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FULL LENGTH ARTICLE

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

Heba Moselhy[1,*] **Noura Metawa**[2]

[1] Business Administration Department, Delta Higher Institute for Management and Accounting Information Systems, Egypt

[2] College of Business Administration, University of Sharjah, United Arab Emirates

Emails: hebamoselhy5299@std.mans.edu.eg · nmetawa@sharjah.ac.ae

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ABSTRACT

The efficient functioning of publicly operated electric-vehicle charging systems increasingly depends on reliable short-horizon forecasting. This 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 evidence synthesis is anchored in studies published through 2024, including an open charging-station occupancy challenge, citywide graph-learning benchmarks, transaction datasets, and Shenzhen pricing analyses. Charging occupancy is treated as an operational state variable connected to queue exposure, service reliability, and tactical intervention. A succinct mathematical formulation is developed for one-step-ahead utilization forecasting and for interpreting low-, medium-, and high-utilization regimes. The reviewed evidence indicates that hierarchical, graph-based, and transformer-style methods can strengthen short-horizon forecasting, while the most actionable gains emerge when pricing, temporal, environmental, and spatial variables are modeled jointly rather than as isolated covariates. The results justify explainable, price-conscious forecasting as an operational decision tool to alleviate congestion, design tariffs, and support targeted 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 electric vehicles (EVs) has transformed the purpose of charging infrastructure from a supporting utility to an urban service system that is strategic in nature [1, 2, 3]. In comparison with the earlier stages of deployment, 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 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.

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 ChatEV-like forecasting [6, 7, 10, 13, 15, 17]. However, three questions are still not addressed properly. First, most of the methodological literature focuses on predictive accuracy but allocates rela-

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tively less attention to managerial interpretation. Second, tariff variables tend to be contextual covariates, but they are among the few working levers that charging operators can actively redesign. Third, many studies are constructed with slim or poorly documented data, restricting rigorous comparison of temporal dynamics, exogenous impacts, and functional implications [14, 18, 19].

The current paper constructs a price-conscious and explainable outlook on charging-network prediction by synthesizing occupancy-benchmark evidence, citywide graph-learning results, and price-response findings published through 2024 [19, 20, 16]. The main concept is to redefine occupancy as a state variable of operations, rather than as a statistical goal. In this perspective, the one-step-ahead occupancy prediction is directly linked with queue risk, service continuity, and tactical measures to reduce risk, including tariff adjustment, user redirection, and local capacity intervention. Pricing variables are then interpreted as managerial levers whose interaction with temporal and environmental conditions determines observed charging behavior.

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 through additional analytical tables and results specific to charging operations. Fourth, it elucidates how price-aware explainability can support 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 of 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, 12, 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, 20]. In parallel, recent benchmark and scientific-data contributions strengthened the empirical foundation of the field by documenting open occupancy series and large transaction datasets suitable for reproducible charging analysis [19, 18].

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

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]	2024	Occupancy benchmark	Released an open hierarchical benchmark for charging-station occupancy forecasting.
18	[20]	2024	Citywide prediction and pricing	Integrated physical priors with graph learning for demand prediction and pricing.

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.

