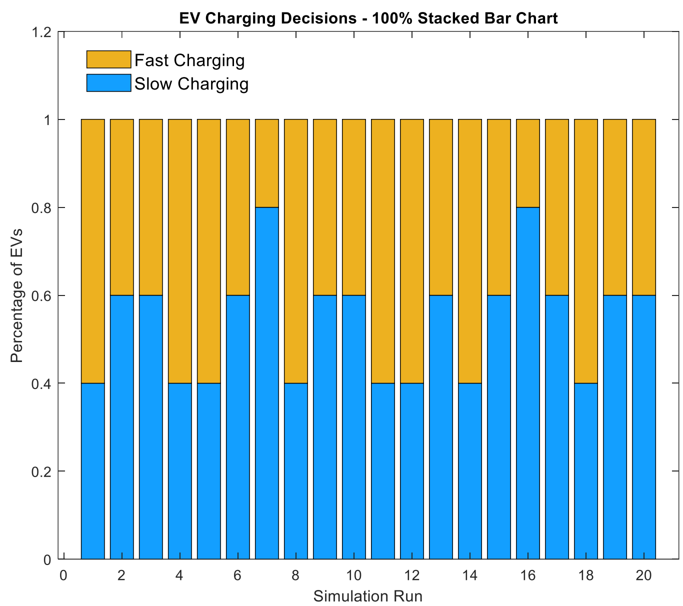

Fig. 2. EV charging decisions across 20 simulation runs. In most runs, the model converges to a specific point, demonstrating the consistency and stability of the model under stochastic input conditions.

To evaluate how the weighting factors influence the proposed model and the subsequent charging behavior of drivers, the price-related weights are varied throughout the 24-hour period. During hours 1–10, all weighting factors remain constant, representing a neutral condition devoid of any pricing bias. In hours 11–20, the weight associated with the price component for fast charging is increased, while the corresponding weight for slow charging is reduced. This setting represents a situation with elevated demand, wherein the system encourages EV users to opt for the more economical slow charging option. Finally, in hours 21–24, the price weight for fast charging is decreased, illustrating conditions with low network loading and inexpensive energy availability.

Figure 3 illustrates the number of EVs selecting slow and fast charging throughout the day across various price-weight scenarios. With equal weights in hours 1–10, both charging options attract a comparable number of vehicles. When the fast-charging price weight rises in hours 11–20, the inclination shifts toward slow charging, causing a noticeable increase in its selection. In the last interval (hours 21–24), the reduced fast-charging price weight makes the fast option more appealing, resulting in a higher number of vehicles choosing it.

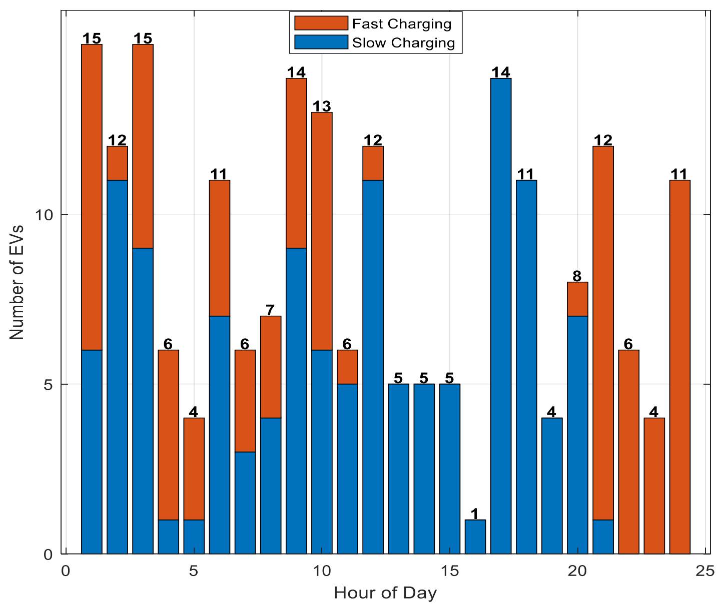

Fig. 3. Hourly EV charging decisions over 24 hours resulting from changes in the weighted price indices of slow and fast charging.

