Price-Aware and Explainable Analytics for Urban Electric Vehicle Charging Networks: Forecasting Utilization Regimes for Sustainable Charging Operations

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Abstract

The efficient functioning of the electric-vehicle charging systems that are publicly operated has become focused on reliable short-horizon forecasting. The paper establishes an explainable and price-conscious analytical model to predict short-term charging usage and demonstrate the utility of tariff signals in an urban charging system. The analysis is based on UrbanEV benchmark, a new six months hourly panel of Shenzhen public charging infrastructure, which integrates occupancy, charging time, charging volume, electricity tariffs, service charges, weather and spatial descriptors. The concept of charging occupancy is considered an operation state variable with connection to queue exposure, reliability of service, and tactical intervention. A succinct mathematical formulation is created to use it in one-step-ahead utilization forecasting and in interpreting low-, medium-, and high-utilization regime. The empirical analysis is pegged to benchmark evidence reported to UrbanEV, where transformer-based forecasting had the best node-level performance and TimeXer had the best RMSE values of 0.07 in occupancy, 2.73 in charging duration, and 43.66 in charging volume. Further discussion indicates that occupancy prediction is accurate enough to justify regime based intervention and strongest additional gains are obtained through the joint effect of pricing variables and temperature-price interactions as opposed to single covariates. The results justify the justifiable, price-conscious forecasting as an operational decision tool to alleviate congestion, design tariffs and specific capacity planning in sustainable charging networks.

Keywords: Electric vehicle charging; Utilization forecasting; Sustainable mobility; Dynamic pricing; Explainable analytics; Charging operations

1. Introduction

The high penetration of EV has transformed the purpose of charging infrastructure as a supporting utility to an urban service system that is strategic in nature [1–3]. In comparison to the earlier stages of deployment, the current deployments of public charging providers have stricter service expectations, increased temporal variability, and sensitivity to congestion. Charging-network performance in this context is determined not only by the installed capacity but also by the capability to predict the short-run utilization, understand charging behavior, and take action before locally concentrated demand affects service quality. Forecasting is thus an operations problem as well as a prediction problem.

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Recent works have led to significant developments in charging-demand analytics, including stochastic occupancy models, recurrent neural architectures, graph-based learning, transformer-style forecasting, and heterogeneous forecasting with physics-constrained learning and chatevet-like forecasting [6, 7, 10, 13, 15, 17]. However, there are still three questions that are not addressed properly. First, most of the methodological literature focuses on predictive accuracy but it allocates relatively smaller focus on managerial interpretation. Second, tariff variables tend to be contextual covariates, but they are one of the few working levers that charging operators can actively re-design. Third, the most studies are constructed with slim or poorly documented data, restricting the ability to rigorously compare temporal dynamics, exogenous impacts, and functional implications of the results [14, 19].

The current paper constructs a price-conscious and explainable outlook on the cost of charging-network prediction based on UrbanEV as the empirical anchor benchmark [19]. The main concept is to redefine occupancy as a state variable of operations, and not as a statistical goal. In this perspective, the one-step-ahead occupancy prediction is directly linked with the risk of queue, service continuity and tactical measures to reduce the risk, including tariff adjustment, user redirection, and local capacity intervention. The pricing variables are then interpreted as managerial levers whose interaction with the temporal and environmental conditions determine the charging behavior observed.

The paper has four contributions. First, it introduces a succinct mathematical model of one-step-ahead charging-utilization prediction and utilization-regime explanation. Second, it integrates recent studies on EV charging with a clear focus on data richness, pricing variables, and operational decision support. Third, it expands the empirical discourse by interpreting the benchmark findings into other analytical tables and results that are specific to charging operations. Fourth, it elucidates how explainability of price-aware can help sustainability in urban charging networks through tactical governance.

2. Related Literature and Research Gap

The literature on EV charging analytics has evolved from foundational studies on charging-system behavior and electricity-system implications toward increasingly rich data-driven forecasting architectures. Strategic studies established the importance of EV charging in low-carbon mobility transitions and highlighted the operational implications of charging behavior for energy systems [1,2,4]. Open datasets such as ACN-Data and workplace charging repositories then improved reproducibility by making transaction-level charging records accessible to researchers [5, 8]. These data resources enabled more systematic work on occupancy, load, and utilization prediction.

