

Article

Optimizing Charging Infrastructure for Battery Electric Trucks in Zero-Carbon Freight Corridors Under State-of-Charge and Service-Capacity Constraints

Haobo Du ¹, Jianhua Song ¹, Yanan Liu ², Chengbing Li ¹ and Chenggong Lin ^{3,*}

¹ Transportation Institute, Inner Mongolia University, No. 49 Xilin Gol South Road, Yuquan District, Hohhot 010070, China; 32424103@mail.imu.edu.cn (H.D.); jianhuas@imu.edu.cn (J.S.); bingbingnihao2008@126.com (C.L.)

² Inner Mongolia Autonomous Region Transportation Development Center, No. 68 South Street Geological Bureau, Saihan District, Hohhot 010021, China; 18547596663@163.com

³ Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, China Academy of Transportation Sciences, No. 240 Huixinli, Chaoyang District, Beijing 100029, China

* Correspondence: lincg@motcats.ac.cn

Abstract

The large-scale deployment of battery electric trucks (BETs) requires well-developed charging infrastructure; however, existing planning approaches often neglect capacity constraints and the uncertainty inherent in microscopic charging behavior. This paper proposes a four-stage charging infrastructure planning methodology comprising energy analysis, single-vehicle Monte Carlo simulation, mixed-integer linear programming (MILP) optimization, and M/G/c post-calibration for long-haul highway freight transport. The method aims to achieve 100% flow capture by embedding path energy constraints into the MILP formulation and introducing peak-hour capacity constraints derived from queueing theory to address service instability. A case study demonstrates that the existing network without optimization is severely overloaded, achieving a capture rate of only 72.7%. Under the baseline scenario with 30% BET penetration, the optimized solution deploys eight charging stations. After station-level M/G/c calibration, the final configuration comprises 54 fast chargers and 271 slow chargers, representing a 33.8% reduction in total charger count compared to the initial MILP solution, effectively eliminating resource redundancy caused by the global capacity assumption. As the penetration rate increases to 60% and 100%, accompanied by technological progress, the required number of stations decreases to five, and the charging network evolves toward a “core node concentration” topology, with total costs exhibiting significant increasing returns to scale. This study provides a quantitative basis for zero-carbon freight corridor infrastructure planning and differentiated investment strategies.



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Keywords: battery electric trucks (BETs); charging infrastructure planning; capacity constraints; M/G/c queueing theory; highway freight transport

1. Introduction

1.1. Background

In the context of global climate change and the energy transition, the decarbonization of the transport sector has become one of the key pathways for countries to achieve carbon emission reduction targets. China has established the goals of achieving carbon peaking

before 2030 and carbon neutrality before 2060, with transportation identified as a key sector for emission reduction [1,2]. Within the transport sector, road freight represents a particularly important and challenging area for decarbonization because of its high energy consumption and carbon-emission intensity. Heavy-duty trucks, although representing a relatively small share of the vehicle fleet, contribute disproportionately to road-transport energy consumption and carbon emissions [3,4]. Consequently, the electrification of freight transport has been widely recognized as a critical pathway for reducing greenhouse gas emissions and local air pollutants in the transport sector [5].

Advances in battery and high-power charging technologies have made battery electric trucks (BETs) increasingly viable for freight transportation. Zero-emission heavy-duty vehicles have already demonstrated operational feasibility in shorter-distance urban and distribution applications [6,7]. However, long-haul BET operations remain more challenging because of longer travel distances, higher energy demand, and stronger dependence on en-route charging. Experimental evidence shows that heavy-duty electric truck energy consumption and driving range are sensitive to operating conditions and payload [8], while economic assessments indicate that adequate charging infrastructure is a critical prerequisite for the competitiveness of battery electric heavy goods vehicles [9].

Compared with vehicle technology, charging infrastructure for long-haul BET operations remains relatively underdeveloped and has become a major constraint on large-scale deployment [10]. BETs impose greater requirements on charging power, station space, and continuous service capability than passenger electric vehicles, making dedicated infrastructure increasingly necessary [11]. The development of Megawatt Charging Systems (MCS) further expands the technical potential for high-power charging along freight corridors [12]. At the same time, the relatively fixed routes and concentrated operating patterns of long-haul trucks generate pronounced spatial and temporal clustering of charging demand [13]. Infrastructure planning must therefore address not only spatial coverage but also station service capacity, grid connection limits, and land availability. As station utilization approaches saturation, insufficient capacity may also lead to rapidly increasing queues and unstable service.

These challenges are particularly relevant in central and western China, where highway service-area charging facilities remain relatively limited and are primarily designed for passenger vehicles. Increasing BET penetration may therefore expose simultaneous deficiencies in spatial coverage and charging service capacity. This motivates an integrated planning approach that links path-energy feasibility, stochastic charging demand, station service capacity, and site-specific engineering constraints to determine cost-effective charging station locations and capacities for long-haul zero-carbon freight corridors.

1.2. Literature Review

The rapid growth of electric vehicles (EVs) and electric freight vehicles is reshaping transportation energy systems. As a critical enabler of transportation electrification, charging infrastructure planning has attracted extensive attention, encompassing charging demand forecasting, spatial deployment, capacity and service-level design, power system integration, and optimization modeling. From a system-level planning perspective, research has evolved from traditional static deployment approaches toward integrated frameworks incorporating multiple objectives and cross-domain interactions [14]. Tao et al. [15] systematically reviewed recent advances in charging infrastructure planning and highlighted the necessity of jointly considering transportation network characteristics, power grid operation, and system costs. From a methodological perspective, Deb et al. [16] classified charging infrastructure planning models into three categories: node-based, path-based, and tour-based models. Metais et al. [14] further argued that path-based models

possess a distinct advantage in long-haul freight applications because they explicitly track vehicle energy-state evolution along OD paths, a capability that cannot be fully captured by node-based approaches.

Accurate charging demand forecasting and realistic characterization of charging behavior are prerequisites for developing infrastructure plans that align with operational requirements. Traditional demand assessment methods primarily rely on spatiotemporal statistical analyses combined with travel behavior models to identify demand hotspots and peak periods. For example, He et al. [17] developed a spatiotemporal charging demand forecasting model based on real-world road network topology and points of interest (POIs), and further investigated charging infrastructure planning by incorporating transportation–power grid coupling. However, Ghanbari Motlagh and Li [18] pointed out that most existing studies inadequately capture behavioral uncertainties arising from user preferences and market dynamics. For BETs, Alam et al. [19] emphasized in their review that charging demand characterization must simultaneously account for the complex interactions among vehicle routing, charging scheduling, and station service capacity. Regarding charging behavior, Speth and Plötz [20] and Shoman et al. [21] demonstrated through empirical analyses that slow charging constitutes the foundation of the BET charging ecosystem, whereas megawatt-level fast charging primarily serves long-haul freight corridors. To further capture such behavioral interactions, Yan et al. [22] recently developed an integrated framework that jointly models truck platooning, driver scheduling constraints, and charging decisions on highway networks, revealing the decisive role of freight operational chains in shaping the spatiotemporal distribution of charging demand.

With respect to spatial siting and deployment optimization, facility location theory has evolved from traditional discrete node coverage models to path-flow interception frameworks. Research on charging infrastructure planning can be traced back to the classical facility location literature of the 1960s and 1970s. The *p*-median problem proposed by Hakimi [23] established the graph-theoretic foundation for node-based location models. Subsequently, the location set covering problem (LSCP) developed by Toregas et al. [24] and the maximal covering location problem (MCLP) proposed by Church and ReVelle [25] addressed facility deployment from full-coverage and maximal-coverage perspectives, respectively. Hodgson [26] introduced the flow-capturing location model (FCLM) in 1990, linking facility deployment to OD flows and marking the transition from node coverage to path coverage. Building upon this concept, Kuby and Lim [27] proposed the flow refueling location model (FRLM), which explicitly incorporated vehicle driving-range constraints into path-based coverage analysis. To improve computational tractability for large-scale networks, Capar et al. [28] reformulated FRLM using an arc-cover/path-cover (AC–PC) representation, substantially reducing model size and enhancing solution efficiency. Upchurch et al. [29] further introduced station capacity constraints into the FRLM framework and proposed the capacity-constrained flow refueling location model (CFRLM), demonstrating that capacity limitations fundamentally alter the topology of optimal charging networks and promote the evolution of path-based planning from pure siting decisions toward integrated siting-and-sizing optimization. More recently, Speth et al. [30] extended the CFRLM framework to battery electric truck applications and verified the significant influence of capacity constraints on charging station deployment and infrastructure scale within the German highway network. At the transportation–energy system interface, Zhang et al. [31] developed a mixed-integer linear programming (MILP) model incorporating both traffic flow distribution and power distribution network constraints, demonstrating the strong coupling between charging station deployment and grid capacity planning.

Following the determination of spatial deployment, research on charging infrastructure sizing, service-level maintenance, and long-term network evolution has gradually

shifted from static planning toward dynamic multi-period expansion strategies. Asna et al. [32] incorporated travel time, waiting time, distribution network losses, and station utilization into a fast-charging station siting and sizing framework to simultaneously satisfy the requirements of users, the power distribution network, and station operators, while Dong et al. [33] revealed a nonlinear relationship between optimal fast-charging station spacing and traffic flow density. Given the progressive nature of long-haul freight corridor development, Shen et al. [34] and Chung and Kwon [35] proposed a sequential siting optimization method and a multi-period investment framework, respectively, to identify optimal phased deployment strategies. Regarding multi-facility coordination and technology diversification, Jin et al. [36] demonstrated the economic benefits of jointly planning charging stations, battery-swapping stations, and charging hubs, whereas Rose and Neumann [37] successfully extended the flow-capturing concept to hydrogen refueling networks for heavy-duty trucks, providing valuable insights for long-distance freight energy infrastructure planning. To address long-term uncertainties, Kinay et al. [38] incorporated stochastic demand and congestion effects into charging station siting and sizing decisions, developing an optimization framework that balances service quality and infrastructure costs. In addition, Li et al. [39] investigated charging infrastructure deployment for electric heavy-duty trucks using freight vehicle trajectory data and highlighted the critical influence of vehicle operating characteristics and spatial demand distributions on planning outcomes.

At the level of BET-specific charging technologies, BETs differ substantially from passenger EVs due to their larger battery capacities, higher single-event charging demand, and relatively fixed operating routes, leading to distinct infrastructure requirements. A comprehensive review by Piedel et al. [40] evaluated several automated charging technologies for heavy-duty trucks, including static conductive charging, overhead catenary systems, dynamic wireless charging, and battery swapping. Their findings indicated that overhead catenary systems represent the most mature dynamic charging technology but face substantial deployment barriers, whereas battery-swapping systems have already entered large-scale commercial deployment in certain regions of China, offering diversified charging solutions for BETs. Meanwhile, the rapid development of Megawatt Charging Systems (MCS) has positioned high-power charging as one of the most promising technological pathways for supporting long-haul electric freight transportation. Bhardwaj et al. [41] noted that, compared with battery swapping, high-power charging technologies eliminate the need for battery inventories and standardized battery designs, thereby providing greater vehicle compatibility and infrastructure flexibility. Liimatainen et al. [42] further emphasized that continued advances in battery technology and high-power charging systems will significantly enhance the feasibility of BET deployment in long-haul freight operations. In this context, Noll et al. [43] and Breed et al. [44] concluded through total cost of ownership (TCO) and market diffusion analyses that early deployment and continuous expansion of charging networks constitute a decisive prerequisite for overcoming market barriers and enabling large-scale BET adoption.

Despite this progression, the principal planning approaches are not interchangeable because they represent vehicle energy states, behavioral uncertainty, station service capacity, and engineering constraints at different levels of detail. Table 1 compares the methodological scope of FRLM, CFRLM, coupled transportation–power planning, BET-specific data-driven approaches, and the framework developed in this study.

Table 1. Methodological comparison of charging infrastructure planning approaches.