Figure 4 presents the hourly EV charging decisions over a 24-hour timeframe when the weighting factors associated with environmental impact and renewable energy availability are modified. During nighttime hours (1–6 and 21–24), when solar generation is minimal, the environmental weight assigned to slow charging is reduced. Conversely, during daylight hours, the weight for fast charging is slightly lowered to reflect the higher availability of renewable energy. The results indicate that, unlike price-related adjustments, changes in environmental and renewable energy weights do not significantly affect the charging choice. Instead, EVs maintain a balance of time, cost, and waiting factors, producing a charging pattern that remains consistent with realistic driver behavior.

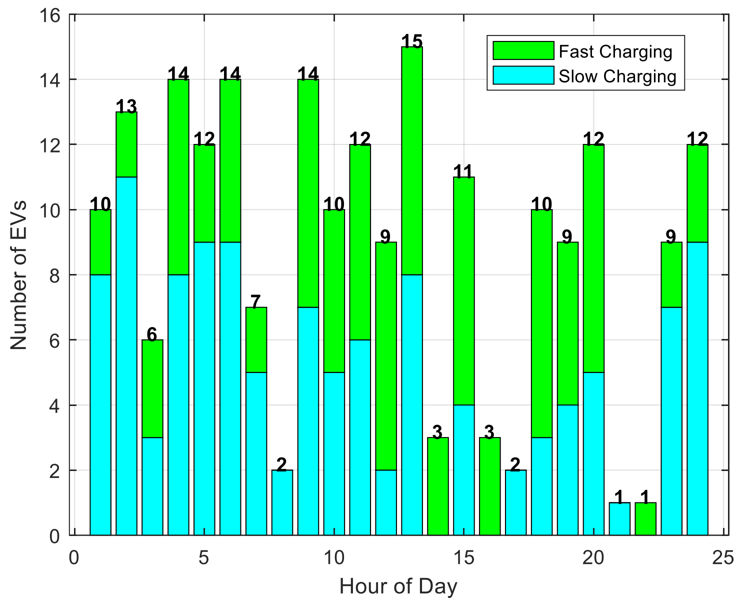

Fig. 4. Hourly EV charging decisions over 24 hours resulting from changes in the weighted environmental and renewable energy indices.

For a more comprehensive comparison, four scenarios are defined, and their corresponding results are presented below:

- **Case 1:** All weighting factors are set to 1 across all 24 hours (baseline scenario).
- **Case 2:** The environmental weight associated with slow charging is reduced by 50% for the entire 24-hour period.
- **Case 3:** The price weight applied to slow charging is reduced by 50% throughout all 24 hours.
- **Case 4:** The time weight assigned to slow charging is reduced by 50% for all 24 hours.

Figure 5 illustrates the EV charging decisions for slow and fast charging options in Case 1 (baseline) and Case 2, where the environmental weight attributed to slow charging is reduced. The results indicate that the environmental factor has only a marginal influence on driver behavior. Reducing this weight does not cause a significant shift toward either charging option. Overall, the distribution between fast and slow charging remains nearly balanced, with Case 2 showing only a slight increase in preference for slow charging, though not significantly influencing the overall decision-making pattern.

Figure 6 presents the EV charging decisions for slow and fast charging options in Case 1 (baseline) and Case 3, where the price weight assigned to slow charging is reduced. In contrast to the environmental adjustment in Case 2, the modification in Case 3 has a more noticeable impact on driver behavior. Reducing the price weight for slow charging enhances its relative appeal, leading to a more substantial move towards slow charging than the trend depicted in Figure 5. Although the shift is not extreme, it is sufficiently pronounced to indicate that price-related weighting plays a more influential role in shaping driver decisions than environmental considerations.