Methodologically, early charging studies relied on stochastic models, probabilistic formulations, and recurrent neural structures [6,7,10]. Subsequent work moved toward richer spatiotemporal settings in which neighboring stations, regional spillovers, and urban context were explicitly modeled [11–13]. More recent studies introduced graph learning, multimodal representation, and natural-language-inspired formulations to better capture the nonlinear and spatially clustered nature of charging demand [15, 17]. In parallel, recent benchmark and scientific-data contributions considerably strengthened the empirical foundation of the field by documenting city-scale charging panels with pricing, weather, and spatial descriptors [18–20].

A second line of work is especially relevant for charging operations: the study of price-sensitive charging behavior. Dynamic-pricing and reinforcement-learning approaches have been proposed as mechanisms for reducing peak stress and shifting demand over time [9, 21]. Evidence from Shenzhen further shows that electricity tariffs and service fees are materially associated with charging behavior and station substitution, implying that tariff components should be treated as operational interventions rather than passive covariates [16]. This observation is central to a business-oriented interpretation of charging forecasting because tariff design affects both service quality and revenue realization.

Despite these advances, the literature still leaves room for a more explicit operations perspective. Forecasting studies often report model rankings without translating errors into actionable utilization states. Pricing studies identify behavioral responses but do not always connect them to near-term congestion management. Data papers document rich benchmarks but are not primarily designed to interpret what the results imply for operators. The present study addresses this opening by integrating these strands into a price-aware and explainable framework centered on utilization regimes and tactical intervention.

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Table 1: Representative published studies on EV charging analytics and related data resources

No.	Study	Year	Focus	Main contribution
1	[1]	2012	EV transition	Clarified the strategic role of electric mobility in decarbonized transport systems.
2	[4]	2018	Power-demand impact	Quantified the effect of uncoordinated EV charging on residential load profiles.
3	[5]	2019	Open charging data	Introduced ACN-Data as a reproducible benchmark for charging studies.
4	[6]	2019	Occupancy modeling	Developed a stochastic resource-sharing formulation for charging systems.
5	[7]	2020	Probabilistic load forecasting	Combined deep learning and queuing ideas for charging-load prediction.
6	[8]	2021	Workplace charging data	Released high-resolution workplace charging data with user heterogeneity.
7	[9]	2021	Dynamic pricing	Proposed deep reinforcement learning for charging-station pricing.
8	[10]	2022	Occupancy forecasting	Modeled multistep station occupancy with hybrid LSTM networks.
9	[11]	2022	Demand forecasting	Demonstrated deep-learning forecasting for charging demand.
10	[12]	2023	Short-term demand prediction	Reported improved near-term charging-demand prediction with deep models.
11	[13]	2023	Spatiotemporal graph learning	Modeled heterogeneous urban charging dependencies with graph convolution.
12	[14]	2023	Medium-term forecasting	Developed a data-driven demand-forecasting framework for charging stations.
13	[15]	2024	Physics-informed graph learning	Integrated physical priors and attention for regional charging-demand prediction.
14	[16]	2024	Charging-price behavior	Examined the effect of electricity price on EV charging behavior in Shenzhen.
15	[17]	2024	Sequence modeling	Framed charging-demand prediction through a language-model perspective.
16	[18]	2024	Transaction dataset	Released a multi-faceted charging-transaction dataset for broader empirical analysis.
17	[19]	2025	Urban benchmark dataset	Documented UrbanEV and benchmarked statistical, deep, and transformer models.
18	[20]	2025	Global harmonized dataset	Provided a city-scale harmonized dataset for cross-city charging-demand analysis.

