Targeted Governance and Performance Enhancement for Supply–Demand Mismatch in Urban Electric Vehicle Charging Infrastructure: A Case Study of Weiyang District, Xi'an

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Abstract: With the accelerating implementation of China's dual-carbon strategy and the rapid proliferation of new energy vehicles (NEVs), the supply–demand imbalance in urban electric vehicle (EV) charging infrastructure has emerged as a critical bottleneck constraining the high-quality development of green transportation. Existing static management frameworks are fundamentally ill-suited to handle the tidal fluctuations of charging loads and the polarised spatial allocation of resources. This study takes Weiyang District, Xi'an, as a representative urban prototype and develops an integrated Smart Charging Digital Twin Command Platform (SCDTCP) encompassing perception, diagnosis, decision-making, and control functions. Multi-source heterogeneous data — comprising Gaode Maps point-of-interest (POI) coordinates, seventh national census grid data, and a 740-respondent micro-level EV owner survey — are fused and subjected to Mahalanobis-distance-based multivariate outlier removal to construct a high-fidelity data foundation. At the macro-spatial level, a three-dimensional kernel density estimation (3D-KDE) method and a Supply–Demand Matching Index (SDMI) are innovatively introduced to precisely identify charging service deserts and their attenuation boundaries. At the micro-level, an ordered logistic regression (O-Logit) model is constructed to quantitatively confirm that perceived ICE vehicle encroachment on charging bays is the primary driver of user satisfaction decline. Subsequently, a Maximum Covering Location Problem (MCLP) model and an M/M/c multi-server queueing model are deeply integrated to adaptively generate spatially targeted station-siting plans and time-of-use (TOU) pricing strategies. Finally, the digital twin platform enables closed-loop hardware–software control spanning from global situational awareness to flexible command dispatch. Empirical evaluation demonstrates that the proposed strategy effectively redistributes 69.23% of peak-hour overload, eliminates inter-street SDMI disparities, and significantly improves infrastructure throughput and user satisfaction. The study advances the paradigm shift in charging governance from ad hoc infrastructure expansion toward data-intelligent targeted management, thereby providing a replicable engineering framework for equitable charging service delivery and low-carbon transport transition.

***Keywords*:** new energy vehicles; charging infrastructure; supply-demand mismatch; targeted governance; flexible dispatch

1. Introduction

With the accelerating implementation of China's dual-carbon strategy and the rapid proliferation of new energy vehicles (NEVs), the supply–demand imbalance in urban electric vehicle (EV) charging infrastructure has emerged as an increasingly critical challenge[1]. As a core node in green transportation networks, the spatial layout and operational efficiency of charging stations directly determine both the stable operation of microgrids and the quality of user mobility experience[2]. Resolving the dual challenge of macro-spatial resource misallocation and micro-level service degradation has become a key bottleneck in advancing the high-quality development of the NEV industry [3-4].

Taking Weiyang District of Xi'an as a representative central urban case, the city's charging network is experiencing complex spatiotemporal supply–demand competition. Conventional uncoordinated deployment patterns have induced severe resource polarisation, with charging facilities overly concentrated in core commercial zones such as Zhangjiabao, while older residential communities such as Xujiawan suffer from serious supply–demand imbalances and have become underserved charging zones. The deep coupling of macro-spatial misallocation and micro-level management blind spots, including ICE vehicle encroachment on charging bays, readily precipitates extreme spatiotemporal dual-peak phenomena, causing localised grid overloads during evening peak hours[5-7]. The peak load share surges to 69.23%, accompanied by sharp increases in queuing congestion.

The challenges exposed in Weiyang District represent a microcosm of issues confronting major cities across China. However, prevailing industry solutions remain predominantly focused on static planning or unidimensional physical capacity expansion[8], failing to address the nonlinear disequilibrium induced by dynamic spatiotemporal supply–demand competition. This highlights the fundamental limitations of conventional static management frameworks in responding to the time-varying demand fluctuations of charging loads[9].

