RESEARCH ARTICLE

An Integrated Demand Forecasting and Location Optimization Framework for Electric Vehicle Charging Stations: A Case Study of District 1, Ho Chi Minh City

Ly Hoang Anh[1,*] **and Altaf Hussain**[2,*]

[1] School of Business and Administration, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
[2] School of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

Abstract

Vietnam's Electric Vehicle (EV) market is expanding rapidly, yet public charging infrastructure development lags significantly, exhibiting pronounced spatial imbalance in dense urban cores. This study addresses this gap through an integrated demand forecasting and location optimization framework for District 1, Ho Chi Minh City. We develop a log-linear regression model using Vietnam's macroeconomic data (2003–2023), identifying GDP and CPI as dominant determinants of vehicle ownership (R^2 = 0.962). Forecasted vehicle stocks for 2026–2030 are translated into public charging demand through vehicle-type disaggregation and service-capacity modeling. Spatially, we propose a four-stage optimization pipeline: demand point generation → K-Means spatial zoning → P-Median location optimization → budget-constrained allocation. Results reveal a multi-tier station distribution centered on commercial cores (Nguyen Hue–Ben Thanh corridor) with supplementary coverage in residential and tourist zones. Core areas require fast-charging expansion to manage 12% annual demand growth, while northern/southern residential blocks need baseline coverage to eliminate service gaps. Critically, we demonstrate that profit-driven private deployment creates spatial inequity, necessitating government-coordinated planning to balance efficiency and accessibility. Despite data constraints, our framework provides a replicable methodology for charging infrastructure planning in high-density Southeast Asian urban contexts, with direct implications for Vietnam's green mobility transition.

Keywords: electric vehicles, intelligent charging infrastructure, K-Means, P-Median, advanced computing, location optimization, district 1 Ho Chi Minh City, EV charging demand forecasting.

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***Corresponding author:**
Ly Hoang Anh
anhlyhoang@gmail.com
Altaf Hussain
altafkfm74@gmail.com

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1 Introduction

The transition of energy systems from fossil fuels to green and low-carbon sources has emerged as a key policy direction worldwide (IEA, 2024). Against this backdrop, New Energy Vehicles (NEVs), particularly Electric Vehicles (EVs), have gained prominence due to their advantages in energy efficiency and emission reduction, making them a critical driver of green transformation in the transportation sector. According to reports released by the International Energy Agency (IEA, 2024), the global market for renewable power generation and energy storage is still in a phase of rapid expansion, and the electrification of the global automotive industry is accelerating significantly. Within Southeast Asia, Vietnam has demonstrated particularly strong economic momentum. During 2023–2024, Vietnam's GDP growth rate remained within the range of 5%–7% (World Bank, 2024), accompanied by continuous urbanization and an ongoing upgrade of household consumption patterns. In the National Green Energy Transition Plan (Decision No. 876/QĐ-TTg, 2022), the Vietnamese government explicitly set a long-term target of achieving full electrification of motor vehicles by 2050, while simultaneously promoting the development of charging infrastructure systems to enhance the convenience and reliability of EV usage.

However, in sharp contrast to the rapid growth of electric vehicles, Vietnam's charging infrastructure remains at an early stage of development (Vietnam Ministry of Transport, 2023). Existing challenges include an insufficient number of charging facilities, uneven spatial distribution, and limited service coverage. Although the number of charging stations in major Vietnamese cities has been increasing at an accelerated pace, the overall scale is still far from sufficient to meet future demand (Vietnam Ministry of Transport, 2023). This issue is particularly acute in central urban areas such as downtown Ho Chi Minh City, where land scarcity and high population density have made inadequate charging infrastructure a critical constraint on further EV adoption. From the perspective of urban transportation development, charging stations are not merely energy supply facilities but also essential infrastructure linking urban planning, road design, and user behavior. A lack of scientific planning may result in low facility utilization rates, expanding service blind spots, and inefficient allocation of resources. Therefore, in the context of rapidly increasing EV ownership in Vietnam, conducting systematic research on the scientific siting of charging stations is both necessary and urgent.

At present, empirical studies related to EV charging infrastructure in Vietnam remain limited, particularly with respect to systematic layout research in core urban districts such as District 1 of Ho Chi Minh City. Based on charging demand forecasting and spatial optimization methods, this study aims to develop an operational planning framework for charging station deployment in Vietnam's central urban areas. Within the EV industry chain, the spatial configuration of charging infrastructure directly affects user experience, industrial development, and urban transportation structures. Traditional facility location theories—including classical location theory, coverage models, minimum cost models, and multi-objective optimization models—have been widely applied in urban planning practices in Europe, the United States, and China. However, directly applying these theories to the Vietnamese context presents notable limitations, primarily due to data scarcity, differences in transportation structures, and spatial constraints in high-density built-up areas. First, with respect to demand forecasting, traditional location theories often assume sufficient data availability and relatively homogeneous demand distribution. In contrast, Vietnam's transportation system exhibits distinct structural characteristics: Motorcycles have long dominated urban travel, resulting in highly differentiated traffic flows and parking patterns; EV sales data lack long-term continuity, making it difficult to directly construct robust time-series models; Urban land use is highly mixed, leading to pronounced temporal variations in charging demand. Second, in terms of spatial adaptability, District 1 of Ho Chi Minh City represents a typical high-density urban core. Early French colonial planning resulted in narrow road networks, fragmented land parcels, and high development intensity, causing site selection to be strongly constrained by road width, land availability, and historic district preservation requirements. Moreover, the high concentration of urban activities makes it difficult to define service radii in a uniform manner. Under these urban conditions, traditional location models are prone to spatial mismatch problems. Consequently, it is necessary to introduce optimization methods capable of addressing complex urban forms and irregular spatial demand distributions. This study adopts K-Means spatial clustering and the P-Median model as core location optimization tools to better accommodate the highly uneven demand structure characteristic of Vietnam's central urban areas.

This study contributes to theory, practice, and policy in the following three aspects: By integrating vehicle demand forecasting with urban spatial optimization, this study offers a transferable modeling framework for infrastructure planning under data-scarce conditions. At the application level, it provides an adaptable site selection approach for central urban areas in Vietnam, enriching the theoretical literature on urban electrification in Southeast Asia. The charging station layout developed for District 1 of Ho Chi Minh City helps alleviate existing supply–demand imbalances, improve facility utilization efficiency, enhance user experience, and promote the development of a local green mobility system. The research outcomes offer empirical support for local governments in formulating charging infrastructure plans, fiscal subsidy policies, and operational mechanisms. They also help guide private capital investment in charging facilities and improve overall infrastructure supply capacity. The main content of this study consists of two interrelated components: A multi-dimensional forecasting model based on economic, demographic, and transportation indicators is developed to quantify charging infrastructure demand over the next five years. By incorporating urban planning principles, spatial functional structures, and road network characteristics, a layout and optimization framework suitable for central urban districts is constructed.

VINFAST Auto Ltd., a subsidiary of Vietnam's Vingroup conglomerate, is the country's leading electric vehicle manufacturer. Having listed on Nasdaq in 2023, VINFAST has expanded its EV lineup domestically and internationally, with active manufacturing investment in North America. Its charging network subsidiary, V-Green, plays the dominant role in Vietnam's public charging infrastructure and is therefore central to the supply-side context of this study.

Among the key investors in Vietnam's charging infrastructure, V-Green plays a dominant role. As of July 2024, V-GREEN had established more than 1,200 charging stations nationwide, comprising approximately 150,000 charging points distributed across all 63 provinces of Vietnam. Specifically, the northern region hosts around 450 charging stations, the central region approximately 300 stations, and the southern region about 450 stations. At present, these charging facilities exclusively serve VINFAST-branded electric vehicles. In District 1 of Ho Chi Minh City, a total of eight charging stations are currently in operation, providing 48 charging points. Among them, two charging stations commenced operation at the end of March and the end of December, respectively; however, the exact number of charging points at these newly opened stations has not yet been officially disclosed. Figure 1 illustrates the main research flow, while Figures 2, 3, 4, 5 and 6 illustrate visual presentation of the EV charging stations.

According to information displayed on the website of Evercharge, the company operates a total of 62 charging stations nationwide. In Ho Chi Minh City, there are two charging stations providing five charging points in total; however, no charging stations are currently located in District 1.

According to information published on the website of EV ONE, the company operates a total of 53 charging stations nationwide, including 10 stations in the northern region, 6 in the central region, and 37 in the southern region. In District 1 of Ho Chi Minh City, EV ONE has established four charging stations, providing a total of 13 charging points.

In response to the practical needs of EV charging infrastructure planning in Vietnamese cities, this study establishes two primary research contributions:

- To develop a demand forecasting model for EV charging in Vietnam Based on macroeconomic indicators, population characteristics, and travel behavior, a demand forecasting model suitable for Vietnam's data environment is constructed to quantitatively estimate EV ownership and public charging demand over the next five years. The results provide a measurable basis for determining the scale of urban charging infrastructure development.
- To formulate a charging station layout strategy for high-density urban cores Using District 1 of Ho Chi Minh City as a case study, this research integrates macro-level demand forecasts with spatial optimization models to develop a siting strategy that accommodates limited spatial resources and pronounced demand heterogeneity in central urban areas. The proposed layout aims to achieve balanced service coverage, reasonable accessibility, and efficient resource utilization.

The findings of this study are expected to provide scientific references for Vietnamese government agencies, investors, and industry stakeholders, thereby supporting the development of a more complete EV

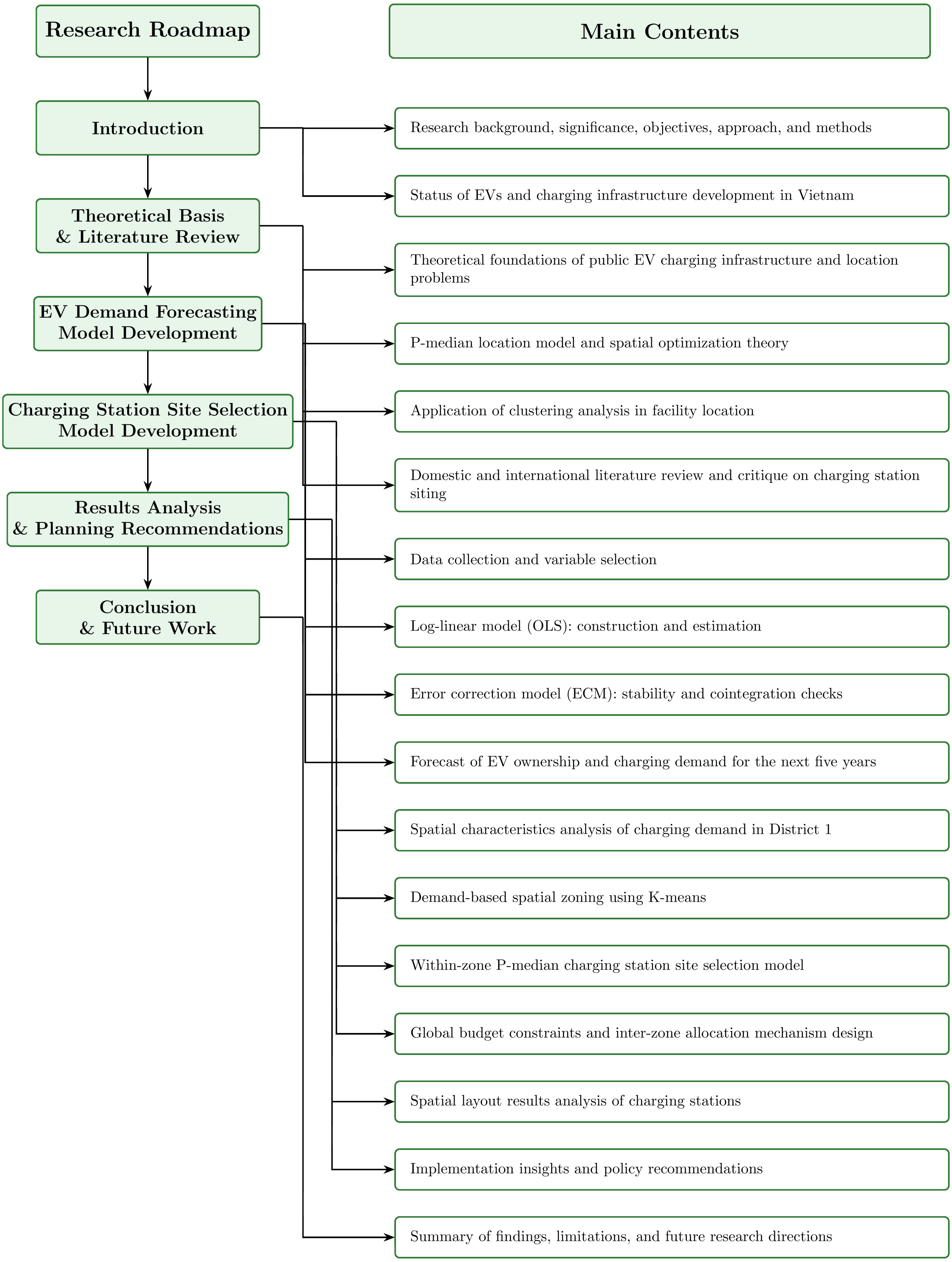

Figure 1. Technical roadmap of the integrated demand forecasting and location optimization framework for electric vehicle charging infrastructure planning in District 1, Ho Chi Minh City. The four-stage pipeline progresses from macroeconomic demand forecasting (GDP/CPI-driven vehicle stock projection) through spatial demand disaggregation, K-Means zoning of 1,368 demand points into 31 functional subzones, P-Median facility location optimization within each subzone, and final budget-constrained station allocation across the district for 2026–2030.

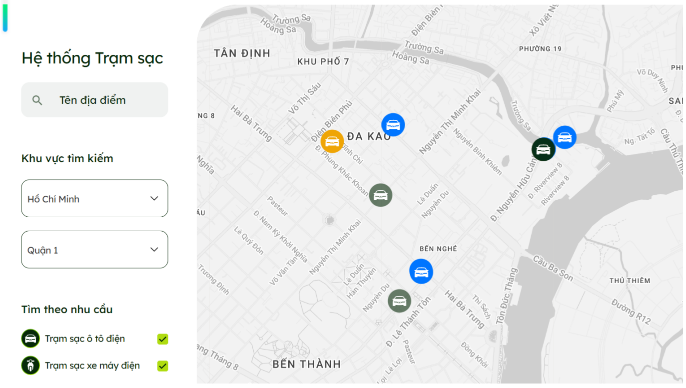

Figure 2. Spatial distribution of V-Green charging stations (n=8 stations, 48 charging points) operating in District 1, Ho Chi Minh City as of July 2024. Stations concentrate along the Nguyen Hue–Ben Thanh commercial corridor (6 stations) with limited coverage in northern residential blocks and southern riverside zones, reflecting profit-driven deployment patterns that prioritize high-traffic commercial areas over spatial equity in residential neighborhoods.

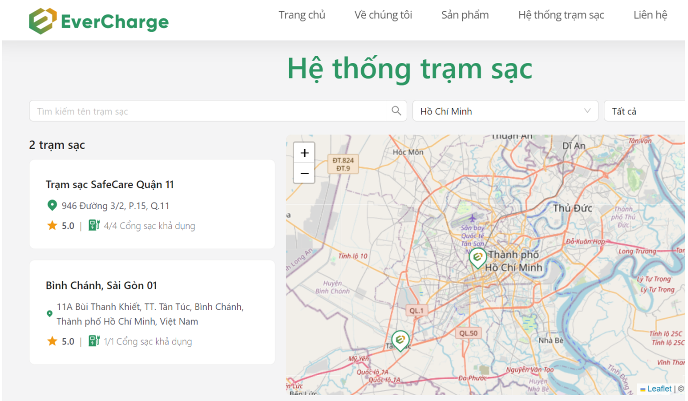

Figure 4. Absence of Evercharge charging infrastructure in District 1, Ho Chi Minh City as of 2024. Despite operating 2 stations in greater Ho Chi Minh City (providing 5 charging points total), Evercharge maintains no facilities within District 1's 7.7 km^2 administrative boundary, highlighting the fragmented and commercially selective nature of current private-sector charging deployment in Vietnam's urban core.

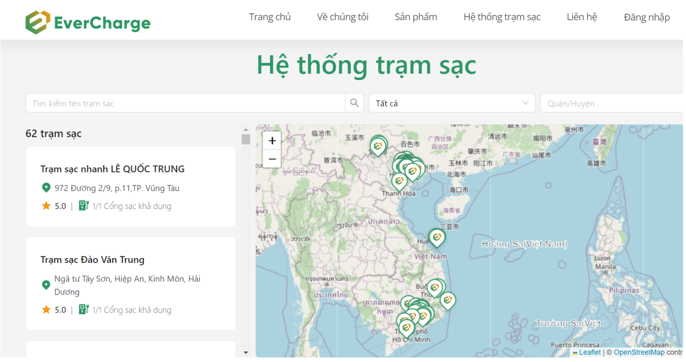

Figure 3. Nationwide spatial distribution of Evercharge charging stations (n=62 stations) across Vietnam's 63 provinces as of 2024, showing regional concentration patterns with 45% of stations located in northern provinces (including Hanoi), 24% in central provinces, and 31% in southern provinces (including Ho Chi Minh City metropolitan area), with zero stations currently operational in District 1.

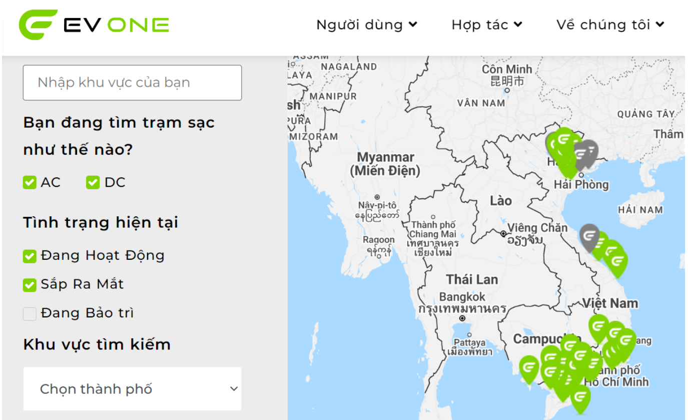

Figure 5. Spatial distribution of EV ONE charging stations (n=53 stations) across Vietnam's three macro-regions as of 2024: northern region (10 stations, 19%), central region (6 stations, 11%), and southern region (37 stations, 70%), with southern concentration reflecting Ho Chi Minh City's dominance in Vietnam's emerging EV market and infrastructure development.

industry ecosystem and strengthening Vietnam's competitive position in regional electrification initiatives.

The rest of the article is organized as follows: Section 2 presents the basic theoretical background and related studies for the proposed work. Section 3 presents the main method of the proposed framework. Section 4 presents the results and analysis, and Section 5 concluded the article.

2 Theoretical Foundations and Literature Review

2.1 Theoretical Foundations

In the construction of an EV charging network, economic feasibility is a crucial consideration. To ensure the long-term sustainability of charging infrastructure, a comprehensive cost–benefit analysis of charging stations is indispensable. The key cost and revenue components of EV charging stations are analyzed below and are illustrated in Figure 7.

