Optimizing Electric Bus Charging Station Locations: An Integrated Land-Use and Transportation Approach

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Abstract: Existing research on optimizing electric bus charging station locations often assumes an exogenous demand, overlooking the feedback effects of station locations on demand. Moreover, the long-term implications of location strategies are deeply influenced by the complex interactions between land-use and transportation systems. To address these two challenges simultaneously, this study develops a bi-level programming model—a hierarchical decision-making framework involving two interconnected problems. Specifically, the upper-level problem is formulated as a mixed integer nonlinear programming model that minimizes the electric bus system's investment, operation, and passenger waiting time costs by optimizing the fleet size of electric buses, the corresponding frequency setting, and the location and capacity of charging stations. The lower-level model is an integrated land-use and transportation model that captures the long-term impacts of upper-level location decisions on transportation and land-use systems. To solve the proposed model, an iterative solution method is devised, which employs Gurobi to generate upper-level decisions via solving a linearized upper-level model and subsequently evaluates the decisions via TRNUS, which is an integrated land-use and transportation model, in the lower-level. Case studies are carried out using real data from Jiangyin City, China. The results demonstrate that the optimal design considering the interaction between land use and transportation attracts a higher number of bus users across various routes and increases the share of passenger kilometers travelled by bus from 19.9% to 20.5%. Meanwhile, it contributes to alleviating traffic congestion by 2.7%, improving regional accessibility by 0.4%, and reducing vehicle carbon emissions by 1.1%, promoting urban sustainability.

Keywords: Electric bus; Charging station location; Integrated land-use and transportation model; Bi-level modelling

1 Introduction

Over the past several decades, accelerated urbanization and rapid population growth have led to a continuous increase in travel demand. This growing demand, however, has outstripped the limited transportation capacity, leading to an exacerbated imbalance between supply and demand for transportation resources (Liu et al., 2019; Yuan et al., 2019; Alvo et al., 2021; Song et al., 2021). This imbalance has resulted in various social issues, including intensified traffic congestion, which has emerged as a global “urban disease” that severely hinders economic and social development and positions the transportation sector as a major contributor to energy consumption, climate change, and deteriorating air quality (Schrank et al., 2021; Zhao et al., 2024). For example, in the United States, congestion-related economic losses—including travel delays and additional energy consumption—exceed \$300 billion annually (NASEM, 2018). Moreover, the International Renewable Energy Agency states that nearly a quarter of global energy-related carbon emissions originate from the transportation sector (IRNEA, 2024). If transportation networks continue to expand while remaining reliant on fossil fuels, global carbon emissions from this sector could rise by nearly 60% by 2050 (World Bank, 2023). In light of these challenges, exploring urban transportation solutions that meet the growing travel demand while promoting sustainable urban development has become imperative (Cheng et al., 2022; Camilleri et al., 2023; Jia et al., 2024a).

Electric buses, recognized for their green, economical, and efficient attributes, have emerged as an important tool in mitigating climate change and fostering sustainable development in urban transportation (Li et al., 2016; Liu et al., 2019; Yıldırım & Yıldız, 2021; Liu et al., 2023; Zeng & Qu, 2023). On one hand, electric buses can help alleviate congestion by reducing private car usage. On the other hand, their zero-emission and low-noise characteristics effectively diminish local environmental pollution (Li et al., 2016; Gao et al., 2017; Li et al., 2024; Tang et al., 2024). With substantial government support, the adoption of electric buses has become a prevailing global trend (Huang & Wang, 2022). For instance, China's New Energy Vehicle Industrial Development Plan envisions electric vehicles comprising the majority of new vehicle sales by 2035—alongside complete electrification of the public fleet (General Office of the State Council of the People's Republic of China, 2020). The European Union has set a strategic target for 100% zero-emission urban buses by 2030, while the United States has implemented financial incentives and supportive policies to promote electric bus adoption (IEA, 2023). This global shift underscores the pivotal role of public transportation electrification in pursuing sustainable urban transportation (Xu et al., 2020; Li et al., 2021).

Realizing the full benefits of electric buses depends on the development of a well-designed and strategically deployed charging infrastructure (Zhu et al., 2016; Gao et al., 2017; Zeng & Qu, 2023;

Qu et al., 2024). Due to electric buses facing challenges such as limited driving range and extended charging times, sub-optimal charging infrastructure will constrain the reliability and efficiency of electric bus service (Wang et al., 2017; Rogge et al., 2018; Bie et al., 2021; Zhou et al., 2022a; Zhao et al., 2024). For example, inadequately distributed or inconveniently located stations compel buses to detour for charging and queue at occupied charging piles, increasing operation cost and degrading service level. Consequently, many scholars have highlighted the critical need for the strategic deployment of charging infrastructure that facilitates rapid, convenient charging (Li et al., 2016; Chen et al., 2018; An, 2020; Xu et al., 2020; Uslu & Kaya, 2021; Manzolli et al., 2022; Perumal et al., 2022; Hu et al., 2024; Qu et al., 2024; Zhou et al., 2024). A well-designed charging infrastructure is not only an operational necessity for preventing electric bus service interruptions during operations but also central to building passenger confidence and stimulating ridership growth, thereby underpinning the long-term sustainability of electric bus systems.

Table 1 Summary of literature

Publications	Demand modelling	Demand source	Impact of station location on demand
An (2020)	Exogenous demand	Random generated	Mode choice and route choice
Esmaeilnejad et al. (2023)	Exogenous demand	Random generated	Mode choice and route choice
Guschinsky et al. (2021)	Exogenous demand	Constant demand	None
He et al. (2019)	Exogenous demand	Constant demand	None
He et al. (2023)	Exogenous demand	Constant demand	None
Hu et al. (2022)	Exogenous demand	Robust demand	Mode choice and route choice
Kunith et al. (2017)	Exogenous demand	Constant demand	None
Liu et al. (2018)	Exogenous demand	Robust demand	Mode choice and route choice
Reda et al. (2024)	Exogenous demand	Constant demand	None
Uslu and Kaya (2021)	Exogenous demand	Constant demand	None
Wang et al. (2022)	Exogenous demand	Constant demand	None
Zeng et al. (2023)	Exogenous demand	Constant demand	Mode choice and route choice
Zhou et al. (2022b)	Exogenous demand	Robust demand	Mode choice and route choice
This paper	Endogenous demand	The integrated land-use and transportation model	Mode choice, route choice, residential and employment location choices, and accessibility

Thus, extensive studies have been devoted to determining the charging station locations, and various strategies and models have been proposed in the literature (de Briñas Gorosabel et al., 2022; Manzolli et al., 2022; Perumal et al., 2022). However, these studies often assume an exogenous travel demand or charging demand. That is, the demand and its distribution are treated as fixed parameters within the model, regardless of the location of charging stations or changes in the transportation system (Wang et al., 2016; Kunith et al., 2017; Xylia et al., 2017; Chen et al., 2018; Wei et al., 2018; He et al., 2019; Guschinsky et al., 2021; Liu et al., 2021; Uslu & Kaya, 2021; Wu et al., 2021; Wang et al., 2022; He et al., 2023; Zeng et al., 2023; Reda et al., 2024). Although a few studies (Liu et al., 2018; An, 2020; Hu et al., 2022; Zhou et al., 2022b; Esmaeilnejad et al., 2023) have explored demand uncertainty via stochastic programming and robust optimization, they still rely on predefined distributions of travel demand, thereby failing to overcome the limitations of exogenous demand assumptions. Table 1 highlights these constraints. For example, An (2020) assumed that travel demand follows a specified normal distribution and employed Latin hypercube sampling to build a limited number of demand scenarios to represent fluctuations in travel demand. Similarly, Zhou et al. (2022b) adopt robust optimization to ensure that the location decisions remain feasible under the worst-case scenario. However, this approach remains dependent on fixed demand estimates to build the worst-case scenario.

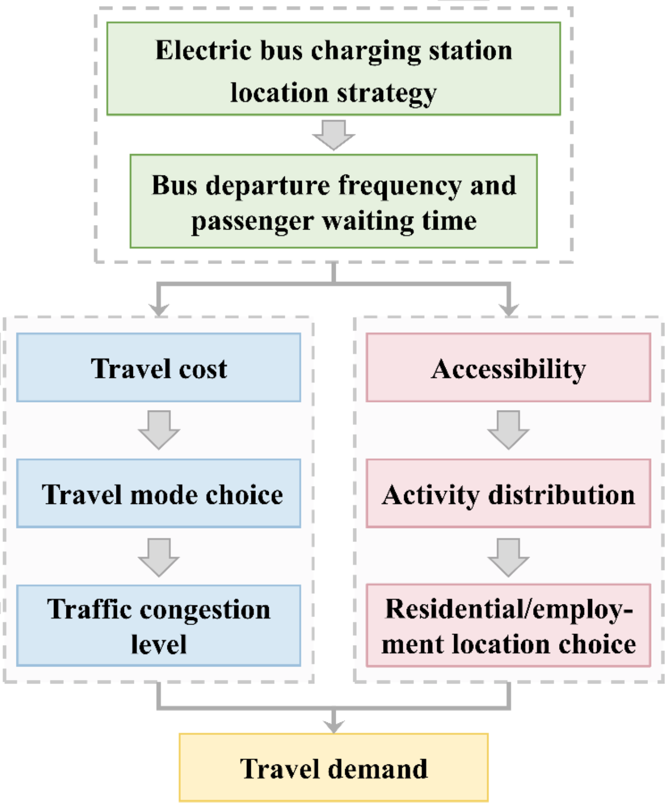

Fig. 1 The impact of electric bus charging station location strategy on travel demand