Approach	Energy and Demand Representation	Behavioral Uncertainty	Capacity and Service Representation	Engineering Constraints and Planning Scope
FRLM	Range-based feasibility along fixed OD paths	Deterministic path flows	No explicit station-capacity or queueing constraint	Candidate-site location to maximize captured flow; charger sizing is outside the basic model
CFRLM	Range-based path feasibility with flow–station allocation	Generally predetermined or aggregate flows	Finite station or charger throughput; stochastic waiting-time reliability is not explicit	Capacitated siting and flow allocation; grid and land constraints are not intrinsic to the basic formulation
Coupled transportation–power planning	Aggregate charging demand linked to transportation and power networks	Mostly deterministic or scenario-based demand	Power and service constraints; limited treatment of SoC-driven service-time heterogeneity	Joint siting and sizing with grid constraints; treatment of land availability varies by study
BET-specific empirical or trajectory-based planning	Empirical routes, duty cycles, or trajectory-derived charging demand	Observed spatial and operational heterogeneity	Charging energy and power requirements; queueing is not usually linked to station-specific sizing	Demand estimation and strategic siting; the combination of grid, land, and service constraints varies
Proposed four-stage framework	Arc-by-arc SoC evolution and recursively generated charging events	Monte Carlo sampling of initial SoC, target SoC, arrivals, and feasible-node choice	M/G/c waiting-time criterion with station-specific post-calibration	Demand generation, siting, flow allocation, and charger sizing under grid-capacity and parking-space limits

Table 1 indicates that FRLM establishes the fundamental logic of range-constrained path coverage, while CFRLM further incorporates finite station capacity and flow allocation. Coupled transportation–power and empirical BET studies additionally improve grid feasibility and demand realism. However, these approaches generally address only part of the planning chain, and rarely integrate vehicle-level stochastic charging behavior, arc-level energy feasibility, queueing-based service reliability, and site-specific engineering constraints within a unified framework. Building on the path-flow logic of FRLM and CFRLM, the proposed framework advances existing approaches by linking arc-level SoC evolution and stochastic charging demand generation with MILP-based siting and sizing, followed by station-specific M/G/c service-capacity calibration.

1.3. Research Gap and Contributions

1.3.1. Research Objectives

This study addresses the growing charging demand of BETs and the relatively lagging development of charging infrastructure in long-haul highway freight transportation. Focusing on charging demand forecasting and infrastructure optimization, the research is motivated by the fact that electric freight infrastructure deployment in western and central China remains at an early stage, while systematic planning methods and mature datasets remain limited. Taking an actual highway freight corridor in western and central China as the study area, this research utilizes a real-world highway network, service area configurations, and freight traffic flow data collected through field investigations. Using

these data and multiple BET penetration scenarios, this study forecasts future charging demand and develops a charging infrastructure planning methodology tailored to highway freight transportation in western and central China.

Building on path-based charging infrastructure planning, the primary objective of this study is to develop an integrated framework that simultaneously captures path-energy feasibility, stochastic charging behavior, station service capacity, and site-specific engineering constraints when determining charging station locations and capacities. The framework aims to minimize infrastructure construction and operating costs while ensuring full path feasibility for long-haul BET flows, thereby supporting the planning of zero-carbon freight corridors.

1.3.2. Main Contributions

To achieve the above objectives, the main contributions of this study are summarized as follows:

(1) A SoC-based stochastic charging demand representation is developed for long-haul BET operations. Rather than treating charging demand as a predetermined aggregate path flow, the proposed approach combines arc-level energy feasibility analysis, recursive charging scenario expansion, and single-vehicle Monte Carlo simulation to explicitly represent heterogeneous initial SoC, target SoC, and feasible charging location choices. This establishes a direct link between vehicle-level SoC evolution and infrastructure-planning inputs by generating arc-level charging demand and station-level arrival-SoC characteristics under stochastic charging behavior.

(2) An integrated MILP siting-and-sizing model is formulated for zero-carbon freight corridors. Building on the path-flow coverage logic of FRLM and CFRLM, the model extends conventional range- and capacity-constrained planning by jointly incorporating path-energy feasibility, station location, charging flow allocation, charger configuration, peak-hour service capacity, grid connection limits, and parking-space constraints. The resulting formulation therefore integrates transportation feasibility, service reliability, and site-specific engineering conditions within a unified infrastructure-planning model, rather than treating spatial coverage and capacity provision separately.

(3) A station-specific Monte Carlo-M/G/c capacity post-calibration mechanism is introduced to refine the initial MILP sizing solution. The MILP necessarily relies on network-wide average service-capacity parameters and continuous flow allocation, which may obscure station-level differences in arrival SoC and concentrate charging demand at particular nodes. The proposed post-calibration procedure re-estimates station loads and service capacities using station-specific arrival-SoC samples and stochastic charging location choices, and then recalculates the required charger quantities through M/G/c queueing analysis. This sequential optimization-simulation procedure improves station-level capacity estimation while preserving the path-feasible siting solution determined by the MILP.

2. Methodology

2.1. Problem Assumptions

To ensure the feasibility of modeling and computation, the following assumptions are adopted for the long-haul highway freight charging problem. Similar simplifications are used in the FRLM framework of Capar et al. [28] and the capacitated CFRLM framework of Speth et al. [30]. The model assumptions are as follows:

- (1) Vehicles travel along the shortest path between an origin-destination pair and do not deviate from the route.
- (2) The traffic volume for each path is known and deterministic.

(3) Drivers have full knowledge of charging station locations along the path and can make rational charging decisions.

(4) Only nodes on the road network are considered as candidate locations for charging stations.

(5) All vehicles have identical and fixed driving ranges.

(6) BETs' energy consumption is represented by an average equivalent energy consumption rate per unit distance [21,45]. Short-term variations caused by payload, road gradient, weather, traffic conditions, and driving behavior are not explicitly modeled. This assumption is adopted to isolate the effects of charging demand distribution and infrastructure configuration while maintaining the tractability of the path-energy feasibility analysis.

(7) The distance from OD points to adjacent road network nodes is negligible.

(8) The initial state of charge (SoC) at departure follows a discrete probability distribution derived from the field survey, and charging is permitted at the destination.

(9) The target SoC for each charging event is randomly drawn from a discrete probability distribution derived from the field survey. Vehicles are served on a first-come, first-served basis upon arrival at charging stations.

These assumptions are adopted to maintain the tractability of corridor-scale infrastructure planning. Deterministic traffic demand and fixed shortest-path routing suppress day-to-day demand fluctuations and route-choice variability, while homogeneous vehicle characteristics and the average energy consumption rate smooth vehicle-level differences in energy use. The full-information and rational-driver assumptions may also affect the spatial distribution of charging demand. Therefore, these simplifications may influence the predicted charging locations, station loads, and charger requirements, but they do not alter the general structure of the proposed path-energy feasibility and siting framework.

2.2. Problem Description and Overall Framework

In long-haul highway freight transport scenarios, BET charging demand exhibits significant spatial heterogeneity and stochasticity. On the one hand, substantial variations exist in the initial state of charge, charging timing, and target state of charge, making it difficult to accurately characterize charging demand through deterministic parameters. On the other hand, charging facility location and capacity allocation are mutually coupled, requiring full path feasibility while simultaneously accounting for all vehicles and the simultaneous consideration of facility construction and operation costs. Existing studies predominantly adopt deterministic demand assumptions, which cannot adequately reflect the impact of microscopic charging behavior on facility planning outcomes. Therefore, this paper constructs a four-stage planning framework comprising "path energy analysis–single-vehicle Monte Carlo simulation–MILP optimal configuration–M/G/c charger count calibration." The research framework is illustrated in Figure 1.

The core tasks of each stage are as follows:

Stage 1: Path energy analysis and sub-scenario tree expansion: Based on the vehicle energy consumption model, mandatory charging events ($\theta_{j,k}^{q,sub} = 1$) along each path are identified, candidate charging node sets $K_{j,k}^{q,S}$ are constructed, and sub-scenarios corresponding to different target SoC values are expanded, providing the coverage constraint framework for subsequent planning.

Stage 2: Single-vehicle Monte Carlo simulation: Considering the stochasticity of vehicle charging behavior, the vehicle operation process is simulated using actual traffic flows as input, yielding the expected charging energy for each road segment and the distribution of arrival SoC at each station, thereby providing demand parameters for facility planning.

Stage 3: MILP location and capacity optimization: With the objective of minimizing the total life-cycle cost, the charging facility layout and initial capacity allocation are optimized by integrating $\theta_{j,k}^{q,sub}$ and $K_{j,k}^{q,S}$, and expected charging demand, achieving full path charging feasibility.

Stage 4: M/G/c charger count post-calibration: After the MILP determines the station construction plan, the single-vehicle Monte Carlo simulation is re-executed to obtain actual station load characteristics. The required number of chargers at each station is then calibrated using the M/G/c queueing model, yielding the final configuration plan.

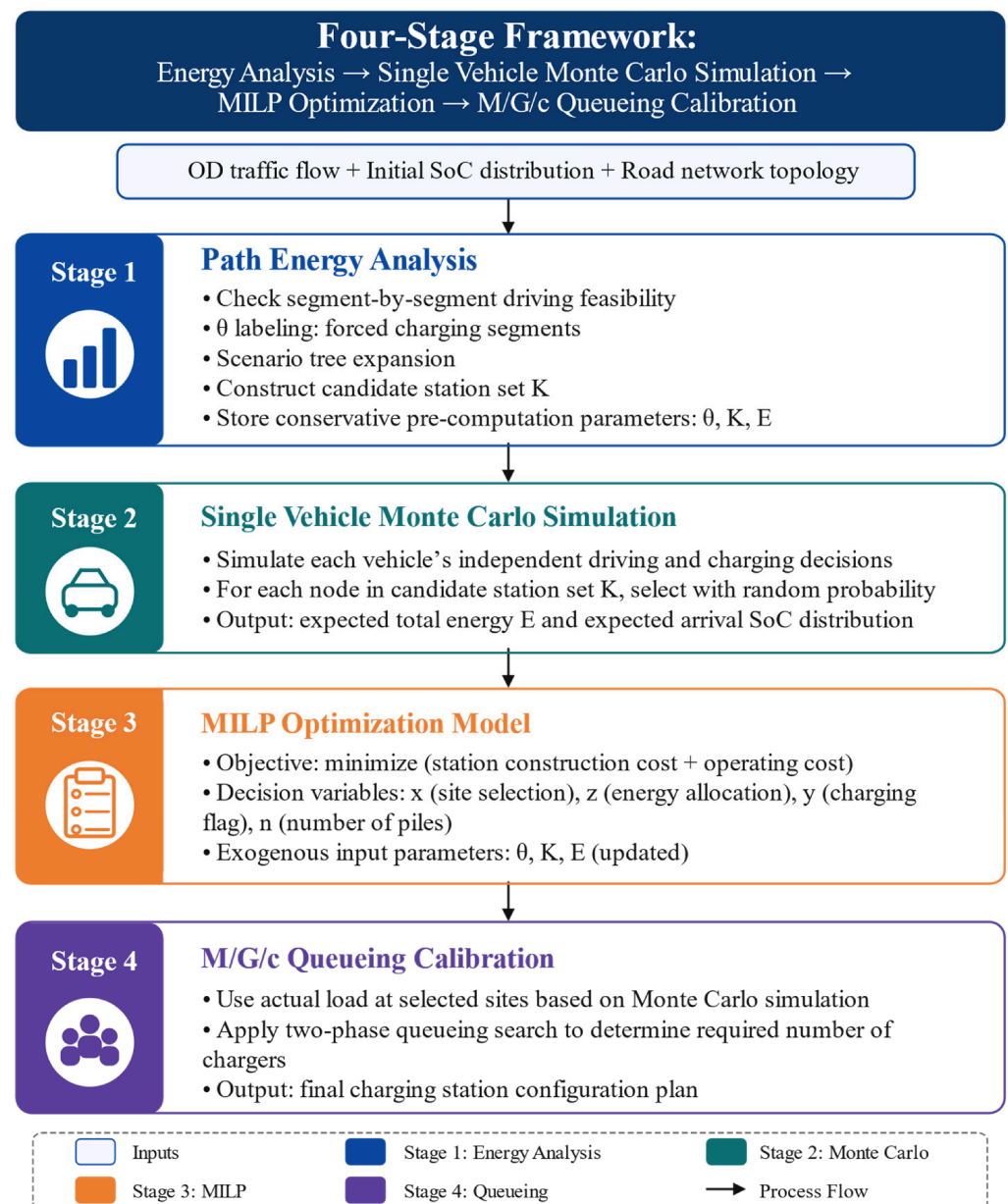


Figure 1. Research framework and four-stage methodology flow chart.