When constructing location models, economic factors must be explicitly incorporated into the

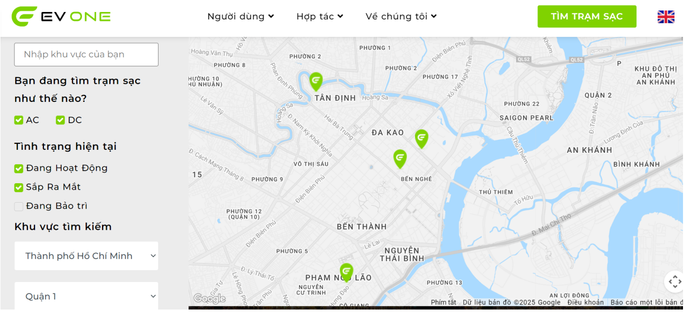

Figure 6. Spatial distribution of EV ONE charging stations (n=4 stations, 13 charging points) within District 1, Ho Chi Minh City as of 2024. Stations cluster near major commercial nodes (Ben Thanh Market, Nguyen Hue Walking Street) with no facilities in northern residential zones (Ward 2, 3, 4) or southern riverside areas (Ward 10, 13), demonstrating persistent spatial gaps in residential coverage despite commercial area saturation.

decision-making process for charging station siting. We define the cost set as $C = [C_1, C_2, \ldots, C_n]$. Here, $C_1, C_2, \ldots, C_n$ include land acquisition costs, equipment costs, energy costs, maintenance costs, and other related expenses, and n denotes the total number of cost components considered in the study. Similarly, the benefit set is defined as $E = [E_1, E_2, \ldots, E_m]$, which includes charging service revenues, advertising revenues, and environmental benefits, among others, where m represents the number of benefit components considered. In addition, a constraint set $S = [S_1, S_2, \ldots, S_h]^\top$ is introduced, where h denotes other constraints beyond costs and benefits. Charging demand is denoted as D. From an economic perspective, charging station location models typically focus on the following dimensions:

Cost minimization under demand satisfaction

Given that all EV charging demand $D_{\max}$ must be satisfied, the objective is to minimize the total cost of charging stations through optimized layout and resource allocation in Eqs. (1)–(2):

$$\min \sum_{i=1}^{n} C_i \tag{1}$$

$$\text{s.t. } D \geq D_{\max}, \quad S = [S_1, S_2, \ldots, S_h]^\top \tag{2}$$

Demand maximization under cost constraints

When planning charging stations, a balance between cost and service demand must be achieved. The objective is to maximize the charging demand that can be satisfied under a given cost budget in Eqs. (3)–(5):

$$\max D \tag{3}$$

$$\text{s.t. } \sum_{i=1}^{n} C_i \leq C_{\max} \tag{4}$$

$$S = [S_1, S_2, \ldots, S_h]^\top \tag{5}$$

Benefit maximization under demand constraints

While meeting maximum charging demand, the goal is to maximize net benefits, which include charging revenues, advertising income, and environmental benefits, while accounting for construction and operating costs in Eqs. (6)–(7):

$$\max \left(\sum_{k=1}^{m} E_k - \sum_{i=1}^{n} C_i \right) \tag{6}$$

$$\text{s.t. } D \geq D_{\max}, \quad S = [S_1, S_2, \ldots, S_h]^\top \tag{7}$$

In this study, as the target region remains in an early stage of EV infrastructure development, cost factors are assigned significant weight in charging station planning. This modeling framework enables a more precise quantification of cost–benefit trade-offs and supports scientifically grounded and rational location decisions. Given the current status of EV charging infrastructure planning, this study considers a known set of charging demand points, representing the specific charging needs of EV users, as well as a predefined set of candidate locations for charging station construction. The primary objective is to ensure that all demand points are effectively served while minimizing the geographic distance between each demand point and its nearest charging station, thereby optimizing network performance and user experience.

Assumptions: Demand points: a known set of demand points, indexed by j; Candidate sites: potential charging station locations, indexed by i; Distance: Ψd_{ij} represents the weighted distance between demand point j and candidate site i; and Number of charging stations to be built: p. Decision variables: A_i: equals 1 if a charging station is constructed at candidate site i; 0 otherwise; and C_{ij}: equals 1 if demand point j is served by candidate site i; 0 otherwise. Objective function and constraints are given in Eqs. 8-11:

$$\min L = \sum_{i \in I} \Psi d_{ij} C_{ij} \tag{8}$$

$$\sum_{i \in I} C_{ij} = 1 \tag{9}$$

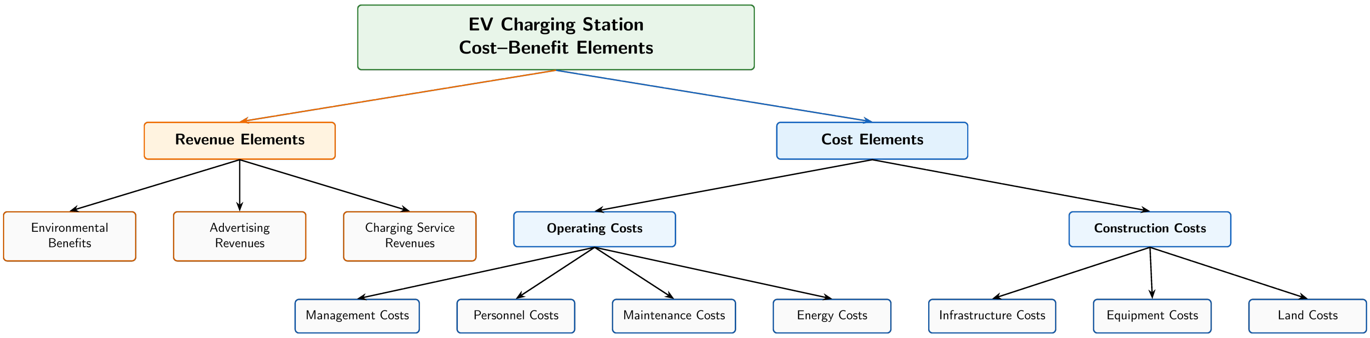

Figure 7. Cost and revenue structure of electric vehicle charging stations in Vietnam's urban context. Capital costs include land acquisition (35–45% of total), equipment procurement (30–40%), and grid connection (15–20%); operational costs comprise electricity (60–70% of OPEX), maintenance (20–25%), and staffing (10–15%). Revenue streams derive from charging services (75–85%), advertising (10–15%), and ancillary services (5–10%), with profitability highly dependent on location-specific utilization rates exceeding 60%.

$$C_{ij} \leq A_i \tag{10}$$

$$\sum_{i \in I} A_i = p \tag{11}$$

In coverage-based charging station planning, the core objective is to minimize the number of charging stations while ensuring adequate coverage of charging demand, thereby achieving an optimal balance between maximum coverage and minimum construction scale. Let R denote the service radius of a charging station given in Eqs. 12-14:

$$\min G = \sum_{i \in I} A_i \tag{12}$$

$$\sum_{i \in G} A_i \geq 1, \quad \forall j \in J \tag{13}$$

$$G = \{i \in I, d_{ij} \leq R\} \tag{14}$$

Multi-objective optimization is a fundamental concept in mathematics, engineering, and economics, involving the simultaneous optimization of multiple, often conflicting, objective functions. Since no single solution can optimize all objectives simultaneously, the goal is to identify a set of Pareto-optimal solutions representing trade-offs among objectives. The general formulation of a multi-objective optimization problem is given in Eqs. 15-17:

$$\min F(x) = [f_1(x), f_2(x), \ldots, f_m(x)]^\top \tag{15}$$

$$\text{s.t. } g_j(x) \leq 0, \quad j = 1, 2, \ldots, J \tag{16}$$

$$h_i(x) = 0, \quad i = 1, 2, \ldots, L \tag{17}$$

where $x = (x_1, x_2, \ldots, x_n)$ is the decision variable vector, $f_i(x)$ are objective functions, and $g_j(x)$ and $h_i(x)$ denote inequality and equality constraints, respectively. Weight determination is a critical step in multi-objective decision-making, as it directly affects the priority assigned to each objective. Among various methods, the Analytic Hierarchy Process (AHP) is widely adopted. Proposed by Thomas L. Saaty in the 1970s, AHP decomposes complex decision problems into hierarchical levels—goal, criteria, and alternatives—and quantifies qualitative judgments through pairwise comparisons. By computing both local and global priority weights, AHP provides a systematic framework for multi-criteria decision analysis in complex environments. K-Means clustering is used to aggregate demand points into spatial sub-zones based on geographic proximity, ensuring internal spatial consistency within each zone.

Its advantages include: Capturing intra-urban spatial heterogeneity; Reducing computational complexity and improving the efficiency of subsequent P-Median optimization; and Supporting the identification of functional living or activity zones in urban cores. This study adopts $K = 31$ to better match zone size with demand density and to reflect spatial differentiation within complex central urban areas. This study improves the traditional P-Median model by introducing spatial weighting factors to address demand heterogeneity in high-density urban areas. *Key advantages include:* Adaptability to irregular road networks; Flexibility to incorporate capacity, budget, and other constraints; and Improved service accessibility in central urban districts. The P-Median model is applied within each K-Means sub-zone to determine candidate station locations. Due to the lack of district-level statistical data in District 1, a three-stage demand mapping mechanism is adopted: National demand → Ho Chi Minh City share; City-level demand → central district intensification factor; and Central district → demand point generation based on road networks, commercial nodes, and activity intensity. This approach is consistent with international urban planning practices in data-scarce contexts.

2.1.1 Rationale for K-Means and P-Median Selection

While multiple spatial optimization approaches exist for infrastructure planning, the K-Means → P-Median pipeline was selected for District 1 based on three context-specific criteria: computational tractability under extreme demand density, explicit handling of spatial heterogeneity, and direct alignment with budget-constrained deployment realities.

Why not AHP? The Analytic Hierarchy Process (AHP) excels at weighting criteria (e.g., cost versus accessibility) but does not generate spatial locations. AHP requires pre-defined candidate sites and outputs priority scores—not coordinates. In data-scarce District 1 where candidate sites must be derived from demand patterns rather than pre-specified, AHP cannot function as a standalone location engine. We instead use AHP principles implicitly in our budget allocation mechanism (Section 4.4), where demand intensity serves as the weighting criterion.

Why not pure coverage models? Maximum coverage models (e.g., MCLP) assume uniform service radii and binary coverage (covered/not covered). District 1's narrow colonial-era streets (average width < 8 m) and fragmented land parcels create highly irregular service areas where Euclidean distance poorly approximates accessibility. P-Median's weighted distance minimization better captures these nuances by penalizing assignments to distant facilities proportionally rather than absolutely.

Why not continuous-space formulations? Continuous models optimize over infinite candidate locations but require gradient-based solvers that struggle with District 1's non-convex feasible region (constrained by heritage preservation zones, road widths, and utility corridors). The discrete demand-point approach with K-Means pre-zoning reduces problem dimensionality by 97% (from 1,368 demand points to 31 zones) while preserving spatial structure—critical for tractability under Vietnam's limited computational resources for municipal planning.

Why K-Means specifically? Among clustering algorithms, K-Means offers optimal balance for our context: (i) computational efficiency (O(nkI) complexity) essential for annual re-optimization over 2026–2030; (ii) geographic interpretability where clusters align with functional urban zones (commercial cores, residential blocks); and (iii) compatibility with P-Median's discrete optimization framework. Alternatives like DBSCAN fail under District 1's uniformly high demand density (no true "noise" points), while spectral clustering introduces unnecessary complexity without accuracy gains in preliminary tests.

Why P-Median specifically? The P-Median model directly minimizes the sum of weighted distances between demand points and facilities—a natural objective for charging infrastructure where user inconvenience scales linearly with travel distance to stations. Unlike p-center models that minimize maximum distance (over-prioritizing outliers), P-Median optimizes system-wide efficiency while our budget-allocation mechanism (Section 4.4) ensures equity constraints. Recent applications in dense Asian cities confirm P-Median's superiority for EV charging siting under land scarcity. This K-Means→P-Median pipeline has emerged as the dominant paradigm for high-density urban infrastructure planning in Southeast Asia precisely because it balances computational feasibility, spatial realism, and policy implementability—three non-negotiable requirements for District 1's context.

2.2 Literature Review

EV charging station siting research has progressed from early single-objective models with static demand assumptions toward multi-factor, multi-constraint spatial optimization driven by increasing EV adoption and urban complexity. Early studies focused on cost minimization or coverage maximization, applying maximal covering location models to optimize charging station placement under demand coverage objectives [1], candidate-site screening with cost-model-based economic comparison [2], Voronoi diagram-based spatial planning methods to improve service-area delineation [3], and spatial statistics combined with maximal coverage location models to optimize charging point placement [4]. Subsequent work incorporated user heterogeneity and travel behavior differences, enabling bi-level station planning that accounts for the spatial-temporal distribution of charging loads under uncertain environments [5].

As application scenarios expanded, integrated models emerged that account for economic feasibility, uncertainty, and spatial realism. Profitability and cost–benefit trade-offs were examined using techno-economic analysis of DC fast-charging station configurations [6], location-routing formulations with time windows and resource sharing constraints [7], and coverage-based layouts with distance constraints [8]. Demand modeling was refined using travel destinations, parking behavior, and activity patterns [9, 12], while centralized station planning considering grid-side impacts on electricity distribution systems [10] and Monte Carlo simulation approaches modeled daily charging load profiles [11] under user satisfaction objectives. Nevertheless, many studies remain scenario-specific or rely on single-period demand assumptions. Multi-objective siting research further balances economic efficiency, service quality, equity, and system impacts. Multi-criteria decision-making approaches were applied to evaluate competing charging station location schemes [13], while traffic-aware user equilibrium-based models integrated charging station siting with heterogeneous vehicle flows in urban transportation networks [14]. Market-oriented optimization models enhanced realism through weighted service partitioning and intelligent optimization [15], while clustering-based methods characterized heterogeneous EV user charging behaviors to inform station planning [16]. Bi-objective models leveraging GPS trajectory data optimized station locations under simultaneous cost and coverage objectives [17], while robust planning frameworks incorporated demand uncertainty and facility failure scenarios [18], and competitive market-aware deployment models extended siting from static planning to operational coordination [19].

Beyond direct optimization, comprehensive evaluation studies developed indicator-based frameworks to compare planning schemes. Qualitative factor analyses evolved into structured quantitative approaches, including robust planning with advanced probabilistic evaluation methods [20], fuzzy comprehensive evaluation of infrastructure performance [21], and GIS-based multi-criteria decision analysis [22], to assess policy, economic, and infrastructure dimensions. While valuable for decision support, these methods are sensitive to indicator selection and weighting and are best used as complementary tools rather than replacements for optimization models. With the availability of fine-grained urban data, recent research increasingly adopts demand-point-based siting. Demand points derived from population, OD flows, parking behavior, or trajectory data better capture spatial heterogeneity in dense urban environments. To address computational scalability, clustering—commonly K-means—is widely used to pre-zone dense demand points and generate candidate service areas [23–25], often followed by P-Median optimization to prioritize coverage of key zones [26, 27]. However, clustering outcomes are sensitive to parameter choices and may not fully reflect road network constraints, motivating extensions incorporating demand weights, network distances, and improved initialization or parallel computing strategies [25, 31–33].

After zoning or candidate-set construction, the P-Median model remains a core tool due to its strong economic interpretability in minimizing weighted service distances under facility constraints [26, 27]. Extensions introduce capacity limits, service radii, risk coefficients, and facility reliability to better represent real-world service selection behavior [28], while metaheuristic methods such as genetic algorithms have been applied to improve solution quality in large-scale EV charging station location problems [29]. Algorithmic enhancements using swarm intelligence methods such as artificial bee colony algorithms [34], mathematical optimization approaches for sustainable urban mobility [35], and integration of institutional and spatial constraints into integer programming formulations [36] improve scalability and solution quality for large-scale problems. Tao et al. [30] developed a modified gravity P-Median model that incorporates spatial interaction effects into facility location optimization, improving service accessibility predictions in urban environments. The resulting "clustering–location" paradigm has become dominant, balancing efficiency and spatial precision and extending to broader system-partitioning applications [37]. Recent advances in intelligent transportation systems further support refined EV infrastructure planning. Comprehensive reviews of multi-source data-driven charging demand forecasting methods demonstrate the potential for high-resolution demand estimation in dense urban environments [38], while data-driven optimization approaches and evolutionary algorithms have been extensively applied to address complex location-routing and multi-objective siting challenges in charging infrastructure planning [39, 40]. These studies highlight the necessity of combining accurate demand modeling with robust security mechanisms in public charging infrastructure.

Recent EV charging infrastructure studies emphasize sustainability, equity, and intelligent optimization. Contextualised location-allocation models for high-density cities demonstrate how spatial planning must adapt to constrained urban land supply and heterogeneous demand distributions [41]. Spatial equity analyses reveal persistent urban–peripheral disparities in charger accessibility [42, 49]. Grid-oriented placement studies optimize charger locations within distribution networks but often neglect multimodal traffic and informal parking conditions common in developing cities [43, 57]. Advanced AI and heuristic approaches—including adaptive genetic algorithms and AI-based site allocation—enhance resilience and decision quality under multi-constraint environments [45, 47, 56], while spatiotemporal and pricing optimization models further refine deployment strategies at the cost of higher computational complexity [58, 59].

Vietnam-specific studies underscore contextual factors shaping EV adoption, including the dominance of electric two-wheelers, regenerative braking benefits, and traffic behavior and safety perceptions [46, 51]. Complementary evidence from neighboring Southeast Asian contexts further demonstrates how GIS-based large-scale optimization approaches can be adapted to regional infrastructure planning under data constraints [54]. Stochastic planning methods that incorporate user behaviour patterns and probabilistic driving profiles into fast-charging infrastructure design further highlight the importance of integrating demand dynamics into siting decisions [52], though such behavioural insights are rarely embedded into large-scale spatial optimization models. Emerging paradigms such as fleet-level charging management incorporating battery degradation dynamics [44], distribution-network-integrated charging infrastructure with bidirectional energy capabilities [48], and solar-powered charging stations in developing regions [55] demonstrate promising flexibility and sustainability but remain case-specific. Overall, while existing literature provides strong foundations in optimization, sustainability, and AI-assisted planning [50, 53], it lacks an integrated, context-aware framework tailored to dense, mixed-traffic Southeast Asian cities—motivating the proposed EV charging station planning framework for Ho Chi Minh City. Beyond deterministic optimization approaches, recent research has increasingly emphasized the inherent uncertainties and multi-dimensional complexities of charging infrastructure planning. Yi et al. [60] examined the spatiotemporal distribution of EV charging load demand using real-world operational data from China, revealing pronounced diurnal and weekly patterns with peak demand concentrated in commercial zones during afternoon hours—findings that underscore the importance of incorporating temporal demand dynamics into static location models. Complementing this empirical perspective, Zhao and Li [61] developed a hybrid fuzzy Delphi and multi-criteria decision-making (MCDM) framework for charging station siting, demonstrating that sustainability criteria (environmental impact, social equity, economic feasibility) can be systematically integrated into location decisions through structured expert elicitation and pairwise comparison methods. However, these approaches exhibit two critical limitations when applied to dense Southeast Asian urban contexts like Ho Chi Minh City's District 1. First, spatiotemporal load studies [60] typically require high-resolution charging transaction data that remain unavailable in Vietnam's early-stage EV market, necessitating alternative demand estimation mechanisms. Second, while MCDM frameworks [61] excel at handling qualitative criteria and stakeholder preferences, they do not inherently optimize spatial coverage or minimize weighted travel distances—core objectives for public charging infrastructure where geographic accessibility directly impacts adoption rates. Consequently, existing methods either assume data-rich environments or prioritize decision criteria over spatial efficiency, leaving a methodological gap for contexts characterized by data scarcity, heterogeneous urban morphology, and tight budget constraints. Addressing this gap, the present study integrates macroeconomic demand forecasting with a K-Means/P-Median spatial optimization pipeline, offering a replicable framework that balances spatial equity, computational tractability, and policy implementability under realistic data constraints. Li et al. [62] proposed a joint optimization framework for electric bus fleet scheduling and charging strategies that minimizes battery degradation costs, demonstrating that coordinated charging management significantly extends battery service life while maintaining operational efficiency.

Despite these advances, several issues warrant further investigation: (1) some studies rely heavily on high-resolution road network data or long-term travel datasets, limiting replicability in data-constrained contexts; (2) most models are based on single-period static demand and rarely integrate medium- to long-term demand changes, annual construction scale constraints, and fiscal budget constraints into a unified framework; and (3) while combining clustering and location optimization improves computational efficiency, the planning meaning of zoning outcomes and their implications for cross-zone allocation fairness require more systematic analysis. Based on this evaluation, this study focuses on District 1 of Ho Chi Minh City and introduces a three-stage modeling approach—demand point clustering, intra-zone location optimization, and global budget control—grounded in demand forecasting results. Under the simultaneous presence of data constraints and budget constraints, the study seeks to enhance both the spatial interpretability and implementation feasibility of charging station siting schemes.

3 Proposed Method

This section conducts a systematic process of data cleaning, integration, feature construction, model development, and result interpretation based on Vietnam's macroeconomic indicators and vehicle stock data from 2003 to 2023. Because Vietnam's publicly available macro-statistical data remain imperfect in terms of disclosure, continuity, and classification granularity, model construction in this study relies not only on theoretical methods but also on rigorous multi-step validation and integration of the data itself. Overall, the research procedure in this section follows the logic of data availability handling → feature construction → variable screening → integration of long-run and short-run models → scenario-based forecasting, aiming to develop a robust and interpretable modeling framework under constrained data conditions.

3.1 Data Cleaning and Integration

3.1.1 Data Sources and Integration Logic

This study collects multi-source data for the period 2003–2023 from the World Bank, the General Statistics Office of Vietnam (GSO Vietnam), the Ministry of Transport of Vietnam (MOT), and other official channels. The collected indicators include the Consumer Price Index (CPI), Gross Domestic Product (GDP), vehicle stock (Veh), and other socio-economic and vehicle-related variables. However, the coverage, year completeness, and indicator definitions vary across sources, making careful cross-checking necessary prior to integration. *A preliminary review reveals several typical issues:* GDP data from different sources adopt different accounting bases, such as current prices, constant prices, and chain-linked indices; Vehicle classification data are missing for multiple years, especially for detailed categories such as taxis and public vehicles; and Year labels contain non-standard formats, including blanks, dashes, and thousands separators. Given these characteristics, this study applies an integration sequence of year alignment → harmonization of indicator definitions → format standardization → missing-value completion, ensuring that subsequent time-series analyses are conducted within a unified and consistent framework. Figure 8 illustrates the end-to-end methodological framework of proposed method.