2. Methodology

2.1 Research Framework

This study leverages EV charging pile load data and user questionnaire data from Weiyang District to construct the Smart Charging Command Platform following a principal workflow of data fusion, bottleneck diagnosis, spatiotemporal simulation, and digital twin control. On the basis of aligning POI records with micro-level user profiles and jointly diagnosing macro- and micro-level supply–demand polarisation, the Maximum Covering Location Problem (MCLP) model and dynamic queueing algorithm are deeply integrated to adaptively generate spatially targeted station-siting plans and time-of-use (TOU) pricing intervention strategies. The complete model stack is subsequently encapsulated within the digital twin platform to achieve closed-loop integrated control spanning global situational awareness to flexible governance command dispatch.

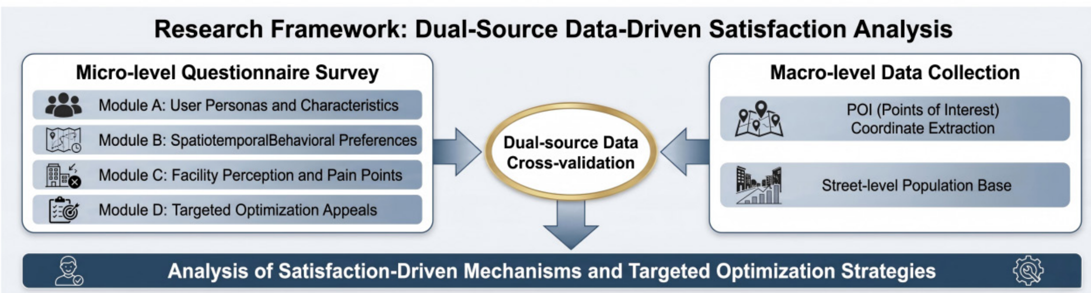

Figure 1. Core Logic Closed-Loop Diagram

2.2 Model Construction

To achieve a quantitative closed loop from platform construction to flexible governance, the simulation platform's underlying architecture strictly adheres to the technical workflow, sequentially embedding and encapsulating three modules: data preprocessing, supply–demand bottleneck diagnosis, and supply–demand equilibrium optimisation.

2.2.1 Multi-Source Data Perception and Data Quality Assessment

Three data sources were collected: geographic coordinates of urban EV charging station points of interest (POIs) from Gaode Maps, seventh national population census grid data, and 740 micro-level EV owner questionnaire responses.

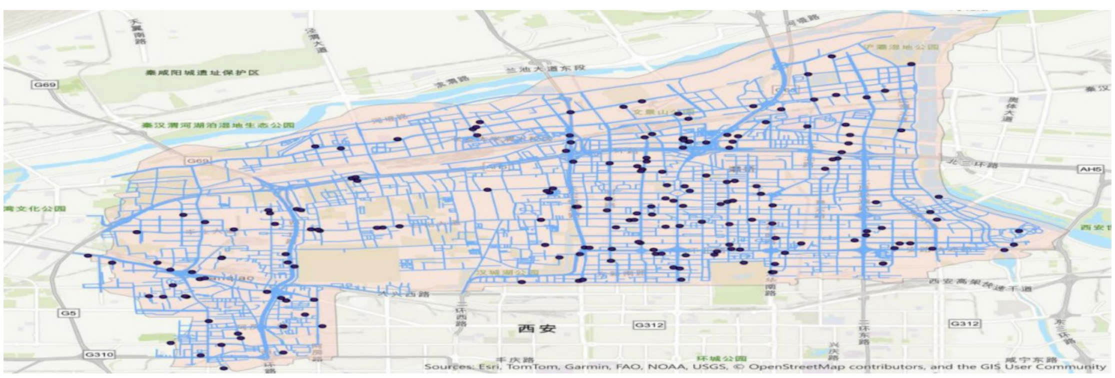

Figure 2. GIS Distribution Map of EV Charging Stations

To prevent contaminated data and internally inconsistent responses from compromising the digital twin platform, an internal consistency measure and a Mahalanobis-distance-based multivariate outlier filtering model were applied to conduct rigorous cleaning of the micro-level sample. Cronbach's α coefficient was adopted for reliability testing, and the Mahalanobis distance $D_{M(x)}$ was employed to identify and remove high-dimensional outliers:

$$
\begin{cases}
\alpha = \dfrac{K}{K-1}\left(1 - \dfrac{\sum_{i=1}^{K}\sigma_i^2}{\sigma_X^2}\right) \\
D_M(x) = \sqrt{(x-\mu)^T \Sigma^{-1} (x-\mu)}
\end{cases}
$$