A crucial aspect has been overlooked is that travel demand is a derived demand, and variations in charging station location can induce feedback effects on travel demand (Szeto et al., 2015; Zhong & Sun, 2022). Specifically, in the short term, deploying electric bus charging stations affects bus departure frequencies, altering users' waiting times and travel costs (Uslu & Kaya, 2021; He et al., 2022). These changes influence travel mode choices and traffic congestion levels, ultimately impacting bus travel demand (Hamdouch et al., 2014; Tyndall, 2018; Zhong & Sun, 2022; Wang et al., 2024b). In the long term, charging station locations also affect regional accessibility, shaping the spatial decisions of residents and enterprises, which further influences bus travel demand, as illustrated in Fig. 1 (Bartholomew & Ewing, 2008; Zhong et al., 2015; Zhong et al., 2022; Liu et al., 2024). Indeed, Kasraian et al. (2016), Wu et al. (2019), Pasha et al. (2020), Guzman et al. (2021), and Ma et al. (2023) have demonstrated that improving public transportation infrastructure can significantly reshape urban land use and spatial structure. Therefore, ignoring the feedback effects of location strategies on travel demand may result in charging stations failing to accommodate actual demand changes (Ye et al., 2021). Such oversight will lead to inefficient resource allocation, thereby lowering charging station utilization and impeding the sustainable development of the electric bus system. To address this issue, it is essential to incorporate feedback effects into the charging station location model. Moreover, charging infrastructure should not only meet current operational needs but also align with the city's long-term development goals to achieve comprehensive economic and social benefits (Szeto et al., 2015; Kuo et al., 2023). However, few studies have evaluated the long-term impacts of location strategies on transportation and land-use systems.

To simultaneously address the challenges of accounting for travel demand feedback effects and analyzing the long-term impacts, this study develops a bi-level programming model. Specifically, the upper-level model optimizes the electric bus charging station locations to minimize the investment, operation, and passenger waiting time costs. The lower-level model, an integrated land-use and transportation model, analyzes the long-term impacts of upper-level location decisions on transportation and land-use systems. By capturing the interaction between land use and transportation systems, the proposed modelling framework can identify the optimal location strategy and quantify its impacts on both land-use and transportation systems. This study not only highlights the importance of the integrated land-use and transportation perspective in the electric bus charging infrastructure planning but also provides valuable insights for policymakers, enabling them to make informed decisions that align with urban development goals and promote sustainable development. The main contributions of this study are listed as follows.

(1) Propose to take into account the interaction between land use and transportation in the context of optimizing charging locations for electric buses.
(2) Propose to evaluate the broader impacts of charging station location strategies, population density, employment density, regional accessibility, travel mode choice, congestion level, and vehicle carbon emissions.

(3) Establish a bi-level programming model that captures the proposed interaction and impacts and develops a solution method to solve the model.

(4) Conduct case studies using real data to validate the proposed model and highlight its implications.

The remainder of this paper is structured as follows: Section 2 introduces the problem and the proposed bi-level programming model. Section 3 applies the model to a practical case in Jiangyin City. Section 4 presents the results and analysis. Section 5 concludes the paper and suggests directions for future research.

2 Methods

2.1 Problem description

This study considers an envisioned scenario wherein all conventional diesel buses in a city are fully replaced by electric buses. Under this transition, the primary challenge for bus operators is to optimize the location and capacity of charging stations, the fleet size and corresponding frequency, with the aim of minimizing electric bus system's investment, operation, and passenger waiting time costs while meeting bus travel demand and passenger waiting time constraints. Meanwhile, the effects of charging station locations on travel demand by either affecting their travel choices or influencing their activity distributions as a result of the changes in accessibility measured by land used model. To facilitate the model development, the following assumptions are made, while all the notations used in the model formulation are provided in Appendix A.

A1) All electric buses are homogeneous, with same battery capacity, discharge rate, and charging rate (Wang et al., 2022).

A2) The battery capacity of each electric bus is sufficient to complete at least one full trip before recharging (Perumal et al., 2022).

A3) Electric buses can only be charged after completing one or more trips; that is, buses are not permitted to go to charging stations from intermediate stops but only from bus terminals (Guschinsky et al., 2021; Hu et al., 2022).

A4) Each bus terminal is served by only one designated charging station (Chen et al., 2018).

A5) Electric buses are allowed to charge during operation periods and occupy an integer number of time intervals on a single charging pile (Pourvaziri et al., 2024).

A6) Bus routes are unidirectional, meaning that outbound and inbound trips are served by separate routes (Zeng et al., 2023).

A7) Each bus route is associated with a unique originating terminal. When multiple bus routes originate from the same physical terminal, their terminals are assigned distinct indices (An, 2020).

A8) Candidate charging stations are distinguished by their geographic locations, and at most one charging station can be constructed at each location (Kunith et al., 2017).

A9) Given the strategic planning scope of this study, both travel and charging demands are aggregated at the originating terminals of each bus route, rather than analyzed at the microscopic level of individual vehicle operations (An, 2020).

2.2 Bi-level programming model

To capture the hierarchical decision-making structure and incorporate the feedback effects of location strategies on bus travel demand in the electric bus charging station location problem, a bi-level programming approach is devised, as illustrated in Fig. 2.

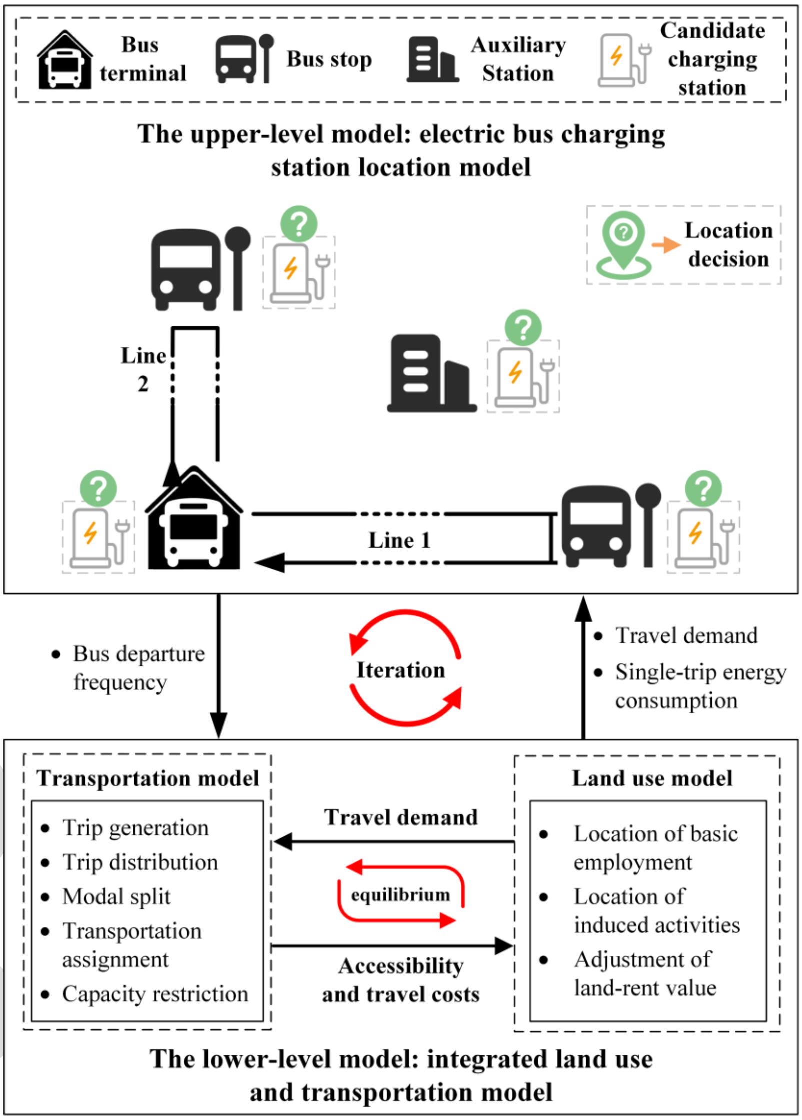

Fig. 2 Overview of the bi-level programming framework

The upper-level model, representing strategic planning decisions, determines the optimal charging station locations based on the bus travel demand and single-trip energy consumption output from the lower-level model. The lower-level integrated land-use and transportation model serves as a behavioral response mechanism, simulating the interactive feedback processes between land-use and transportation systems under a given charging station location strategy (characterized by bus departure frequency), thus capturing the impact of the location strategy on travel demand and single-trip energy consumption. By incorporating the feedback relationships between land use and transportation systems, the bi-level programming model not only identifies the optimal charging station location strategy but also quantifies its broader impacts.

2.3 The upper-level model

2.3.1 Model formulation

Let I represent the set of bus terminals. J denotes the set of candidates charging stations, which could include bus terminals, bus stops, and off-route auxiliary stations. This study divides an operation day into a series of hourly time intervals $t \in T = \{1, 2, 3..., h\}$ where $h = 24$, and T_{day} and T_{night} denote the set of time intervals in bus operation and non-operation hours. The travel demand at bus terminal i during time interval t, denoted P_{it}, is obtained from the lower-level integrated land-use and transportation model. Similarly, energy consumption of a whole trip on bus route originating from terminal i during time interval t, denoted e_{it}, is also output from the lower-level model and depends on road traffic conditions.