In the above four stages, the MILP is responsible for facility layout and resource configuration optimization, while the Monte Carlo simulation is responsible for charging demand and operational load assessment. Together, they achieve unified modeling from microscopic charging behavior to macroscopic charging network planning.

2.3. Charging Demand Prediction

The core task of Stage 1 is to establish a complete knowledge system identifying “on which arcs vehicles must charge and at which stations they can charge,” providing a deterministic constraint framework for the MILP model. Its outputs include: (1) mandatory charging arc markers θ , determining where the MILP needs to create decision variables z ; (2) candidate node sets K , defining the feasible domain of each z variable; and (3) sub-scenario enumeration and probability weights, defining the MILP constraints and the sampling space for Monte Carlo simulation. These three outputs provide the structural basis for the subsequent stages.

2.3.1. Charging Trigger Identification

For a given OD path $P = \{v_0, v_1, \dots, v_m\}$, where v_0 is the origin O and v_m is the destination D, the vehicle departs from the origin v_0 with an initial battery charge SoC_0 . As the vehicle traverses each arc (v_j, v_k) along the path, the energy consumed is $d_{j,k}/R$, where $d_{j,k}$ represents the length of that arc in kilometers and R denotes the maximum driving range. The remaining SoC when the vehicle arrives at node v_j is calculated as follows:

$$SoC_j = SoC_0 - \frac{1}{R} \sum_{i=0}^{j-1} d_{v_i, v_{i+1}} \quad (1)$$

The condition for the vehicle to traverse the next arc (v_j, v_k) is $SoC_j \cdot R \geq d_{j,k}$. If this condition is satisfied, the vehicle proceeds normally. If not, the vehicle triggers a mandatory charging event on that arc, denoted as $\theta_{j,k}^{q,sub} = 1$.

2.3.2. Scenario Tree Expansion

When $\theta_{j,k}^{q,sub} = 1$ is triggered, the vehicle must complete charging before entering the arc (v_j, v_k) . The candidate charging node set $K_{j,k}^{q,S}$ is accordingly defined as all nodes from the previous trigger position to the current node v_j . The “previous triggering position” is defined as the starting point v_j of the arc where $\theta_{j,k}^{q,sub} = 1$ was triggered due to insufficient remaining driving range. For the first triggering, the previous triggering position is the starting point v_0 of the path (the logistics origin O). The specific charging logic is illustrated in Figure 2.

The definition of $K_{j,k}^{q,S}$ is purely geometric and independent of specific SoC states or charging location assumptions, ensuring that the candidate set is complete and does not miss any possible energy-replenishment node. During the recursive expansion of the sub-scenario tree, for each arc with $\theta_{j,k}^{q,sub} = 1$, branching is performed according to the probability distribution of target SoC(soct) in the set S_{target} : {80%:0.5, 90%:0.3, 100%:0.2}. Each branch represents a sub-scenario in which the vehicle selects a different charging target. The condition for branch survival is that there exists at least one node in $K_{j,k}^{q,S}$ at which the vehicle, after charging to the target SoC, can successfully reach v_k . The conservative pre-computation of downstream SoC uses the first node in $K_{j,k}^{q,S}$ as the reference charging node to ensure that no potential downstream event with $\theta_{j,k}^{q,sub} = 1$ is missed.

2.3.3. Monte Carlo Simulation

The expansion of the sub-scenario tree described above establishes a comprehensive $\theta - K - E$ parameter framework for the MILP. However, the conservative pre-computation assumptions implicitly embed a concentrated behavior assumption that “all vehicles charge at the same node,” which cannot capture the behavior of drivers randomly selecting charging stations within the candidate set $K_{j,k}^{q,S}$. To address this, this paper introduces a

single-vehicle Monte Carlo simulation module (hereinafter abbreviated as MC simulation), which takes actual traffic flows as input and independently performs and simulates each vehicle's complete trip and charging decisions independently. The MC simulation flow is illustrated in Figure 3.

Example route: O4–D4; departure SoC = 80%; each recharge restores SoC to 80%

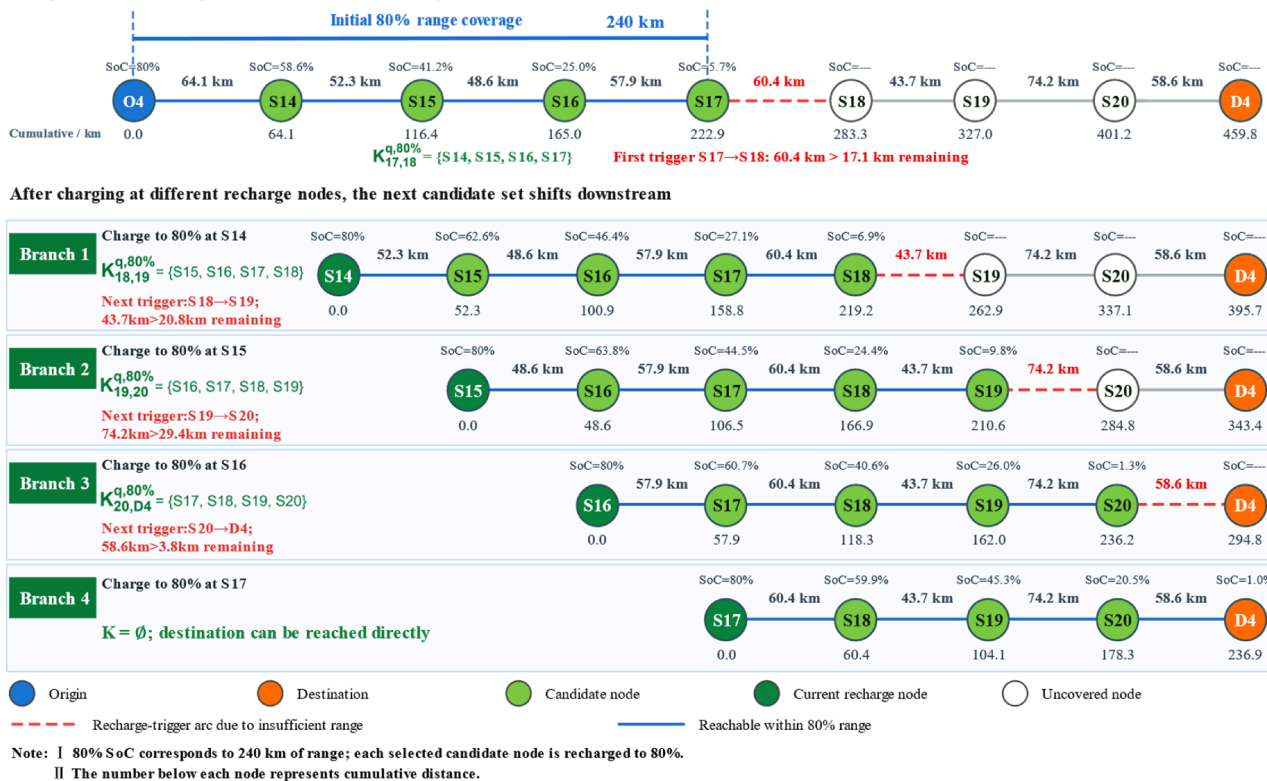


Figure 2. Charging logic illustration.

The core process of the single-vehicle simulation is as follows:

(1) Vehicle generation: The expected number of vehicles is obtained by multiplying the daily traffic volume of each OD path by the BET penetration rate. The daily vehicle population is generated through Poisson sampling. For each vehicle, the initial SoC is independently drawn according to the initial SoC probability distribution.

(2) Path traversal: Vehicles travel segment by segment along the shortest path. When $SoC_j \cdot R \geq d_{j,k}$ holds, the vehicle proceeds normally and updates its SoC. When $SoC_j \cdot R < d_{j,k}$, a $\theta = 1$, a charging event is triggered.

(3) Selection of charging nodes: At the $\theta = 1$ arc segment, the candidate node set K is constructed using the geometric constraints from Stage 1. Since the location decision constraints of mixed integer linear programming (MILP) have not been introduced in this phase, all potential service nodes in the K set are considered available. For each combination of a candidate node i in K and a target SoC value, the following screening and quantification procedure is executed: First, reachability verification is performed, eliminating combinations outside the feasible domain where charging would still fail to reach the downstream node v_k . Second, based on the remaining SoC_{last} from the previous stage, the instantaneous SoC_{arr} upon arriving at the node i is calculated, from which the charging demand for the following event is determined:

$$E = \max(0, soct - SoC_{arr}) \times B \quad (2)$$

B represents the rated capacity of the battery. Finally, the system performs weighted random sampling of the verified combinations based on the target SoC probability distribution ρ_t . Each selection outcome directly influences the subsequent SoC trajectory and charging location. This mechanism is designed to ensure that the target SoC strictly follows the predefined probability distribution while uniformly sampling candidate nodes within the feasible space, thereby eliminating location-scheme bias in the generated charging demand and arrival SoC states and enhancing the robustness of the simulation environment.

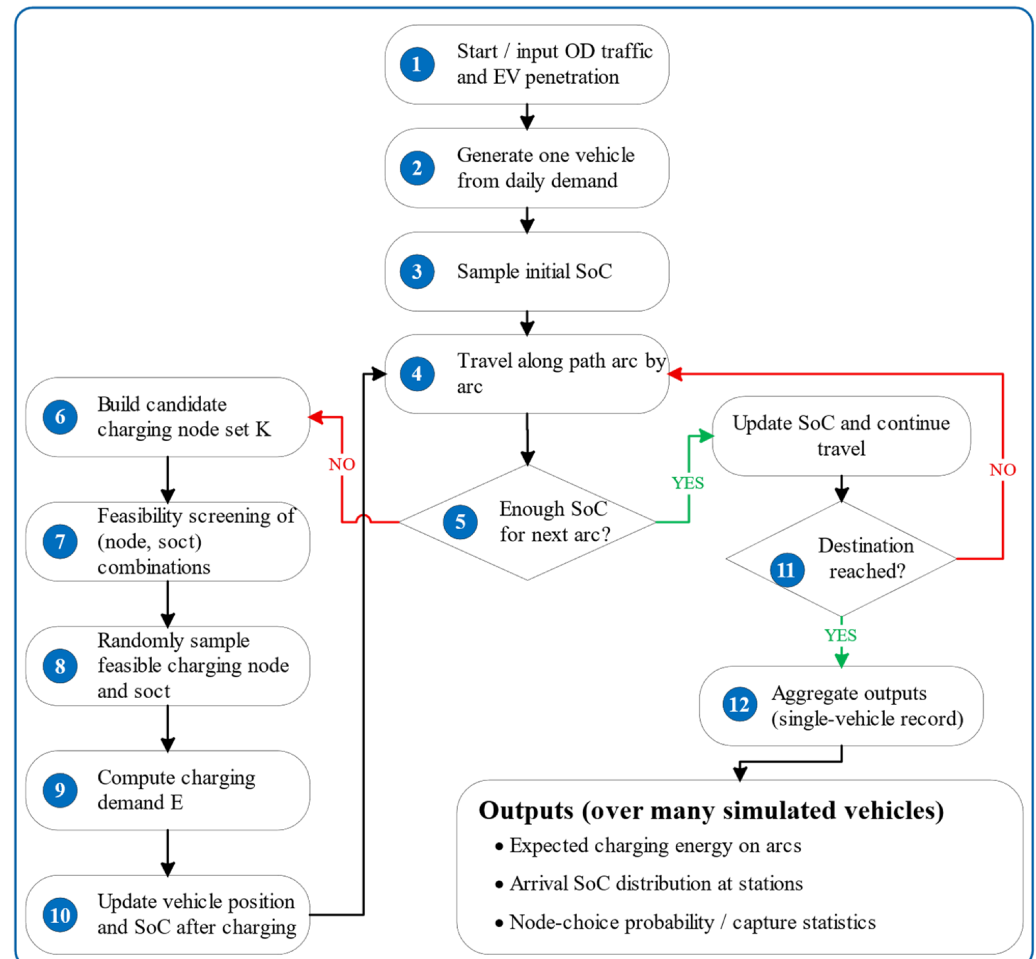


Figure 3. Single-vehicle Monte Carlo simulation flow chart.