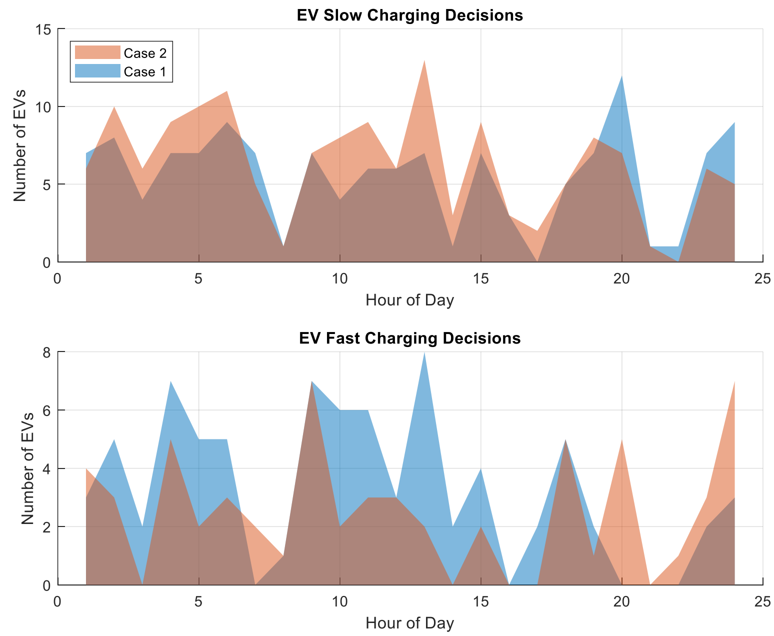

Fig. 5. Comparison of EV charging decisions for slow and fast charging options in Case 1 (baseline) and Case 2 (reduced environmental weight on slow charging).

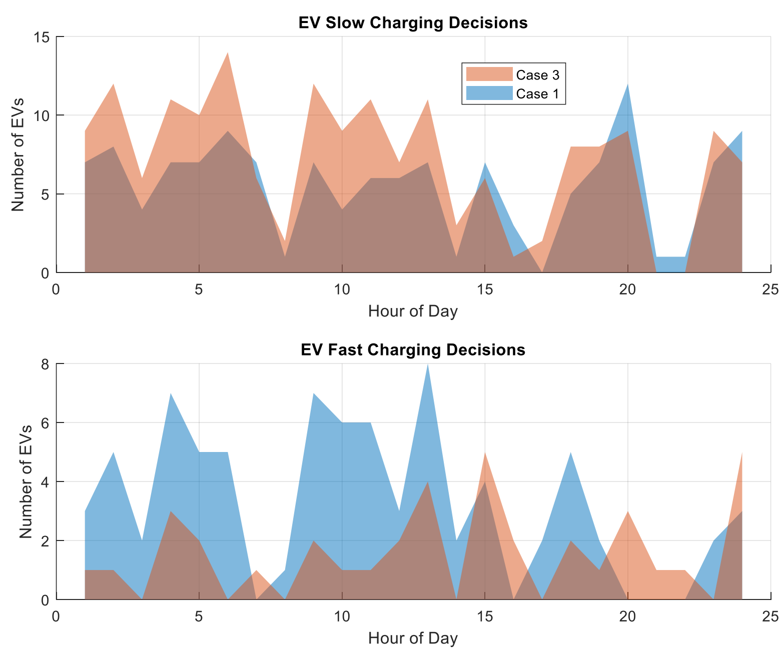

Fig. 6. Comparison of EV charging decisions for slow and fast charging options in Case 1 (baseline) and Case 3 (reduced price weight on slow charging).

Figure 7 compares EV charging decisions for slow and fast charging in Case 1 (baseline) and Case 4, where the time weight for slow charging is reduced. The results show a significant preference for slow charging across the majority of hours in Case 4. Only in a few hours, such as hours 3, 4, 13, 18, 19, and 20, a small number of vehicles choose fast charging, and in each of these hours only one vehicle selects it. This indicates that reducing the time weight for slow charging strongly encourages drivers to choose the slow charging option, demonstrating that time-related weighting can be a dominant factor in influencing EV charging behavior when other weights remain unchanged.