This study calculates the energy consumption at bus terminal i during time interval t as $\frac{e_{it} f_{it}}{Q}$, measured in bus*hours, based on departure frequency f_{it}, single-trip energy consumption e_{it}, and charging efficiency of a charging pile Q (An, 2020). Since electric buses need not be charged immediately after energy consumption, operators can delay charging as operation needs to dictate. This study defines q_{it} as the cumulative charging demand at bus terminal i till time interval t, which is an integer variable. To avoid resource waste, we assume each bus can request at most t time intervals for charging after operation for t intervals during the operation periods T_{day}. Accordingly, when $t \in T_{\text{day}}$, the cumulative charging demand q_{it} takes the smaller value between $\left\lfloor \sum_{n=1}^{t} \frac{e_{in} f_{in}}{Q} \right\rfloor$ and $\sum_{n=1}^{t} f_{in}$, where $\sum_{n=1}^{t} \frac{e_{in} f_{in}}{Q}$ is rounded down to avoid overcharging electric buses. At the end of an operation day, the total cumulative charging demand at bus terminal i, denoted as q_{ih}, must be fully met before the next day's operation, that is, $q_{ih} = \left\lceil \sum_{t \in T} \frac{e_{it} f_{it}}{Q} \right\rceil$.

In this study, an electric bus can be assigned to charge for an integer number of time intervals.

While a bus is charging at a charging station, its assigned charging pile is temporarily unavailable to other electric buses. To incentivize off-peak charging, minimize energy costs, and alleviate strain on the power grid, this study adopts a time-of-use electricity price C_t and applies different rates for operation periods T_{day} and non-operation periods T_{night}.

Based on the above description, the bus operator must make the following decisions:

(1) The locations of charging stations, $x_j,\ \forall j \in J$, which is a binary variable indicating whether a charging station is constructed at candidate location j.

(2) Bus terminal assignment, $y_{ij}, \forall i \in I, j \in J$, which is a binary variable representing whether bus terminal i is assigned to charging station j, meaning that the buses of all the bus line departing from terminal i are assigned to be charged at station j.

(3) Charging pile deployment, $s_j, \forall j \in J$, which is an integer variable denoting the number of charging piles installed at charging station j.

(4) Bus departure frequency, $f_{it},\ \forall i \in I, t \in T$, which is an integer variable representing the bus departure frequency from bus terminal i during time interval t, to ensure that passenger travel demand can be met.

(5) Number of charging buses, $w_{ijt}, \forall i \in I, j \in J, t \in T$, which is an integer variable denoting the number of electric buses from bus terminal i charging at station j during time interval t.

(6) Fleet size, $z_i, \forall i \in I$, which is an integer variable indicating the total electric bus fleet at terminal i. Since electric buses can be charged during operation periods T_{day}, z_i should still be able to meet travel demand even when some buses are assigned to charge.

The electric bus charging station location optimization problem can be expressed as:

$$\min \underbrace{\sum_{j\in J} G^{\text{sta}} x_j + \sum_{j\in J} G^{\text{chg}} s_j + \sum_{i\in I} G^{\text{bus}} z_i}_{\text{investment cost}} + \underbrace{\sum_{i\in I}\sum_{j\in J} G^{\text{dis}} D_{ij} q_{ih} y_{ij} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} C_t w_{ijt}}_{\text{operation cost}} + \underbrace{\sum_{i\in I}\sum_{t\in T_{\text{day}}} \frac{1}{2} \text{Vowt}\, P_{it} \frac{60}{f_{it}}}_{\text{passenger waiting time cost}} \quad (1)$$

subject to

$$y_{ij} \le x_j, \quad \forall i \in I, j \in J \quad (2)$$

$$\sum_{j\in J} y_{ij} = 1, \quad \forall i \in I \quad (3)$$

$$\sum_{i\in I} w_{ijt} \le s_j x_j, \quad \forall j \in J, t \in T \quad (4)$$

$$w_{ijt} \le s_j y_{ij}, \quad \forall i \in I, j \in J, t \in T \quad (5)$$

$$s_j \le \mathrm{Chg}^{\max} x_j, \quad \forall j \in J \tag{6}$$

$$s_j \ge \mathrm{Chg}^{\min} x_j, \quad \forall j \in J \tag{7}$$

$$\frac{1}{2}\frac{60}{f_{it}} \le \mathrm{Wt}^{\max}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{8}$$

$$\mathrm{Cap}^{\mathrm{bus}} f_{it} \ge P_{it}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{9}$$

$$\sum_{n=1}^{t} w_{ijn} \le q_{it} y_{it}, \quad \forall i \in I, j \in J, t \in T_{\mathrm{day}} \tag{10}$$

$$\sum_{n=1}^{h} w_{ijn} = q_{ih} y_{it}, \quad \forall i \in I, j \in J \tag{11}$$

$$f_{it} + \sum_{j \in J} w_{ijt} \le z_i, \quad \forall i \in I, t \in T \tag{12}$$

$$\mathrm{cec}_{it} \le \sum_{n=1}^{t} \frac{e_{in} f_{in}}{Q}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{13}$$

$$\mathrm{cec}_{it} \ge \sum_{n=1}^{t} \frac{e_{in} f_{in}}{Q} - 1 + \frac{1}{M}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{14}$$

$$q_{it} \le \sum_{n=1}^{t} f_{in}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{15}$$

$$q_{it} \le \mathrm{cec}_{it}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{16}$$

$$q_{it} \ge \sum_{n=1}^{t} f_{in} - M\alpha_{it}, \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{17}$$

$$q_{it} \ge \mathrm{cec}_{it} - M(1 - \alpha_{it}), \quad \forall i \in I, t \in T_{\mathrm{day}} \tag{18}$$

$$q_{ih} \ge \sum_{t \in T} \frac{e_{it} f_{it}}{Q}, \quad \forall i \in I \tag{19}$$

$$q_{ih} \le \sum_{t \in T} \frac{e_{it} f_{it}}{Q} + 1 - \frac{1}{M}, \quad \forall i \in I \tag{20}$$

$$\sum_{t \in T_{\mathrm{night}}} \sum_{j \in J} w_{ijt} \le \sigma z_i, \quad \forall i \in I \tag{21}$$

$$x_j, y_{ij}, \alpha_{it} \in \{0,1\}, \quad \forall i \in I, j \in J, t \in T \tag{22}$$

$$s_j, f_{it}, w_{ijt}, z_i, \mathrm{cec}_{it}, q_{it} \in \mathbb{Z}_+, \quad \forall i \in I, j \in J, t \in T. \tag{23}$$

The objective Eq. (1) is to minimize the total costs, which contain three parts. The first term represents the investment cost of the electric bus system, where G^{sta}, G^{chg}, and G^{bus} respectively represent the daily fixed construction cost per charging station, the daily installation cost per charging pile, and the daily purchase cost per electric bus The second term represents the operation cost of electric buses, including the travel costs associated with electric buses traveling to charging stations and charging costs. Here, D_{ij} denotes the distance from bus terminal i to charging station j and G^{dis} denotes the unit travel cost for an electric bus to the charging station. The third term calculates the passenger waiting time cost, aiming to enhance service quality, where Vowt represents the value of passengers' waiting time.

Constraint (2) ensures that charging assignments only occur at charging stations that are in operation. Constraint (3) mandates that each bus terminal must be assigned to one charging station for charging. Constraint (4) stipulates that, during any time interval, the number of buses assigned to a charging station cannot exceed the number of charging piles installed at that station. Constraint (5) further restricts electric bus charging exclusively to the assigned charging stations. Constraints (6) and (7) impose upper and lower bounds on the number of charging piles at each station, preventing both resource wastage and insufficient supply (Wang et al., 2024a). In constraints (6) and (7), $\text{Chg}^{\max}$ and $\text{Chg}^{\min}$ represent the maximum and minimum number of charging piles installed in a charging station, respectively. Constraint (8) ensures that the departure interval of electric buses is shorter than the maximum acceptable waiting time $\text{Wt}^{\max}$ for bus passengers. Constraint (9) guarantees that the bus travel demand P_{it} at each terminal is fully met, avoiding any shortfall in service. Cap^{bus} represents bus capacity. Constraint (10) restricts electric buses from overcharging and allows for delayed charging during operation periods T_{day}. This permits an imbalance between energy consumption and charging during operation periods T_{day}. Constraint (11) requires that the total cumulative charging demand q_{ih} must be fully satisfied by the end of an operation day to meet the operation requirements of the next day. Constraint (12) ensures that the fleet size z_i at bus terminal i remains sufficient to meet travel demand during operation periods T_{day} when some buses are assigned to charging. During non-operation periods T_{night}, constraint (12) also stipulates that z_i is not less than the number of vehicles requiring charging. In constraint (12), $\sum_{j\in J} w_{ijt}$ calculates the number of buses requiring charging at bus terminal i during time interval t. Constraints (13)–(14) define the cumulative energy consumption cec_{it} at bus terminal i till time interval t and set it to $\left\lfloor \sum_{n=1}^{t} \frac{e_{in} f_{in}}{Q} \right\rfloor$, with M denoting a sufficiently large positive constant. Constraints (15)–(18) specify that during operation periods T_{day}, the cumulative charging demand q_{it} at bus terminal i is the minimum of the cumulative energy consumption cec_{it} and $\sum_{n=1}^{t} f_{in}$ (An, 2020). A binary variable α_{it} is introduced to select between these two values. Constraints (19)–(20) require that the total cumulative charging demand q_{ih} at bus terminal i for a whole day be equal to $\left\lceil \sum_{t\in T} \frac{e_{it} f_{it}}{Q} \right\rceil$. Constraint (21) sets the maximum charging supply capacity during non-operation periods T_{night}, preventing the postponement of all charging demands to non-operation periods and ensuring that it does not exceed the total depleted-state charging demand for the entire fleet. The parameter σ represents the number of hours required to fully recharge a depleted electric bus. In practical operations, buses rarely deplete their batteries completely (often retaining a 20% reserve) (Zhou et al., 2016; An, 2020; Li et al., 2021; Hu et al., 2022). Constraints (22) and (23) specify the domain of decision variables (Zhou et al., 2022b; Huang et al., 2023).