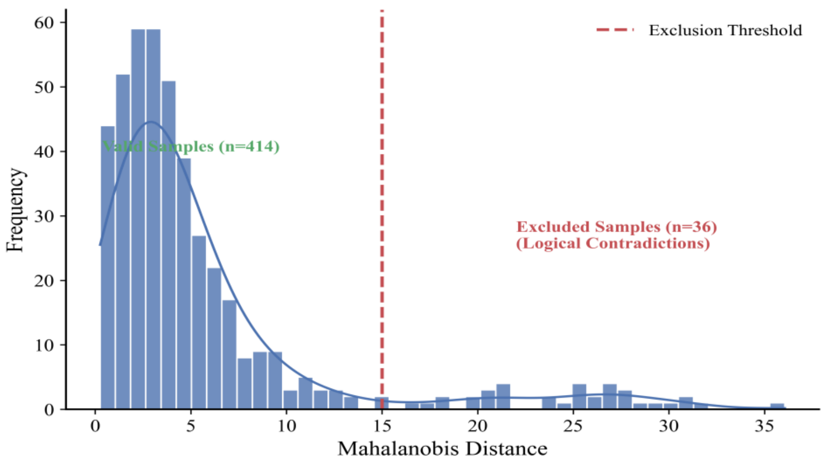

Figure 3. Questionnaire Cleaning Distribution Based on Multivariate Outlier Detection

2.2.2 Spatial Mismatch Joint Quantification and Diagnostic Model

At the macro-spatial mismatch level, a per-10,000-population Supply–Demand Matching Index (SDMI) and three-dimensional kernel density estimation (3D-KDE) are introduced, whereby discrete POIs are transformed into continuous spatial density distributions via a Gaussian kernel function:

$$
\begin{cases}
f(x,y) = \dfrac{1}{nh^2}\sum_{i=1}^{n} K\left(\dfrac{d_i}{h}\right) \\
SDMI_i = \dfrac{S_i}{D_i} \times 10000
\end{cases}
$$

Where d_i denotes the spatial distance from a grid cell to the nearest charging station, and S_i and D_i represent the regional supply and demand quantities, respectively. This model suite delineates the resource polarisation phenomenon in core commercial areas and the service attenuation boundaries of underserved charging zones in older residential communities.

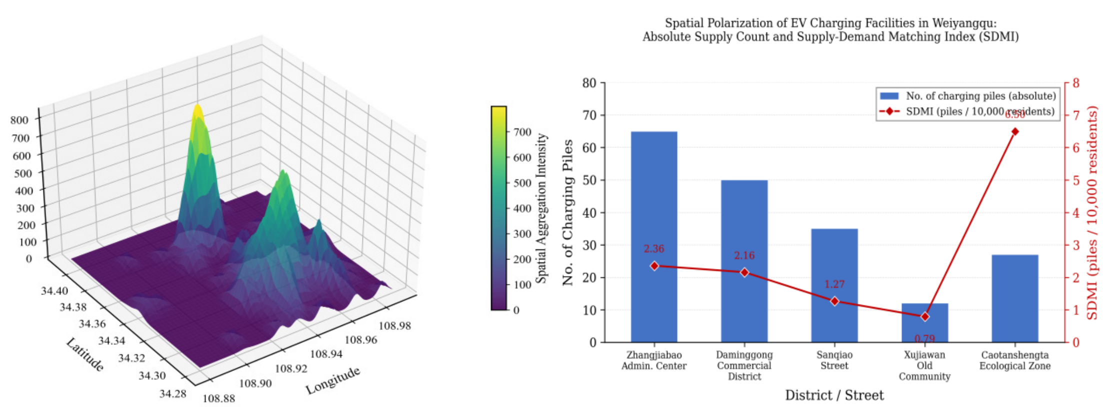

Figure 4. Spatial Polarisation Measurement Results of EV Charging Facilities in Weiyang District Based on 3D-KDE and SDMI

The 3D-KDE provides a physical spatial projection, while the SDMI supplies a socio-economic supply–demand benchmark. Superimposing the two layers delineates the resource over-concentration polarisation in core commercial zones and mathematically demarcates the true service radius of underserved zones in older residential communities, thereby providing objectively grounded spatial anchors for subsequent targeted station siting.