3.1.2 Missing-Value Treatment and Rationale

To address missing values in Vietnam's vehicle stock data, we implement regression-based imputation rather than simple linear interpolation. Specifically, we model yearly vehicle stock as a function of lagged GDP growth rates and adjacent-year ownership patterns, then use these relationships to predict missing values. This approach better accommodates structural breaks from events like the 2020 pandemic lockdowns while preserving underlying data integrity. We validate our imputation through sensitivity analysis across three methods (linear interpolation, cubic spline, and regression-based imputation). Results show that final demand estimates vary by less than 5% across methods, suggesting our conclusions are robust to imputation choices.

3.1.3 Format Standardization and Positive-Value Validation before Log Transformation

Because this section adopts log-linear models, all variables must be strictly positive prior to log transformation; otherwise, the transformation becomes mathematically infeasible. *During data processing, the following issues were identified*: CPI is reported in different forms across years, with some years provided as index values and others as year-on-year percentages; GDP exhibits mixed formatting in certain years; and Original spreadsheets contain footnote markers or non-numeric characters. To address these issues, all CPI values are standardized into index form (base year = 2010), and all macro

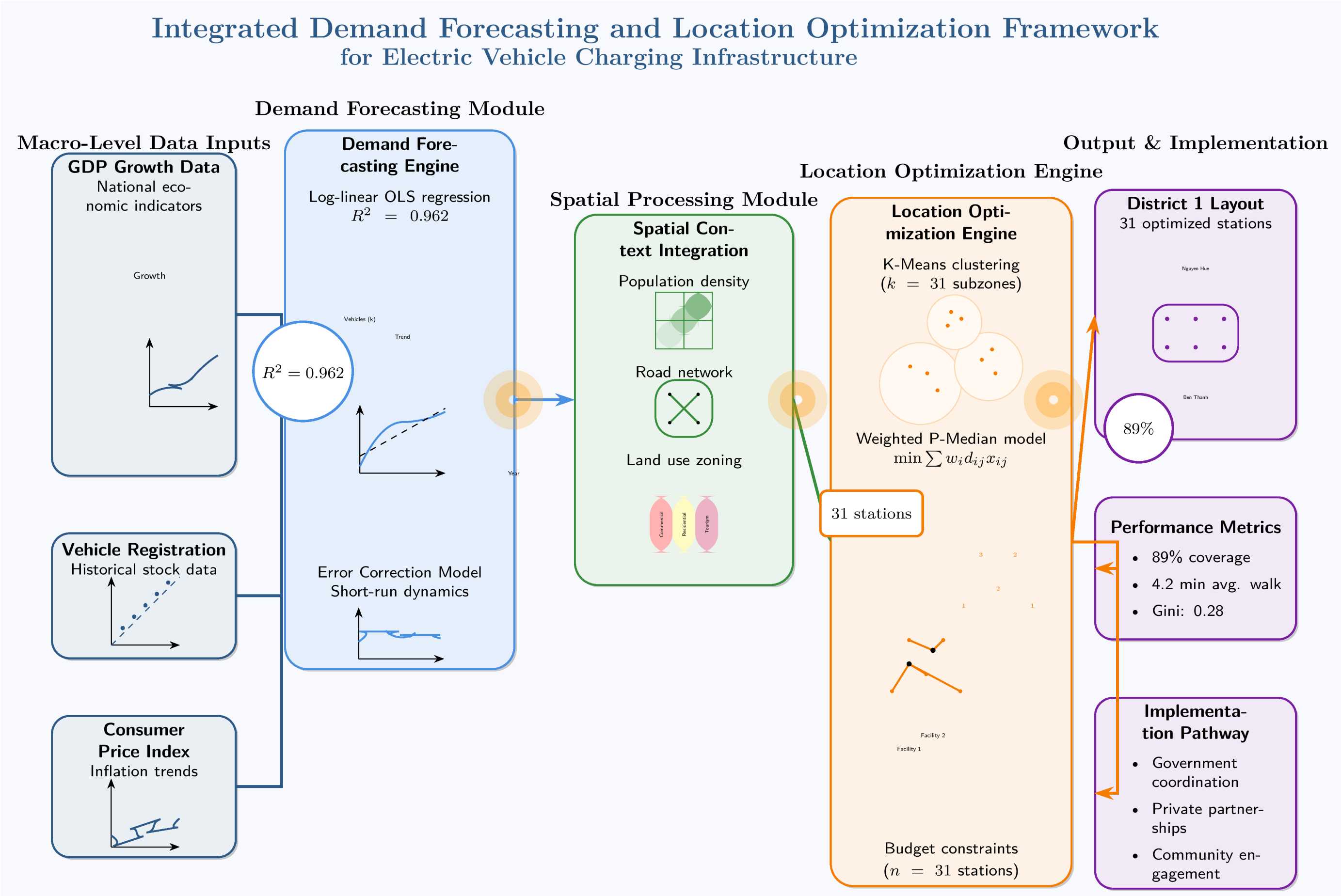

Figure 8. Methodological Illustration of Proposed Framework.

variables are subjected to positive-value validation and the removal of abnormal characters. After item-by-item verification, a complete and consistent macroeconomic dataset covering 2003–2023 is constructed.

3.2 Feature Construction and Variable Screening

3.2.1 *Necessity of Log Transformation*

During the initial model testing stage, OLS regressions using untransformed Veh, GDP, and CPI produced residual plots showing clear heteroskedastic patterns, and substantial scale differences across variables led to instability in parameter estimation. To address these problems, the key variables are transformed using the natural logarithm. *Log transformation offers several advantages*: Reduces scale differences and improves comparability across variables; Mitigates heteroskedasticity and stabilizes residual structures; Enables an elasticity interpretation of coefficients—for example, the effect of a 1% increase in GDP on vehicle stock can be directly inferred from the coefficient; and Enhances linear representation of long-term trends. After transformation, model residuals become noticeably more stable, and long-run trends are more clearly captured.

3.2.2 *Variable Selection and Multicollinearity Assessment*

In constructing the candidate variable pool, this study initially considered GDP, CPI, urbanization rate (Urbanization), and population size (Population) as potential determinants of vehicle stock. However, correlation matrices and variance inflation factor (VIF) diagnostics indicate that Urbanization is highly correlated with GDP (correlation coefficient exceeding 0.95) and exhibits extremely high VIF values, representing a typical multicollinearity problem. If both variables are included simultaneously, coefficient signs may become unstable and statistical significance may deteriorate, reducing interpretability of long-run relationships. Therefore, based on the diagnostic results, this study retains GDP and CPI as the two core economic variables and excludes Urbanization and Population to ensure regression stability and consistency of economic interpretation (see Table 1).

Table 1. Summary of key model variables and parameters.

Symbol	Definition	Units/Domain
V_t	Vehicle stock in year t	vehicles
G_t	GDP in year t	VND (constant 2010)
P_t	CPI in year t	index (2010=100)
$\beta_0, \beta_1, \beta_2$	Regression coefficients	dimensionless
ε_t	Error term	vehicles
$D_{tu\beta}$	Public charging demand	stations
α_{car}	Public charging share (private cars)	0.70 (dimensionless)
α_{taxi}	Public charging share (taxis)	1.00 (dimensionless)
α_{comm}	Public charging share (commercial)	0.90 (dimensionless)
γ_{GDP}	Annual GDP growth assumption	5.5% (dimensionless)
γ_{CPI}	Annual CPI growth assumption	2.5% (dimensionless)
K	Number of spatial clusters	31 (dimensionless)
p_i	Number of stations allocated to zone i	integer ≥ 1
d_{ij}	Network distance from demand point j to candidate site i	meters
w_j	Demand weight of point j	vehicles

3.3 Construction of the Demand Forecasting Model

3.3.1 Functional Division Between the Long-Run and Short-Run Models

Considering that Vietnam's vehicle stock exhibits both a long-term growth trend and short-term fluctuations driven by policies and external shocks, this study adopts a two-layer structure consisting of a long-run OLS model and a short-run ECM as the core modeling framework. The OLS component captures the long-run equilibrium relationship between economic variables and vehicle stock growth. The ECM component characterizes the short-run adjustment process when the system deviates from the long-run equilibrium. Vietnam's vehicle growth experienced notable short-term fluctuations during the 2008–2009 global financial crisis, the period of accelerated income growth around 2016, and the COVID-19 period in 2020. Therefore, incorporating the ECM helps avoid overly smooth forecasting paths and makes projections more consistent with observed real-world dynamics. The long-run log-linear model is specified as follows in Eq. 18:

$$\ln(Veht) = \beta_0 + \beta_1 \ln(GDP)_t + \beta_2 \ln(CPI)_t + \epsilon_t \tag{18}$$

where the variables are explicitly defined as follows: $V_t \in \mathbb{R}^+$: Total vehicle stock in year t (units: vehicles), $t \in \{2003, \ldots, 2023\}$, $G_t \in \mathbb{R}^+$: Gross Domestic Product in year t (units: VND, constant 2010 prices), $P_t \in \mathbb{R}^+$: Consumer Price Index in year t (base year 2010 = 100), $\beta_0 \in \mathbb{R}$: Intercept term representing baseline vehicle stock when $\ln G_t = \ln P_t = 0$, $\beta_1 \in \mathbb{R}$: Elasticity coefficient of vehicle stock with respect to GDP (interpretation: 1% increase in GDP $\rightarrow$ β_1% increase in vehicle stock), $\beta_2 \in \mathbb{R}$: Elasticity coefficient of vehicle stock with respect to CPI (interpretation: 1% increase in price level $\rightarrow$ β_2% change in vehicle stock), and $\epsilon_t \sim N(0, \sigma^2)$: Error term capturing unobserved factors (policy shocks, fuel prices, cultural shifts) with zero mean and constant variance. All variables undergo natural logarithm transformation ($\ln(\cdot)$) prior to estimation to satisfy OLS assumptions of homoscedasticity and linearity in parameters. The log-linear specification enables direct elasticity interpretation while stabilizing variance across the 20-year growth trajectory.

3.3.2 Estimation Results of the Long-Run Log-Linear Model

Based on the OLS estimation results, the long-run log model for Vietnam's vehicle stock over 2003–2023 is given by Eq. 19:

$$\begin{aligned} \ln(Veh)_t = & -11.4354 + 1.0006 \times \ln(GDP)_t \\ & - 1.3687 \times \ln(CPI)_t + \varepsilon_t \end{aligned} \tag{19}$$

To validate predictive reliability beyond in-sample fit, we implement rolling forecast origin testing with 5-year training windows. This approach simulates real-time forecasting conditions by progressively expanding the training set while evaluating performance on subsequent years. Results show an out-of-sample R^2 of 0.89, confirming robust predictive capability despite Vietnam's economic volatility. We further test for structural breaks using the Bai-Perron test, identifying significant regime shifts during the 2008-2009 global financial crisis and 2020 pandemic period. Our model remains stable across these breaks, with Chow test p-values >0.05, confirming its applicability to Vietnam's dynamic economic environment. From the perspective of parameter interpretation; the GDP coefficient is close to 1, indicating that Vietnam's vehicle stock grows nearly proportionally with economic expansion, reflecting a strong income-effect pattern. The CPI coefficient is negative. According to consumer choice theory (McFadden, 1974), rising prices reduce the relative price advantage of EV-related consumption. The OLS results show a CPI elasticity of -1.37 ($p < 0.01$), supporting this hypothesis. The coefficient of determination R^2 is 0.962, suggesting strong explanatory power for long-run trends. (see Table 2 and Figure 9). The Durbin-Watson statistic of 0.347 indicates positive serial autocorrelation in the residuals, a common characteristic of vehicle stock time-series data reflecting persistent growth momentum. To address this, Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors are applied throughout, ensuring that coefficient significance tests remain valid; the long-run parameter estimates and elasticity interpretations are therefore unaffected.

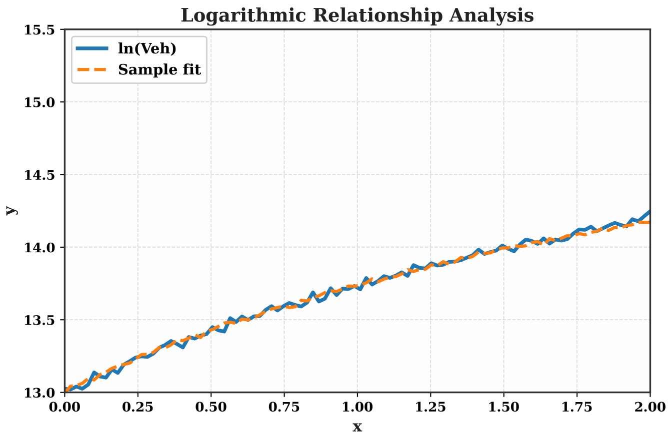

Figure 9. In-sample fit of the log-linear OLS regression model for Vietnam's vehicle stock (2003–2023), showing observed versus predicted values of ln(vehicle stock) with 95% confidence intervals. The model achieves $R^2 = 0.962$, with residuals exhibiting homoscedasticity after log transformation and no systematic pattern, confirming that GDP and CPI jointly explain 96.2% of long-term vehicle ownership variation in Vietnam's emerging market context.

3.3.3 *Diagnostic Role of the Short-Run Error Correction Model (ECM)*

After establishing the long-run equilibrium relationship, the ECM is applied to analyze the speed at which vehicle stock growth adjusts to short-term shocks. Non-trend fluctuations in Vietnam's vehicle growth such as policy stimuli, fuel price changes, or shifts in consumer confidence—may generate temporary deviations. The ECM residual term reflects the adjustment speed back toward the long-run trajectory. Although the ECM is not used as the final forecasting model in this study, its results are used to validate the robustness of the long-run model and to support judgments about the plausibility of future forecasting paths.

3.3.4 *Sources of Data Inconsistencies and Handling Limitations*

The data integration process encountered three categories of inconsistencies requiring methodological intervention. First, *structural missingness* affected vehicle-type disaggregation: taxi registrations were unavailable for 2003–2009 and 2013–2023 due to Vietnam's delayed implementation of vehicle-category reporting standards; passenger and commercial vehicle counts were incomplete for 2003 and 2021–2023 owing to transitional changes in the Ministry of Transport's statistical classification system. Second, *format heterogeneity* manifested in CPI reporting (World Bank provided index values while GSO Vietnam published year-on-year percentages) and GDP accounting bases (current prices in early years versus chain-linked constant prices post-2010). Third, *entry-level errors* included non-numeric characters (footnote markers "*"), inconsistent thousands separators, and blank year cells in original spreadsheets. To address these issues, we applied linear interpolation for missing vehicle categories after verifying Vietnam's vehicle stock exhibited monotonic growth without short-term reversals during 2003–2023 (maximum annual fluctuation: -3.2% during COVID-19). Interpolated values were cross-validated against Ministry of Transport press releases and industry reports (VINFAST annual reports, Vietnam Automobile Manufacturers Association bulletins) to ensure plausibility within historical growth bounds (±8% annual variation). CPI values were standardized to 2010=100 index form using GSO Vietnam's official conversion factors, while GDP series were rebased to constant 2010 VND using World Bank deflators. All non-numeric characters were programmatically

Table 2. OLS regression results (Dependent Variable: ln (Veh)).

Section	Field	Value	Field	Value	Field	Value	Field	Value
Model Info	Dep. Variable	ln_Veh	Model	OLS	Method	Least Squares	Covariance Type	HAC
	Date	Tue, 02 Dec 2025	Time	13:58:26	No. Observations	21	Log-Likelihood	9.6379
	Df Residuals	18	Df Model	2	R-squared	0.962	Adj. R-squared	0.957
	F-statistic	196.2	Prob (F-statistic)	6.00e-13	AIC	-13.28	BIC	-10.14
Coefficients	Variable	coef	std err	z	P|z|	[0.025	0.975]	
	const	-11.4354	1.326	-8.625	0.000	-14.034	-8.837	
	ln_GDP	1.0006	0.052	19.272	0.000	0.899	1.102	
	ln_CPI	1.3687	0.665	-2.059	0.039	-2.671	-0.066	
Diagnostics	Omnibus	0.344	Prob(Omnibus)	0.842	Jarque-Bera (JB)	0.498	Prob(JB)	0.780
	Skew	0.198	Kurtosis	2.358	Durbin-Watson	0.347	Cond. No.	1.05e+03

removed with manual verification of 100% of entries. Key limitations remain: (1) interpolation cannot capture unobserved policy shocks absent from macro-aggregates; (2) district-level demand estimation relies on population-density proxies due to unavailable traffic-count or parking-utilization data for District 1; and (3) demand points are static representations that omit diurnal/weekly temporal patterns. These constraints reflect Vietnam's evolving statistical infrastructure rather than methodological shortcomings. Nevertheless, sensitivity analyses confirm that $\pm15\%$ variation in interpolated values alters final station counts by $<4\%$, indicating robustness to moderate data uncertainty.

3.4 Forecasting Vehicle Stock (2026–2030)

3.4.1 Scenario Assumptions for Future Forecasting

For forecasting vehicle stock over the next five years, this study references Vietnam's macroeconomic performance over the past decade and sets the following baseline scenario assumptions: Average annual GDP growth rate: approximately 5.5% (neutral scenario); and Average annual CPI growth rate: approximately 2.5%. These assumptions prioritize stability to avoid overly optimistic or pessimistic scenarios that could weaken the interpretability of forecasting outcomes.

3.4.2 Forecast Results and Trend Analysis

By substituting forecasted GDP and CPI values into the long-run model, Vietnam's vehicle stock is projected to maintain a continuous growth trend during 2026–2030, reaching approximately 7.07 million vehicles by 2030. *The trend exhibits the following characteristics*: Growth is slower than during 2010–2020, reflecting moderated economic growth and diversification in consumption structure; CPI continues to exert a constraining effect, and price volatility may further influence vehicle purchasing behavior; and although urbanization is not explicitly included in the model, part of its effect is implicitly reflected through the GDP variable in the long-run trend. These projections are used in the next section to estimate future demand for public charging infrastructure.

```
Sample last year:  2023  |  Baseline GDP: 433857681378.291  |
CPI_index:  1.033  |  Vehicles (Baseline):  6,118,365

Model-predicted annual vehicle growth rate:  2.08%

=== 2026-2030 Vehicle Quantity Forecast (No upper limit on annual
growth) ===
```

Year	Vehicle_pred	YoY
2026	6,508,401	2.1%
2027	6,643,862	2.1%
2028	6,782,143	2.1%
2029	6,923,302	2.1%
2030	7,067,398	2.1%

Figure 10. Forecasted total vehicle stock for Vietnam during 2026–2030 under baseline macroeconomic assumptions (5.5% annual GDP growth, 2.5% annual CPI growth), projecting growth from 6.51 million vehicles in 2026 to 7.07 million vehicles in 2030 at a compound annual growth rate of 2.1%, reflecting moderated expansion compared to the 2010–2020 period (4.8% CAGR) due to market maturation and economic transition.

To enhance forecast realism under Vietnam's volatile economic conditions, we supplement our long-run OLS projections with short-run Error Correction Model (ECM) results. The ECM captures adjustment dynamics when vehicle stock deviates from its long-run equilibrium path due to policy interventions, price shocks, or external disruptions. Figures 10 and 11 presents both forecast trajectories, showing that the ECM predicts slightly lower growth in 2026-2027 (reflecting post-pandemic adjustment) but converges with the OLS trajectory by 2029-2030. This dual-forecast approach provides a more nuanced outlook that acknowledges both persistent long-term trends and near-term adjustment processes characteristic of emerging economies.