2.3.2 Model linearization

Due to nonlinear relationships within the objective function and constraints, the upper-level model belongs to a mixed-integer nonlinear optimization problem, which significantly increases the complexity of solving the problem. To address this challenge, the model is linearized and reformulated as a mixed-integer linear programming model via the following procedures.

Firstly, to linearize the second term of the objective function (1) and constraint (11), we define auxiliary decision variables l_{ijh} to represent $q_{ih} y_{ij}$. The objective function (1) is then equivalently transformed into equation (24), while constraint (11) is replaced with the linear constraint (25).

$$\min \underbrace{\sum_{j\in J} G^{\text{sta}} x_j + \sum_{j\in J} G^{\text{chg}} s_j + \sum_{i\in I} G^{\text{bus}} z_i}_{\text{investment cost}} + \underbrace{\sum_{i\in I}\sum_{j\in J} G^{\text{dis}} D_{ij} l_{ijh} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} C_t w_{ijt}}_{\text{operation cost}} + \underbrace{\sum_{i\in I}\sum_{t\in T_{\text{day}}} \frac{1}{2} \text{Vowt}\, P_{it} \frac{60}{f_{it}}}_{\text{passenger waiting time cost}} \quad (24)$$

$$\sum_{t\in T} w_{ijt} = l_{ijh}, \quad \forall i \in I, j \in J. \quad (25)$$

Meanwhile, to ensure $l_{ijh} = q_{ih} y_{ij}, \forall i \in I, j \in J$, the following linear constraints (26)–(29) are introduced, requiring that when $y_{ij} = 1$, $l_{ijh} = q_{ih}$; otherwise, $l_{ijh} = 0$.

$$l_{ijh} \le M y_{ij}, \quad \forall i \in I, j \in J \quad (26)$$

$$l_{ijh} \le q_{ih}, \quad \forall i \in I, j \in J \quad (27)$$

$$l_{ijh} \ge q_{ih} - M\left(1 - y_{ij}\right), \quad \forall i \in I, j \in J \quad (28)$$

$$l_{ijh} \in \mathbb{Z}_+, \quad \forall i \in I, j \in J. \quad (29)$$

Secondly, to linearize the third term of the objective function, this study introduces a continuous variable d_{it} to represent $\frac{1}{f_{it}}$. By using d_{it} as a surrogate, the objective function (24) is further transformed into equation (30).

$$\min \underbrace{\sum_{j\in J} G^{\text{sta}} x_j + \sum_{j\in J} G^{\text{chg}} s_j + \sum_{i\in I} G^{\text{bus}} z_i}_{\text{investment cost}} + \underbrace{\sum_{i\in I}\sum_{j\in J} G^{\text{dis}} D_{ij} l_{ijh} + \sum_{i\in I}\sum_{j\in J}\sum_{t\in T} C_t w_{ijt}}_{\text{operation cost}} + \underbrace{\sum_{i\in I}\sum_{t\in T_{\text{day}}} 30\text{Vowt} P_{it} d_{it}}_{\text{passenger waiting time cost}}. \quad (30)$$

Moreover, to link d_{it} with discrete departure frequency f_{it}, this study introduces the linear constraints (31)–(38). Since f_{it} is an integer variable with a limited feasible range, we define the set of possible values as $\{f_{it1},...,f_{itk},...,f_{itK}\}$, $\forall i\in I, t\in T_{\text{day}}$. Let f_{itk} , $k\in K$ denote the k-th feasible value of f_{it} and K denote the number of discrete values. Because f_{it} must choose exactly one value from the set $\{f_{it1},...,f_{itk},...,f_{itK}\}$, we introduce a binary variable β_{itk} to indicate whether f_{it} takes the value f_{itk}. Specifically, if $\beta_{itk}=1$, then $f_{it}=f_{itk}$; otherwise, f_{itk} is not selected.

$$f_{it} = \sum_{k\in K} \beta_{itk} f_{itk}, \quad \forall i\in I, t\in T_{\text{day}} \quad (31)$$

$$\sum_{k\in K} \beta_{itk} = 1, \quad \forall i\in I, t\in T_{\text{day}} \quad (32)$$

$$d_{it} \geq \frac{1}{f_{itk}} - M\left(1-\beta_{itk}\right), \quad \forall i\in I, t\in T_{\text{day}}, k\in K \quad (33)$$

$$d_{it} \leq \frac{1}{f_{itk}} + M\left(1-\beta_{itk}\right), \quad \forall i\in I, t\in T_{\text{day}}, k\in K \quad (34)$$

$$0 < d_{it} \leq 1, \quad \forall i\in I, t\in T_{\text{day}} \quad (35)$$

$$d_{it} = 0, \quad \forall i\in I, t\in T_{\text{night}} \quad (36)$$

$$d_{it} \in \mathbb{R}_+, \quad \forall i\in I, t\in T \quad (37)$$

$$\beta_{itk} \in \{0,1\}, \quad \forall i\in I, t\in T, k\in K. \quad (38)$$

Next, instead of using d_{it} to replace $\frac{1}{f_{it}}$ in constraint (8), we transform constraint (8) into its equivalent linear form, presented as equation (39).

$$30 \leq \text{Wt}^{\max} f_{it}, \quad \forall i\in I, t\in T_{\text{day}}. \quad (39)$$

Constraints (4), (5), and (10) are also converted into their equivalent linear forms, denoted as constraints (40), (41), and (42), respectively. Constraints (40)–(42) ensure that when charging station j is constructed ($x_j=1$) or when bus terminal i is assigned to charging station j ($y_{ij}=1$), the constraints revert to their original form. Conversely, when $x_j = 0$ or $y_{ij} = 0$, a sufficiently large constant M relaxes these constraints, making them non-binding to represent cases where the charging station j is not selected or assigned for charging.

$$s_j \geq \sum_{i \in I} w_{ijt} - M\left(1 - x_j\right), \quad \forall j \in J, t \in T \tag{40}$$

$$s_j \geq w_{ijt} - M\left(1 - y_{ij}\right), \quad \forall i \in I, j \in J, t \in T \tag{41}$$

$$q_{it} \geq \sum_{n=1}^{t} w_{ijn} - M\left(1 - y_{ij}\right), \quad \forall i \in I, j \in J, t \in T_{\text{day}} . \tag{42}$$

Finally, the linearized electric bus charging station location model comprises the objective function (30), along with constraints (2), (3), (6), (7), (9), (12)–(23), (25)–(29), and (31)–(42). This resultant model can be solved using off-the-shelf optimization solvers such as Gurobi.

2.4 The lower-level model

This study employs the TRANUS model as the lower-level integrated land-use and transportation model to assess the impacts of charging station location strategies on land-use and transportation systems. The TRANUS model integrates several foundational theories, including the discrete choice model, random utility theory, spatial microeconomics, input-output theory, and the transportation assignment model, enabling it to effectively capture the complex interactions between land-use and transportation systems (de la Barra et al., 1984; Zhong et al., 2015; Yuan et al., 2017; Capelle et al., 2019).

In TRANUS, a decision-maker or individual makes a series of land-use and transportation decisions according to the principle of utility maximization. Let V denote the decision option set. Land use decision options include residential location, employment location, etc., while transportation options include travel mode and travel route. The random utility function, $u_g\left(W_o\right)$, associated with individual g choosing decision option $o \in V$ can be expressed as:

$$u_g\left(W_o\right) = v_g\left(W_o\right) + \epsilon_g, \quad \forall o \in V , \tag{43}$$

where $v_g\left(W_o\right)$ represents the deterministic part of the utility function; ϵ_g represents its random part; W_o denotes the measurable characteristics associated with decision option o. The probability that individual g chooses decision option o is:

$$\text{prob}_{go} = \text{prob}\left[u_g\left(W_o\right) > u_g\left(W_{o'}\right)\right], \quad \forall o' \neq o, o \in V . \tag{44}$$

Then, by generalizing the above principle for computing the probability of selecting an option from a given set, the TRANUS model can determine decision-makers' sequential choice probabilities.

For example, before choosing the travel mode and route from home to work, individuals must first decide on their residential and employment locations. These interrelated decision chains underpin the land-use and transportation sub-models within TRANUS, which will be elaborated in the following subsections.