(4) Recursive charging process: After each charging event, the vehicle's SoC and location are updated before continuing its trip. Multiple $\theta = 1$ events may be triggered recursively until the destination is reached or no feasible node remains in set K, resulting in capture failure.

The single-vehicle simulation produces the following outputs: (a) the expected charging demand E for each $\theta = 1$ arc, calculated as the mean charging amount of traversing vehicles and used to replace the conservative estimates from Stage 1, and (b) the arrival SoC distribution at each station for M/G/c parameter calibration in Stage IV. In addition, when re-executed using the MILP siting results in Stage 4, the simulation additionally provides candidate node selection probabilities within $K_{j,k}^{q,s}$ and corresponding capture-rate statistics for case analysis.

For reproducibility, each Monte Carlo realization represents one complete operating day. The number of BETs on each OD path is generated through Poisson sampling based on the corresponding expected daily flow, and each generated vehicle is simulated inde-

pendently over its complete trip. Because the MC module is a vehicle-trajectory sampling procedure rather than an iterative optimization algorithm, it does not employ a fixed iteration number or an optimization-style convergence stopping criterion; the reported charging demand and arrival-SoC statistics are obtained by aggregating the simulated vehicle trajectories.

2.4. M/G/c-Based Capacity Estimation

Both the arrival time of vehicles at charging stations and their target SoC exhibit stochasticity, resulting in significant fluctuations in charging service duration. If charging points are configured solely based on the daily average arrival rate, severe queueing congestion will arise during peak hours. This section employs an M/G/c queueing model to estimate the peak-hour service capacity per charger, Cap^{peak} , subject to the maximum waiting time constraint. The resulting service capacity is subsequently applied in both the MILP model and the post-optimization calibration procedure.

The M/G/c model is adopted because charging service time is not well represented by an exponential distribution: it depends on stochastic arrival and target SoC. Monte Carlo samples yield a squared coefficient C_v^2 of variation of approximately 0.022–0.025, far below the value of 1 for an exponential distribution; thus, M/M/c would produce overly conservative waiting-time and capacity estimates. Compared with discrete-event simulation, the M/G/c approximation provides an analytically tractable relationship among arrival rate, service-time variability, charger count, and expected waiting time, making it more suitable for repeated capacity evaluation in infrastructure planning. The steady-state approximation is adopted because the model focuses on representative peak-hour capacity rather than short-term transient queue dynamics.

Let $\overline{SoC}_{arr}$ denote the average arrival SoC, and let target SoC(soct) in S_{target} follow the discrete distribution ρ_t . Given the charging power P , the charging service time T_t and its first two moments are given as follows:

$$T_t = \frac{(soct - \overline{SoC}_{arr}) \times B}{P} \quad (3)$$

$$E[T] = \sum_t \rho_t T_t \quad (4)$$

$$V[T] = \sum_t \rho_t T_t^2 - (E[T])^2 \quad (5)$$

The average service rate per charger is given by $\mu = 1/E[T]$, and the squared coefficient of variation in service time is calculated as $C_v^2 = V[T]/E[T]^2$.

For an M/G/c queueing system consisting of c identical chargers, the expected queue wait time during the peak hour, and W_q is estimated using the Lee–Longton approximation.

$$W_q \approx \frac{1 + c_v^2}{2} \cdot \frac{C(c, \rho)}{c \cdot \mu \cdot (1 - \rho)}, \quad \rho = \frac{\lambda}{c \cdot \mu} \quad (6)$$

$C(c, \rho)$ denotes the Erlang C value, and $\lambda = N_{daily} \times \beta \times \alpha$ represents the peak hour arrival rate, where α is used for fast charging and $1 - \alpha$ for slow charging. The peak-hour factor is set to $\beta = 0.12$.

To determine the safe service capacity, the maximum acceptable waiting time is specified as $W_q^{max} = 0.1$ h (6 min). A bisection search is performed over $\rho \in [0, 0.999]$ to identify the maximum utilization rate ρ^* satisfying $W_q \leq W_q^{max}$. The corresponding safe peak-hour service capacity per charger is then obtained as follows:

$$Cap^{peak} = \mu \times \rho^* \quad (7)$$

Fast- and slow-charging parameters, (P_{fast}, α) and $(P_{slow}, 1 - \alpha)$, are substituted into the above formulation to derive Cap_{fast}^{peak} and Cap_{slow}^{peak} , respectively. In the MILP stage, these two constants are calculated once using the network-wide average arrival SoC obtained from the single-vehicle simulation. During the post-calibration stage, station-specific arrival SoC samples are used to re-estimate the capacities for each station individually.

2.5. MILP Formulation

Having obtained the complete $\theta - K - E$ parameter system from Stages 1 and 2 and the capacity parameters Cap^{peak} from Section 2.4, this section establishes a mixed-integer linear programming (MILP) model. The model jointly optimizes station location, flow allocation, and charger count configuration with the objective of minimizing total life-cycle cost.

2.5.1. Symbols and Abbreviations

To facilitate subsequent model construction and solution, the relevant symbols are uniformly defined. Table 2 lists the sets describing the road network structure and charging scenarios, Table 3 lists the model parameters for each stage, and Table 4 lists the optimization decision variables.

Table 2. Sets.

Symbol	Meaning
Q	Candidate transportation path set corresponding to OD freight demand
q	Path index $q \in Q$
A_q	Set of directed arcs (links) on path q
(j, k)	A directed arc in the path, pointing from node j to node k
N	Set of candidate charging station nodes
i	Candidate charging station node index $i \in N$
N_{exist}	Set of existing charging stations
S_{init}	Set of initial state of charge (soc) scenarios for vehicles
S_{target}	Set of target state of charge (soct) scenarios for single vehicle replenishment
S_{sub}	Set of vehicle operation sub-scenarios (combination of path $\times$ soc $\times$ charging target sequence)
$K_{j,k}^{q,s}$	Set of candidate replenishment nodes that make arcs (j, k) passable on path q under the driving range constraints of the initial power scenario and expected charging target
θ_1	Set of all arc segments where $\theta = 1$

Table 3. Parameters.

Symbol	Meaning
ρ_s	Probability of the vehicle's initial soc scenario
ρ_t	Probability of the vehicle's target soct scenario during charging
$f_{q,s}$	Average daily flow of battery electric trucks (veh/day) on path q under initial soc scenario s
$f_{q,sub}$	Actual daily flow of sub-scenario sub , $f_{q,sub} = f_{q,s} \times p_{sub}$
α_q	Proportion of traffic flow requiring fast charging on path q
β	Peak Hour Factor, representing the proportion of peak hour traffic volume to the average daily traffic volume
η	Electric vehicle penetration rate
$d_{j,k}$	Driving distance of arcs (j, k) (km)
e	Energy consumption per unit mileage of electric trucks (kWh/km)
B	Available battery capacity of electric trucks (kWh)

Table 3. Cont.

Symbol	Meaning
R	Maximum driving range of electric trucks (km)
$\theta_{j,k}^{q,sub}$	Arc-level replenishment trigger parameter; takes 1 if arcs (j,k) on path q under sub-scenario sub is a mandatory replenishment arc; otherwise it takes 0
$\bar{E}_{j,k}^{q,sub}$	Expected single replenishment energy at arcs (j,k) under sub-scenario sub (kWh)
F_i	Fixed investment cost for constructing a charging station at node i (CNY)
C_{fast}, C_{slow}	Construction and equipment cost of a single fast/slow charger
O_i^{fix}	Annual fixed operation cost of the charging station at node i (CNY/year)
O_{fast}, O_{slow}	Annual variable operation and maintenance cost of a single fast/slow charger (CNY)
c_i^{elec}	Unit power purchase cost in the area where node i is located (CNY/kWh)
$Cap_{fast}^{peak}, Cap_{slow}^{peak}$	Maximum service vehicle capacity (veh/h) of a single pile during peak hours obtained via inverse solution based on M/G/c queueing theory
p^{fast}, p^{slow}	Rated power of a single fast/slow charger (kW)
p_i^{max}	Maximum total charging load power allowed to connect to the grid in the area where node i is located (kW)
W_i^{max}	Maximum number of parking spaces available for constructing chargers in the service area/parking lot where node i is located
W_q^{max}	Maximum acceptable queueing waiting time (h)
D	Total number of operating days in the planning period (taken as 365 days)

Table 4. Decision variables.

Symbol	Meaning
x_i	Binary variable: takes 1 if a charging station is constructed at node i ; otherwise, it takes 0
n_i^{fast}	Integer variable: number of fast chargers configured at node i
n_i^{slow}	Integer variable: number of slow chargers configured at node i
$y_{q,sub}$	Binary variable: takes 1 if path q is feasible under the energy constraints of the sub-scenario sub
$z_{i,j,k}^{q,sub}$	Continuous variable: proportion allocated to station i among the traffic flow triggering mandatory replenishment before passing arcs (j,k) under sub-scenario sub on path q

Note on variable y : In the mathematical formulation, $y_{q,sub}$ is defined as a binary variable $\{0,1\}$. In this case study, a capture rate of 100% is strictly required, and all $y_{q,sub}$ are forced to 1. In a more general problem setting (e.g., allowing some sub-scenarios to be infeasible), the variable y retains its binary semantics and its value is freely determined by the solver.

Note on variable z : The variable $z_{i,j,k}^{q,sub}$ has a five-dimensional structure (i, j, k, q, sub) — i denotes the charging station, q denotes the OD path, sub denotes the sub-scenario identifier, and (j, k) denotes the arc segment that triggers $\theta_{j,k}^{q,sub} = 1$. The variable z is created only when $\theta_{j,k}^{q,sub} = 1$ and $K_{j,k}^S$ is non-empty. Its physical meaning is “the station-level flow allocation proportion for a specific path–sub-scenario–arc combination.”

2.5.2. Objective Function

The model minimizes total life-cycle cost. The objective function consists of two components: construction investment cost Z_{inv} and operation and maintenance (O&M) cost Z_{ops} over the planning horizon.

$$\text{Min } Z = Z_{inv} + Z_{ops} \quad (8)$$

Construction cost: This includes the fixed station construction cost and the procurement cost of fast and slow chargers.

$$Z_{inv} = \sum_{i \in N} \left(F_i \cdot x_i + C_{fast} \cdot n_i^{fast} + C_{slow} \cdot n_i^{slow} \right) \quad (9)$$

Operation and maintenance cost: This includes annual fixed operating costs, charger maintenance costs, and electricity procurement costs. Here, V_i denotes the average daily charging demand served by station i .

$$Z_{ops} = \sum_{i \in N} \left(O_i^{fix} \cdot x_i + O_{fast} \cdot n_i^{fast} + O_{slow} \cdot n_i^{slow} + D \cdot V_i \cdot c_i^{elec} \right) \quad (10)$$

$$V_i = \sum_{q \in Q} \sum_{sub \in S_{sub}} \sum_{(j,k): \theta_{j,k}^{q,sub} = 1} f_{q,sub} \cdot \bar{E}_{j,k}^{q,sub} \cdot z_{i,j,k}^{q,sub} \quad (11)$$

The variable V_i is coupled with the siting and capacity decisions through the z variables, enabling the electricity procurement cost in the objective function to capture differences in energy consumption across alternative station deployment schemes.

The economic boundary of the present model includes station construction, charger procurement, fixed and variable O&M, and electricity procurement costs. Grid and land conditions are represented as feasibility constraints through the maximum grid connection capacity and available parking spaces at each candidate site, rather than as endogenous investment decisions. Accordingly, grid reinforcement, land acquisition, renewable-energy and storage investment, and charging service revenue are outside the current objective. These components can be incorporated when corresponding project-level cost and revenue data are available.