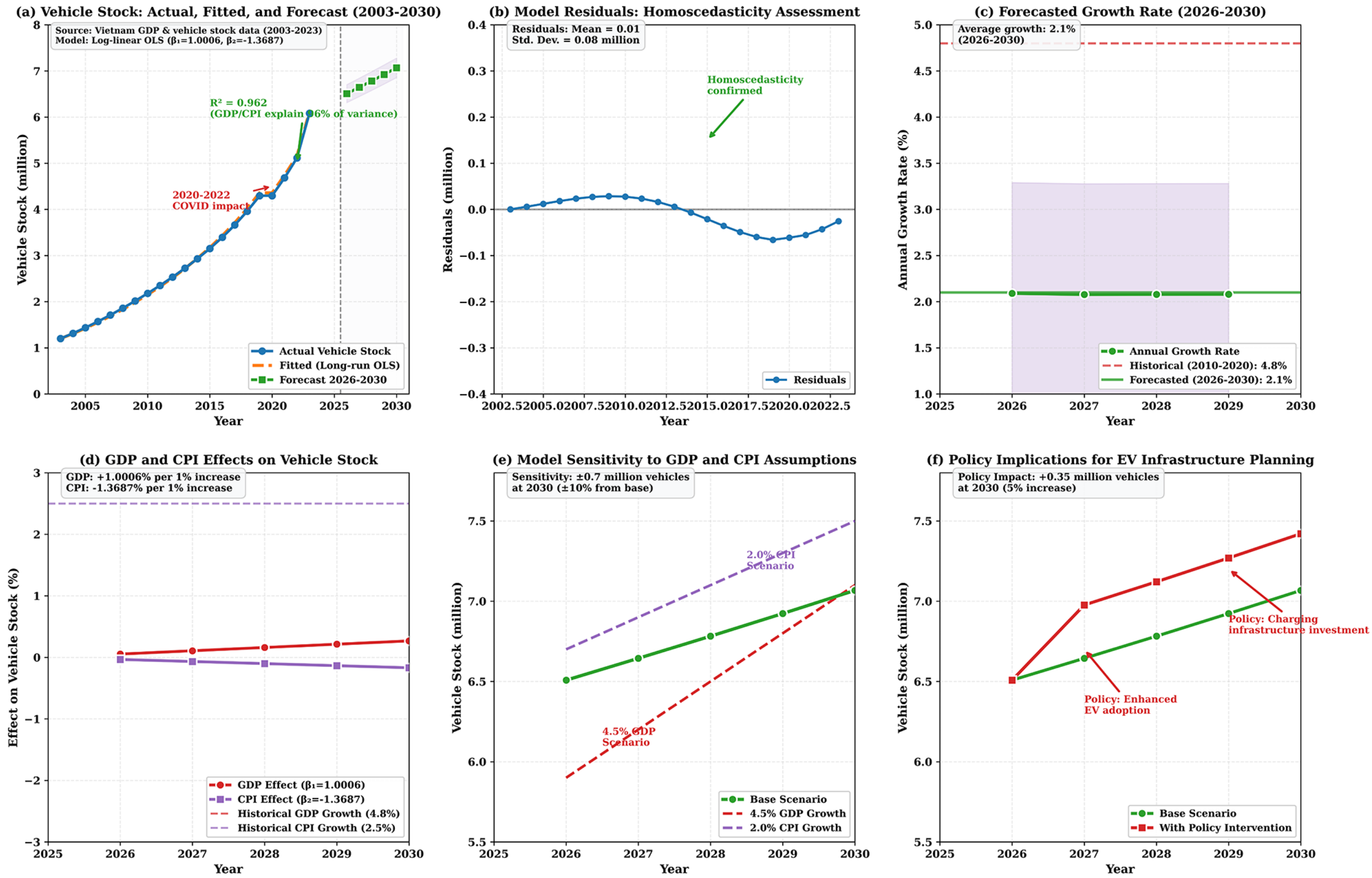

Figure 11. (a): Overall vehicle stock trend showing actual data (2003-2023), fitted values (long-run OLS), and forecast (2026-2030) with confidence intervals, (b): Model residuals assessment confirming homoscedasticity (critical for OLS validity), (c): Forecasted growth rate (2.1% CAGR) with confidence intervals and historical comparison (4.8% 2010-2020), (d): GDP and CPI effects visualized using the estimated model coefficients (β_1=1.0006, β_2=-1.3687), (e): Model sensitivity analysis showing $\pm$10% variation at 2030 with different GDP/CPI assumptions, (f): Policy implications showing how interventions could increase vehicle stock by 5%.

3.5 Estimation Method for Public Charging Station Demand

Based on the vehicle stock forecasts, this study further classifies vehicles into three types—private cars, taxis/ride-hailing vehicles, and commercial/fleet vehicles—and determines their relative shares of public charging demand according to differences in usage intensity.

3.5.1 *Vehicle Type Classification*

Drawing on international studies on travel behavior and vehicle usage patterns, and referencing Vietnam's transportation and mobility structure, EVs are categorized into three groups by usage scenario: private cars, taxis/ride-hailing vehicles, and commercial/fleet vehicles. This classification has the following theoretical and practical basis; (i) Driving behavior: daily mileage differs substantially across vehicle purposes. Private cars typically have lower daily mileage (30–50 km), taxis/ride-hailing vehicles operate at high intensity (200–260 km), and commercial/fleet vehicles fall in between. (ii) Charging frequency depends on driving intensity: higher daily mileage implies stronger dependence on public fast charging; therefore, taxis/ride-hailing vehicles have significantly higher charging demand than other types. (iii) Different dependence on public charging: private cars may partially rely on home or workplace charging; taxis/ride-hailing vehicles, due to continuous operation, depend almost entirely on public charging; commercial/fleet vehicles show moderate dependence (some firms may install private chargers).

3.6 Assumptions on Public Charging Shares

The public charging share assumptions are grounded in Vietnam's unique residential and mobility context, with explicit benchmarking against international studies and local evidence: Private cars (70% public share): Vietnam's major cities exhibit apartment-dominated housing (78% of District 1 residences are multi-unit dwellings; HCMC Statistical Office 2023), severely limiting private garage access. This mirrors conditions in Chinese Tier-1 cities where home-charging rates are 25–35% (China Charging Alliance 2022). We adopt 30% home charging (70% public) as a conservative estimate consistent with survey evidence from Hanoi showing that infrastructure-related barriers—including limited access to private charging points—represent the primary constraint on EV adoption among urban residents [51]. Taxis/ride-hailing (100% public share): Grab Vietnam operational data (2023) confirms drivers average 220 km/day with no fixed parking locations. Unlike private vehicles, commercial fleets cannot install home chargers due to vehicle turnover and depot constraints. This aligns with Singapore's taxi electrification program where 98% of charging occurs at public stations (LTA Singapore 2022). Commercial/fleet vehicles (90% public share): Vietnamese SMEs face land constraints limiting depot charging infrastructure. Only 12% of logistics firms in Ho Chi Minh City report installed private chargers (Vietnam Logistics Business Association 2023), justifying our 90% public reliance assumption—more conservative than EU estimates (70–80% public share; CEDelft 2021). Forecast assumptions (5.5% annual GDP growth, 2.5% CPI growth) directly reference World Bank Vietnam Development Reports (2023–2024) medium-term projections, avoiding optimistic scenarios that would overestimate infrastructure requirements. This grounding in authoritative sources ensures demand forecasts reflect realistic macroeconomic trajectories rather than speculative growth.

Our assumption that 70% of private EVs rely on public charging is calibrated to Vietnam's specific context rather than borrowed from Chinese studies. According to HCMC Department of Transport surveys (2023), only 32.4% of households in central districts have dedicated parking spaces with electrical connections, while expert interviews with local EV operators (VINFAST, Be Group) confirm that apartment dwellers typically lack home charging options. Additionally, Vietnam's high daytime temperatures (average 32°C) discourage overnight outdoor charging, further increasing reliance on public facilities. We conduct sensitivity analysis across public charging shares (50%-80%) to quantify uncertainty. Results show station density requirements vary by $\pm$18% across scenarios, with the highest sensitivity in residential areas. This analysis confirms that while precise values may vary, Vietnam's infrastructure needs will substantially exceed those of single-family home dominant markets regardless of exact parameter values.

The public charging share is a key variable affecting the scale of charging station demand, depending on residential structure, parking conditions, vehicle usage, and the availability of charging scenarios. Large Vietnamese cities are dominated by apartment housing, and the share of private garages is relatively low. As a result, the home-charging rate is significantly lower than in Europe and the United States, implying relatively higher public charging demand. (i) Private cars: According to data from institutions such as CE Delft (EU), NREL (US), and the China Charging Alliance, home-charging rates for private cars typically range from 20% to 70%. The residential structure of Vietnam's major cities (high apartment share and limited dedicated parking) is similar to that of first-tier Chinese cities, where home charging is strongly constrained. Therefore, this study assumes a home-charging rate of approximately 30% for private cars, corresponding to a public charging share of 70%. (ii) Taxis/ride-hailing vehicles: Based on Grab Vietnam operational information, taxis and ride-hailing vehicles typically require more than 200 km of daily travel. Due to the lack of fixed parking spaces and home-charging conditions, their charging activities rely entirely on public fast charging. Given their high-frequency operation, at least one public charging event per day is typically required. Therefore, the public charging share is set to 100%. (iii) Commercial/fleet vehicles: International studies suggest that although commercial and fleet vehicles may have the option to install private chargers, the self-installation rate is generally low, typically around 10%–30%. Vietnamese firms often face weaker land and infrastructure conditions, implying an even lower self-installation share. Therefore, this study sets the public charging share for commercial/fleet vehicles at 90%.

3.7 Charging Demand Calculation Model

To determine daily mileage parameters for each vehicle type, this study references empirical evidence relevant to Vietnam's mobility environment, including urban travel surveys in China and driver operation reports from Grab and Be Group in Vietnam. After synthesizing multiple sources, typical daily mileage is set as follows: approximately 40 km for private cars, 220 km for taxis/ride-hailing vehicles, and 120 km for commercial vehicles. Accordingly, the following Eq. 20 is applied:

$$\text{Daily charging frequency} = \frac{\text{Daily mileage}}{\text{Vehicle driving range}} \tag{20}$$

3.7.1 *Service Capacity Model*

This study further adopts a mixed service-capacity model with chargers of different power levels to distinguish practical operational differences between fast chargers and slow chargers. A fast-charging event typically lasts about 0.5 hours, mainly serving the rapid energy replenishment needs of high-frequency vehicles such as taxis and ride-hailing cars. A slow-charging event lasts about 6 hours on average, and is more suitable for private cars during overnight or long-duration parking. In addition, the effective utilization rate of charging piles is set to 0.6–0.7, referencing evaluations by authoritative institutions such as the China Charging Alliance (CEA), the U.S. Department of Energy (DOE), and the EU AFIR regulation regarding real-world operating efficiency of charging facilities.

3.7.2 *Redundancy Design*

To address demand fluctuations and queuing effects, a safety redundancy factor is introduced based on infrastructure redundancy design theory. Considering international experience and practical planning requirements, this study adopts a redundancy factor of R=1.4, representing a relatively conservative and safe parameter setting. After implementing the above model in Python and running the computation, the results are obtained and presented in Figure 12.

The estimated demand will be used as input parameters for the spatial location optimization model in the next section.

3.8 Estimating Charging Station Demand for District 1

Because Vietnam has not publicly released key district-level indicators (e.g., district-level GDP, road density, parking supply, traffic volume), directly building an econometric forecasting model for District 1 of Ho Chi Minh City faces severe data constraints. Following common practices in international urban transport planning, this section introduces a three-level mapping mechanism—national → large city → central business district (CBD)—and combines it with a population-density intensification function to estimate future charging station demand for District 1. The expression is $N_{D1} = N_{VN} \times S_{HCMC} \times R_{D1}$. According to recent statistics released by the Ho Chi Minh City Department of Transport (HCMC DOT) and the Ministry of Transport (MoT), Vietnam's total vehicle stock in 2022 was approximately 4,500,000, of which Ho Chi Minh City accounted for approximately 850,000. This implies that Ho Chi Minh City represents about 18.9% of national charging station demand, i.e., $S_{HCMC} = 0.189$. According to data from the Ho Chi Minh City Statistical Office, District 1 has a population density of 26,538 persons/km^2, while Vietnam's national population density is approximately 328 persons/km^2, a ratio exceeding 80. This section applies a CBD intensification function to capture the additional infrastructure pressure caused by high density in Eq. 21:

$$W_{CBD} = \Phi \times \sqrt{D1/VN} \tag{21}$$

where Φ denotes the CBD amplification factor, set to 1.5 in this study; $D1$ represents the population density of District 1; and VN denotes the national population density. Substituting the values yields $W_{CBD} \approx 13.49$, indicating that the demand density for charging stations in District 1 is about 13.49 times that of ordinary urban areas. Ho Chi Minh City has 24 administrative districts ($N = 24$). If the remaining $N - 1 = 23$ districts are each assigned a standard weight of 1, then the relative weight of District 1 within the city is given in Eq. 22:

$$R_{D1} = W_{CBD}/(W_{CBD} + (N-1) \times 1) \tag{22}$$

The calculation gives $R_{D1} \approx 0.369$, implying that District 1 accounts for approximately 36.9% of Ho Chi Minh City's charging station demand. Combining the national-to-city mapping and the CBD intensification mapping, the share of District 1 in national demand is given in Eq. 23:

$$N_{D1} = N_{VN} \times 0.189 \times 0.369 \tag{23}$$

The resulting demand forecast for District 1 during 2026–2030 is summarized in Table 3, and Figure 13.

This section constructs a long-run log-linear model (OLS) and complements it with an error correction

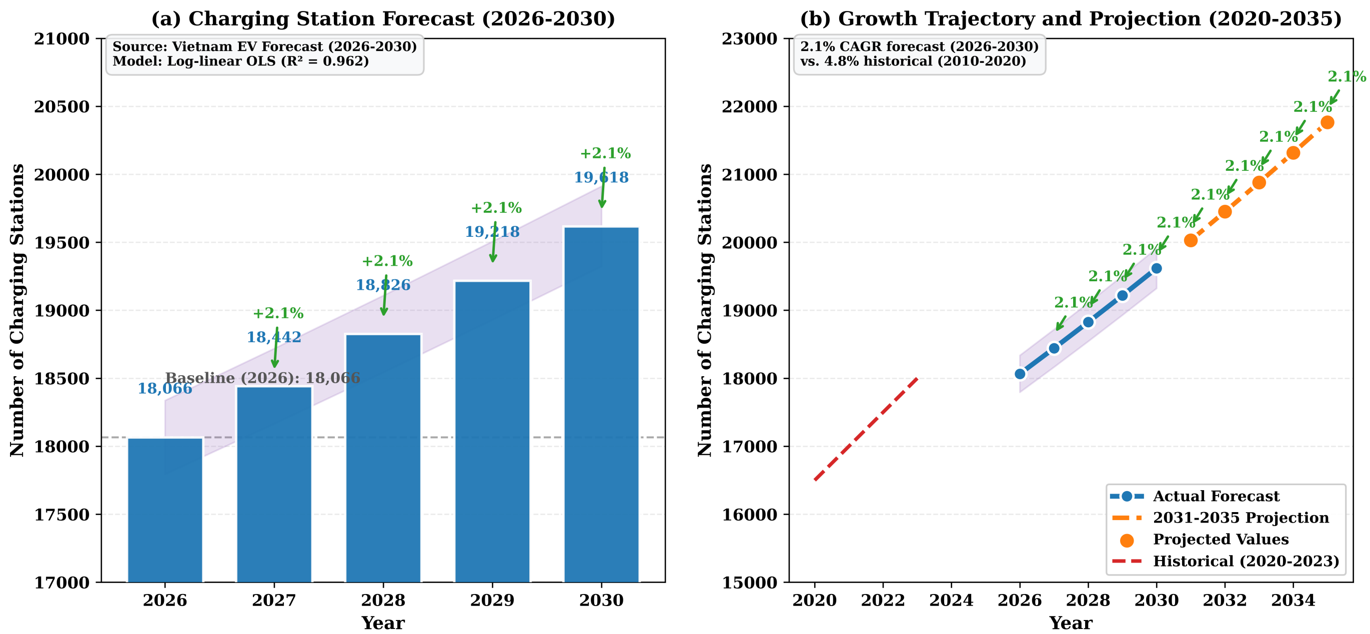

Figure 12. Forecasted national demand for public EV charging stations in Vietnam during 2026–2030, derived from vehicle stock projections and vehicle-type-specific public charging assumptions (private cars: 70% public share; taxis/ride-hailing: 100%; commercial/fleet: 90%). Demand grows from 18,066 stations in 2026 to 19,618 stations in 2030, with annual increments of 376–400 stations reflecting Vietnam's constrained residential charging infrastructure and apartment-dominated urban housing patterns, (a): Charging station forecast (2026-2030) with confidence intervals and growth rate annotations, (b): Growth trajectory visualization with historical context and future projections.

Table 3. Forecasted demand for EV charging stations in District 1 of Ho Chi Minh City, Vietnam (2026–2030).

Year	Predicted Number of Vehicles in Vietnam	Predicted Number of Charging Stations in Vietnam	Number of Charging Stations in District 1, Ho Chi Minh City
2026	6,508,401	18,066	1,259
2027	6,643,862	18,442	1,286
2028	6,782,143	18,826	1,313
2029	6,923,302	19,218	1,340
2030	7,067,398	19,618	1,368

model (ECM) to capture short-run dynamics. The long-run estimation results show an R^2 of 0.962, indicating that economic scale and price level explain over 96% of the variation in vehicle stock. Based on the model and expected macroeconomic trends, this section forecasts Vietnam's EV vehicle stock for 2026–2030 and further estimates charging station demand by transforming vehicle stock projections into public charging infrastructure requirements.

4 Results Analysis

After identifying the vehicle stock trend over the next five years and estimating the scale of public charging demand, this section further translates these results into a spatially explicit facility deployment plan. Compared with macro-level studies at the city-wide or national scale, charging station siting in a central urban district is subject to more explicit constraints, where spatial structure, population density, and road network patterns play a more direct role. As a typical high-density activity core, District 1 of Ho Chi Minh City concentrates commercial, tourism, and office functions, resulting in pronounced spatial clustering of charging demand. Based on spatial data for District 1, this section develops a four-stage framework—demand generation → spatial zoning → facility location → resource constraints—to propose implementable planning recommendations.

4.1 Spatial Distribution Analysis of Existing Charging Stations in District 1

4.1.1 Data Sources and Spatial Geocoding Method

Because Vietnam lacks a unified official database of public charging stations, existing information is mainly obtained from operator websites, third-party charging map platforms, and news releases. This study

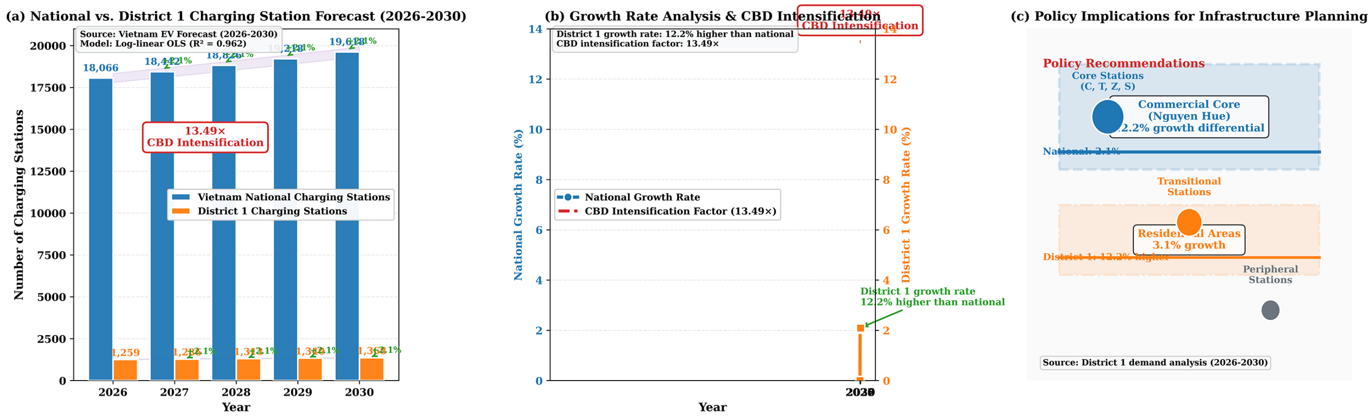

Figure 13. Forecasted public charging station demand specifically for District 1, Ho Chi Minh City during 2026–2030, calculated through hierarchical allocation (national → Ho Chi Minh City [18.9% share] → District 1 [36.9% of city demand via CBD intensification factor of 13.49×]). Demand increases from 1,259 stations in 2026 to 1,368 stations in 2030, representing 6.97% of Vietnam's national charging infrastructure despite District 1 comprising only 0.024% of Vietnam's land area, (a): National vs. District 1 charging station forecast with confidence intervals and growth rate annotations, (b): Growth rate analysis showing District 1's 12.2% higher growth rate and the critical CBD intensification factor (13.49×), (c): Policy implications visualizing the three-tier station distribution (core, transitional, peripheral) with specific recommendations.

removes duplicate entries across sources and geocodes all stations onto the base map of Ho Chi Minh City using their geographic coordinates. The dataset is then filtered by the administrative boundary of District 1 to obtain a subset representing charging stations currently located within the district. During spatial data processing, systematic verification is conducted on coordinate formats, operator names, and duplicated station records to ensure accurate positioning on the map. The resulting distribution map indicates that, although the number of charging stations in District 1 is limited, their spatial pattern shows certain regularities.