(1) Land-use sub-model

The land-use sub-model in TRANUS simulates the production and consumption relationships among various land-use sectors based on input-output theory (Zhong et al., 2023). First, the model allocates land resources across different zones and determines the number and spatial distribution of "basic employment" sectors (e.g., government, industry) in the base year, according to external socioeconomic conditions. Basic employment refers to sectors whose output is not consumed by other sectors. We define a zone set H and a basic employment set B. As urban development occurs, changes in basic employment $m \in B$ are allocated incrementally to different zones, represented by:

$$\mathrm{be}_a^{m,\tau} = \mathrm{be}_a^{m,\tau-1} + \Delta\mathrm{be}^{m,\tau} \frac{u_a^{m,\tau}}{\sum_{a \in H} u_a^{m,\tau}}, \quad \forall a \in H, m \in B, \tau = 1,2,\dots,\mathrm{Tp}, \tag{45}$$

where $\mathrm{be}_a^{m,\tau}$ represents the number of basic employment of type m in zone a at time τ; $\mathrm{be}_a^{m,\tau-1}$ is its value in the previous time, and $\mathrm{be}_a^{m,0}$ represents the number of basic employment at base year; $\Delta\mathrm{be}^{m,\tau}$ represents the total increment of basic employment of type m at time τ compared to $\tau-1$; $u_a^{m,\tau}$ represents the utility of basic employment m in zone a at time τ, calculated based on available land area, accessibility, and other factors in the previous period (Zhong et al., 2015); Tp represents the total number of time slots.

Second, the formation and growth of basic employment not only generates land demand but also induce population growth and other employment activities, such as education, services, and health. Let N denote the induced activity set. The spatial location decisions of these induced activities $n \in N$ are determined by:

$$\mathrm{ia}_{ab}^{mn,\tau} = \mathrm{be}_a^{m,\tau} L^{mn,\tau} \frac{\mathrm{ldsup}_b^{\tau} \left(\mathrm{Attr}_b^{n,\tau}\right)^{\delta^{n,\tau}} u_{ab}^{n,\tau}}{\sum_{b \in H} \mathrm{ldsup}_b^{\tau} \left(\mathrm{Attr}_b^{n,\tau}\right)^{\delta^{n,\tau}} u_{ab}^{n,\tau}}, \quad \forall a,b \in H, n \in N, m \in B, \tau = 1,2,\dots,\mathrm{Tp}, \tag{46}$$

where $\mathrm{ia}_{ab}^{mn,\tau}$ represents the number of induced activity of type n in zone b generated by basic employment m in zone a at time τ; $L^{mn,\tau}$ is the coefficient matrix indicating the number of induced activity n generated by basic employment m at time τ; ldsup_b^{τ} represents the available land area in zone b at time τ; $\mathrm{Attr}_b^{n,\tau}$ is the attraction coefficient of zone b for induced activity

n at time τ; $\delta^{n,\tau}$ represents the aggregation tendency parameter; $u_{ab}^{n,\tau}$ represents the utility of induced activity n in zone b relative to the generating zone a at time τ. Utility $u_{ab}^{n,\tau}$ is calculated as follows:

$$u_{ab}^{n,\tau} = \exp\left(-\chi^{n}\, \mathrm{tc}_{ab}^{n,\tau} - \vartheta^{n}\, \mathrm{ldval}_{b}^{\tau}\right), \quad \forall a,b \in H, n \in N, \tau = 1,2,\ldots,\mathrm{Tp}, \tag{47}$$

where $\mathrm{tc}_{ab}^{n,\tau}$ represents the travel cost of induced activity n from zone a to zone b at time τ; $\mathrm{ldval}_{b}^{\tau}$ represents the land-rent value of zone b at time τ; χ^{n} and ϑ^{n} are the spatial location decision function parameters.

As various land-use activities are induced and formed, the land-use sub-model iteratively updates and adjusts land-rent values at time τ by considering the interaction between land supply and demand. Land-rent value is defined as the economic cost or price of utilizing land in a specific location.

Finally, changes in land-rent value feed back into the distribution and consumption of induced activities, causing the land-use sub-model to iterate until reaching equilibrium.

(2) Transportation sub-model

The transportation sub-model in TRANUS simulates urban traffic flows generated by the production and consumption activities within the land-use sub-model. TRANUS employs the four-step transportation model to analyze urban transportation activities: trip generation, trip distribution, modal split, and route assignment. The trip distribution process can be summarized as follows:

$$\mathrm{tvol}_{ab}^{\tau} = \frac{\omega^{\tau} \cdot \mathrm{ia}_{ab}^{\tau}}{\left(\mathrm{tc}_{ab}^{\tau}\right)^{\theta^{\tau}}}, \quad \forall a,b \in H, \tau = 1,2,\ldots,\mathrm{Tp}, \tag{48}$$

where $\mathrm{tvol}_{ab}^{\tau}$ represents the travel volume from zone a to zone b at time τ; ia_{ab}^{τ} is obtained from equation (46); tc_{ab}^{τ} is the travel cost from zone a to zone b at time τ; ω^{τ} and θ^{τ} are the trip-generation elasticity parameters.

In the transportation sub-model, individuals choose travel modes and routes according to the principle of expected utility maximization, influenced by factors such as travel time, travel cost, waiting time, and penalty factor. TRANUS is capable of modeling various travel modes, such as private car, public transportation, walking, and bicycle, along with multimodal trips (de la Barra et al., 1984). For instance, a traveler may walk to a bus stop, take the bus, and then complete the journey by another mode. Let R represent the travel mode set and Z represent the travel route set. Mode choice and route assignment are represented by:

$$\mathrm{tvol}_{ab}^{r,\tau} = \mathrm{tvol}_{ab}^{\tau} \frac{\exp\left(-\gamma^{\tau}\,\mathrm{tc}_{ab}^{r,\tau}\right)}{\sum_{r\in R}\exp\left(-\gamma^{\tau}\,\mathrm{tc}_{ab}^{r,\tau}\right)}, \quad \forall a,b \in H, r\in R, \tau = 1,2,...,\mathrm{Tp}, \tag{49}$$

$$\mathrm{tvol}_{ab}^{rp,\tau} = \mathrm{tvol}_{ab}^{r,\tau} \frac{\mathrm{Rcap}^{rp,\tau}\exp\left(-\mu^{r,\tau}\,\mathrm{tc}_{ab}^{rp,\tau}\right)}{\sum_{p\in Z}\left[\mathrm{Rcap}^{rp,\tau}\exp\left(-\mu^{r,\tau}\,\mathrm{tc}_{ab}^{rp,\tau}\right)\right]}, \quad \forall a,b \in H, r\in R, p\in Z, \tau = 1,2,...,\mathrm{Tp}, \tag{50}$$

where $\mathrm{tvol}_{ab}^{r,\tau}$ is the travel volume from zone a to zone b via mode r at time τ; $\mathrm{tvol}_{ab}^{rp,\tau}$ is the travel volume via mode r on route p at time τ; $\mathrm{Rcap}^{rp,\tau}$ represents the bottleneck capacity for travel mode r on route p at time τ; γ^{τ} and $\mu^{r,\tau}$ are mode choice and route assignment parameters, respectively.

For bus users, the travel cost $\mathrm{tc}_{ab}^{\mathrm{bus},\tau}$ incorporates explicit and implicit costs. The explicit cost is the bus fare $\mathrm{Fare}^{\mathrm{bus},\tau}$, while the implicit cost includes travel time cost and waiting time cost:

$$\mathrm{tc}_{ab}^{\mathrm{bus},\tau} = \mathrm{Fare}^{\mathrm{bus},\tau} + \mathrm{Vott}^{\tau}\cdot \mathrm{tt}_{ab}^{\mathrm{bus},\tau} + \mathrm{Vowt}^{\tau}\cdot \mathrm{wt}_{ab}^{\mathrm{bus},\tau}, \quad \forall a,b\in H, \tau=1,2,...,\mathrm{Tp}, \tag{51}$$

where $\mathrm{tt}_{ab}^{\mathrm{bus},\tau}$ and $\mathrm{wt}_{ab}^{\mathrm{bus},\tau}$ denote the travel time and waiting time from zone a to zone b at time τ, respectively; Vott^{τ} and Vowt^{τ} are the values of travel time and waiting time at time τ, respectively. The average waiting time depends on the bus departure frequency. For private car users, travel costs are primarily determined by travel time and energy consumption, while for bicyclists and pedestrians, their costs depend on travel time.

Due to the limited road capacity, travelers' decisions are influenced not only by their activity but also by the travel behaviors of other users. The transportation sub-model thus adjusts travel times at time τ according to the volume of each mode. The adjusted travel times feed back into the trip generation process, initiating a new iteration of the transportation sub-model.

It is important to note that changes in the transportation system can lead to alterations in travel costs and accessibility, which in turn affect land-use attributes, structure, and spatial distribution (Geurs and Van Wee, 2004). TRANUS iterates between the land-use and transportation sub-models until they reach equilibrium.

After the TRANUS model reaches equilibrium, the energy consumption of different bus routes can be calculated based on road traffic conditions (de la Barra et al., 1984; Zhong et al., 2023). Since the travel speeds output by the transportation sub-model is link-based, energy consumption is calculated on a link-by-link basis. Let L denote the road link set. Energy consumption ec^{rc} per vehicle per unit distance for travel mode r on link $c\in L$ is calculated by:

$$\mathrm{ec}^{rc} = \mathrm{Ec}^{r,\min} + \left(\mathrm{Ec}^{r,\max} - \mathrm{Ec}^{r,\min}\right)\exp\left(-\varpi^{r}\,\mathrm{ts}^{rc}\right), \quad \forall r\in R, c\in L, \tag{52}$$

where $\mathrm{Ec}^{r,\min}$ is the minimum energy consumption per unit distance for a vehicle operating at free-flow speed; $\mathrm{Ec}^{r,\max}$ is the maximum energy consumption per unit distance for a vehicle operating at congested speed; ts^{rc} is the travel speed of travel mode r on link c; ϖ^{r} is the parameter regulating the steepness of the energy consumption curve. The total energy consumption of a single bus along the whole route is the sum of energy consumption across all links traveled.