2.5.3. Constraints

(1) Charging trigger consistency constraint: Each arc with $\theta = 1$ must be charged at at least one station within the candidate station set K .

$$\sum_{i \in K_{j,k}^{q,S}} z_{i,j,k}^{q,sub} = \theta_{j,k}^{q,sub} \cdot y_{q,sub} \quad \forall q \in Q, \forall sub \in S_{sub}, \forall (j,k) \in A_q, \theta_{j,k}^{q,sub} = 1 \quad (12)$$

For each $\theta = 1$ arc, the sum of charging flow allocation proportions across all candidate stations in K must equal $y_{q,sub}$. This constraint ensures that (i) whenever $y_{q,sub} = 1$, at least one charging event occurs within K , and (ii) only one charging event is assigned to each $\theta = 1$ arc.

(2) Station construction logic constraint: Charging flow can only be assigned to stations that are selected for construction.

$$z_{i,j,k}^{q,sub} \leq x_i \quad \forall q \in Q, \forall sub \in S_{sub}, \forall (j,k) \in A_q, \forall i \in K_{j,k}^{q,S} \quad (13)$$

Flow allocation to node i is only permitted if $x_i = 1$; otherwise, all associated z variables are forced to zero.

(3) Fast-charging peak-hour capacity constraint: The number of fast-charging vehicles arriving during the peak hour shall not exceed the total fast-charging service capacity of the station.

$$\beta \cdot \sum_{q \in Q} \sum_{sub \in S_{sub}} \sum_{\substack{(j,k): \theta_{j,k}^{q,sub}=1 \\ i \in K_{j,k}^{q,sub}}} f_{q,sub} \cdot \alpha \cdot z_{i,j,k}^{q,sub} \leq n_i^{fast} \cdot Cap_{fast}^{peak} \quad \forall i \in N \quad (14)$$

The left-hand side represents the daily fast-charging demand assigned to station i , converted into a peak-hour arrival rate using the peak-hour factor β . The right-hand side represents the number of fast chargers multiplied by the safe peak-hour capacity per charger. This constraint ensures that the peak-hour waiting time does not exceed W_q^{max} .

(4) Slow-charging peak-hour capacity constraint: This constraint is analogous to Constraint (3), with α replaced by $1 - \alpha$ and Cap_{fast}^{peak} replaced by Cap_{slow}^{peak} .

(5) Parking-space capacity constraint:

$$n_i^{fast} + n_i^{slow} \leq W_i^{max} \cdot x_i \quad \forall i \in N \quad (15)$$

If a station is constructed ($x_i = 1$), the total number of fast and slow chargers cannot exceed the maximum number of parking spaces available at that site. If $x_i = 0$, the right-hand side becomes zero, forcing the number of chargers to be zero. This constraint reflects the physical limitation imposed by land availability.

(6) Grid connection capacity constraint:

$$P_{fast} \cdot n_i^{fast} + P_{slow} \cdot n_i^{slow} \leq P_i^{max} \cdot x_i \quad \forall i \in N \quad (16)$$

The total rated charging power installed at each station shall not exceed the maximum grid connection capacity available at the site, ensuring secure grid operation.

(7) Full-capture constraint:

$$y_{q,sub} = 1 \quad \forall q \in Q, \forall sub \in S_{sub} \quad (17)$$

Because the objective of zero-carbon freight corridors is to guarantee uninterrupted operation of battery electric trucks, 100% capture is adopted as the baseline planning target. This serves as a hard constraint in the case study and ensures the global feasibility of the optimized solution. Lower reliability levels may be explored in future studies.

(8) Existing-station retention constraint (construction phase):

$$x_i = 1 \quad \forall i \in N_{exist} = \{S4, S7, S12, S16, S19\} \quad (18)$$

Under the construction/expansion scenario, five existing charging stations are retained mandatorily. Under the decommissioning scenario, this constraint is removed, and all candidate stations are treated equally.

(9) Variable domains:

$$x_i \in \{0, 1\}, \quad y_{q,sub} \in \{0, 1\}, \quad z_{i,j,k}^{q,sub} \in [0, 1], \quad n_i^{fast}, n_i^{slow} \in \mathbb{Z}^+ \cup \{0\} \quad (19)$$

2.6. Post-Optimization Calibration

After obtaining the station siting decisions (x_i) and initial charger allocations (n_i) from the MILP model, a post-calibration procedure is performed to refine the charger quantities. The discrepancy in charger allocation primarily arises from two factors.

First, the capacity parameter Cap^{peak} is treated as a global constant derived from the network-wide average arrival SoC, which cannot capture the service efficiency differences between upstream stations, where vehicles arrive with relatively high SoC and require shorter charging times, and downstream stations, where lower arrival SoC results in longer charging durations.

Second, the continuous flow-allocation variable z tends to concentrate the charging demand of a given sub-scenario at a single station, thereby overestimating the peak load at certain locations. In contrast, the single-vehicle Monte Carlo (MC) simulation naturally distributes charging demand across feasible nodes within the candidate set $K_{j,k}^{q,S}$. This concentration leads to overestimated peak demand at some stations and consequently results in oversized charger allocations.

The Monte Carlo module is not intended to replace the MILP optimizer. Instead, it serves as a behavioral evaluation layer that estimates station-level loads under stochastic charging decisions.

The calibration procedure is implemented as follows:

Using the station set selected by the MILP model as a filtering condition, the single-vehicle simulation described in Section 2.3.3 is re-executed, retaining only the constructed stations within each candidate set K . The resulting arrival SoC samples at station i are denoted by S_i . The daily arrival volume is calculated as $N_i^{daily} = |S_i|$, and the corresponding peak-hour fast-charging arrivals are estimated as $N_i^{fast} = N_i^{daily} \times \beta \times \alpha$, with an analogous calculation for slow charging. For each station, the sample set S_i is then used as input to the M/G/c queueing model described in Section 2.4. Combined with a bisection search procedure, the minimum numbers of fast and slow chargers, $n_i^{fast(new)}$ and $n_i^{slow(new)}$, satisfying $W_q \leq 0.1$ h are obtained.

Unlike the MILP stage, which uses a network-wide average arrival SoC, the calibration stage estimates service capacity separately for each selected station using its local arrival-SoC samples. The calibrated charger counts replace the initial MILP allocations, while the selected station set is retained because siting is primarily governed by path-coverage and full-capture constraints. Station-level calibration effects are reported in Section 3.3.2.

The calibrated charger allocations replace the initial MILP solution and constitute the final deployment plan, while the station siting decisions remain unchanged. Fundamentally, the MILP model addresses the combinatorial problem of determining where charging stations should be deployed. The siting solution is driven by the coverage constraints associated with the θ and K sets and the full-capture requirement ($\gamma = 1$), which are independent of capacity parameters. Consequently, the station locations identified by the MILP model remain valid. The inaccuracy lies primarily in the charger allocation results, which are affected by the use of the global capacity parameter Cap^{peak} , leading to conservative rather than precise charger quantities. The calibration stage therefore retains the optimal station locations while refining charger allocations using station-specific operational data, thereby transforming conservative capacity estimates into accurate charger-sizing decisions.

3. Results and Discussion

3.1. Study Area and Data

This study considers a regional highway network in China consisting of three origins (O1, O2, and O4), four destinations (D1, D2, D3, and D4), and twenty candidate service nodes (S1–S20). The network comprises a total of 27 nodes and 26 road segments, with segment lengths corresponding to actual highway service area spacing and conforming to national design standards. Five OD paths and their associated average annual daily traffic (AADT) volumes were derived from traffic survey data and rounded up, yielding a total traffic volume of 7500 veh/day, as detailed in Table 5. Assuming an electrification rate of

30%, the resulting average daily BET flow is 2250 veh/day. In addition to network and traffic data, field surveys were conducted to collect BET charging behavior information, including the SoC at departure and drivers' preferred target SoC for en-route charging.

Table 5. Path parameters and traffic volumes.

OD Path	Passing Nodes	Total Length (km)	AADT	BET Flow (veh/day)
O1 → D1	S1~S5	343	2000	600
O2 → D2	S9~S11, S7~S8	265	1500	450
O2 → D3	S9~S13	285	1200	360
O4 → D4	S14~S20	444	1000	300
O1 → D3	S1~S13 (via S6/S7/S11)	441	1800	540

The main model parameters are summarized in Table 6. The planning horizon is set at 365 days. Existing stations S4, S7, S12, S16, and S19 are mandatorily retained during the construction period ($x = 1$). Based on these field-survey data, the probability distributions of the initial SoC (denoted as soc) and target SoC (denoted as soct) were constructed, and the SoC values reported in the survey were subsequently discretized into representative levels for Monte Carlo simulation. Accordingly, the initial SoC was represented by four levels, i.e., 70%, 80%, 90%, and 100%, with probabilities of 0.1, 0.2, 0.2, and 0.5, respectively, while the target SoC was represented by three levels, i.e., 80%, 90%, and 100%, with probabilities of 0.5, 0.3, and 0.2, respectively. The resulting distributions preserve the main behavioral characteristics identified from the survey, namely that most trucks depart with relatively high battery levels, while drivers tend to prefer partial rather than full recharging during en-route charging. BETs technical parameters are derived from electric heavy-duty truck product specifications.

Table 6. Model parameters.

Parameter Category	Parameter	Value
Vehicle parameters	Battery capacity B	300 kWh
	Maximum driving range R	300 km
	Energy consumption per unit mileage	1.0 kWh/km
Demand parameters	Initial soc distribution	{70%: 0.1, 80%: 0.2, 90%: 0.2, 100%: 0.5}
	Target soct distribution	{80%: 0.5, 90%: 0.3, 100%: 0.2}
	Peak hour factor β	0.12
	Fast charging proportion α (baseline 30% penetration)	0.3
Cost parameters	Station fixed construction cost F_i	4 million CNY/station
	Fast charger purchase cost C_{fast}	350,000 CNY/unit
	Slow charger purchase cost C_{slow}	150,000 CNY/unit
	Fast charger annual O&M cost O_{fast}	17,500 CNY/unit
	Slow charger annual O&M cost O_{slow}	7500 CNY/unit
	Unit power purchase price c_i^{elec}	0.12 CNY/kWh
Physical constraints	Maximum parking spaces per station W_i^{max}	80
	Maximum grid capacity per station P_i^{max}	25,000 kW
	Fast charging power P^{fast} (30% penetration)	480 kW
	Slow charging power P^{slow} (30% penetration)	180 kW
Solve parameters	MIP gap	0.5%
	Solution time limit	120 s
	Planning period D	365 days

3.2. Baseline Evaluation

Prior to optimization, the current situation with only five existing stations (S4, S7, S12, S16, S19) is evaluated. Each existing station is equipped with one fast charger (480 kW) and nine slow chargers (180 kW), totaling 50 charging points. Since no systematic design or planning has been undertaken, vehicle charging timing is determined solely by driver experience. The charging logic is set as follows: when a vehicle arrives at each existing station, if the remaining range is insufficient to reach the next station or the destination, the vehicle charges to 100% SoC at that station before continuing. If the current node is not a station and the range is insufficient, capture fails. This baseline scenario represents the situation of “retaining only existing infrastructure without incremental investment” and is used to measure the improvement achieved by the optimization solution.

3.2.1. Capture Rate Analysis

Under the non-optimized scheme, among the 2250 daily electric trucks in the entire network, 1635 vehicles are successfully captured, yielding a capture rate of only 72.7%. The distribution of the 615 uncaptured vehicles across paths is presented in Table 7.

Table 7. Distribution of uncaptured vehicles under the non-optimized scheme.