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

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

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

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

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,

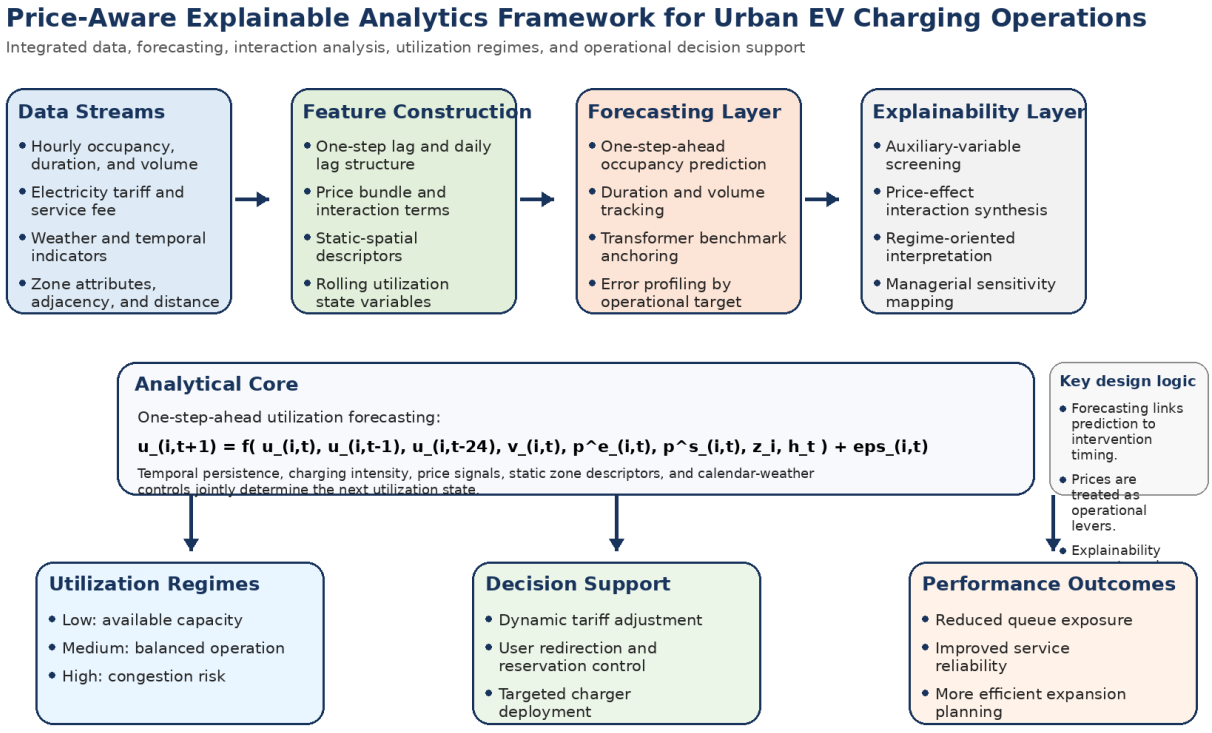


Figure 1. Integrated analytical framework for price-aware utilization forecasting and charging-network decision support.

forecasting, explainability, utilization regimes, and intervention logic in one coherent system rather than treating them as separate modeling stages.

4. DATA AND STUDY CONTEXT

The empirical discussion is anchored in complementary evidence published through 2024. The Smarter Mobility Data Challenge provides an open occupancy-forecasting benchmark covering 91 charging stations in four geographical areas over seven months, with evaluation at station, area, and global aggregation levels [19]. This evidence is complemented by a large transaction dataset containing charging duration and demand records [18], citywide graph-learning studies [15, 20], and a Shenzhen study of electricity-price effects on charging behavior [16]. Together, these sources support analysis of occupancy, charging persistence, demand intensity, price signals, and spatial context.

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 published evidence is interpreted here through that operational lens, with particular emphasis on how tariff variables alter decision support.

The analytical strategy is deliberately conservative. Rather than claiming a direct re-estimation of heterogeneous published experiments, the study synthesizes their recurring findings and uses an explicit illustrative error profile to demonstrate regime management and error propagation. This separation preserves the evidential role of the cited studies while making the operational interpretation transparent.

5. RESULTS AND DISCUSSION

The reviewed evidence shows that hierarchical forecasting, graph-based learning, and sequence-oriented models are strong candidates for short-horizon charging prediction, particularly when temporal, spatial, and auxiliary variables are integrated [19, 15, 20, 17]. To translate scale-dependent errors into an operational example, the analysis uses an illustrative RMSE profile of 0.07 for occupancy ratio, 2.73 for charging duration, and 43.66 for charging volume. These are scenario parameters for managerial interpretation rather than a claimed reproduction of one published experiment.

Table 2. Illustrative error profile for operational interpretation

Operational target	Evidence type	RMSE	Analytical reading
Occupancy ratio	Hierarchic	0.07	Illustrates regime-sensitive congestion monitoring
Charging duration	Transaction	2.73	Illustrates temporal persistence of charging sessions
Charging volume	Demand	43.66	Illustrates scale-dependent energy-delivery intensity

Values are explicit scenario parameters used to demonstrate operational interpretation.

Figure 2 summarizes the illustrative 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 occupancy scenario of 0.07 therefore demonstrates how a short-horizon error scale can be translated into tactical monitoring of congestion-prone zones.