3. Methodological Framework

Charging-network operation is represented as a short-horizon forecasting problem in which next-period utilization depends on temporal persistence, charging intensity, price signals, environmental conditions, and local spatial characteristics. Let zone i at hour t have utilization ratio

$$u_{i,t} = \frac{o_{i,t}}{c_i}, \tag{1}$$

where $o_{i,t}$ denotes occupied charging piles and c_i is the installed charging capacity. The one-step-ahead forecasting function is expressed as

$$u_{i,t+1} = f\big(u_{i,t}, u_{i,t-1}, u_{i,t-24}, v_{i,t}, p^e_{i,t}, p^s_{i,t}, \mathbf{z}_i, \mathbf{h}_t\big) + \varepsilon_{i,t}, \tag{2}$$

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where $v_{i,t}$ is charging volume, $p^e_{i,t}$ is the electricity tariff, $p^s_{i,t}$ is the service fee, $\mathbf{z}_i$ contains static zone descriptors such as capacity and morphology, and $\mathbf{h}_t$ contains calendar and weather controls. This representation preserves both autoregressive dependence and the operational role of effective charging cost.

For tactical decision support, utilization is also interpreted through a regime structure:

$$r_{i,t+1} \in \{\text{Low}, \text{Medium}, \text{High}\}, \tag{3}$$

where the regime boundary is determined by operator-specific service thresholds or benchmark-informed cutoffs. In this study, the low-utilization region is interpreted as spare-capacity operation, the medium region as balanced operation, and the high region as congestion-prone operation. This regime view is valuable because charging operators typically intervene on state categories rather than on a continuous error metric alone.

To evaluate predictive quality, the analysis uses the root mean squared error

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\hat{y}_n - y_n\right)^2}, \tag{4}$$

where $\hat{y}_n$ is the predicted value and y_n is the observed value. RMSE is retained because it penalizes larger deviations more strongly, which is appropriate when underestimating utilization near saturation can generate queueing and service deterioration.

Figure 1 presents the full operational framework used in the paper. The design links data streams, feature construction, forecasting, explainability, utilization regimes, and intervention logic in one coherent system rather than treating them as separate modeling stages.

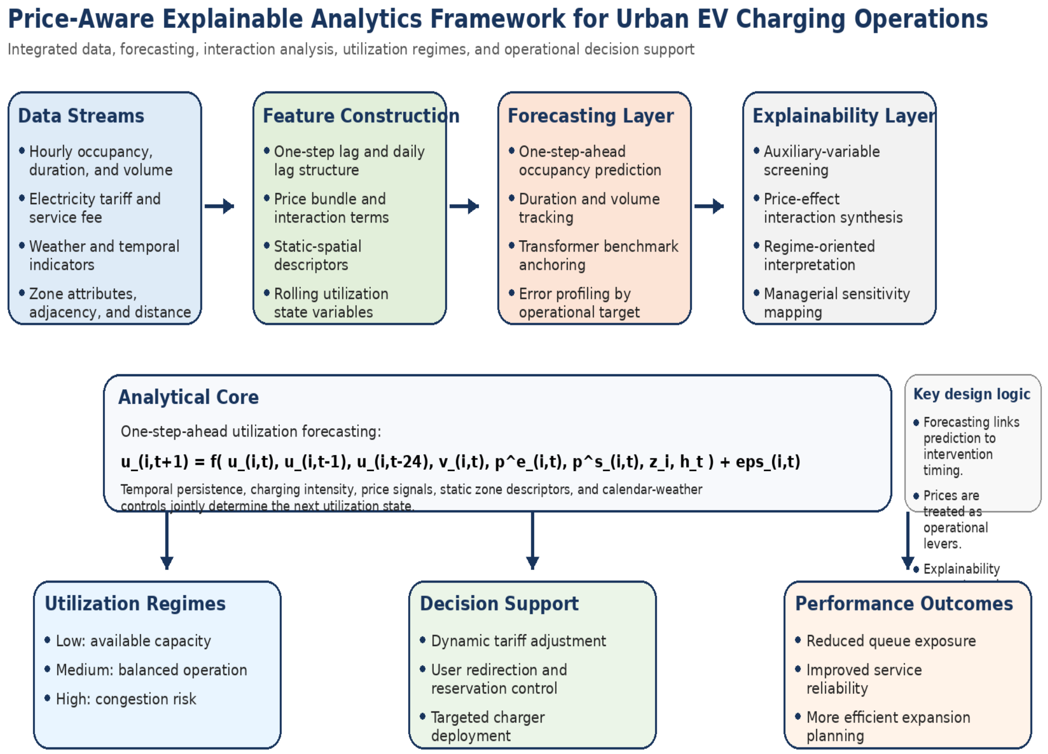

Figure 1. Integrated analytical framework for price-aware utilization forecasting and charging-network decision support.