At the micro-level of individual service degradation, an Ordered Logistic Regression (O-Logit) evaluation framework is constructed to address user satisfaction erosion, with variable level-transition probabilities estimated via maximum likelihood estimation:

$$\ln\left(\frac{P(Y \leq j)}{1-P(Y \leq j)}\right)=\alpha_j-\sum_{k=1}^{m}\beta_k X_k$$

Where β_k denotes the regression coefficient for each bottleneck factor. This model isolates hardware-related confounding variables and quantitatively confirms the sensitivity coefficients of satisfaction loss attributable to ICE vehicle encroachment on charging bays and spatiotemporal dual-peak queuing congestion.

2.2.3 Spatiotemporal Supply–Demand Simulation and Collaborative Decision Algorithm

To adaptively generate a combined intervention strategy of spatially targeted station siting and time-of-use pricing, the decision core integrates the Maximum Covering Location Problem (MCLP) model and M/M/c multi-server queueing theory:

$$Max\sum_{i\in I} d_i y_i \quad \text{(MCLP objective function for targeted station siting)}$$

$$P_w=\frac{(c\rho)^c}{c!(1-\rho)}P_0 \quad \text{(Waiting probability for multi-server queueing)}$$

The MCLP model maximises coverage of demand nodes d_i, directing investment toward underserved zones with critically low SDMI values through targeted capital allocation. The M/M/c model dynamically simulates the high-load operation probability P_w across c charging piles during evening peak periods, thereby triggering TOU dynamic pricing adjustment commands to achieve peak shaving and valley filling.

2.3 Management Strategy Performance Evaluation

The extreme spatiotemporal supply–demand competition scenario in Weiyang District, Xi’an, is selected as the representative case for empirical examination of the implementation effectiveness of two core collaborative management strategies: spatially targeted station deployment and temporally flexible intelligent governance.

2.3.1 Spatial Targeting Strategy: Polarisation Mitigation Effectiveness

Addressing the severe spatial resource mismatch, the MCLP maximum covering location strategy demonstrates strong spatial corrective capability. Prior to intervention, SDMI in core commercial zones reached 2.36, indicative of severe resource idleness, while peripheral community SDMI was as low as 0.79, qualifying these areas as absolute underserved zones. Following spatial targeting intervention, new construction targets were directed toward long-tail communities with SDMI values below the threshold of 1.0.

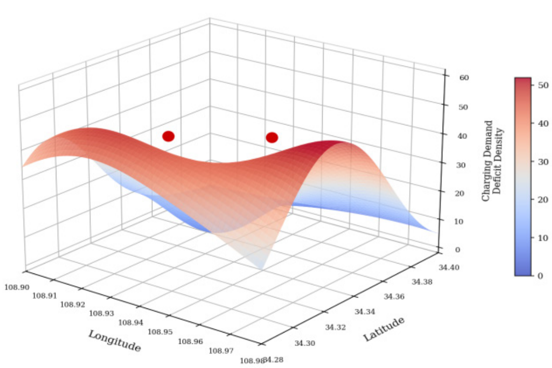

Figure 5. Spatial Targeting Simulation for New Station Construction Based on the MCLP Maximum Covering Model

Empirical simulations demonstrate that this strategy effectively eliminates regional supply disparities, resolves the charging service desert problem in older residential communities, and achieves a significant reduction in the spatial Gini coefficient of the regional charging network.