2.5 Solution method

An iterative solution method is developed to solve the bi-level programming model, where the upper-level employs Gurobi to solve the linearized model, while the lower-level runs TRANUS, the integrated land-use and transportation model, to return the variables required to evaluate the upper-level objective. Fig. 3 provides an overview of the solution algorithm which involve the following steps.

Step 0. Collect data, including land-use distribution, population density, transportation network, and bus departure frequencies. Use the data to establish the lower-level integrated land-use and transportation model.

Step 1. Run the lower-level model to simulate the transportation and land-use systems under the current development pattern. This provides the upper-level model with the data on bus travel demand and single-trip energy consumption of electric buses.

Step 2. Using the output from the lower-level model, solve the upper-level electric bus charging station location optimization problem to obtain the optimal charging station locations, station capacities, bus departure frequencies, and bus fleet sizes.

Step 3. When the stopping criteria is met, the bi-level model iteration stops, and the optimal solution is output. Otherwise, go to ***Step 1***, feeding the newly determined charging station location strategy back into the lower-level model for re-simulation, entering a new iteration round.

The stopping criteria in this study is defined as: the change in the average economic cost per trip of the electric bus system between successive location solutions is small enough, where the average economic cost is calculated as the total cost divided by the total bus travel demand, that is,

$$\frac{\left(\underbrace{\sum_{j\in J}G^{\mathrm{sta}}x_j+\sum_{j\in J}G^{\mathrm{chg}}s_j+\sum_{i\in I}G^{\mathrm{bus}}z_i}_{\text{investment cost}}+\underbrace{\sum_{i\in I}\sum_{j\in J}G^{\mathrm{dis}}D_{ij}q_{ih}y_{ij}+\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}C_t w_{ijt}}_{\text{operation cost}}+\underbrace{\sum_{i\in I}\sum_{t\in T_{\mathrm{day}}}\frac{1}{2}\mathrm{Vowt}\,P_{it}\frac{60}{f_{it}}}_{\text{passenger waiting time cost}}\right)}{\sum_{i\in I}\sum_{t\in T_{\mathrm{day}}}P_{it}}. \quad (53)$$

Adopting an average cost as the stopping criteria, rather than the total cost (the objective function of the upper-level model), enables normalized comparisons across different travel demand scales and avoids biases arising from demand variations.

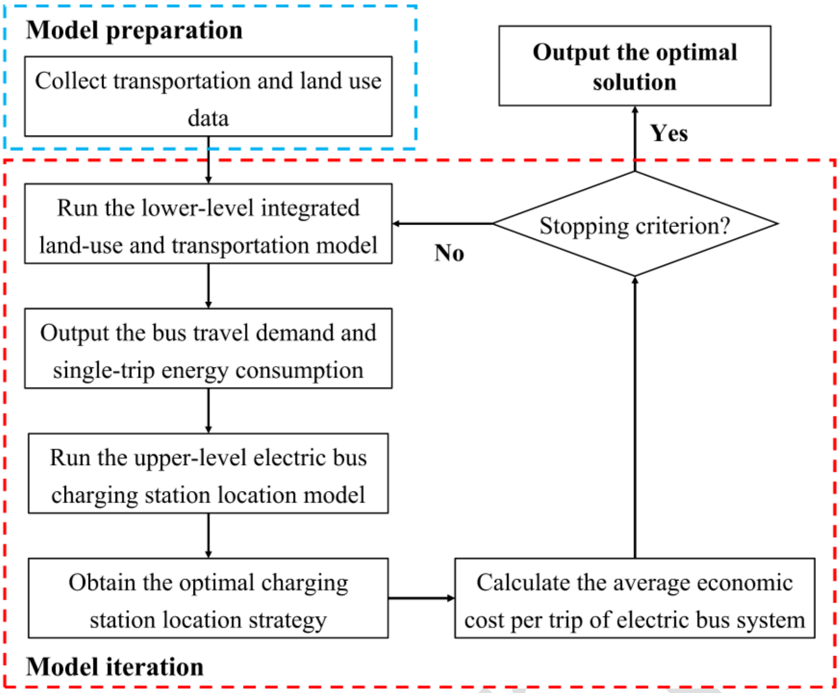

Fig. 3 Overview of the solution algorithm

3 Case study

3.1 Study area

This study selects Jiangyin City as the case study. It is located in the southeastern of Jiangsu Province, China, and is situated within the Yangtze River Economic Belt, benefiting from a geographically advantageous location and robust economic growth. In recent years, Jiangyin has been experiencing rapid urbanization, with the city size expanding and the population growing rapidly. This urban growth has been accompanied by a steady increase in motor vehicle ownership and travel demand, leading to severe traffic congestion and air pollution problems. In response, the urban planning department has proposed vigorously electrifying transit systems to alleviate traffic congestion and promote sustainable urban development. A critical component of this initiative is the strategic planning and deployment of electric bus charging stations.

We apply the proposed model to 30 bus routes within Jiangyin City, as depicted in Fig. 4. The data on bus route lengths and origins and destinations of each bus route are provided by the Jiangyin Municipal Transportation Bureau. There are 30 bus terminals, $I = 30$, and 70 candidate charging stations, including 18 bus terminals (since some routes share identical terminals, 12 terminals are removed, leaving 18 unique bus terminals), 42 bus stops, and 10 available construction locations given by Jiangyin City's land space planning.

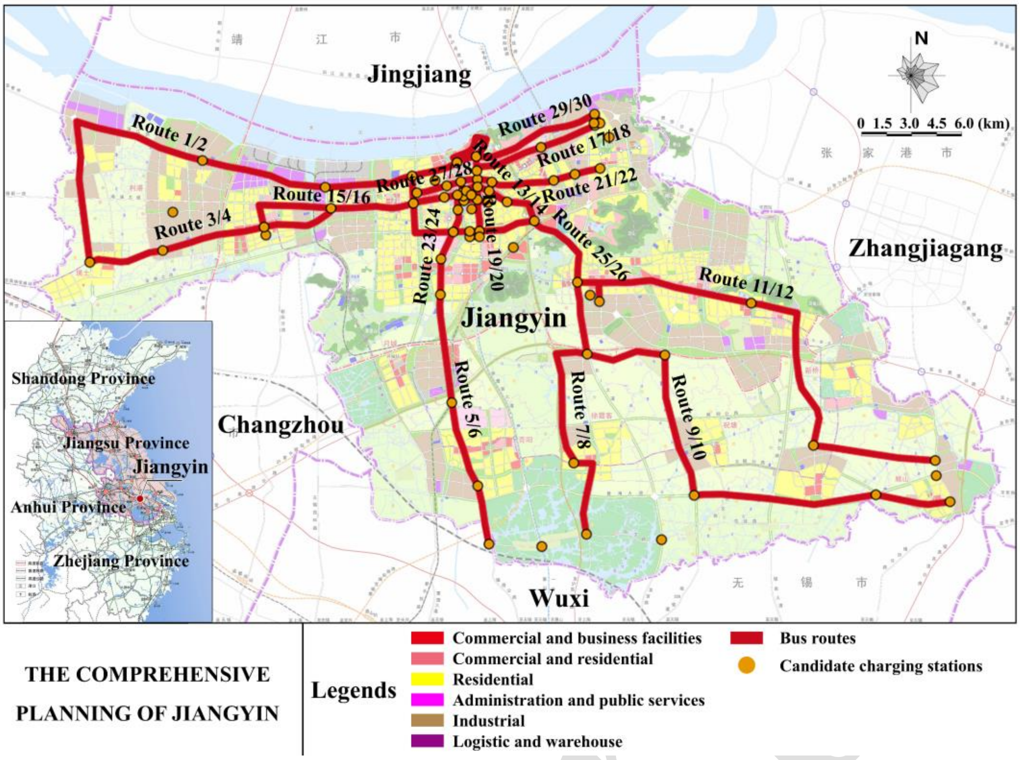

Fig. 4 Study area map

3.2 Parameter settings and data sources

The type of electric buses to be operated is assumed to be the BYD K9 electric bus, and the bus operation parameters are set accordingly. Specifically, based on BYD (2017) and An (2020), the electric bus driving range is set to 250 km, the battery capacity to 324 kWh, and the charging time to 6 hours. Given the differing service lives of charging stations, charging piles, and electric buses, this study uses daily costs, obtained by dividing their acquisition costs into the corresponding service life (He et al., 2019; An, 2020; Wang et al., 2022), to represent the related costs, including: $G^{\mathrm{sta}} = 46.6$ (charging station construction cost), $G^{\mathrm{sta}} = 6.9$ (charging pile installation cost), and $G^{\mathrm{bus}} = 79.5$ (electric bus purchase cost). Specifically, the charging station price is set at \$204,000 with a service life of 12 years (Chen et al., 2018; He et al., 2023); the charging pile price is set at \$25,250 with a service life of 10 years (An, 2020); and the electric bus purchase cost comprises both vehicle and battery components, with the vehicle priced at \$280,000 and a service life of 12 years, and the battery priced at \$105/kWh with a service life of 6 years (Zhou et al., 2016; He et al., 2019; An, 2020; Sina Technology, 2020; He et al., 2023). The charging efficiency of a charging pile (Q) is set to 54 kWh/h. Time-of-use electricity prices (C_t) follow the current electricity pricing standards of Jiangsu Province (State Grid Jiangsu Electric Power Company, 2024). The number of charging piles installed at a charging station is restricted to between 5 ($\mathrm{Chg}^{\min}$) and 30 ($\mathrm{Chg}^{\max}$) according to the Jiangsu Province public charging infrastructure construction regulation (Jiangsu New Energy Vehicle Promotion and Application Coordination Group, 2015) and previous research assumptions (Pourvaziri et al., 2024). Distances between bus terminals and candidate charging stations (D_{ij}) are calculated using the shortest driving routes, according to Baidu Map. The other parameter values applied in the upper-level model are provided in Table 2.