OD Path	AADT	BET Flow (veh/day)	Uncaptured Flow (veh/day)	Uncaptured Proportion
O1 → D1	2000	600	270	45.0%
O2 → D2	1500	450	135	30.0%
O2 → D3	1200	360	108	30.0%
O4 → D4	1000	300	30	10.0%
O1 → D3	1800	540	72	13.3%
Total	7500	2250	615	27.3%

The primary reason for failure is the “first-station blind spot”: all five existing stations are located in the middle and later segments of the routes (e.g., S4 is the fourth node on the O1 → D1 route, approximately 207 km away from the origin). Vehicles with a low initial SoC, such as 70% to 80%, deplete their driving range before reaching the first existing station. For instance, on the O1 → D1 route, a vehicle with an initial SoC of 70% has a full driving range of 210 km; however, its safe driving range—after deducting a 20% reserve margin—is only 150 km, which is insufficient to reach S4. This highlights a significant coverage gap in the spatial layout of the existing stations, characterized by a complete absence of charging infrastructure in the early segments of the routes.

3.2.2. Queueing Congestion Analysis

Table 8 presents the M/G/c queueing analysis results for the five existing stations under the non-optimized scheme. All stations are severely overloaded.

Table 8. Station congestion analysis under the non-optimized scheme.

Station	Daily Avg Arrivals (veh)	Fast Charging ρ	Slow Charging ρ	Fast Charging W_q (min)	Slow Charging W_q (min)	Status
S4	420	6.77	4.68	∞	∞	Severely Congested
S7	693	10.38	7.18	∞	∞	Severely Congested
S12	252	3.90	2.70	∞	∞	Severely Congested
S16	270	3.97	2.75	∞	∞	Severely Congested
S19	270	3.92	2.71	∞	∞	Severely Congested

Note: ∞ means time tends to infinity.

The service intensity ρ for both fast and slow charging at each station far exceeds 1.0 (fast-charging $\rho = 3.9\text{--}10.4$, slow-charging $\rho = 2.7\text{--}7.2$), indicating that the queue length will grow without bound ($W_q \rightarrow \infty$). Two factors account for this outcome: (1) each station has only one fast charger, whereas the peak-hour fast-charging arrival rate is approximately 9–25 veh/h, far exceeding the safe service capacity of approximately 2.3 veh/h for a single fast charger, and (2) each station has only nine slow chargers, which similarly cannot meet the peak-hour slow-charging demand of 21–58 veh/h.

Moreover, the severe shortage of fast chargers is particularly pronounced—the five stations collectively have only five fast chargers, accounting for 10% of the total charger count, while fast-charging demand accounts for 30% of the total. Since the service efficiency of fast chargers is approximately 2.67 times that of slow chargers, each missing fast charger causes far greater congestion losses than a missing slow charger.

Overall conclusion: the non-optimized scheme can neither guarantee a basic capture rate (72.7%) nor meet the minimum service level requirements at any station (all stations $\rho > 1$). The facility configuration is severely inadequate in terms of both spatial coverage and capacity provision. Consequently, under current conditions, only a very small number of electric trucks can be operated, and they must strictly follow battery charge standards to avoid failing to reach their destinations. The majority of freight transport continues to rely on fossil fuel-powered heavy-duty trucks.

3.3. Optimization Results

3.3.1. Site Selection Results

The MILP model optimally selected eight station locations from 20 candidate S-nodes: S1, S4, S7, S11, S12, S16, S18, and S19. Among them, S4, S7, S12, S16, and S19 are existing stations, while S1, S11, and S18 are newly constructed sites. All 178 sub-scenarios were successfully satisfied, achieving a 100% capture rate. The spatial configuration of the selected sites is illustrated in Figure 4.

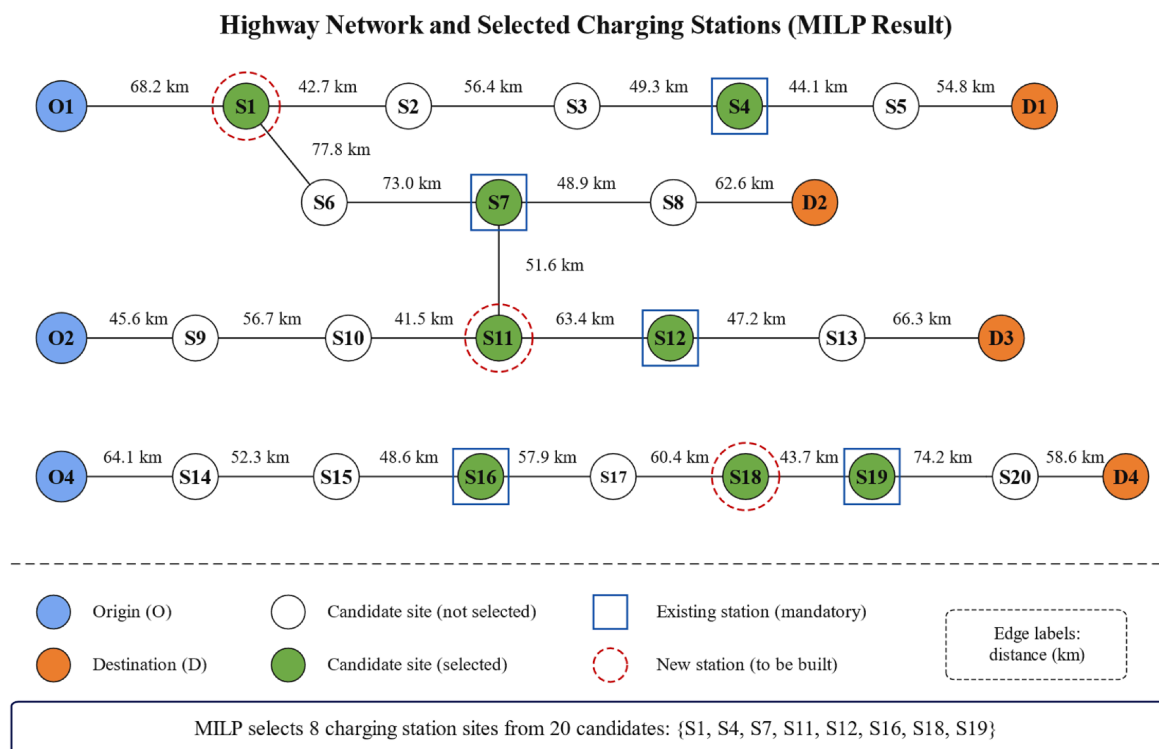


Figure 4. Spatial layout of selected charging stations.

Compared to the non-optimized scheme (only five existing stations), the three newly added stations in the optimized solution precisely cover the coverage gaps on the three paths caused by excessive inter-station distances, ensuring full path feasibility.

3.3.2. Charger Count Configuration and Calibration

The initial MILP solution yields a total charger count of 491 units (56 fast chargers + 435 slow chargers). After load calibration through the single-vehicle MC simulation (method described in Section 2.6), the charger counts at each station decrease significantly, with the final scheme totaling 325 chargers (54 fast chargers + 271 slow chargers), representing a 33.8% reduction. Table 9 provides a station-by-station comparison of the two schemes.

Table 9. Station-by-station comparison of MILP initial scheme and MC calibration scheme.

Station	MILP Fast Charging	MILP Slow Charging	MILP Total	MC Fast Charging	MC Slow Charging	MC Total	Decrease
S1	8	64	72	4	19	23	−68.1%
S4	9	71	80	10	55	65	−18.8%
S7	9	71	80	7	38	45	−43.8%
S11	8	58	66	10	53	63	−4.5%
S12	9	71	80	7	36	43	−46.3%
S16	6	47	53	7	33	40	−24.5%
S18	4	29	33	4	17	21	−36.4%
S19	3	24	27	5	20	25	−7.4%
Total	56	435	491	54	271	325	−33.8%

The station with the largest charger count reduction is S1 (−68.1%). S1 is located in the upstream segment of the path. In the Stage 2 MC simulation with all 20 nodes open, the average arrival SoC of vehicles at S1 is 63.9%, with a service time of only approximately 0.10 h per vehicle. The service efficiency per charger is approximately 3.6 times the MILP capacity assumption (based on the network-wide average arrival SoC of 36.6%). S12 (−46.3%) exhibits the second-largest reduction. Its arrival SoC is only 18.7%, well below the network average. The conservative MILP assumption over-allocated charging resources to this station, but in the MC simulation, after vehicles dispersed to various nodes in the K set, the peak load was far lower than expected, resulting in the deviation.

S11 has a daily average arrival of 499 vehicles, making it the highest-load station in the entire network. It is located at the intersection area of the three radial paths O2 → D2, O2 → D3, and O1 → D3, giving it the widest service coverage. The initial MILP solution did not reflect load differences among stations. After calibration, S11 is allocated 63 chargers, S7 is allocated 45 chargers, and S12 is allocated 43 chargers, with the charger counts at each station becoming consistent with the proportional relationship of their actual daily average arrivals of 499, 324, and 281 vehicles, respectively. S11 remains a high-allocation station, but still achieves a 4.5% saving compared to the initial MILP solution.

S7 receives a daily average of 324 vehicles, with a noticeable increase in load compared to the Stage 2 simulation (an average of 229 daily arrivals when all 20 nodes were open). The reason is that the MILP did not select S13—part of the end-segment charging demand on the O2 → D3 path was reallocated to S7, making its actual load higher than expected. After calibration, S7 is configured with seven fast chargers and 38 slow chargers (45 units), a 43.8% reduction from the initial MILP solution.

The proportion of fast chargers increased from 11.4% (56/491) in the initial MILP model to 16.6% (54/325) after calibration. Rather than being predetermined, this ratio is endogenously derived from the M/G/c queueing model, driven by the service efficiency discrepancy between fast (480 kW) and slow (180 kW) charging (a factor of ~2.67). Conse-

quently, the higher turnover rate of fast chargers reduces the required quantity below the intuitive expectation based on the 30% traffic flow ratio ($\alpha = 30\%$).

3.3.3. Cost Analysis

Table 10 presents a comparison of the total life-cycle costs between the initial MILP solution and the MC-calibrated solution.

Table 10. Life-cycle cost comparison between MILP initial and MC-calibrated schemes.

Cost Item	MILP Initial Scheme (10,000 CNY)	MC-Calibrated Scheme (10,000 CNY)	Change
Construction investment Z_{inv}	11,685.0	9155.0	−21.7%
Operation and maintenance Z_{ops}	2707.6	2581.1	−4.7%
Total life-cycle cost	14,392.6	11,736.1	−18.5%

The MC-calibrated solution yields a total cost of approximately 117.36 million RMB, achieving an 18.5% (26.57 million RMB) reduction against the initial MILP baseline. These savings are predominantly driven by capital expenditure (CAPEX): slow chargers decrease from 435 to 271 units (saving ~25.30 million RMB in procurement), while fast chargers are marginally reduced from 56 to 54 units. In contrast, operation and maintenance (O&M) costs decrease by merely 1.27 million RMB. This marginal O&M reduction stems from the invariant total energy demand across the network, which fixes electricity procurement costs regardless of stall counts and thus dampens the impact of reduced maintenance expenses.

3.3.4. Service Level Verification

Based on the arrival SoC samples at each station from the MC-calibrated scheme, M/G/c verification of the queueing waiting times for both fast and slow charging is conducted at each station. The calibrated charger count configuration ensures that W_q at all eight stations satisfies the constraint $W_q \leq 6$ min (specific W_q and ρ values are presented in Table 11 and Figure 5).

Table 11. Service levels at each station after calibration.

Station	Number of Chargers	Daily Avg Arrivals (veh)	Avg Arrival SoC	ρ_{fast}	W_q^{fast} (min)	ρ_{slow}	W_q^{slow} (min)
S1	23	343	0.652	0.672	2.13	0.880	4.16
S4	65	493	0.270	0.810	3.15	0.916	3.35
S7	45	324	0.258	0.772	3.88	0.885	3.20
S11	63	499	0.295	0.791	2.57	0.929	4.81
S12	43	281	0.197	0.726	2.75	0.878	3.25
S16	40	308	0.311	0.682	1.63	0.901	4.91
S18	21	163	0.406	0.545	1.38	0.798	2.52
S19	25	145	0.218	0.510	0.84	0.793	2.31
Mean	40.6	319.5	0.326	0.689	2.29	0.873	3.69

Post-calibration, W_q at all eight stations remains below the 6 min threshold. Slow-charging parameters constitute the primary bottleneck across stations, with an average slow-charging $\rho_{slow} = 0.873$ and a maximum at S11 (0.929), which does not reach the saturation boundary. The average fast-charging $\rho_{fast} = 0.689$, with a maximum at S4 (0.810), still within the safe range. This confirms the service feasibility of the final configuration; the station-level SoC heterogeneity underlying these differences is examined in Section 3.4.