2.3.2 Temporal Flexible Governance: Peak Shaving and Valley Filling Effectiveness

In response to extreme congestion driven by the spatiotemporal dual-peak phenomenon, M/M/c queueing simulation triggers an efficient temporal intervention. Targeting the abnormal surge of evening peak grid load to 69.23%, off-peak dynamic pricing commands are precisely dispatched, and a demand price elasticity matrix is employed to successfully redirect price-sensitive EV owners toward off-peak charging periods. Performance data confirm that the flexible governance strategy substantially reduces the probability of concentrated peak-period queuing, smoothly redistributing localised overload to nocturnal off-peak periods, thereby considerably alleviating the safety-loading pressure on local microgrids.

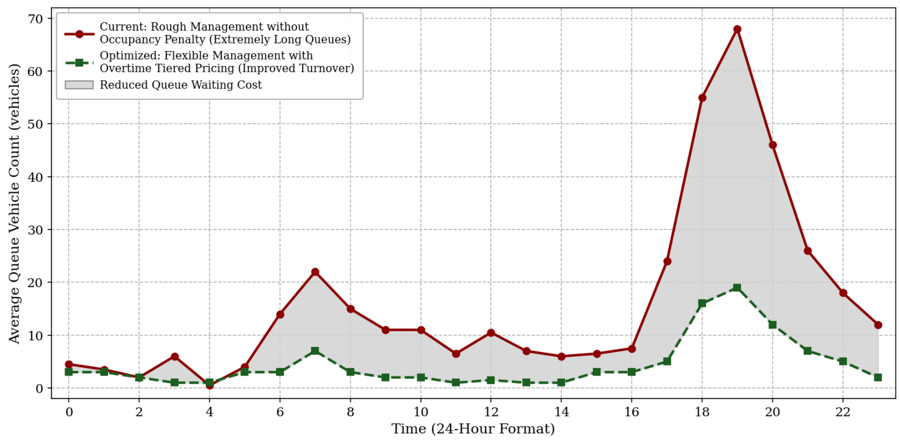

Figure 6. Comparison of Average Queue Length at Charging Stations Before and After Flexible Management

3. Innovations and Contributions

3.1 Advancing Beyond Static Assessment: Construction of the SDMI and 3D-KDE Spatial Polarisation Measurement Model

Addressing the limitations of absolute-quantity-based evaluation approaches, a Supply–Demand Matching Index and three-dimensional kernel density estimation are introduced. By coupling Gaussian kernel functions with population grids, the model precisely characterises the spatial differentiation patterns of commercial-zone agglomeration and community-level supply deficits. From a geographic-topological perspective, it scientifically delineates the service attenuation boundaries of underserved charging zones, providing objective spatial anchors for targeted station siting.

3.2 Isolating Hardware Confounders: Proposing the O-Logit Micro-Level Experience Attribution Framework

To address the challenge of micro-level service degradation, Mahalanobis-distance-based multidimensional outlier removal is combined with ordered logistic regression modelling. This framework effectively isolates hardware facility confounders, precisely quantifies the sensitivity coefficients of satisfaction loss attributable to ICE vehicle encroachment and queuing congestion, converts subjective user dissatisfaction into quantifiable governance targets, and supplements the micro-perspective deficiencies of traditional management frameworks.

3.3 Replacing Indiscriminate Expansion: Proposing a Spatiotemporal Dual-Dimensional Flexible Governance Decision Mechanism

To address spatiotemporal supply–demand imbalances, the decision core integrates MCLP and M/M/c multi-server queueing theory. In the spatial dimension, new construction targets are directed toward coverage-deficit zones; in the temporal dimension, extreme loads are dynamically simulated and TOU pricing adjustments are adaptively triggered. This approach fundamentally overturns the indiscriminate infrastructure expansion model, achieving peak shaving, valley filling, and closed-loop supply–demand control.

4. Conclusion and Application Prospects

The spatial polarisation measurement model developed in this study can assist planning authorities in precisely identifying underserved charging zones. Based on empirical evidence from Weiyang District, Xi'an, the proposed approach effectively bridges the supply gap between SDMI values of 2.36 and 0.79, significantly improving the utilisation efficiency of fiscal subsidies and land resources. Concurrently, the data-intelligent flexible governance mechanism drives operators toward a strategic transformation from conventional electricity retailing to algorithm-driven operations management. By applying the demand price elasticity matrix, 69.23% of peak-hour overloaded loads are smoothly redistributed to nocturnal off-peak periods, simultaneously reducing grid expansion costs and substantially improving the round-the-clock turnover rate of charging equipment.