Table 2 Parameter settings of the upper-level model

Parameter	Notation	Value	Reference
Daily construction cost per charging station	G^{sta}	\$46.6	Chen et al. (2018); He et al. (2023)
Daily installation cost per charging pile	G^{sta}	\$6.9	An (2020)
Daily purchase cost per electric bus	G^{bus}	\$79.5	Zhou et al. (2016); He et al. (2019); An (2020); Sina Technology (2020); He et al. (2023)
Unit travel cost for an electric bus to a charging station	G^{dis}	\$0.34/km*bus *hour	BYD (2017); An (2020)
Operation period electricity price	$C_t,\ t \in T_{\text{day}}$	\$0.09/kWh	State Grid Jiangsu Electric Power Company (2024)
Non-operation period electricity price	$C_t,\ t \in T_{\text{night}}$	\$0.04/kWh	State Grid Jiangsu Electric Power Company (2024)
Maximum number of charging piles at a charging station	Chg^{max}	30	Pourvaziri et al. (2024)
Minimum number of charging piles at a charging station	Chg^{min}	5	Jiangsu New Energy Vehicle Promotion and Application Coordination Group (2015)
Charging efficiency of a charging pile	Q	54kWh/h	BYD (2017); An (2020)
Value of waiting time	Vowt	\$0.07/minute	Jiangyin Municipal Bureau of Statistics
Maximum acceptable waiting time for bus passengers	Wt^{max}	10 minutes	Chen et al. (2024)

The lower-level integrated land-use and transportation model is established based on publicly available official statistical data from Jiangyin City, which has been calibrated and applied in Zhong et al. (2022) and Zhong et al. (2023). Specifically, the model comprises two main components: the land use system and the transportation system (including physical supply and operational supply). Their detailed components and corresponding data sources are summarized in Table 3. The land-use sub-model simulates six employment categories (including industrial, government, retail, entertainment, health, and education employment), population, and seven land-use types (including industrial, retail, residential, office, health, education, and entertainment land). Among these, industrial and government employment are modeled as basic employment, while the other land-use sectors are treated as induced activities. The transportation sub-model incorporates four travel modes (including bus, private car, walking, and bicycle) and four network types (including road network, bus network, and cycling and walking lanes).

Table 3 Data sources of the lower-level model

Category		Main components	Data description	Data source
Land use		Industrial employment, government employment, retail employment, entertainment employment, health employment, education employment, population, industrial land, retail land, residential land, office land, health land, education land, and entertainment land	Land-use type, area, and price, population, and employment in each zone.	Jiangsu Institute of Urban Planning and Design, Jiangyin Municipal People's Government, and Jiangyin Municipal Bureau of Statistics
Transportation	Physical supply	Road network, bus network, and cycling and walking lanes	Road name, type, capacity, length, speed limit, distance-related cost by mode.	Jiangyin Bureau of Transportation
	Operational supply	Bus, private car, walking, and bicycle	Bus: operation time, speed, fares, operation cost, schedule, and carrying capacity; Private car: average occupancy, operation cost, and speed; Bicycle and walking: speed.	Jiangyin Bureau of Transportation and Jiangyin Public Transportation Company

The base year of the lower-level model is set to 2010, with simulations configured to run at five-year intervals from 2010 to 2030. Considering that the impact of transportation infrastructure projects, such as electric bus charging stations, on urban land use requires time to manifest, this study utilizes the land-use and transportation results in 2030 to comprehensively assess the influence of charging station location strategies on Jiangyin City. The basic analytical unit of the lower-level model is the traffic analysis zone, with the study area divided into 265 zones. To enhance the precision and reliability of the model, a piecewise estimation method is adopted for calibrating parameters within the land-use and transportation sub-models and their interrelationships. Further details on this calibration process can be found in Zhong et al. (2023).

All the experiments were conducted on a laptop with an AMD Ryzen 7 5800H 3.20 GHz CPU and 16 GB of RAM.

4 Results and analysis

4.1 Optimal charging station location

The bi-level model in this study ensures a feasible solution throughout the iterative process. In the event of excessive travel or charging demand at bus terminals, these demands can be allocated to dummy links with penalty costs to maintain the feasibility of the solution. Fig. 5 plots the changes in the average economic cost per trip of the electric bus system over iterations. Supplementary Fig. 1 further presents the change in its three parts, namely, the average investment, operation, and passenger waiting time costs per trip, across iterations. It can be observed that the reduction rate of the average cost becomes very low starting from the eighth iteration. The average cost stabilizes after 10 iterations, and the iteration ends. The location strategy with minimum cost value is considered the optimal charging station location strategy. Under this optimal strategy, 11 charging stations equipped with a total of 130 charging piles are constructed in Jiangyin City. To facilitate a smooth transition from traditional to electric buses, the electric bus fleet size is 221. Supplementary Tables 1 and 2 detail the departure headways and operational fleet sizes for each bus route under the optimal location strategy, using the morning peak hour (07:00−08:00) and the off-peak hour (10:00–11:00) as representative periods for illustration. The daily investment cost of the electric bus system is $18,971, the operation cost is $5,245, and the passenger waiting time cost is $85,579.

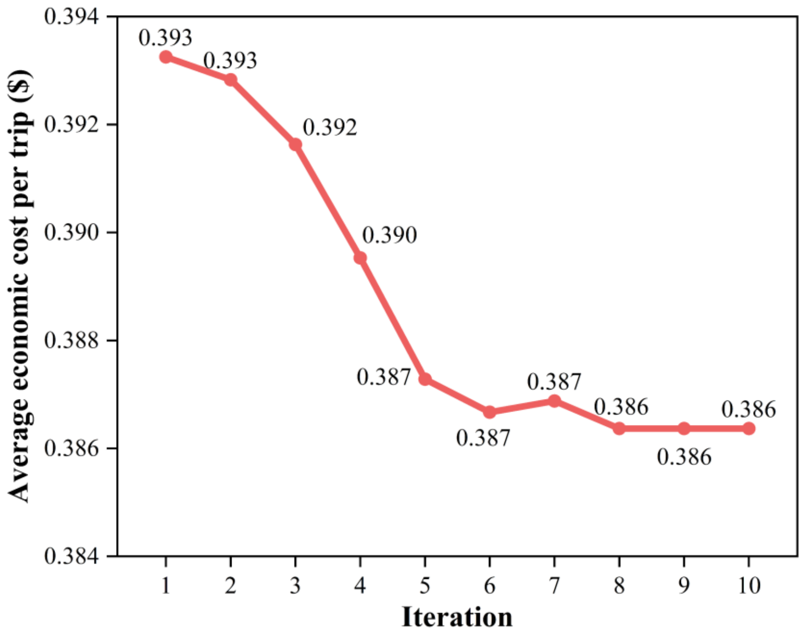

Fig. 5 Changes in the average economic cost per trip of the electric bus system with the iteration times

Fig. 6 presents the optimal charging station locations, and the number of charging piles installed at each station. All eleven charging stations are strategically located in zones with dense bus routes or high travel demand, there-by enabling efficient operations and timely charging while minimizing resource underutilization. Specifically, stations 1, 8, and 50 are located in the urban center, where bus routes converge, and travel demand is high. Deploying charging stations in these locations allows for cost-effective service of more bus terminals and buses. Stations 2 and 9 are located in the western of the city, where employment and commuting demand are substantial, and can effectively meet peak-hour charging demand. Station 14 is located in the urban sub-center, serving routes that connect the sub-center to the urban center. Stations 3, 4, 5, 6, and 10 are located on major bus routes in the eastern and southern of the city, where routes are sparse and distant from other selected charging stations. Deploying charging stations in these locations not only reduces operation costs associated with long-distance travel for charging but also efficiently meets the charging demand of the routes they locate.

Furthermore, the number of charging piles at each charging station has been optimized according to the charging demand. For instance, 30 piles are installed at charging station 1 to meet high charging demand of the urban center, whereas station 3, primarily serving southern routes, is installed with 7 piles, sufficient for the zone's lower demand.