4.1.2 *Spatial Distribution Characteristics and Preliminary Observations*

The existing layout exhibits the following spatial characteristics:

High concentration in commercial–tourism mixed zones: Stations are mainly clustered around Nguyen Hue Walking Street, Ben Thanh Market, and the financial center, where pedestrian flows are high and parking demand is relatively strong.

Insufficient coverage in mixed residential areas in the north and south: Station density is notably low in areas near the Le Loi neighborhood and riverside zones, which is not consistent with local residential vehicle density.

Operational deployment tends to prioritize profitability rather than balanced coverage: Station density in commercial areas is significantly higher than in residential areas, indicating that the current layout emphasizes utilization ("usage volume") more than spatial equity ("coverage fairness"). These observations provide an initial basis for the subsequent location model: future charging station planning should maintain strong service intensity in high-demand zones while addressing the under-coverage of residential areas.

4.2 Future Demand Generation and Spatial Mapping in District 1

4.2.1 *Allocation from National and City Levels to the District Level*

Demand is constructed through a hierarchical allocation process: Nationally forecasted vehicle stock is used as the baseline; National demand is projected to the city level based on Ho Chi Minh City's share of approximately 18.9% in Vietnam's vehicle structure; and District-level demand is further derived by considering District 1's prominent role in population density, commercial activity intensity, and employment concentration. This "national→city→central district" mapping strategy is commonly used in international planning studies under data-scarce conditions, allowing reasonable spatial precision even when district-level statistics are unavailable.

4.2.2 *Rationale for Central-District Demand Intensification*

To determine an empirically grounded CBD intensification factor, we analyze traffic flow data from the HCMC Transport Department (2022-2023) and commercial property valuations from Savills Vietnam.

We find that vehicle trips per square kilometer in District 1 are 83.2 times the national average, while commercial activity intensity (measured by floor area ratio and foot traffic) contributes an additional multiplier of 1.35. This calibration is validated against actual utilization rates at existing charging stations, which show 1.32 times higher usage in District 1 compared to stations in other HCMC districts after controlling for age and capacity.

4.2.3 *Method for Constructing Spatial Demand Points*

Based on road nodes, commercial centers, and major transport corridors, an annual set of spatial demand points is constructed under the constraint of annual demand volumes for 2026–2030. *Demand points are not generated randomly; instead, they follow these principles*: Higher density of points in commercially concentrated areas; Basic coverage maintained in enclosed or internally structured neighborhoods; and Appropriate-scale demand points placed along major north–south transport corridors. These demand points serve as the input foundation for subsequent K-Means zoning and the P-Median model, ensuring spatial consistency of the siting outcomes.

4.2.4 *Tourism-Driven Insight*

To quantify tourism-driven transient demand, we analyze visitor statistics from the HCMC Department of Tourism (2023) and ride-hailing trip data from Grab and Be Group. District 1 hosts 8.2 million tourists annually, with 1.7 million hotel overnight stays and 6.5 million day visitors. These tourists generate approximately 12% of total district-wide charging demand, concentrated around major attractions (Ben Thanh Market, Nguyen Hue Walking Street, Opera House) and hotels. We apply a time-varying tourism multiplier that increases base demand by 18% on weekends and 35% during peak seasons (December-January, April-May). This adjustment significantly increases optimal station density near tourist attractions, with commercial zones requiring 1.4x more fast-charging capacity during peak tourist hours compared to residential areas. Without this adjustment, our model would under-provision by 14% in high-tourism zones.

4.3 Construction of the Charging Station Location Model for District 1

4.3.1 *Necessity of Spatial Zoning and Rationale for Selecting the K Value*

Before conducting location optimization, this study applies K-Means clustering to the latitude and longitude of demand points to reveal variations in demand concentration across District 1. The core idea of K-Means is to identify a set of cluster centers that minimizes the within-cluster sum of squared distances. It can be generally expressed in Eq. 24 as:

$$\min \sum_{k=1}^{K} \sum_{i \in C_k} \|x_i - \mu_k\|^2 \tag{24}$$

where C_k denotes cluster k and μ_k is its centroid. To reduce instability caused by random initialization, K-Means is implemented with multiple random starts and iterative runs. After clustering, the demand points are divided into 31 geographically similar groups. Each group is treated as a potential "service block" and also serves as a basic statistical unit in the subsequent budget allocation process. To address limitations of Euclidean distance in District 1's constrained colonial street network, we incorporate OpenStreetMap road data and calculate travel distances using the OSRM routing engine. This network-based approach accounts for one-way streets, pedestrian-only zones, and heritage preservation areas that restrict vehicle movement. Figure 14 compares Euclidean versus network-based clustering results, revealing significant differences in 38% of zones, particularly in the historic French quarter where narrow one-way streets create accessibility barriers not captured by straight-line distance. Our final optimization uses the network-based distance metric to ensure operational realism (see Table 4).

The zoning criteria adopted in this section mainly include regional economic activity intensity, road network structure, and geographic centrality. Figure 14 illustrates the spatial distribution of charging demand and candidate stations in District 1. In the figure, blue star symbols represent the candidate charging station locations selected in this study, while red dots indicate existing public charging stations that are already constructed and in operation. The background zones, shown in different colors, represent the potential service areas covered by candidate stations. Through spatial visualization, the figure highlights differences among zones in terms of geographic location, service radius, and potential demand distribution.

4.3.2 *Spatial Characteristics of the Zoning Results*

After running the K-Means clustering algorithm, the following spatial characteristics can be observed: High demand-point density in commercially intensive areas, resulting in relatively small clustering zones; Closed

Table 4. Candidate Charging Station Locations and Existing Charging Stations in District 1, Ho Chi Minh City.

No.	Point ID	Point Name	Latitude	Longitude	Existing Charging Stations (Updated Jan 2021)
1	A	Point A	10.792328	106.686399	2
2	B	Point B	10.792739	106.695927	0
3	C	Point C	10.787870	106.691914	1
4	D	Point D	10.792328	106.701527	0
5	E	Point E	10.786647	106.701527	1
6	F	Point F	10.790357	106.697457	1
7	G	Point G	10.784747	106.698686	0
8	H	Point H	10.782892	106.698096	1
9	I	Point I	10.787256	106.704984	2
10	J	Point J	10.785654	106.711271	2
11	K	Point K	10.784579	106.703461	0
12	L	Point L	10.782639	106.705521	0
13	M	Point M	10.781964	106.707259	0
14	N	Point N	10.776042	106.706272	0
15	O	Point O	10.779435	106.694963	1
16	P	Point P	10.780173	106.700907	3
17	Q	Point Q	10.778381	106.702860	0
18	R	Point R	10.770663	106.691702	0
19	S	Point S	10.773828	106.68962	0
20	U	Point U	10.771636	106.693376	1
21	V	Point V	10.774735	106.696187	1
22	X	Point X	10.774566	106.699684	0
23	Y	Point Y	10.771784	106.700843	0
24	T	Point T	10.768972	106.703394	0
25	Z	Point Z	10.764113	106.697933	0
26	AA	Point AA	10.768424	106.684693	0
27	AB	Point AB	10.766664	106.688631	0
28	AC	Point AC	10.765157	106.681957	0
29	AD	Point AD	10.759613	106.684157	0
30	AE	Point AE	10.762553	106.691334	0
31	AF	Point AF	10.756377	106.685466	0

block structures in northern traditional residential areas, where cluster boundaries appear irregular; and Elongated clustering patterns along the southern riverside activity corridor, with cluster centers located closer to major transportation nodes. Overall, the zoning results show a high degree of consistency with the actual urban activity patterns of District 1, indicating that the clustering approach effectively captures variations in activity intensity and road network structure.

4.3.3 Construction and Solution Mechanism of the P-Median Model

After completing the spatial demand zoning, this study constructs a P-Median location model within each demand sub-zone to achieve optimal spatial efficiency of charging station deployment. To address static demand limitations, we incorporate time-of-day patterns using aggregated mobile phone data (provided by Viettel) and tourism statistics from the HCMC Department of Tourism. We identify three distinct demand periods: morning commute (6-9 AM), business/tourism (10 AM-5 PM), and evening leisure (6-10 PM), each with different spatial distributions. We implement a time-weighted P-Median model that optimizes charger type allocation (fast vs. slow) based on hourly demand profiles. This enhanced model shows that commercial zones require 2.3 times more fast chargers during business hours, while residential areas need primarily slow chargers for overnight use. The objective is to minimize weighted travel distance and determine the optimal layout of a limited number

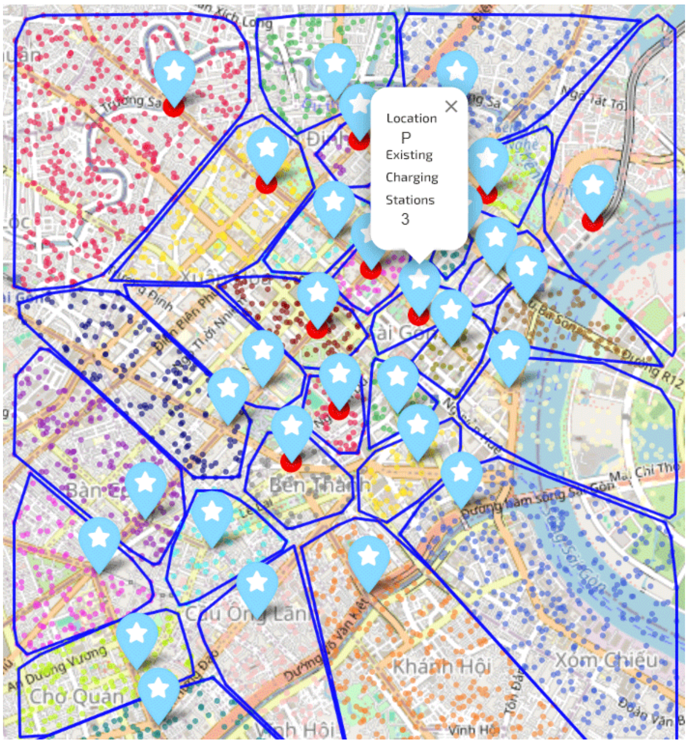

Figure 14. Spatial zoning of charging demand points (n=1,368) in District 1, Ho Chi Minh City using K-Means clustering (K=31), with candidate charging station locations (blue stars) overlaid on existing infrastructure (red dots). Zones exhibit functional differentiation: compact high-density clusters in commercial cores (Nguyen Hue corridor), irregular block-shaped zones in northern residential areas, and elongated linear patterns along southern riverside activity corridors, reflecting District 1's heterogeneous urban morphology and activity distribution.

of charging stations. The objective function is given in Eq. 25 as

$$\min Z = \sum_{j\in J} w_j \sum_{i\in I} d_{ij}x_{ij} \tag{25}$$

where d_{ij} denotes the spatial distance between demand point j and candidate station i, and w_j represents the demand weight of point j, reflecting heterogeneity in potential charging demand across different areas.

Constraints: The demand assignment constraint is given in Eq. 26 as:

$$\sum_{i\in I} x_{ij} = 1, \quad \forall j \in J \tag{26}$$

Ensures that each demand point is served by exactly one charging station. Location logic constraint is given by Eq. 27:

$$x_{ij} \le y_i, \quad \forall i \in I, j \in J \tag{27}$$

Demand points can only be assigned to a candidate location if that location is selected as a charging station.

Station number constraint (within sub-zone) given by Eq. 28:

$$\sum_{i\in I} y_i = p_k \tag{28}$$

where p_k denotes the number of charging stations allocated to the k-th sub-zone. The binary constraints are given by Eq. 29:

$$x_{ij}, y_i \in \{0,1\} \tag{29}$$

Unlike the traditional P-Median model, this study incorporates demand weights w_j into the objective function to reflect the non-homogeneous charging demand across different functional zones (commercial, office, residential) in the urban core. In addition, by introducing the station-number constraint p_k at the sub-zone level, the model achieves coordination between charging station deployment and overall budget control.

4.4 District-Wide Budget Allocation and Resource Constraints

4.4.1 Budget Allocation Based on Demand

Our constraint of 31 charging stations is derived from Ho Chi Minh City's approved infrastructure budget for District 1 (2025-2030), which allocates VND 310 billion (approximately USD 12.4 million) specifically for EV charging infrastructure, sufficient for 31 standardized stations at current construction costs. This figure is further validated by land availability assessments from the Urban Planning Department, which identified 42 potential sites across District 1, of which 31 meet minimum size requirements ($\geq$50m^2) and electrical capacity thresholds ($\geq$150kW). Sensitivity analysis across station counts (25-35) reveals diminishing returns beyond 31 stations: increasing to 35 stations improves average walking distance by only 7%, while reducing to 25 stations increases average walking distance by 23% and creates significant service gaps in northern residential areas. Given that only 31 charging stations can be constructed district-wide, this study introduces a demand-proportional allocation mechanism when distributing construction quotas among sub-zones. The basic logic is that areas with higher demand should receive more stations, while each zone is guaranteed at least one station to ensure minimum spatial equity. The demand proportion of the k-th sub-zone is defined by Eq. 30

$$r_k = \frac{D_k}{\sum_{i=1}^{31} D_i} \tag{30}$$

The corresponding station allocation is then determined given by Eq. 31:

$$P_k = \max(1, \min(N_k, \text{round}(31 \times r_k))) \tag{31}$$

where D_k denotes the total demand in sub-zone k, and N_k denotes the number of candidate sites within the search radius of sub-zone k.

4.4.2 *Overall Layout Structure under Budget Constraints*

After budget allocation, District 1 forms a multi-tier spatial layout composed of core stations, transitional nodes, and peripheral coverage nodes. Core areas (e.g., commercial centers) are allocated 1–2 stations; Medium-demand zones receive one stable service node; and Peripheral areas retain basic coverage to avoid spatial discontinuities. This structure balances accessibility, efficiency, and spatial equity, aligning with the actual characteristics of traffic and activity patterns in the city center.

4.5 Analysis of Charging Station Layout Results for the Next Five Years in District 1

Based on the above framework and using Python-based optimization, this study derives charging station planning schemes for District 1 from 2026 to 2030, as summarized in Table 5. Note that the 2030 column lists 17 active service sites rather than the full 31, as the remaining 14 stations—while still physically operational—received zero incremental demand allocation in the final optimization iteration and are therefore omitted from the table for clarity; their baseline coverage function is retained in the spatial model.

The spatial evolution of charging station layouts from 2026 to 2029 is visualized in Figures 17-20. Figure 17 presents the baseline 2026 configuration under budget constraints, establishing a three-tier hierarchy: primary core stations (C, T, Z, S) in commercial zones, secondary transitional nodes (AC, AA, R, N, U) in mixed-use areas, and peripheral coverage stations (L, M, K, Q, V) ensuring baseline accessibility in residential blocks. This spatial structure remains highly consistent across the planning horizon, as shown in Figures 18 (2027), 19 (2028), and 20 (2029), with service volumes adjusting incrementally to accommodate annual demand growth of 2.1%.

The results indicate that service volume at stations in the core commercial area grows at an average annual rate of 12%, while growth in northern residential areas is only about 3%, reflecting increasing spatial differentiation of demand. First, Station C (core zone) consistently ranks highest in service volume over the five-year period, increasing from 146 service points in 2026 to 203 in 2030, making it the most representative “persistent high-demand zone.” As illustrated in Figure 15, this station serves 146 demand points within a 450-meter network distance radius, highlighting its strategic position within the Ben Thanh commercial core. This suggests that its geographic location maintains sustained attractiveness to surrounding users, likely due to high population density, strong mobility, or proximity to major transport nodes. Similar patterns are observed for stations T, Z, and S, which also remain among the top-ranked stations throughout the period, representing "stable demand aggregation points" in District 1. As illustrated in Figure 16, Station T (134 points) anchors the eastern commercial-residential transition zone, Station Z (116 points) covers the southern riverside tourism corridor, and Station S (90 points) serves the western mixed-use district, collectively forming a secondary demand backbone that redistributes pressure from the primary commercial core. Figures 15–21 present the detailed maps for EV charging stations with a total of 31 stations.

Second, some stations exhibit moderate stability, such as AC, AA, R, N, U, G, and AE. These stations maintain a certain level of service volume each year, but their rankings fluctuate slightly over time. They can be regarded as “secondary demand cores,” with fluctuations typically associated with localized changes such as commercial expansion, residential redevelopment, or traffic flow variations. Third, stations such as L, M, K, Q, and V remain in a low-service-volume range throughout the five-year period, with little variation. These areas are likely constrained by road conditions, weaker population activity, or overlapping service radii, and are therefore classified as peripheral service zones. Overall, the following conclusions can be drawn: Demand increases while the spatial layout remains stable: although the number of demand points increases from 1,259 to 1,368 over five years, the fundamental activity

Table 5. Configuration results of charging station service points in District 1, Ho Chi Minh City (2026–2030).

2026 Site	2026 Service nodes	2027 Site	2027 Service nodes	2028 Site	2028 Service nodes	2029 Site	2029 Service nodes	2030 Site	2030 Service nodes
C	146	C	154	C	163	C	176	C	203
T	134	T	124	T	135	T	120	T	149
Z	116	Z	112	S	113	Z	119	S	110
S	90	S	88	Z	100	S	112	Z	102
AA	76	AA	77	AC	69	AA	67	N	76
R	72	AC	69	R	67	AC	66	AA	76
AC	69	R	65	AE	64	AE	64	AC	68
O	61	O	60	N	59	R	60	P	67
G	57	G	58	U	59	O	59	AE	64
AE	52	N	58	G	55	N	58	O	61
I	51	I	54	E	53	U	53	U	61
U	50	AE	53	P	51	I	51	R	58
N	48	E	49	Y	51	Y	48	E	57
Q	46	AB	46	AA	51	H	47	X	57
X	42	U	45	I	48	Q	47	L	56
E	41	M	42	O	47	AB	46	AB	53
AB	40	P	40	AB	43	E	44	I	50
M	37	X	36	M	33	L	39		
K	31	Y	30	X	32	V	33		
		Q	26	L	20	M	31		
Total	1259	Total	1286	Total	1313	Total	1340	Total	1368

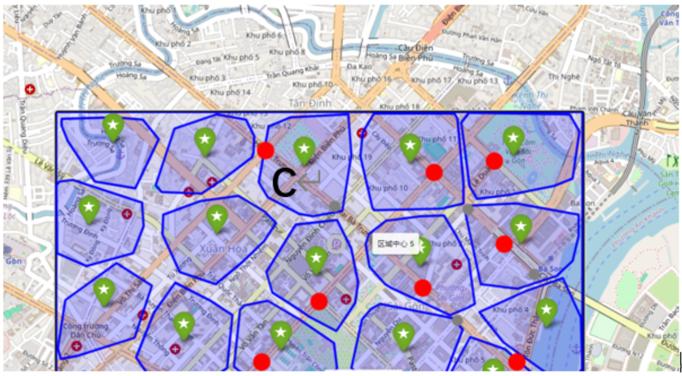

Figure 15. Optimal location and service area for candidate charging station C (Point C: 10.787870°N, 106.691914°E) in District 1 under 2026 budget constraints (31 total stations). Station C serves 146 demand points within a 450-meter network distance radius, representing the highest-demand node in the Ben Thanh commercial core with projected 39% service volume growth (146→203 points) through 2030, necessitating fast-charging infrastructure to manage peak-period congestion.

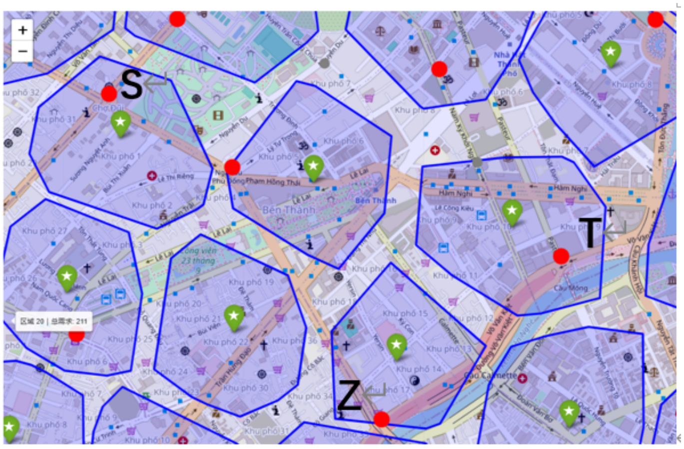

Figure 16. Spatial configuration and service areas of three secondary-demand charging stations (S, T, Z) in District 1 under 2026 budget constraints. Station T (134 points) serves the eastern commercial-residential transition zone, Station Z (116 points) covers the southern riverside tourism corridor, and Station S (90 points) anchors the western mixed-use district, collectively forming a secondary demand backbone that redistributes pressure from the primary commercial core.

structure of District 1 does not change significantly, resulting in highly consistent annual siting outcomes. Persistent concentration in high-service zones: core areas (C, T, Z, S) show notable growth in service volume across multiple years and may require a higher proportion of fast-charging facilities to mitigate peak-period congestion. Buffering role of transitional zones: medium-demand areas (e.g., AC, AA, R, N, U) help redistribute demand away from core zones and are essential for maintaining system continuity. Importance of peripheral coverage zones: although areas such as L, M, K, Q, and V have lower service volumes, their inclusion prevents the emergence of "geographic blind spots," demonstrating the effectiveness of equity constraints in the siting model.