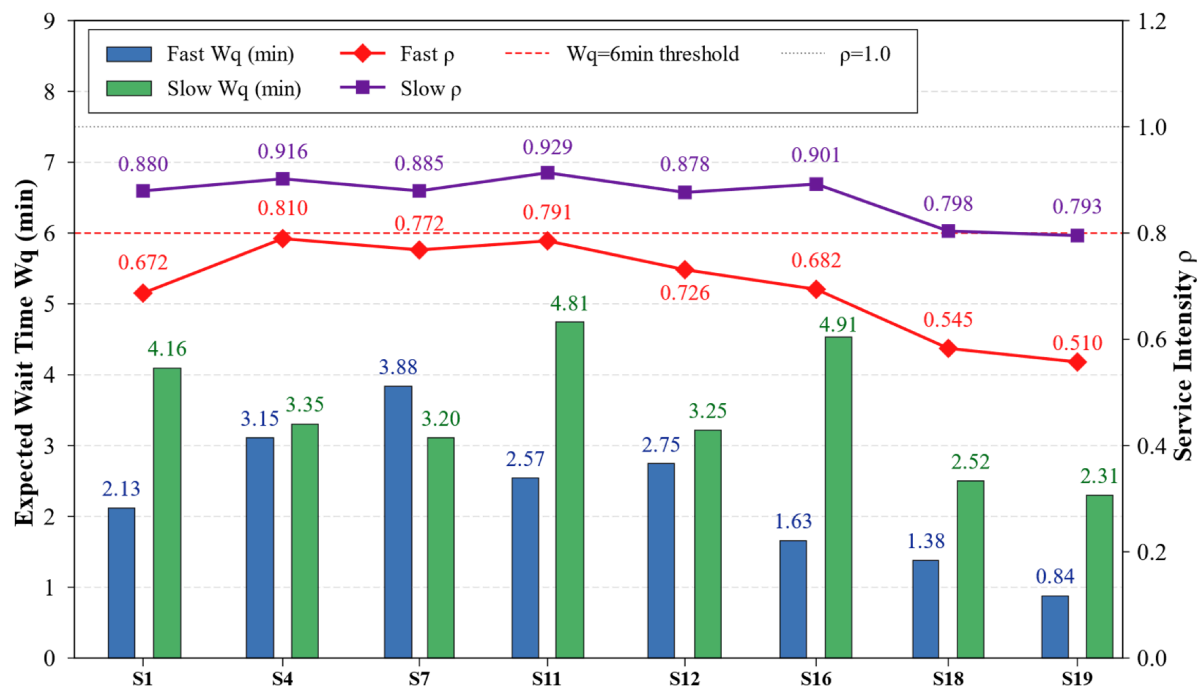


Figure 5. Illustration of service levels at each station after calibration.

3.4. Monte Carlo Behavioral Analysis

The single-vehicle MC simulation not only provides load data for charger count calibration but also reveals several regularities regarding driver charging behavior. These findings provide supporting evidence for understanding the model mechanisms and explaining the necessity of charger count calibration.

(1) Pronounced spatial gradient of arrival SoC: Figure 6 displays the arrival SoC distribution at each constructed station. S1, located at the front segment of the path, has the highest average arrival SoC (65.2%), whereas the other selected stations range from 19.7% to 40.6%, with the end-point station S12 exhibiting the lowest value at only 19.7%.

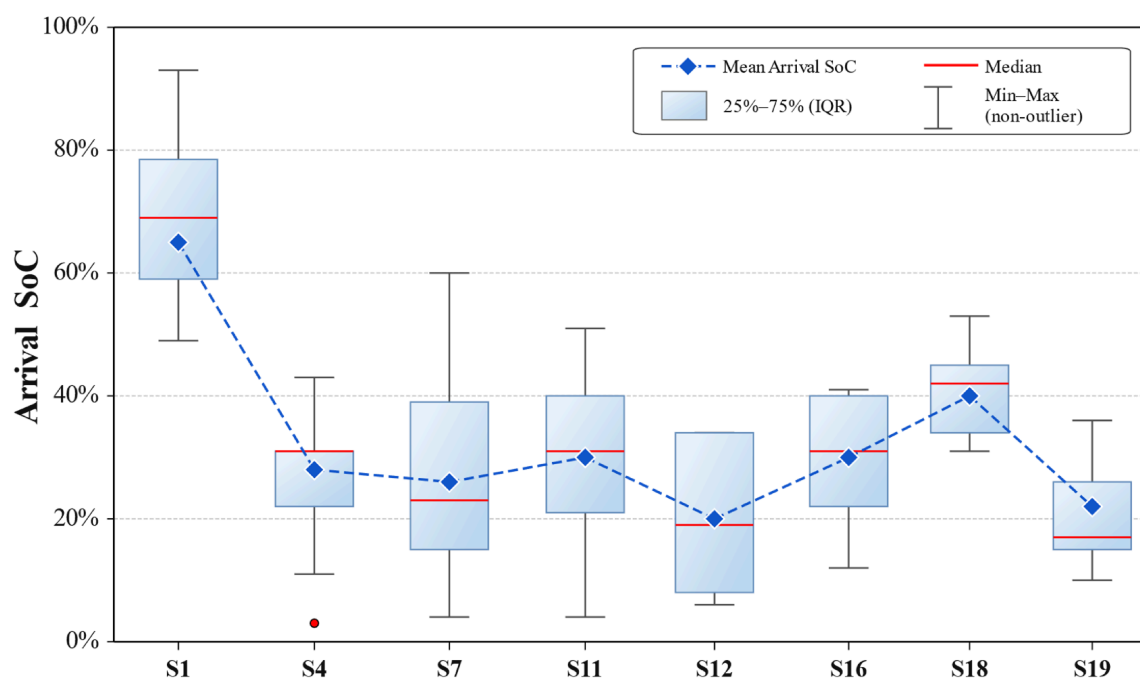


Figure 6. Spatial gradient of average arrival SoC at each station.

The lower the arrival SoC, the greater the single-charging energy demand ($E = (SoC_{oct} - SoC_{arr}) \times B$), the longer the charging time ($T = E/P$), and, consequently, the greater the number of chargers required. The 45-percentage-point gradient from S1 (65.2%) to S12 (19.7%) validates the physical principle that “the later the charging, the greater the charging intensity,” and explains why end-point stations require more chargers in both the MILP and calibration—this gradient constitutes the empirical basis for the necessity of station-level calibration rather than a uniform capacity assumption.

(2) Flow dispersion is a systematic deviation between MILP concentration and MC dispersion. In the MILP model, the continuous variable z , under relaxed capacity constraints, tends to concentrate 100% of the flow of the same sub-scenario onto a single economically optimal station (typically the later station in the K set—closest to the trigger point, with minimal remaining travel consumption). In contrast, the single-vehicle simulation reveals that flow is naturally dispersed among constructed station nodes. For example, on the $S4 \rightarrow S5$ arc of the $O1 \rightarrow D1$ path, the MILP allocates 100% of the flow to S4. However, the MC simulation shows that S1 handles 52.5% and S4 handles only 47.5%, with S1, as a newly constructed station, effectively diverting the peak load away from S4.

This discrepancy constitutes the fundamental reason why the MILP charger count is inflated (491 units) while the MC-calibrated charger count is lower (325 units)—the MILP assumes that all vehicles are concentrated at S4 for charging, thus requiring a large number of chargers (80 units) at S4 to cope with the peak. In reality, vehicles disperse to various nodes in the K set, and the peak load at S4 is far lower than the MILP assumption. Approximately 15 of the 80 chargers are redundant. Flow dispersion reduces the peak load at each station—this is the microscopic mechanism enabling the substantial charger count reduction (−33.8%) after calibration.

(3) Physical interpretation of MILP concentrated allocation: The MILP’s concentrated allocation is not a model deficiency but rather an inevitable behavior of linear programming under relaxed capacity constraints; if a particular station is more cost-effective than the alternatives (closer to the trigger point, shorter remaining travel distance, slightly lower electricity procurement cost), the solver naturally concentrates vehicle flow onto that station in the absence of tight capacity constraints. This precisely illustrates the rationality of the division of labor between the MILP and the MC simulation: the MILP is responsible for identifying which stations are worth building (combinatorial search), while the MC simulation is responsible for evaluating the actual loads of these stations under dispersed behavior (accurate assessment).

3.5. Comparative Validation Against Benchmark Planning Strategies

Large-scale long-haul BET charging operations are still at an early stage in the study region, and sufficiently complete station-level operational datasets are not yet available. Therefore, the proposed framework is evaluated against two benchmark strategies: the existing infrastructure configuration and the initial MILP solution before station-specific Monte Carlo calibration. The comparison is summarized in Table 12.

The comparison reveals two distinct advantages of the proposed framework. First, compared with the existing infrastructure, the optimized network increases capture from 72.7% to 100% and removes the severe queueing overload.

Second, compared with the initial MILP solution, station-specific MC and M/G/c calibration maintains 100% capture while reducing charger count from 491 to 325 (−33.8%) and total modeled life-cycle cost from RMB 143.93 million to RMB 117.36 million (−18.5%). These results indicate that the additional stochastic behavioral and queueing calibration layers do not merely change the numerical configuration but correct the capacity redundancy produced by network-wide average service assumptions.

Table 12. Comparison of benchmark and proposed planning strategies.

Indicator	Existing Infrastructure	MILP Initial Planning	Proposed MC-Calibrated Planning
Number of stations	5	8	8
Total chargers	50	491	325
Fast chargers	5	56	54
Slow chargers	45	435	271
Capture rate	72.7%	100%	100%
Queueing/service condition	Severely overloaded	Capacity feasible under global assumption	All stations satisfy $W_q \leq 6$ min
Construction investment	—	116.85 million CNY	91.55 million CNY
O&M cost	—	27.076 million CNY	25.811 million CNY
Total life-cycle cost	—	143.926 million CNY	117.361 million CNY

Thus, the proposed framework simultaneously improves flow coverage, service reliability, and infrastructure efficiency relative to the two benchmark configurations, although future validation with large-scale operational charging data remains necessary. These findings are consistent with previous capacity-constrained charging infrastructure studies showing that station capacity can substantially affect infrastructure location and scale [29,30]. The present results further indicate that station-specific arrival SoC and stochastic charging location choices can significantly affect charger-sizing requirements, extending this capacity perspective from aggregate station constraints to vehicle-level charging heterogeneity.

3.6. Scenario Analysis of BET Penetration and Technology Evolution

To examine how future BET technology evolution may affect charging infrastructure requirements, two additional scenarios are considered. The 60% and 100% scenarios simultaneously incorporate improvements in battery capacity and driving range, higher charging power, and expanded site-side capacity, as summarized in Table 13. In particular, fast-charging power increases from 480 kW to 660 kW and 900 kW, representing the progression toward megawatt-class charging. These scenarios therefore represent integrated technology–market evolution rather than the isolated effect of BET penetration.

Table 13. Comparison of key parameters across the three scenarios.

Parameter	Baseline Scenario (30%)	Medium Penetration (60%)	High Penetration (100%)
Electric vehicle penetration rate	30%	60%	100%
Daily avg BET flow (veh)	2250	4500	7500
Battery capacity B (kWh)	300	380	420
Driving range R (km)	300	380	420
Fast charging power P^{fast} (kW)	480	660	900
Slow charging power P^{slow} (kW)	180	309	480
Fast charging proportion α	0.300	0.557	0.900
Grid capacity P_i^{max} (kW)	25,000	50,000	83,333
Maximum parking spaces W_i^{max}	80	88	100
Station strategy	Construction phase (existing retained)	Demolition phase (free decision)	Demolition phase (free decision)
Total number of sub-scenarios	178	84	64

3.6.1. Site Selection and Charger Counts

A comparison of MILP site selection and MC calibration results across the three scenarios is presented in Table 14.