The solution exhibits strong replicability. Scaling from Weiyang District to core urban areas nationwide would enable substantive alleviation of grid capacity pressure caused by the rapid growth in NEV ownership through peak shaving and valley filling. At the micro level, queuing anxiety among users would be mitigated; at the macro level, the green low-carbon transition of the transportation sector would be accelerated, generating far-reaching social and economic effects.

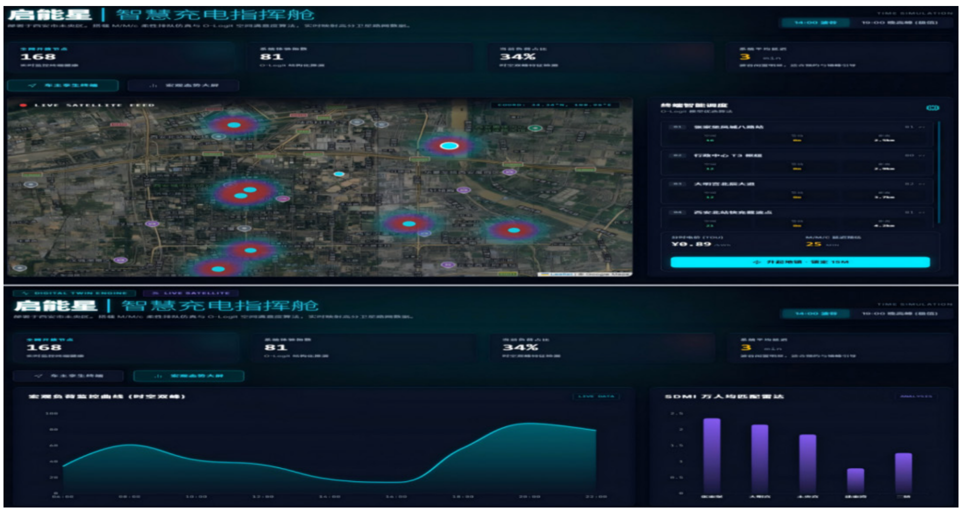

Figure 7. Intelligent Charging Monitoring Platform

References

[1] Song Y F. Research on Optimisation Design of Location and Capacity of Electric Vehicle Charging Stations Based on Multi-Source Information Fusion [D]. Lanzhou Jiaotong University, 2024.

[2] Gao C W, Dong C Y, Xue F. Design and implementation of electric vehicle charging behaviour simulation software based on multi-agent systems [J]. Proceedings of the CSEE, 2012, 32(31): 68–77+220.

[3] Yan G G, Liu H N, Han N H, et al. Optimal siting and capacity planning of charging stations considering the spatiotemporal distribution of electric vehicles [J]. Proceedings of the CSEE, 2021, 41(18): 6271–6284.

[4] Zeng M, Xue S, Liu H Z, et al. Regional electric vehicle operation modes and optimal grid-connected capacity planning model [J]. Power System Technology, 2012, 36(06): 175–181.

[5] Xie Y D, Zhang L, Deng S L, et al. Research on optimised network layout of electric vehicle charging facilities [J]. Mathematics in Practice and Theory, 2020, 50(10): 168–176.

[6] Ren Y L, Shi L F, Zhang Q, et al. Research on optimal distribution and scale of electric vehicle charging stations [J]. Automation of Electric Power Systems, 2011, 35(14): 53–57.

[7] Hosseini M, MirHassani S A. Selecting optimal location for electric recharging stations with queue[J]. KSCE Journal of Civil Engineering, 2015, 19(7): 2271-2280.

[8] Li R Q, Su H Y. Optimal configuration of electric vehicle charging facilities based on queueing theory [J]. Automation of Electric Power Systems, 2011, 35(14): 58–61.

[9] Zhou H C, Li H F. Research on location optimisation model of electric vehicle charging stations based on game theory [J]. Science Technology and Industry, 2011, 11(02): 51–54.