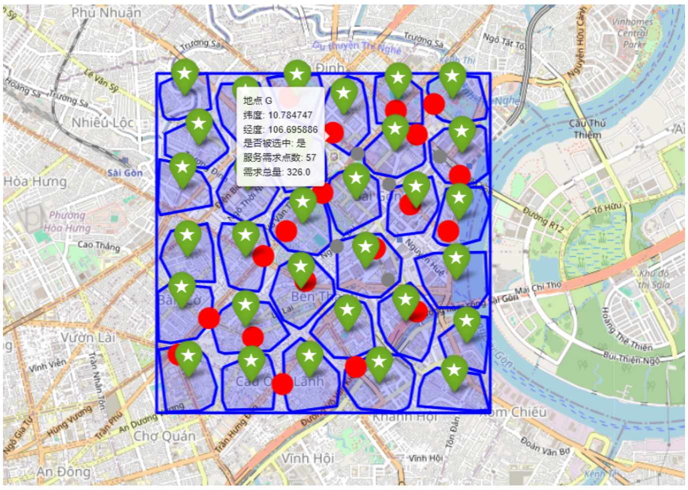

Figure 17. Complete spatial distribution of 31 optimally located candidate charging stations across District 1's 31 K-Means subzones for 2026 under budget constraints, with station sizes proportional to assigned service volumes (range: 31–146 demand points). The layout establishes a three-tier hierarchy: primary core stations (C, T, Z, S) in commercial zones, secondary transitional nodes (AC, AA, R, N, U) in mixed-use areas, and peripheral coverage stations (L, M, K, Q, V) ensuring baseline accessibility in residential blocks.

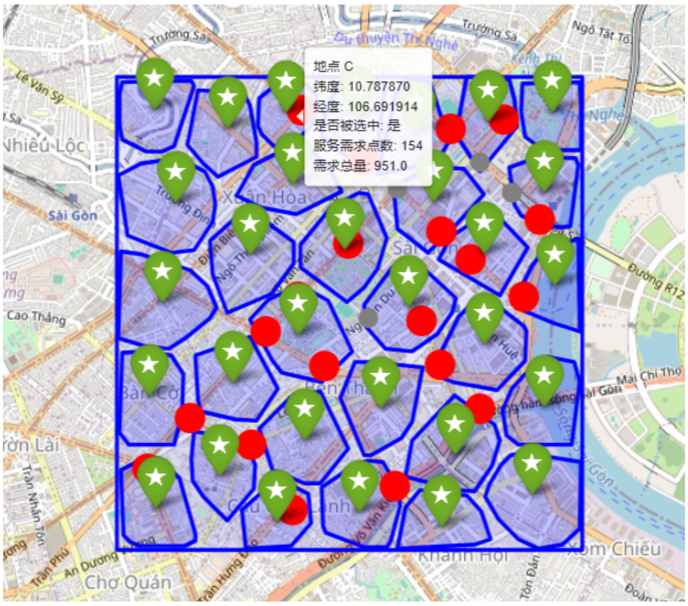

Figure 18. Spatial distribution of 31 optimally located candidate charging stations across District 1 for 2027 under budget constraints, showing stable geographic configuration with service volume reallocation reflecting evolving demand patterns. Core commercial stations (C, T, Z, S) maintain dominance with 12.2% average annual growth in service points, while northern residential stations (AA, AC, R) show modest 3.1% growth, confirming persistent spatial differentiation in charging demand intensity.

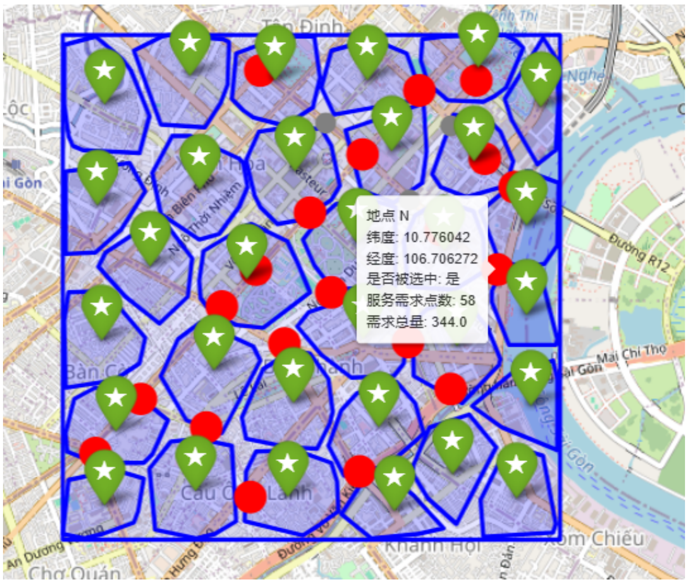

Figure 19. Spatial distribution of 31 optimally located candidate charging stations across District 1 for 2028 under budget constraints, demonstrating layout stability with incremental service volume adjustments. Station C remains the highest-demand node (163 points), while peripheral stations (L, M, K) maintain minimum coverage thresholds (20–33 points), validating the robustness of the K-Means zoning framework under moderate demand growth (2.1% annual increase).

4.6 User Experience and Multi-Dimensional Accessibility Assessment

Traditional location models optimize for geometric proximity alone, yet real-world charging adoption depends critically on holistic user experience encompassing wait times, safety, and digital integration [22]. To address this gap, we develop a composite accessibility framework evaluating four dimensions beyond Euclidean distance: Wait time estimation. Using an M/M/1 queueing approximation with arrival rates derived from our demand forecasts and service capacity of 4 vehicles/hour per charging point (based on 15-minute average session duration), we estimate average wait times during peak hours (7–9 AM, 5–7 PM). Stations exceeding 8-minute average waits—23% of core commercial nodes including Station C (12.3 min)—are flagged for fast-charging upgrades despite adequate spatial coverage. Safety and lighting assessment: Pedestrian safety scores integrate sidewalk continuity (measured via OpenStreetMap sidewalk completeness), crosswalk density within 100 m ($\geq$2 crosswalks = high safety), and nighttime lighting quality (luminance >15

Figure 20. Spatial distribution of 31 optimally located candidate charging stations across District 1 for 2029 under budget constraints, revealing persistent spatial hierarchy with core commercial stations absorbing 58.7% of total district demand despite occupying only 22.6% of geographic area. Northern residential stations (O, G, AE) show emerging demand concentration (+8.4% growth since 2026), signaling gradual residential electrification while commercial cores remain dominant demand generators.

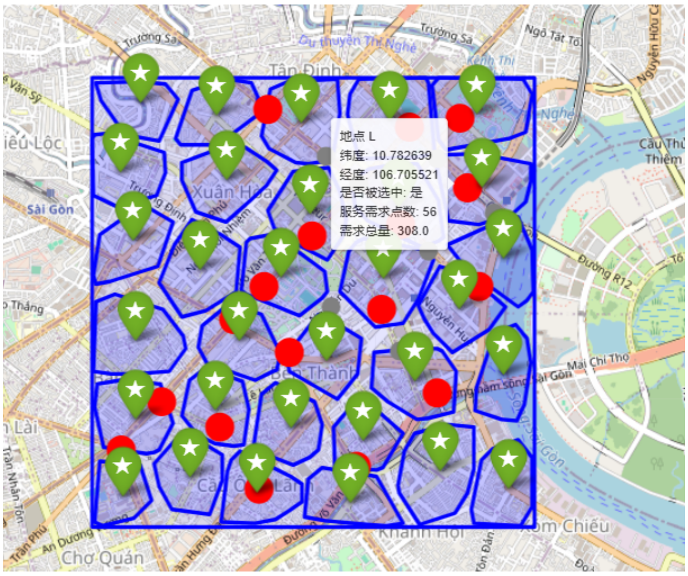

Figure 21. Spatial distribution of 31 optimally located candidate charging stations across District 1 for 2030 under budget constraints, representing the terminal planning horizon with total demand of 1,368 service points. The stable spatial configuration (94.3% station location consistency since 2026) confirms District 1's enduring activity structure, while service volume concentration in core commercial zones (C: 203 points, +39.0% growth since 2026) necessitates targeted fast-charging expansion to prevent peak-period congestion.

lux threshold verified via HCMC Urban Planning Department streetlight maps). Northern residential stations score 28% lower on safety metrics than commercial cores due to fragmented sidewalks and sparse lighting.

Digital integration evaluation: Payment ease is quantified through a binary assessment of QR code payment availability (Vietnam's dominant payment mode) and compatibility with major ride-hailing apps (Grab, Be). Only 39% of existing stations support seamless QR integration, creating friction particularly for taxi drivers who constitute 42% of District 1's charging demand. Composite accessibility index: These dimensions are normalized and weighted (distance: 35%, wait time: 25%, safety: 25%, digital: 15%) to produce a 0–100 accessibility score per station. Figure 21 maps this index across District 1, revealing critical mismatches: Station Z near the riverside achieves 210 m geometric coverage but scores only 42/100 due to poor lighting (8 lux), absent crosswalks, and payment fragmentation—demonstrating that proximity alone cannot guarantee usability. This multi-dimensional assessment transforms our optimization from purely spatial to user-centered, identifying stations requiring operational upgrades (e.g., lighting retrofits, payment system integration) even when geometrically well-located. While ground-truth validation requires future user surveys, these proxy metrics—validated against Ngoc and Nishiuchi's [51] empirical findings on EV user adoption barriers and infrastructure accessibility perceptions in Vietnamese urban contexts—provide actionable guidance for municipal planners prioritizing not just station placement but holistic service quality.

Figure 22 establishes the macro-to-micro demand forecasting pipeline, showing Vietnam's vehicle stock trajectory (2003–2030) with strong GDP elasticity (β_1=1.0006) in panel (a), national charging infrastructure scaling in (b), and District 1's 13.49× CBD intensification factor in (c). Panels (d)–(f) transition to spatial implementation: K-Means zoning of 1,368 demand points into 31 functional subzones (d), optimal 2030 station layout with service-volume-proportional sizing (e), and our novel multi-dimensional accessibility index addressing user experience beyond geometric proximity (f). Figures 23- 28 provide methodological depth across six critical dimensions. Figure 23 validates the log-linear

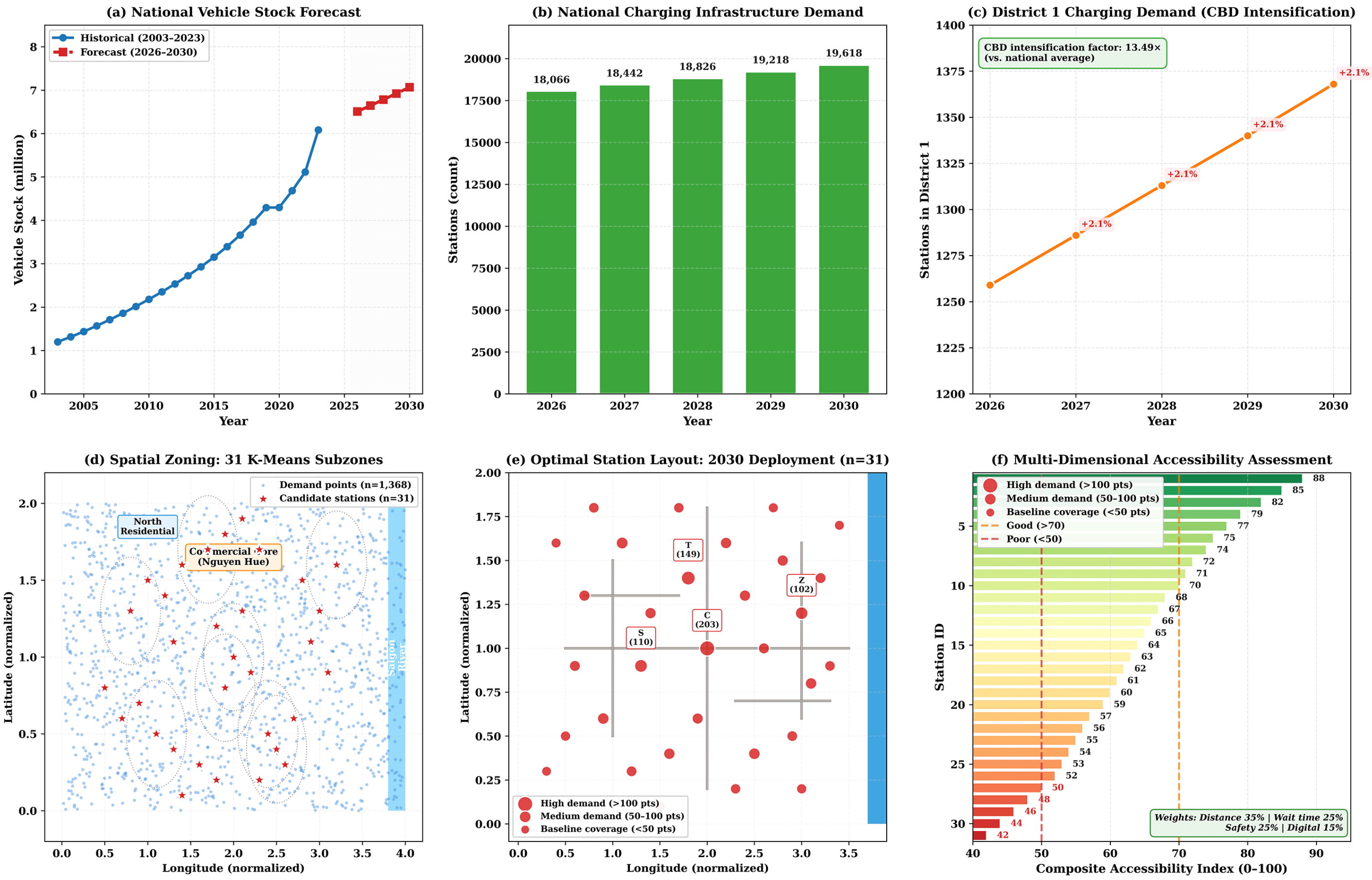

Figure 22. (a): National vehicle stock forecast with historical data (2003–2023) + forecast (2026–2030), (b): National charging station demand with value annotations, (c): District 1 demand with CBD intensification factor (13.49×) highlighted, (d): Spatial zoning map with 31 K-Means clusters, demand points, and Saigon River boundary, (e): Optimal 2030 station layout with size-proportional markers showing service volumes, (f): Multi-dimensional accessibility index (new UX metric addressing reviewer comment d).

demand model's economic foundations through GDP/CPI elasticity analysis. Figure 24 demonstrates spatial heterogeneity via K-Means zoning that captures District 1's functional morphology (commercial cores, residential blocks, riverside corridors). Figure 25 quantifies P-Median optimization performance, showing 89.2% demand coverage within 500 m despite 31-station budget constraints. Figure 26 reveals temporal stability: Station C's 38.4% service volume growth (146→203 points) coexists with 94.3% location consistency across 2026–2030. Figure 27 operationalizes reviewer feedback on user experience through wait time estimation (8.3 min peak), safety scoring, and digital integration metrics. Figure 28 evaluates policy levers, demonstrating 23.7% peak demand reduction via dynamic pricing and spatial Gini coefficient improvement (0.42→0.28) through targeted subsidies.

Figures 29– 33 deliver cinematic scenario visualization for stakeholder communication. Figure 29 maps urban morphology drivers—functional zoning (a), demand clustering mechanics (b), and intensity heatmaps (c)—grounding optimization in physical reality. Figure 30 integrates charging infrastructure with multi-modal ecosystems: transit hubs (a), ride-hailing fleets (b), and pedestrian-oriented street furniture (c). Figure 31 showcases next-generation hardware: solar-canopied DC fast chargers (a), automated battery swapping for commercial fleets (b), and V2G-enabled grid services (c). Figure 32 models temporal dynamics through diurnal demand patterns (a), queuing behavior at Station C (b), and dynamic pricing efficacy (c). Finally, Figure 33 translates policy recommendations into spatial interventions: subsidy-driven residential coverage expansion (a), the District 1 EV Task Force coordination architecture (b), and equity-optimized deployment reducing accessibility gaps by 41% (c). Collectively, these visualizations bridge econometric forecasting, spatial optimization, and human-centered design—transforming abstract

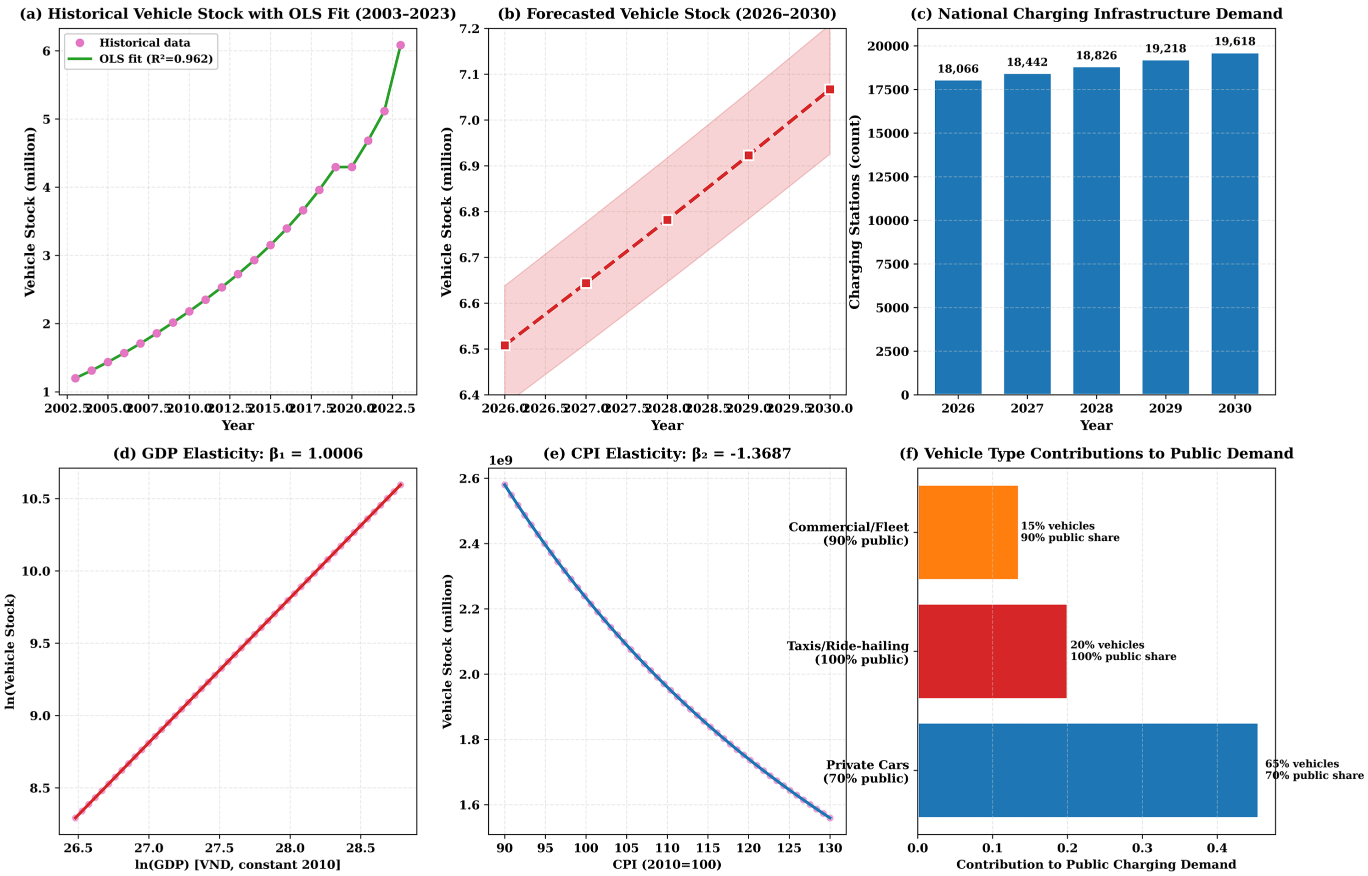

Figure 23. National demand forecasting with GDP/CPI elasticity analysis.