Table 14. Comparison of optimization results across the three scenarios.

Indicator	Baseline (30%)	Medium Penetration (60%)	High Penetration (100%)
Number of stations built	8	5	5
Station composition	S1, S4, S7, S11, S12, S16, S18, S19	S1, S7, S13, S17, S19	S1, S11, S13, S15, S19
New construction	S1, S11, S18	S1, S13, S17	S1, S11, S13, S15
demolition	-	S4, S11, S12, S16, S18	S4, S7, S12, S16, S18
MILP initial number of chargers (fast + slow)	491 (56 + 435)	285 (95 + 190)	154 (124 + 30)
MC calibrated number of chargers (fast + slow)	325 (54 + 271)	202 (74 + 128)	129 (100 + 29)
Calibration decrease	33.8%	29.1%	16.2%
Fast charging proportion	16.6%	36.6%	77.5%

The increase in driving range directly reduces the number of charging events; the number of sub-scenarios decreases from 178 to 84 and further to 64, and the number of entries triggering charging events correspondingly decreases from 1272 to 600 and further to 458. This narrows the MILP's location search space, reducing the number of stations from 8 to 5.

The resulting core-node concentration pattern is driven by the combined effects of range extension, charging power improvement, and network re-optimization. Longer driving ranges weaken the need for intermediate stations that primarily provide range coverage, while higher charging power shortens service times and increases charger throughput, allowing larger BET flows to be accommodated at fewer stations. In addition, existing stations are no longer mandatorily retained in the 60% and 100% scenarios, enabling the MILP to re-optimize the network from a greenfield perspective rather than presupposing a “build first, demolish later” sequence. Under the fixed station investment and full-capture requirement, this greater locational flexibility encourages the model to favor nodes with high topological value, such as those serving multiple paths or occupying critical positions along long-distance routes. Consequently, marginal coverage-oriented stations gradually lose their necessity, whereas topologically critical and high-throughput nodes retain greater planning value. The observed concentration is therefore a joint outcome of technology evolution, network topology, and infrastructure re-optimization rather than increased BET penetration alone.

This mechanism is reflected in the cross-scenario siting results. S1 and S19 are selected in all three scenarios because of their critical positions in maintaining path-energy feasibility: S1 serves as a key upstream charging node on the O1 → D1 corridor, whereas S19 provides critical coverage near the end of the longest O4 → D4 path. In contrast, the remaining stations undergo systematic substitution as driving range and charging power improve, while nodes capable of serving overlapping path demands become increasingly valuable. Table 15 summarizes the cross-scenario status of the candidate stations and provides a basis for differentiated infrastructure investment strategies.

The policy implications of this pattern are clear: S1 and S19, as stations robust across all scenarios, are suitable for irreversible, permanent heavy-asset investment, and their location decisions can be locked in at the early planning stage. The remaining nine stations are not essential across all scenarios: although S7 is selected in the 30% and 60% scenarios, it is replaced by S11 in the 100% scenario—the inertia of an existing station is not a permanent

guarantee. Stations such as S11, S13, and S15 enter or leave the optimal solution as technological conditions change. S4, S12, S16, S17, and S18 are only selected in a single scenario—these stations shift with technological progress and are not suitable for heavy-asset lock-in. They are better suited for modular, relocatable, flexible deployment modes: as technological iteration drives the evolution of the optimal layout, earlier stations can be downgraded or decommissioned, with resources concentrated toward core nodes. This differentiated strategy of “heavy-asset for core stations, modular for remaining stations” provides a quantitatively robust investment framework across a wide parameter range of 30–100% penetration.

Table 15. Cross-scenario status of each station.

Station	Baseline (30%)	Medium Penetration (60%)	High Penetration (100%)	Cross-Scenario Stability
S1	Selected	Selected	Selected	Core station (selected in all scenarios)
S4	Existing retained	Unselected	Unselected	Needed only for baseline
S7	Existing retained	Existing retained	Unselected	Exits with technological progress
S11	Selected	Unselected	Selected	Exists across scenarios
S12	Existing retained	Unselected	Unselected	Needed only for baseline
S16	Existing retained	Unselected	Unselected	Exits with technological progress
S17	Unselected	Selected	Unselected	Transition window
S18	Selected	Unselected	Unselected	Needed only for baseline
S19	Existing retained	Existing retained	Existing retained	Core station (selected in all scenarios)
S13	-	Selected	Selected	Added in high penetration
S15	-	-	Selected	Added in high penetration

Thus, battery and range improvements primarily relax the spatial coverage requirement, whereas higher charging power shortens service time and increases charger throughput, thereby reducing the station-level capacity requirement. Their combined effect shifts the network from range-driven broad coverage toward a smaller number of high-throughput charging nodes.

3.6.2. Cost Trajectory and Economic Viability

Table 16 presents the post-calibration total life-cycle costs and unit indicators for the three scenarios.

Table 16. Cost comparison across the three scenarios.

Indicator	Baseline (30%)	Medium Penetration (60%)	High Penetration (100%)
Construction investment Z_{inv} (10,000 CNY)	9155	6510	5935
Operation and maintenance Z_{ops} (10,000 CNY)	2581	3199	3531
Total life-cycle cost (10,000 CNY)	11,736	9709	9466
Daily Avg BET flow (veh)	2250	4500	7500
Unit EV cost (10,000 CNY/veh-year)	5.22	2.16	1.26
Total number of chargers	325	202	129
Unit EV pile count (units/1000 veh)	144.4	44.9	17.2

Three core findings are identified:

(1) Declining Total and Unit Costs: Across the integrated scenarios, daily EV traffic increases 3.33-fold (from 2250 to 7500 veh), while the post-calibration total life-cycle cost decreases by 19.3% (from RMB 117.36 million to RMB 94.66 million). Accordingly, the unit EV cost falls by 75.8% (from approximately RMB 52,200 to RMB 12,600 per veh-year). This pattern reflects the combined effects of higher BET penetration, longer driving range, higher charging power, relaxed site-capacity constraints, and the change in the existing-station retention rule; it should therefore not be interpreted as the isolated effect of penetration rate. Although traffic growth raises total energy demand, the lower charging frequency and higher charger throughput offset much of the volume-driven cost increase.

(2) Technology-Driven Decline in Capital Expenditure (CAPEX): Based on the MC-calibrated final schemes, CAPEX, including station construction and charger procurement costs, decreases from RMB 91.55 million in the 30% scenario to RMB 65.10 million in the 60% scenario and RMB 59.35 million in the 100% scenario, representing an overall reduction of 35.2%. This counterintuitive pattern is associated with the combined range extension (300 to 420 km), charging power upgrade (480 to 900 kW for fast charging), and greenfield re-optimization of the station network. The resulting 60.3% reduction in the total number of chargers (from 325 to 129 units) produces equipment savings that more than offset the infrastructure requirements created by higher traffic demand.

(3) Increasing Share of Operational Expenditure (OPEX): OPEX, including O&M and electricity procurement costs, rises from RMB 25.81 million in the 30% scenario to RMB 35.31 million in the 100% scenario, while its share of total life-cycle cost increases from 22.0% to 37.3%. With the total charger count reduced to 129 units, of which 77.5% are fast chargers, the marginal benefit of further charger-count reduction diminishes. Electricity procurement, which increases with traffic and charging demand, consequently accounts for a larger share of total cost. Under high-penetration conditions, cost-control priorities should therefore shift from infrastructure downsizing toward energy-cost management, including integrated solar-storage-charging systems and demand-response strategies.

3.7. Computational Efficiency and Scalability

The computational performance of the MILP model under the three planning scenarios is summarized in Table 17. Using Gurobi 13.0.1 with a relative MIP gap tolerance of 0.5%, the three scenarios are solved in 0.08, 0.02, and 0.02 s, respectively, with final optimality gaps below the 0.5% tolerance, indicating good tractability at the corridor scale. The smaller future-scenario models mainly reflect fewer charging sub-scenarios as driving range increases. For substantially larger highway networks, however, the number of path–sub-scenario–station combinations may increase rapidly, and scenario pruning, candidate-site screening, or decomposition methods may be required to improve scalability.

Table 17. Computational performance and model size across different BET penetration scenarios.

Metric	30% Baseline	60% Medium	100% Advanced
Decision variables	1504	653	495
Integer variables	238	124	124
Binary variables	198	84	84
Constraints	1934	805	603
Charging sub-scenarios	178	84	64
MILP Solution time (s)	0.08	0.02	0.02
Optimality gap	0.36%	0.40%	0.42%

4. Conclusions and Future Work

4.1. Conclusions

Addressing long-haul battery electric truck (BET) charging infrastructure planning, this study develops and evaluates a four-stage framework integrating path-energy analysis, single-vehicle Monte Carlo simulation, MILP optimization, and M/G/c post-calibration for long-haul BET charging infrastructure planning. The main conclusions are as follows:

(1) The proposed path-energy and Monte Carlo approach provides a structured representation of stochastic BET charging demand. Arc-level energy feasibility analysis identifies mandatory charging requirements, while vehicle-level simulation captures heterogeneity in initial SoC, target SoC, and charging location choices, thereby linking microscopic charging behavior with corridor-level infrastructure planning.

(2) The integrated MILP and station-specific M/G/c calibration improve both planning feasibility and capacity efficiency. The MILP jointly determines station locations and initial charger capacities under path-coverage, service-level, grid-capacity, and parking-space constraints. Subsequent station-specific calibration corrects conservative sizing caused by network-wide average service assumptions and dispersed charging behavior; in the baseline scenario, the total charger requirement is reduced by 33.8% while maintaining full path feasibility and the prescribed service level.

(3) Technology evolution progressively shifts the network toward fewer, higher-throughput, and more strategically located charging nodes. Longer driving ranges reduce coverage-driven station requirements, while higher charging power increases charger throughput. Consequently, robust core stations are more suitable for long-term capital-intensive investment, whereas technology-sensitive marginal stations can adopt staged, modular, or relocatable deployment strategies. This provides a practical basis for adaptive infrastructure planning as BET technology and market penetration evolve.

4.2. Future Work

While this study adopts certain simplifying assumptions in model construction and case analysis, several directions merit further exploration:

(1) Bi-directional Iterative Feedback Mechanism: The current framework relies on a unidirectional data flow from MILP siting decisions to MC traffic assignment. Feeding MC simulation results back into the MILP optimization process would enable co-optimization of spatial layout and capacity allocation. Although technical interfaces are pre-established for this closed-loop iteration, convergence behavior and computational efficiency require further investigation.

(2) Multi-Period Dynamic Programming: Rather than treating penetration scenarios as independent snapshots without temporal dependencies, future work should incorporate the sequential growth of BET penetration alongside infrastructure expansion and retirement timelines. Transitioning from static scenario analysis to progressive deployment pathway optimization will better support long-term infrastructure planning.

(3) Large-Scale Network Scalability: To extend the model beyond the current controlled network size to expansive real-world expressway networks with hundreds of routes and thousands of candidate nodes, acceleration strategies must be developed. Addressing the computational bottleneck of scenario tree expansion will require adapting clustering, pruning, and decomposition algorithms to this framework.

(4) Multi-Source Uncertainty Integration: The current model uses an average equivalent energy consumption rate and does not explicitly capture short-term variations caused by payload, road gradient, weather, traffic conditions, or driving behavior. Other uncertainties, including traffic demand fluctuations, battery degradation, electricity prices, and technological evolution, are also not considered. Future research could integrate physics-

based or data-driven energy models with robust optimization or stochastic programming to evaluate their impacts on demand, siting, and sizing.

(5) Economic Boundary Extension: Future extensions may broaden the economic boundary by endogenizing grid reinforcement and land-acquisition costs, incorporating renewable generation and energy-storage investments, and introducing charging service revenue. This would enable the framework to evolve from infrastructure cost minimization toward integrated operator-oriented investment and profitability analysis.

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