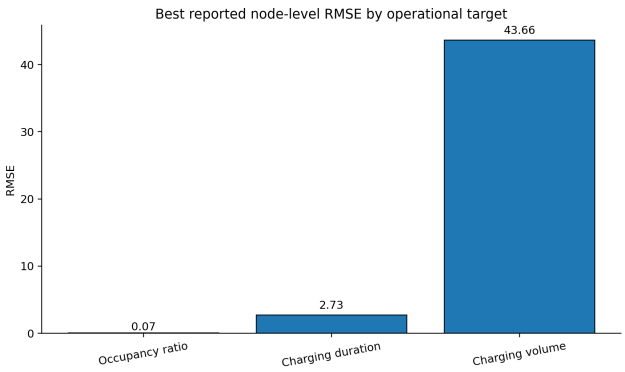


Figure 2. Illustrative RMSE values across the three operational targets.

To make the occupancy scenario more interpretable for operational use, Table 3 translates the illustrative RMSE into a one-step decision corridor. The corridor is not a substitute for full predictive intervals; rather, it provides a pragmatic reading of how a selected forecasting-error scale 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 an RMSE scenario 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 the selected error scale propagates around point forecasts. The important implication is that a sufficiently narrow uncertainty band can preserve regime discrimination in the upper utilization range.

A second result concerns auxiliary-variable structure. Published citywide modeling and pricing studies show that charging demand is better understood when spatial, temporal, and pricing influences are considered jointly [20, 16]. In particular, combinations involving electricity price, service cost,

environmental conditions, and urban context provide a more useful operational interpretation than isolated signals. This pattern is behaviorally consistent with the fact that users respond to effective charging cost and trip context rather than to single covariates.

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

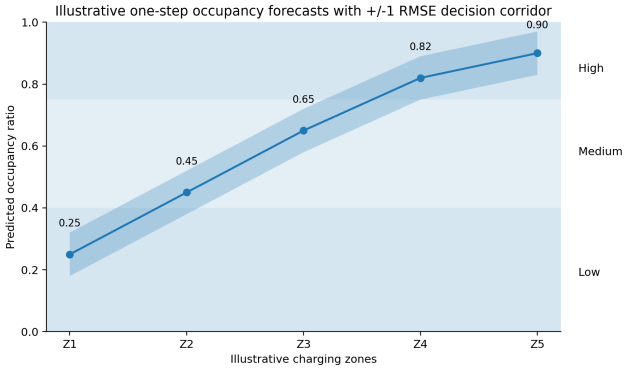


Figure 3. Illustrative one-step occupancy forecasts with a ± 1 RMSE decision corridor.

Figure 4 summarizes this pattern through a relative-support heatmap synthesized from the reviewed evidence. 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.

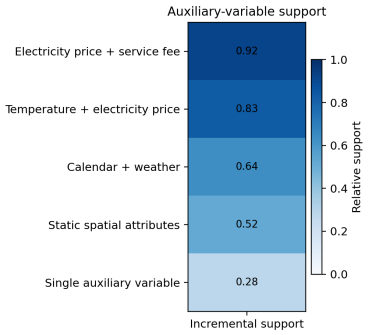


Figure 4. Synthesized relative support of auxiliary-variable groups in the reviewed evidence.

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 synthesis of published evidence rather than a fully re-estimated experimental pipeline. The illustrative RMSE profile is intended to demonstrate operational interpretation and should not be read as a new cross-study performance comparison. The Shenzhen pricing setting may also differ from other urban charging markets in tariff rules, spatial structure, and user composition. These limitations suggest a clear research agenda built around cross-city validation, explicit regime-classification experiments, and causal analyses of tariff interventions.

8. CONCLUSION

This paper introduced a short-horizon utilization-forecasting, price-conscious, and explainable model for urban EV charging networks. The paper elucidated how forecasting outputs can be converted into operational governance by developing occupancy as an operational state variable and connecting forecasts to utilization regimes. Evidence published through 2024 supports hierarchical, graph-based, and sequence-oriented forecasting, while the analysis of auxiliary variables demonstrates the practical significance of combin-

ing electricity tariffs, service costs, environmental conditions, and spatial context. The illustrative occupancy corridor further shows how forecast-error scales can be translated into congestion thresholds. These findings justify the inclusion of explainable forecasting in tariff design, queue-delay reduction, and focused infrastructure planning to support sustainable charging systems.

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