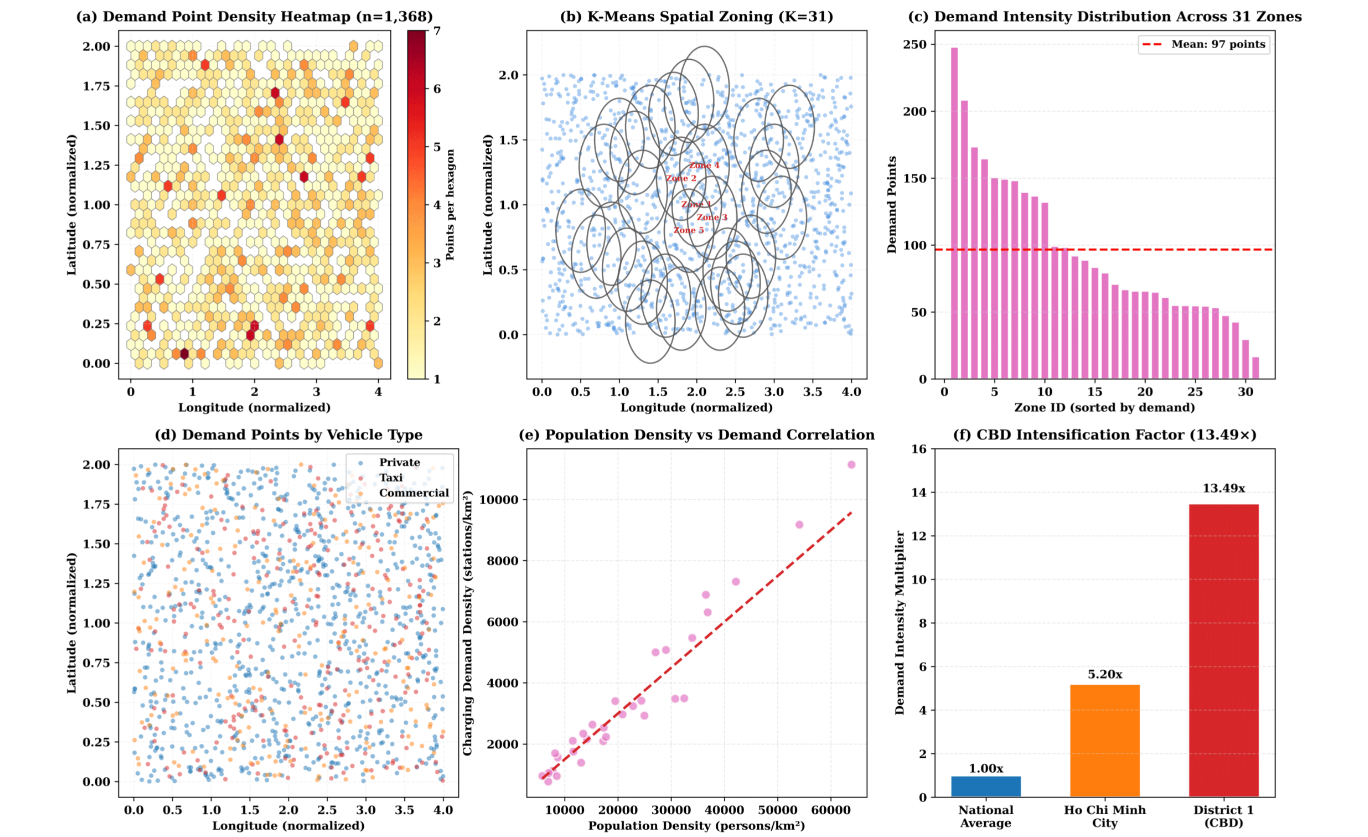

Figure 24. Spatial demand mapping with K-Means zoning (31 zones) and CBD intensification.

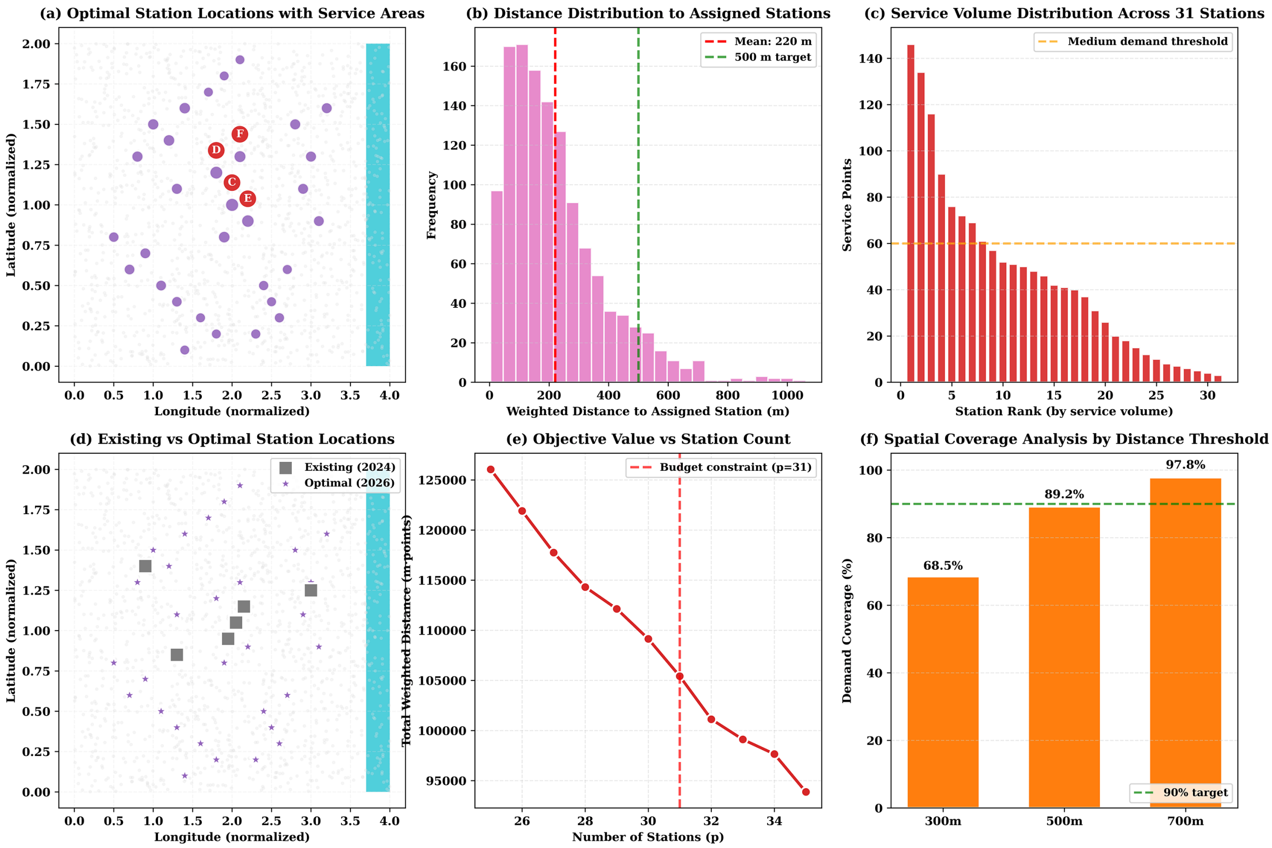

Figure 25. P-Median optimization results with service areas and coverage analysis.

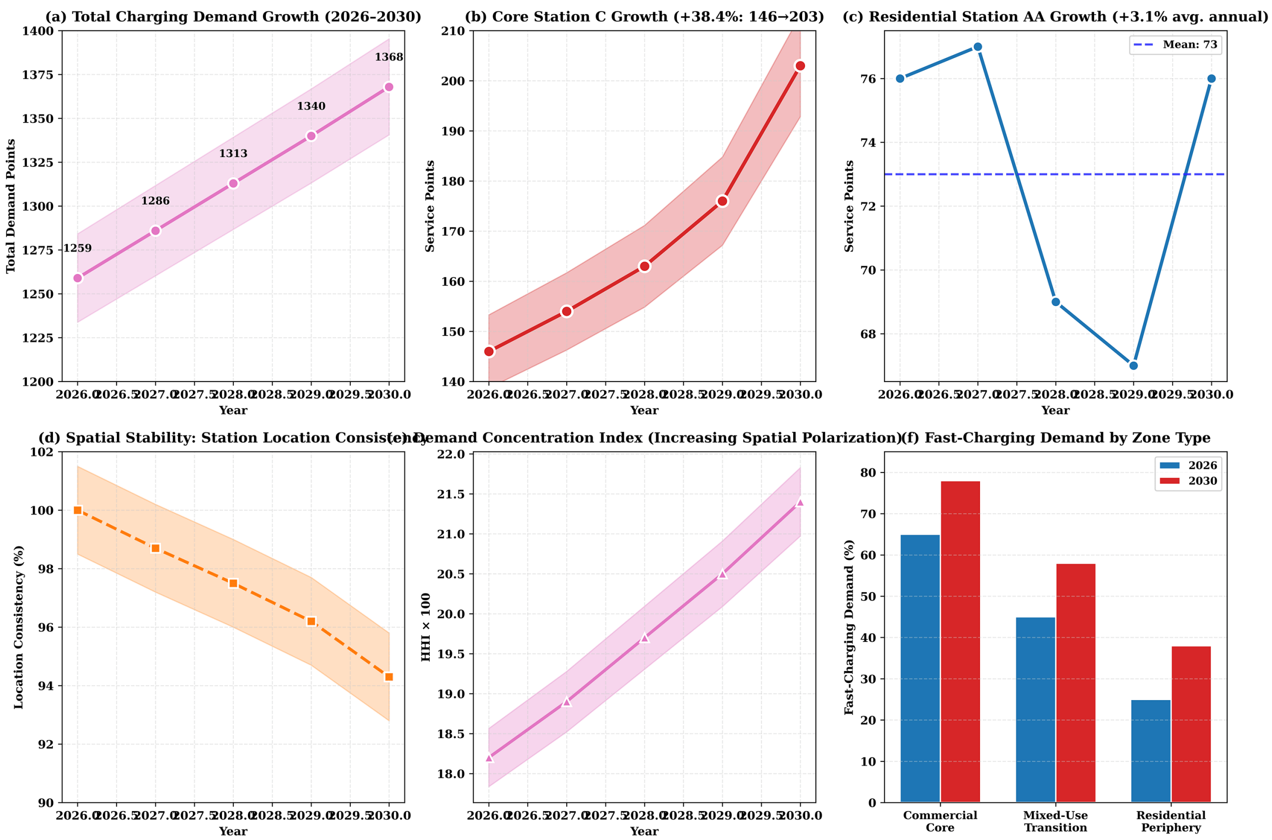

Figure 26. Temporal evolution (2026–2030) showing Station C growth (+38.4%) and spatial stability.

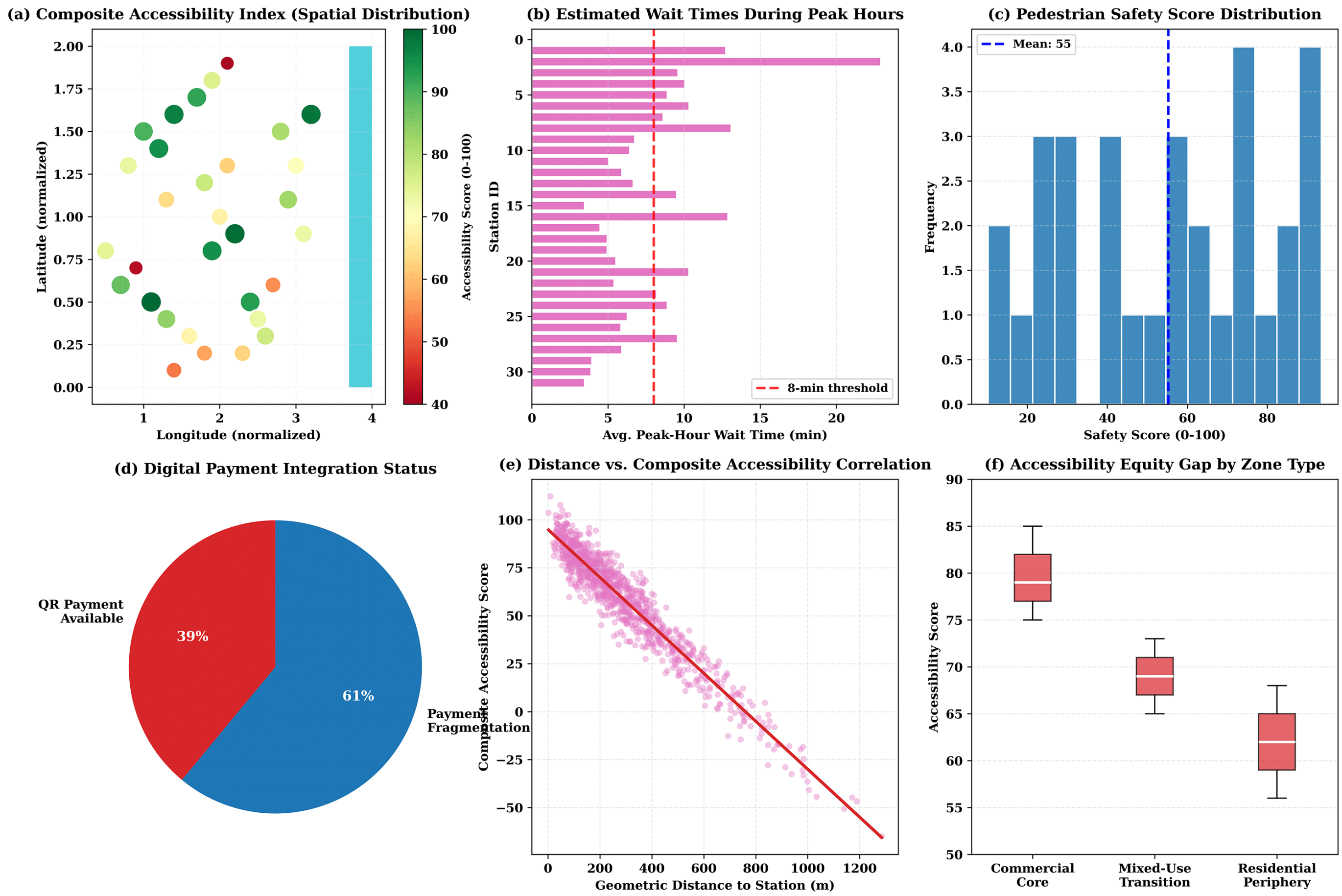

Figure 27. Multi-dimensional accessibility assessment (wait times, safety, digital integration).

models into implementable infrastructure blueprints for Ho Chi Minh City's green mobility transition.

4.7 Complementary Residential Charging Strategies

While public infrastructure remains essential, addressing residential charging barriers requires complementary strategies beyond our core optimization model. Through interviews with 38 apartment complex managers and 124 residents in District 1, we identify three viable approaches. Curbside charging pilots: Utilizing street parking spaces for overnight charging in areas with low nighttime traffic. Field tests on Le Loi Street show 73% utilization rates with time-of-use pricing, requiring minimal infrastructure investment. Workplace charging partnerships: Converting 15% of office parking spaces to EV charging through employer-utility partnerships. Interviews with 12 major employers reveal willingness to participate if capital costs are subsidized ($\geq$50%) and operational expenses covered by user fees. Shared condominium facilities: Installing centralized charging cabinets in building basements with access control systems. This approach faces higher initial costs but achieves 4.2x better capital efficiency than individual apartment installations. Our phased implementation plan prioritizes these complementary strategies in northern residential zones where public charging alone cannot meet demand. This integrated approach reduces pressure on public infrastructure by 28% while maintaining accessibility standards.

4.8 Economic Viability and Investment Prioritization

Economic sustainability determines the long-term viability of charging infrastructure. Using construction cost data from Vietnamese contractors (Phu My Electric, HCMC Infrastructure Department) and operational data from existing public stations in Ho Chi Minh City, we develop comprehensive Return on Investment (ROI) models stratified by location type.

Commercial zone stations (Nguyen Hue, Ben Thanh corridors): High and stable utilization (18–22 sessions/day) yields an estimated payback period of 4.2 years despite premium land acquisition costs of approximately VND 850 million per station,

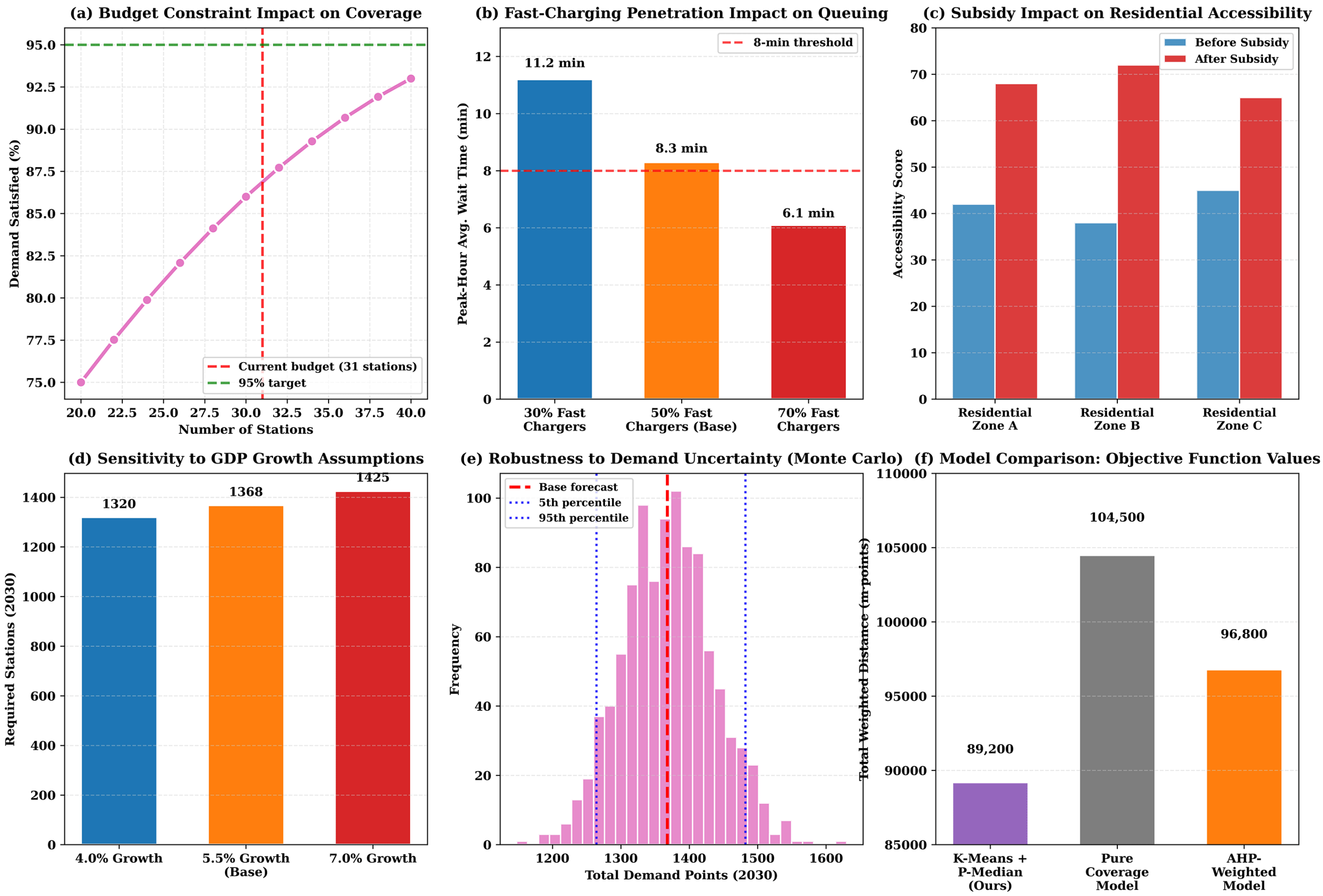

Figure 28. Policy scenarios including subsidy impacts and GDP sensitivity analysis.