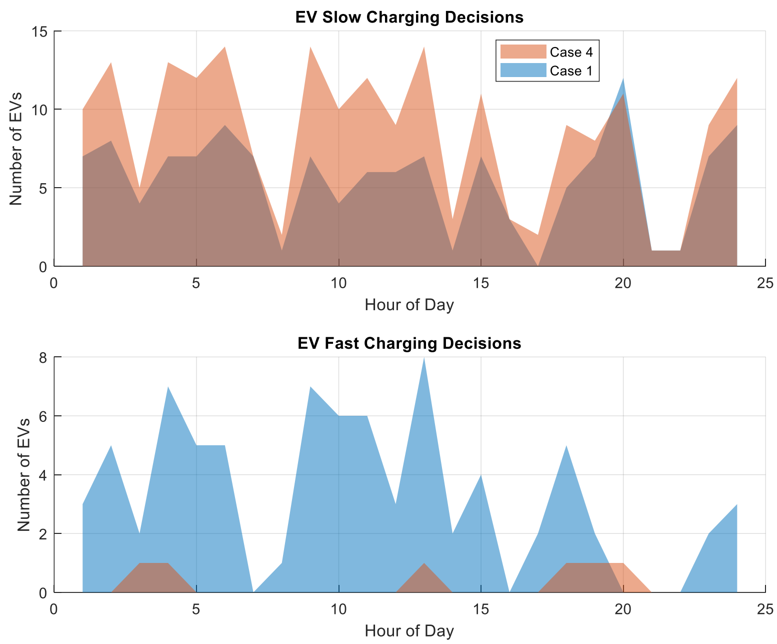

Fig. 7. Comparison of EV charging decisions for slow and fast charging options in Case 1 (baseline) and Case 4 (reduced time weight on slow charging).

To provide a clear comparison of the four cases, Table 2 shows the total number of EVs and their charging choices under each case.

Table 2. Summary of EV charging decisions under four cases.

Case	Total Number of EVs	Number of EVs Choosing Slow Charging	Number of EVs Choosing Fast Charging
Case 1	211	133	78
Case 2	211	150	61
Case 3	211	173	38
Case 4	211	205	6

5. Conclusions

This paper proposed a weighted index-based model to realistically capture EV charging behavior by accounting for driver preferences, battery state, time sensitivity, price sensitivity, and environmental considerations. The model computes distinct indices for slow and rapid charging for each EV by multiplying the weighted sum of time, price, and environmental indices by the SoC index. The EV then selects the charging option with the lower index value, reflecting the more favorable choice according to its individual profile.

Simulation results for five EVs demonstrated that the model accurately represents diverse driver behaviors: vehicles with low battery levels or high time sensitivity tended to select fast charging, while those with higher initial SoC or greater price sensitivity opted for slow charging. Across 20 iterations, the selection pattern remained consistent, with 40–60% of EVs choosing slow charging and the remainder choosing fast charging, showing only minor fluctuations. The hourly simulations also revealed that environmental weighting had only a modest impact; increasing the environmental weight raised the probability of selecting slow charging by approximately 12%. In contrast, modifying the price weight produced a more noticeable shift, increasing the tendency toward slow charging by about 30%. The strongest influence originated from time weighting, where adjusting the time-related weight resulted in an approximately 54% increase in preference for slow charging. Overall, the proposed methodology demonstrates stable, realistic, and interpretable modeling of EV charging choices, consistent with observed driver behavior.

Authors' contributions

Reza Hemmati: Methodology, Software, Data curation, Investigation, Writing- Original draft preparation

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials

All data, models, or code generated or used during the study are available in a repository or online.

Reference

[1] Sayarshad, H.R., Integrating renewable energy and electric vehicle participation in regulation markets for empowering grid stability. Energy Conversion and Management, 342 (2025), p. 120041, https://doi.org/10.1016/j.enconman.2025.120041

[2] Sultan, V., A. Aryal, H. Chang, and J. Kral, Integration of EVs into the smart grid: A systematic literature review. Energy Informatics, 5 (1), (2022), p. 65. https://doi.org/10.1186/s42162-022-00251-2

[3] Hemmati, R. and H. Saboori, A hybrid data-driven and physics-informed energy management model for electrical grids with spatio-temporal cyberattack detection-reconstruction using digital twin. Energy Conversion and Management, 348 (2026), p. 120728, https://doi.org/10.1016/j.enconman.2025.120728

[4] Mehrjerdi, H., Resilience oriented vehicle-to-home operation based on battery swapping mechanism. Energy, 218 (2021), p. 119528, https://doi.org/10.1016/j.energy.2020.119528

[5] Alyami, S., Management of diverse smart homes: Coordination among controllable loads, EVs, and PVs. Energy Reports, 12 (2024), p. 5221-5233, https://doi.org/10.1016/j.egyr.2024.10.030

[6] Abiassaf, G.A. and A.A. Arkadan, Impact of EV charging, charging speed, and strategy on the distribution grid: a case study. IEEE Journal of Emerging and Selected Topics in Industrial Electronics, 5 (2), (2024), p. 531-542, https://doi.org/10.1109/jestie.2024.3352505