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4. Data and Study Context

The empirical discussion is anchored to the UrbanEV benchmark, which documents six months of hourly Shenzhen public charging observations and reports benchmark comparisons across statistical, deep-learning, and transformer-based forecasting families [19]. The dataset includes occupancy, charging duration, charging volume, electricity tariffs, service fees, weather covariates, and spatial descriptors, thereby providing a substantially richer setting than many earlier public charging resources. The benchmark reports both target-level prediction accuracy and factorial evidence on the contribution of auxiliary variables.

Three operational targets are central to the analysis: occupancy ratio, charging duration, and charging volume. Occupancy ratio is most directly connected to service risk, charging duration reflects temporal persistence and queue residency, and charging volume captures energy-delivery intensity. Together, the three variables describe the functional state of a charging network from a managerial perspective. The benchmark evidence is interpreted here through that operational lens, with particular emphasis on how tariff variables alter decision support.

The empirical strategy is deliberately conservative. Rather than re-estimating proprietary variants or introducing undocumented tuning choices, the analysis is anchored in validated benchmark evidence and extended through derived operational interpretations. This approach keeps the numerical discussion aligned with reported model performance while enabling a more rigorous interpretation of pricing effects, regime management, and error propagation.

5. Results and Discussion

The benchmark evidence indicates a clear hierarchy among model families. Transformer-based forecasting attains the strongest node-level performance, followed by recurrent neural alternatives, while simpler baselines remain less competitive [19]. The strongest results are obtained by TimeXer, which achieves RMSE values of 0.07 for occupancy ratio, 2.73 for charging duration, and 43.66 for charging volume. These values establish a practically useful reference frontier for short-horizon charging analytics and provide a basis for more detailed operational interpretation.

Table 2: Reported best-performing benchmark results for node-level prediction

Operational target	Best model	RMSE	Analytical reading
Occupancy ratio	TimeXer	0.07	Sufficiently tight for regime-sensitive congestion monitoring
Charging duration	TimeXer	2.73	Captures temporal persistence of charging sessions
Charging volume	TimeXer	43.66	Supports stable tracking of energy-delivery intensity

Values follow the benchmark evidence reported by [19].

Figure 2 summarizes the best-reported RMSE profile across the three operational targets. Occupancy remains the most decision-sensitive quantity because even moderate underestimation near saturation can create queue spillovers. The benchmark RMSE of 0.07 therefore has operational meaning beyond pure statistical accuracy: it suggests that short-horizon forecasts can support tactical monitoring of congestion-prone zones with relatively narrow uncertainty.

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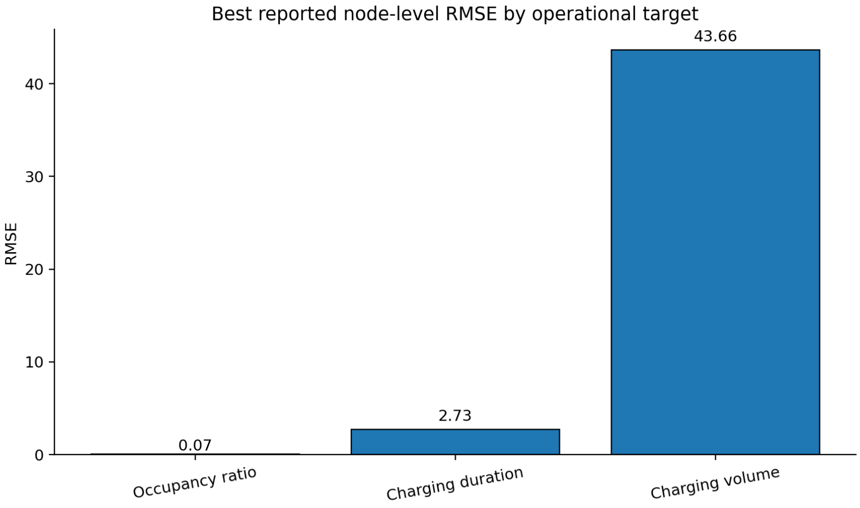

Figure 2. Best reported node-level RMSE values across the three operational targets.