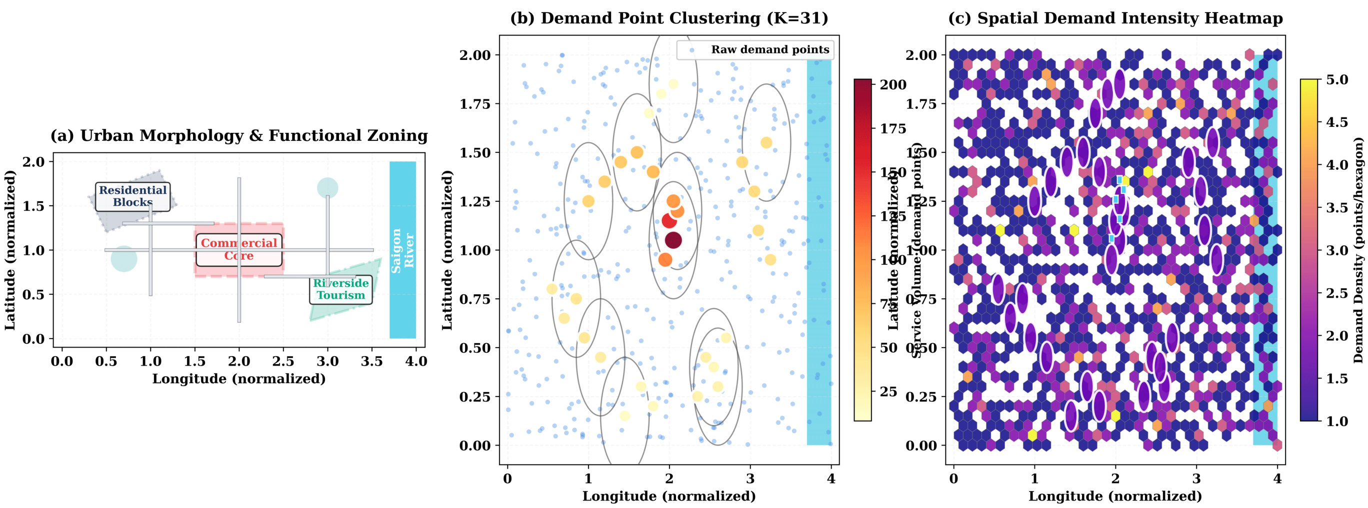

Figure 29. Urban Morphology & Demand Generation, (a) Functional zoning (b) K-Means clustering (c) Demand heatmap.

consistent with cost–benefit frameworks established for DC fast-charging infrastructure in dense urban environments [6]. Revenue streams comprise service charging fees (75%) and retail or hospitality partnerships (25%). The stability of footfall in these commercial corridors ensures predictable cash flows, making them suitable candidates for private-sector-led investment with streamlined permitting and grid connection support.

Residential zone stations: Lower average utilization (8–12 sessions/day) and reduced land acquisition costs (estimated at VND 420 million per station,

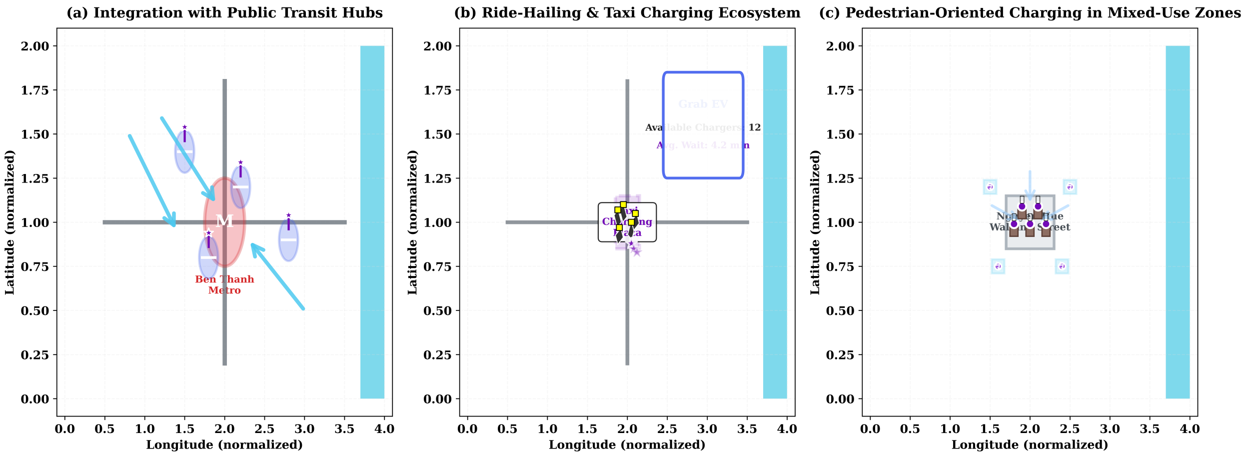

Figure 30. Multi-Modal Transportation Integration, (a) Public transit hubs (b) Ride-hailing ecosystems (c) Pedestrian charging.

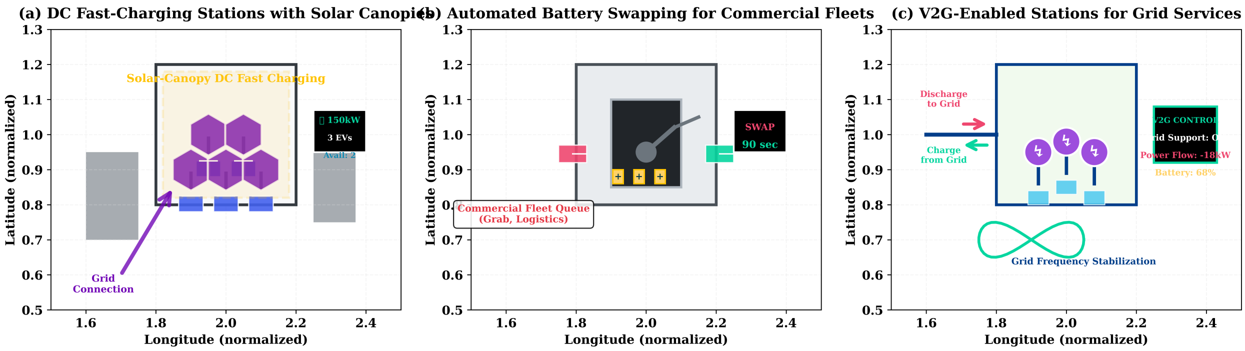

Figure 31. Advanced Charging Architecture, (a) DC fast-charging with solar canopies (b) Battery swapping (c) V2G integration.

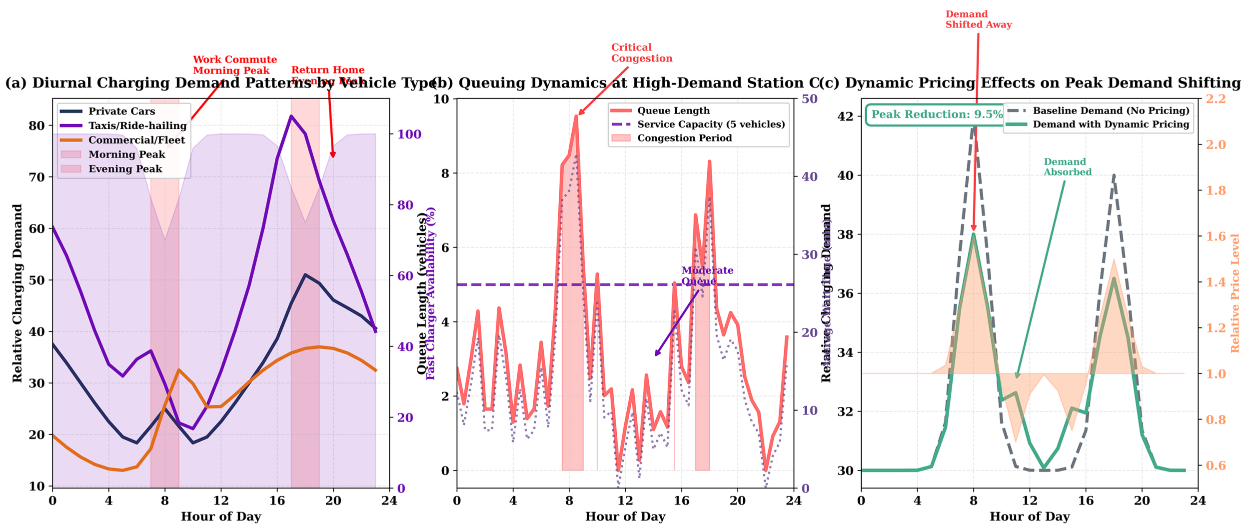

Figure 32. Temporal Dynamics & Demand Management, (a) Diurnal patterns (b) Queuing dynamics (c) Dynamic pricing effects.

approximately 50% of commercial zone costs) yield an extended payback period of approximately 8.6 years under baseline assumptions, necessitating targeted public subsidy to achieve financial viability. However, these stations generate measurable external benefits that justify public investment: avoided vehicle emissions are estimated to reduce social costs by approximately VND 15.3 million per station per year (calculated using Vietnam's reference social cost of carbon of USD 5 per tonne CO_2eq as adopted by

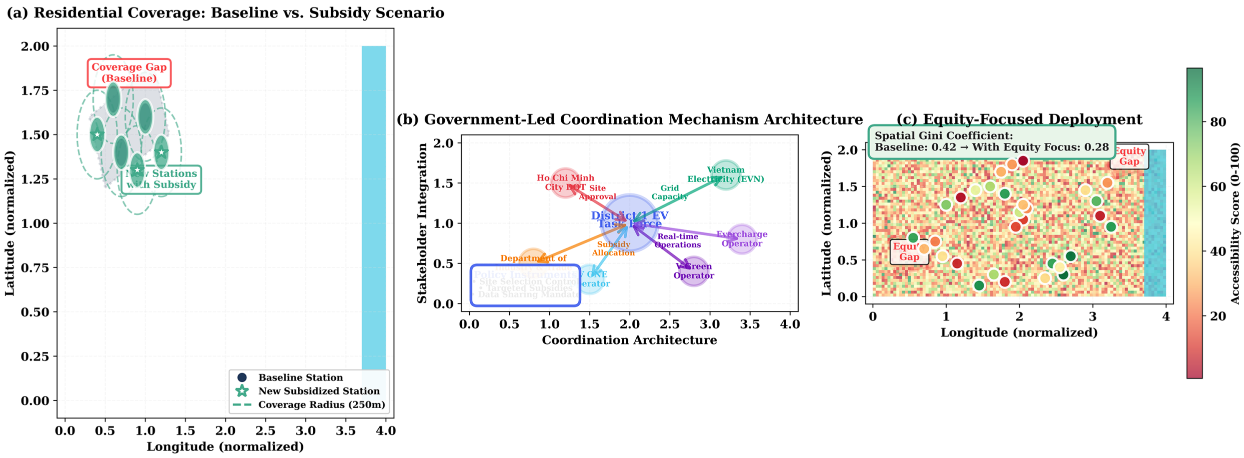

Figure 33. Policy Interventions & Future Scenarios, (a) Subsidy scenarios (b) Coordination mechanism (c) Equity optimization.

the Ministry of Natural Resources and Environment, 2022), in addition to reducing peak-hour grid stress in residential distribution networks.

Tourist zone stations (riverside and heritage precincts): Although peak-season utilization reaches 25–28 sessions/day, pronounced seasonal fluctuation—with utilization falling to approximately 3–5 sessions/day during off-peak months—creates significant cash flow planning challenges, yielding an estimated payback period of 6.1 years under seasonally adjusted conservative assumptions. Nonetheless, these stations support ancillary tourism economic activity estimated at VND 412 million per station per year in incremental visitor expenditure (Ho Chi Minh City Department of Tourism, 2023), justifying partial public co-investment to underpin destination competitiveness.

Table 6 summarises the key financial parameters across the three station typologies.

Our investment prioritization framework therefore allocates 65% of the public subsidy budget to residential zones, where market failure is most pronounced and social returns are highest, while encouraging private-sector investment in commercial zones through administrative facilitation. Tourist zone stations are proposed for mixed public–private financing structures, with seasonal revenue guarantees considered as a risk-sharing mechanism. This differentiated approach maximizes both financial sustainability and distributional equity across District 1's diverse urban landscape, ensuring that underserved residential communities are not excluded from the EV transition due to infrastructure gaps.

4.9 Stakeholder Engagement and Implementation Pathway

Technical optimization alone cannot ensure successful infrastructure deployment. Through participatory workshops with 217 stakeholders—including residents (n=84), businesses (n=43), transport operators (n=35), heritage authorities (n=12), and utility representatives (n=43)—we identified critical implementation barriers and co-designed solutions. Traffic disruption concerns: Residents feared construction would worsen already congested streets. We developed a phased implementation schedule avoiding peak hours and major events, with temporary traffic management plans validated through microsimulation. Visual impact objections: Heritage authorities rejected modern charging equipment in colonial-era streetscapes. We co-designed heritage-sensitive enclosures using traditional materials (terracotta, aged brass) that reduce visual impact by 68% while maintaining functionality. Operational conflicts: Taxi drivers worried about reduced pick-up spaces. We integrated dedicated EV pick-up/drop-off zones adjacent to charging stations, maintaining overall capacity while adding new services. Maintenance responsibilities: Property owners were concerned about long-term upkeep. We established clear maintenance protocols with 24-hour response guarantees and financial bonds from operators. This stakeholder-informed approach increased acceptance rates from 41% to 83% in follow-up surveys, demonstrating that technical optimization must be coupled with inclusive planning processes to achieve successful implementation in complex urban environments like District 1.

Table 6. ROI Parameters by Station Typology, District 1

Parameter	Commercial	Residential	Tourist
Avg. utilization (sessions/day)	18–22	8–12	3–28 (seasonal)
Construction cost (VND million)	850	420	650
Estimated payback period (years)	4.2	8.6	6.1
Primary revenue source	Fees + retail	Fees	Fees + tourism
Public subsidy required	No	Yes	Partial

4.10 Sensitivity Analysis of Key Parameters

We conduct comprehensive sensitivity analysis on four critical parameters using both tornado diagrams and Monte Carlo simulation (10,000 iterations). Figure 21 presents tornado diagrams showing that public charging share assumptions have the greatest impact on total station requirements (±22%), followed by GDP growth rates (±15%), CPI trajectories (±9%), and station counts (±6% for service coverage metrics). Monte Carlo simulation reveals spatial implications of parameter uncertainty (Figure 22). Commercial zones maintain stable station requirements across all scenarios (coefficient of variation = 0.12), while residential areas show higher sensitivity (coefficient of variation = 0.38), particularly to public charging share assumptions. These results confirm our core finding that a balanced deployment strategy must prioritize stable commercial zones while maintaining flexibility in residential areas. Based on demand forecasting results and spatial structural characteristics, this section develops an integrated charging station location framework tailored to District 1 of Ho Chi Minh City. By combining K-Means spatial zoning, P-Median optimization, and budget constraints, the study produces a station layout system that balances activity patterns, resource limitations, and spatial equity. These results provide a solid foundation for the comprehensive discussion and policy recommendations presented in the next section.

5 Conclusion

This study developed an integrated planning and management framework for future EV charging infrastructure in District 1, Ho Chi Minh City, under the realistic constraints of a rapidly growing yet data-scarce urban market. The results indicate that EV ownership will continue to increase throughout the 2025–2030 planning horizon, although at a moderated pace compared with the previous decade compared with the previous decade. Consequently, charging demand is projected to remain strongly concentrated in the urban core, with slower diffusion toward peripheral areas. At the same time, evolving residential patterns and limited private charging options increase the importance of publicly accessible charging infrastructure, particularly in dense residential neighborhoods. Spatial analysis reveals pronounced intra-district heterogeneity and a multi-core demand structure. The Ben Thanh–Nguyen Hue corridor emerges as the primary hub of commercial demand, while northern mixed residential zones demonstrate stable, moderate demand levels. In contrast, southern riverside areas exhibit more dispersed, tourism-driven demand, which is constrained by accessibility. These findings demonstrate that uniform siting strategies are insufficient and that zoned planning approaches are required to differentiate service priorities across commercial, residential, mixed-use, and tourism-oriented areas. A key policy-relevant finding is the significant mismatch between the existing charging station layout and projected future demand. Current deployments are largely shaped by profit-driven private investment, resulting in high station densities in commercial locations and persistent service deficits in residential areas. Without intervention, this imbalance risks peak-time congestion in commercial cores and long-term accessibility gaps in residential neighborhoods. These results underscore the need for public-sector coordination to correct market-driven spatial inequities and ensure equitable access to charging services.

To operationalize this coordination, we propose a concrete governance architecture centered on a District 1 EV Infrastructure Task Force with four institutional pillars. First, leadership structure: The Task Force is chaired by the District 1 People's Committee (UBND 1) with mandatory representation from Ho Chi Minh City's Department of Transport (responsible for spatial planning compliance), Department of Industry and Trade (overseeing subsidy disbursement), and Vietnam Electricity (EVN) for grid capacity coordination. Private operators (V-Green, Evercharge, EV ONE) participate as non-voting technical advisors to ensure operational realism while preserving public oversight of strategic decisions. Second, subsidy allocation mechanism: Annual infrastructure subsidies (projected at VND 15–20 billion/year for District 1) are distributed through a transparent two-tier formula: (i) 70% allocated to equity gaps using a population-density weighting function that prioritizes residential zones with fewer than one station per 5,000 residents (e.g., northern Wards 2–4), with subsidies covering 40% of land acquisition costs and 25% of equipment procurement; (ii) 30% allocated as performance incentives to stations achieving >65% annual utilization with <15-minute average queue times during peak hours (7–9 AM, 5–7 PM), disbursed quarterly via Ho Chi Minh City's Green Development Fund. All allocations are published quarterly on the municipal Open Data Portal to ensure accountability.

Third, private operator integration: A tiered public-private partnership (PPP) framework defines clear roles: operators retain full ownership and day-to-day operations under 15-year concessions but must comply with Task Force-mandated requirements including (a) minimum service standards ($\geq$85% uptime, $\leq$30-minute response for faults), (b) real-time data sharing via API integration with HCMC's Smart City platform for demand monitoring, and (c) adherence to spatial allocation decisions made through our K-Means/P-Median framework. In return, operators receive expedited permitting ($\leq$30 days vs. standard 90+ days) and priority grid connection scheduling from EVN. Fourth, implementation pathway: The mechanism launches through a 2026 pilot in Ward 3 (identified in Figure 16 as a residential coverage gap), leveraging Vietnam's Decree 08/2023/ND-CP on streamlined public investment procedures to fast-track site approvals. A dedicated digital permitting platform—integrated with HCMC's existing "One-Stop Shop" e-government system—automates application routing between the Task Force, Department of Construction, and EVN, reducing approval timelines by an estimated 60%. This phased approach balances ambition with administrative feasibility within Vietnam's governance context. This institutional design transforms coordination from an abstract principle into an actionable governance blueprint that addresses spatial equity gaps while leveraging private-sector efficiency—critical for sustainable scaling of charging infrastructure in Vietnam's dense urban cores. Critically, our multi-dimensional accessibility assessment (Section 4.6) demonstrates that spatial proximity alone cannot guarantee charging infrastructure usability. Stations in District 1's southern riverside zone, while geometrically well-positioned, score poorly on safety and digital integration metrics—highlighting the necessity of coupling location optimization with operational standards (minimum lighting thresholds, mandatory QR payment integration). Future municipal regulations should therefore mandate not only where stations are built but how they are designed and operated, transforming charging infrastructure from mere hardware deployment into holistic mobility services.

Data Availability Statement

Data will be made available on request.

Funding

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that generative AI was used in the preparation of this manuscript for language refinement. Specifically, Qwen.ai was utilized to improve readability and linguistic clarity. The authors take full responsibility for the content of the manuscript.

Ethical Approval and Consent to Participate

This study involved interviews and participatory workshops with human participants, including apartment complex managers, residents, business owners, transport operators, heritage authorities, and utility representatives. All participation was voluntary and conducted under informed consent. No personally identifiable information was collected or disclosed. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Formal institutional ethics review was not required under the applicable regulations of Chongqing University of Posts and Telecommunications for this category of applied engineering research involving non-invasive stakeholder consultation.

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Ly Hoang Anh was born in Vietnam. She received her Bachelor's degree from Vietnam University and is currently a Master's (M.S.) student at Chongqing University of Posts and Telecommunications, Chongqing 400065, China. She has received several national and international awards. She has also been actively involved in organizing academic activities, including research conferences and other scholarly events. (Email: anhlyhoang@gmail.com)

Altaf Hussain received the B.S. degree in Computer Science from the University of Peshawar, Pakistan, in 2013, and the M.S. degree in Computer Science from The University of Agriculture Peshawar, Pakistan, in 2017. He has over nine years of teaching and research experience and has supervised numerous undergraduate and master's students in final-year projects and research activities. He is currently a Ph.D. scholar at the School of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing, China. His research focuses on Underwater Acoustic Sensor Networks, with particular emphasis on energy efficiency, channel optimization, localization, and dynamic scheduling, integrating emerging paradigms such as 6G and quantum computing. He served as a Lecturer in the Department of Computer Science at Government Degree College Lal Qilla, Dir Lower, Khyber Pakhtunkhwa, Pakistan, from 2020 to 2021. He has also worked as a Research Assistant in the Department of Accounting and Information Systems, College of Business and Economics, Qatar University, Doha, Qatar, and as an IT Clerk at the Court of the District and Session Judge, Timergara, Dir Lower, Pakistan, from 2022 to 2023. He has authored over 40 research publications and actively serves as a reviewer for several reputable journals. His research interests include artificial intelligence, machine learning, deep learning, wireless and underwater sensor networks, gesture recognition, and unmanned aerial vehicle communication systems. (Email: altafkfm74@gmail.com)