[7] Soomro, A.M., M.K. Rathi, A. Shaikh, L. Kumar, M.E.H. Assad, and M. Ehyaei, Techno-economic analysis of stand-alone hybrid PV-hydrogen-based plug-in electric vehicle charging station. Energy Reports, 12 (2024), p. 3279-3290, https://doi.org/10.1016/j.egyr.2024.09.019

[8] Khalid, M., J. Thakur, S.M. Bhagavathy, and M. Topel, Impact of public and residential smart EV charging on distribution power grid equipped with storage. Sustainable Cities and Society, 104 (2024), p. 105272, https://doi.org/10.1016/j.scs.2024.105272

[9] Hemmati, R., S. Mahdavi, and H. Mehrjerdi, A resilient microgrid formation framework: Mobile battery-swapping station deployment for effective load restoration and voltage collapse prevention. Energy, 318 (2025), p. 134754, https://doi.org/10.1016/j.energy.2025.134754

[10] Ma, C.-T., System planning of grid-connected electric vehicle charging stations and key technologies: A review. Energies, 12 (21), (2019), p. 4201, https://doi.org/10.3390/en12214201

[11] Mehrjerdi, H., Off-grid solar powered charging station for electric and hydrogen vehicles including fuel cell and hydrogen storage. International journal of hydrogen Energy, 44 (23), (2019), p. 11574-11583, https://doi.org/10.1016/j.ijhydene.2019.03.158

[12] Gönül, Ö., A.C. Duman, and Ö. Güler, Multi-objective optimal sizing and techno-economic analysis of on-and off-grid hybrid renewable energy systems for EV charging stations. Sustainable Cities and Society, 115 (2024), p. 105846, https://doi.org/10.1016/j.scs.2024.105846

[13] Eid, A., O. Mohammed, and H. El-Kishky, Efficient operation of battery energy storage systems, electric-vehicle charging stations and renewable energy sources linked to distribution systems. Journal of Energy Storage, 55 (2022), p. 105644, https://doi.org/10.1016/j.est.2022.105644

[14] Zhao, D., J. Gao, and N. Liu, Exploring user satisfaction and improvement priorities in electric vehicle segments. Transportation Research Part D: Transport and Environment, 125 (2023), p. 103996, https://doi.org/10.1016/j.trd.2023.103996

[15] Amin, A., A. Mahmood, A.R. Khan, K. Arshad, K. Assaleh, and A. Zoha, A two-stage multi-agent EV charging coordination scheme for maximizing grid performance and customer satisfaction. Sensors, 23 (6), (2023), p. 2925, https://doi.org/10.3390/s23062925

[16] Zhao, Z., M. Xu, and C.K. Lee, Capacity planning for an electric vehicle charging station considering fuzzy quality of service and multiple charging options. IEEE Transactions on Vehicular Technology, 70 (12), (2021), p. 12529-12541, https://doi.org/10.1109/TVT.2021.3121440

[17] Tahir, M.U., A. Sangwongwanich, D.-I. Stroe, and F. Blaabjerg, Overview of multi-stage charging strategies for Li-ion batteries. Journal of Energy Chemistry, 84 (2023), p. 228-241, https://doi.org/10.1016/j.jechem.2023.05.023

[18] Muratori, M., E. Kontou, and J. Eichman, Electricity rates for electric vehicle direct current fast charging in the United States. Renewable and Sustainable Energy Reviews, 113 (2019), p. 109235, https://doi.org/10.1016/j.rser.2019.06.042

[19] Shern, S.J., M.T. Sarker, M.H.S.M. Haram, G. Ramasamy, S.P. Thiagarajah, and F. Al Farid, Artificial Intelligence Optimization for User Prediction and Efficient Energy Distribution in Electric Vehicle Smart Charging Systems. Energies, 17 (22), (2024), p. 5772, https://doi.org/10.3390/en17225772

[20] Ullah, I., K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, Modeling of machine learning with SHAP approach for electric vehicle charging station choice behavior prediction. Travel Behaviour and Society, 31 (2023), p. 78-92, https://doi.org/10.1016/j.tbs.2022.11.006