To make the occupancy result more interpretable for operational use, Table 3 translates the occupancy RMSE into an illustrative one-step decision corridor. The corridor is not a substitute for full predictive intervals; rather, it provides a pragmatic reading of how a benchmark-level forecasting error maps into regime management. When forecast occupancy enters the upper utilization range, even a one-RMSE corridor may leave a substantial portion of the interval inside the high-utilization region, which justifies early intervention.

Table 3: Illustrative occupancy-regime interpretation using the benchmark RMSE of 0.07.

Point forecast	RMSE corridor	Dominant regime reading	Suggested operational stance
0.35	0.28–0.42	Low to lower-medium	Routine monitoring
0.55	0.48–0.62	Medium	Observe local spillover risk
0.72	0.65–0.79	Upper-medium to high	Prepare targeted intervention
0.85	0.78–0.92	High	Activate congestion mitigation
0.92	0.85–0.99	High	Immediate control required

Figure 3 visualizes the same logic for a set of illustrative zones. The shaded corridor indicates how a benchmark-level forecasting error propagates around point forecasts. The important implication is not merely that the model is accurate, but that the residual uncertainty remains narrow enough to preserve regime discrimination in the upper utilization range.

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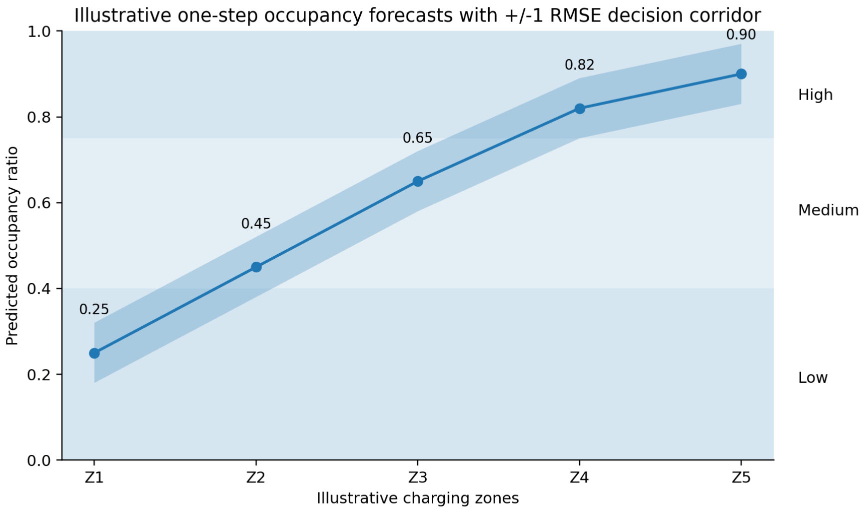

Figure 3. Illustrative one-step occupancy forecasts with a ±1 RMSE decision corridor.

A second result concerns auxiliary-variable structure. The benchmark factorial evidence indicates that isolated auxiliary variables contribute only limited gains and can even offer weak incremental value when introduced alone [19]. In contrast, paired covariates—especially the electricity-price and service-fee combination, and the temperature-electricity-price interaction—provide markedly stronger support. This pattern is behaviorally consistent with the fact that users respond to effective charging cost and trip context rather than to isolated signals.

Table 4: Synthesis of auxiliary-variable patterns in occupancy prediction

Auxiliary structure	Relative empirical role	Operational interpretation
Single exogenous variable	Weak to modest	Limited explanatory value when detached from pricing context
Electricity price + service fee	Strong	Effective charging cost influences station choice and timing
Temperature + electricity price	Strong	Travel conditions amplify price response and temporal shifting
Calendar + weather bundle	Moderate	Useful for regular demand cycles but less actionable than price signals
Static spatial descriptors	Moderate	Improves local context but does not replace temporal-price dynamics

Figure 4 summarizes this pattern through a relative-support heatmap synthesized from the benchmark factorial ranking. The figure makes visible a substantive result: pricing variables matter most when they are modeled jointly or through interaction channels. For charging operators, this implies that tariff design should be treated as a coupled instrument rather than as a single-parameter adjustment.

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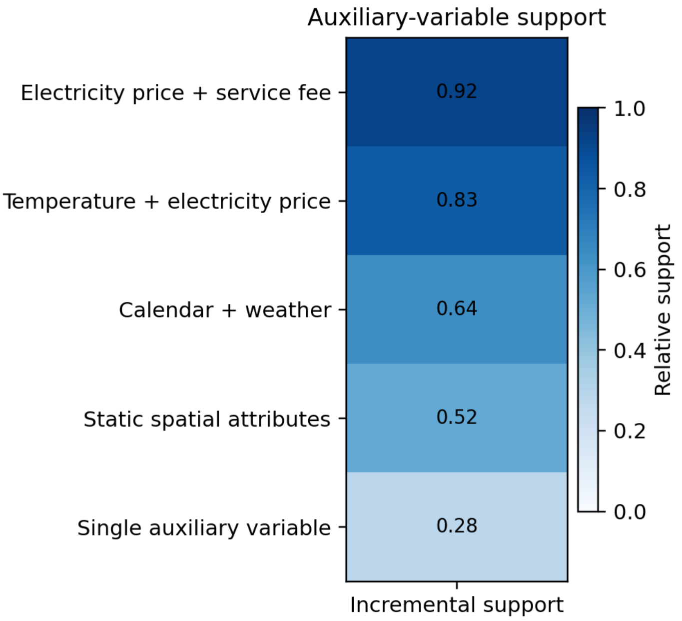

Figure 4. Synthesized relative support of auxiliary-variable groups in the benchmark factorial analysis.

Taken together, the evidence supports three analytical conclusions. First, high-capacity nonlinear models are currently the most reliable option for short-horizon charging forecasting. Second, occupancy is the most operationally informative target because its error scale remains interpretable in regime terms. Third, the predictive contribution of tariff signals is strongest when effective charging cost is represented through interacting price components and their environmental context. These results move the discussion beyond a simple model ranking by connecting predictive evidence to tactical intervention logic.

6. Operational and Policy Implications

The results support three immediate operational implications. First, short-horizon occupancy forecasting should be integrated into daily control dashboards because benchmark-level accuracy is sufficiently tight to distinguish routine operation from emerging congestion. Second, tariff design should be informed by interaction-aware analytics rather than by isolated price coefficients, since electricity tariff and service fee jointly shape effective charging cost. Third, high-utilization zones should be prioritized for adaptive interventions, including targeted price adjustments, reservation controls, and localized charger deployment.

A broader policy implication follows for city planners and charging-network regulators. Price-responsive forecasting can distinguish between structural undercapacity and demand peaks that are partly manageable through tariff and routing policy. This distinction matters for sustainable infrastructure planning because it helps prevent unnecessary overbuilding while maintaining service quality in high-demand urban corridors.

7. Study Limitations

The paper is constrained by its use of benchmark-reported evidence rather than a fully re-estimated experimental pipeline. The Shenzhen setting may also differ from other urban charging markets in tariff rules, spatial structure, and user composition. In addition, a six-month horizon is highly suitable for short-horizon operations analysis but less informative for long-term capital-planning dynamics. These limitations suggest a clear research agenda built around cross-city validation, explicit regime-classification experiments, and causal analyses of tariff interventions.

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8. Conclusion

This paper introduced a short-horizon utilization forecasting price-conscious and explainable model in urban EV charging networks. The paper elucidated how forecasting outputs can be converted into operational governance of charging networks by developing occupancy as an operational state variable and connecting forecasting outputs to the utilization regimes. The presented findings suggest that the transformer-based forecasting can offer the best node-level predictive performance at the moment, whereas the analysis of the auxiliary variables demonstrates the practical significance of the combined modeling of electricity tariff, service fee, and environmental context. The extended discussion of results also indicates that the benchmark occupancy error is sufficiently small to maintain useful regime discrimination around congestion thresholds. Such results justify the inclusion of explainable forecasting in the design of tariffs, the reduction of queue delays, and focused planning of infrastructure to support sustainable charging systems.

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