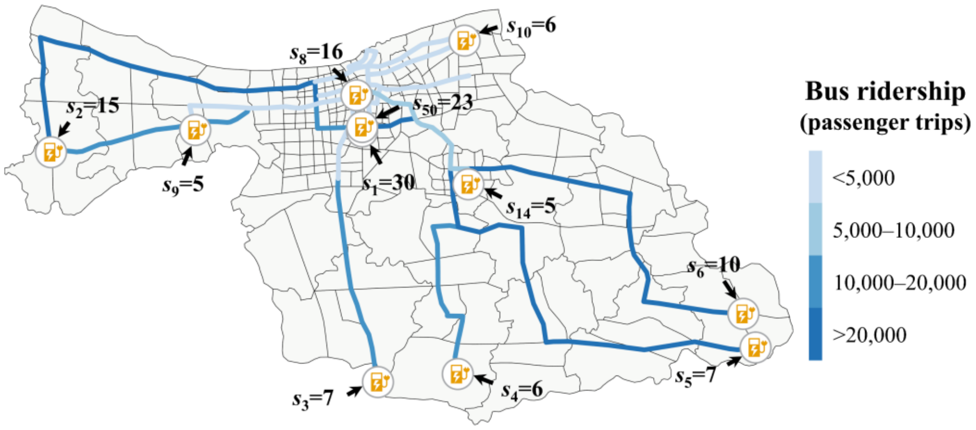

Fig. 6 The optimal electric bus charging station location strategy

Fig. 7 compares bus travel demand under the initial strategy to the optimal location strategy, which takes into account the feedback between charging station locations and travel demand. The initial strategy, which assumes fixed and exogenous travel demand, supports only current passengers and struggles to attract new users. By contrast, the optimal strategy strategically deploys charging stations to reduce user waiting times (see Table 4 and Supplementary Fig. 2) and enhance the appeal of electric buses (Tang et al., 2024). This improvement stimulates growth in bus travel demand, particularly on routes connecting urban center with peripheral zones, where the demand increase is more pronounced. The total bus travel demand increased from 272,021 to 284,170 passenger trips (see Table 4 and Supplementary Fig. 2). Sections 4.2 and 4.3 further discuss the broader impacts of the optimal location strategy on land-use and transportation systems, as well as the underlying reasons for changes in bus travel demand.

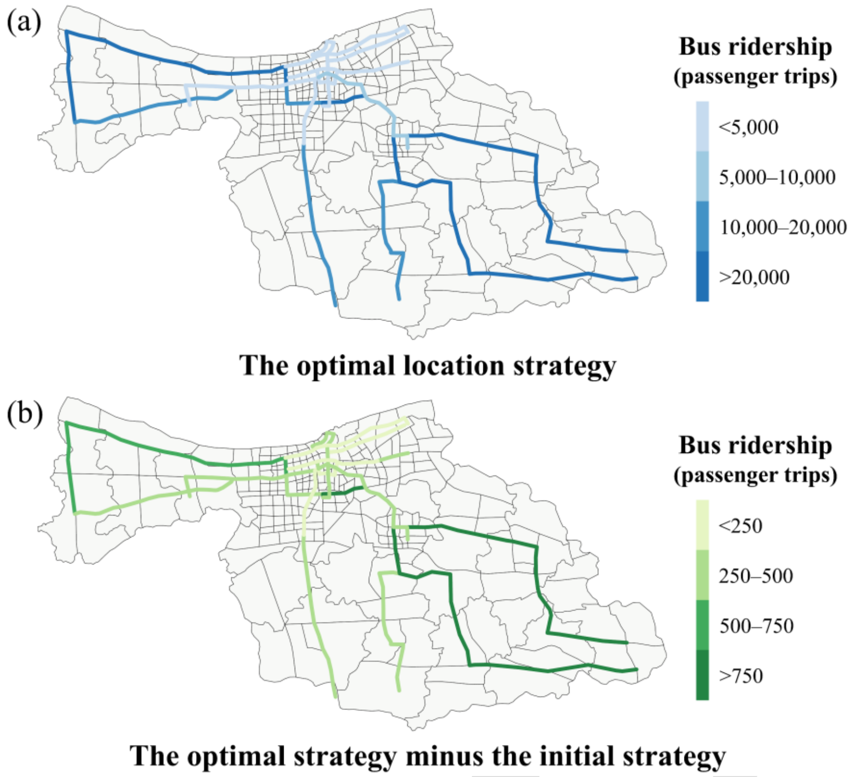

Fig. 7 The effect of the optimal location strategy on bus travel demand relative to the initial strategy

4.2 Land-use impact analysis

Based on the 3Ds indicators of the urban built environment (i.e., density, diversity, and design) (Cervero and Kockelman, 1997; Bartholomew & Ewing, 2008), this study employs population density, employment density, and accessibility to evaluate the impact of the optimal charging station location strategy on land-use system. Accessibility measures the ease of access to activities via the transportation network and depends on the number of activities (defined as employment in this study) within each zone and the difficulty of traveling between zones, calculated by the equation (54).

$$\mathrm{access}_a = \sum_b \mathrm{acty}_b \cdot \Gamma\left(\mathrm{tt}_{ab}^{\min}\right) = \sum_b \mathrm{acty}_b \left[\eta \exp\left(\phi + \varsigma \cdot \mathrm{tt}_{ab}^{\min}\right)\right], \quad \forall a, b \in H, \tag{54}$$

where access_a is the accessibility of zone a; acty_b is the number of activities in zone b; $\mathrm{tt}_{ab}^{\min}$ is the minimum travel time between zone a and zone b; $\Gamma\left(\mathrm{tt}_{ab}^{\min}\right)$ is the travel time impedance function; η, ϕ, and ς are the impedance parameter. This study sets $\eta = 0.01$, $\phi = -0.4$, and $\varsigma = -0.15$ (Cervero and Kockelman, 1997).

As shown in Fig. 8(a), optimizing electric bus charging station locations not only enhances bus service levels but also promotes increased population density in the urban center. By improving bus service levels and shortening commuting times, the optimal strategy enhances the convenience and efficiency of travel within the urban center. As a result, more residents are drawn to central zones, leading to higher population density (Supplementary Fig. 3). These findings align with Chatman & Noland (2014), Litman, (2015), and Ibraeva et al., (2020), which demonstrate that better bus services boost urban population density through greater transportation convenience and reduced commuting times.

The optimal charging station location strategy also affects employment distribution, as shown in Fig. 8(b) and Supplementary Fig. 3(b). Compared to the initial strategy, the optimal charging station location strategy leads to a greater concentration of employment opportunities in the well-served urban center, increasing employment density (Chatman & Noland, 2014). This trend is primarily driven by improved commuting convenience and lower travel costs, enabling enterprises to attract a broader labor pool without raising salaries to offset commuting expenses (Pasha et al., 2020). Consequently, it has become more attractive for enterprises to establish and expand office spaces in the urban center.

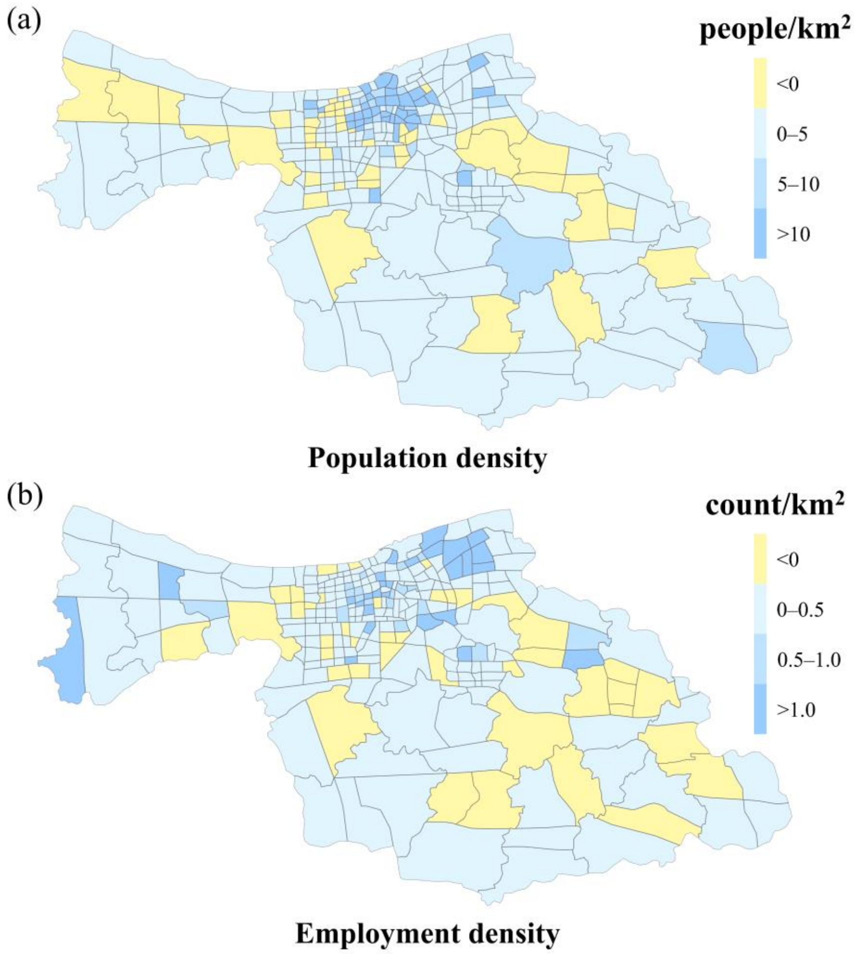

Fig. 8 The effect of the optimal location strategy on population and employment density relative to the initial strategy. (a) population density; (b) employment density. The legend shows the difference in values between the two strategies.

Changes in the spatial distribution of population and employment, along with the traffic congestion level (discussed in Section 4.3) further affect regional accessibility, as depicted in Fig. 9

(Geurs and Van Wee, 2004). The results indicate that the optimal location strategy improves accessibility across all zones in Jiangyin City. The average regional accessibility increases from 31.19 to 31.31 (Table 4 and Supplementary Fig. 3), and urban center zones exhibit the most pronounced improvements.

It is crucial to highlight that the spatial separation of land use fundamentally drives travel demand. Therefore, changes in residents' choice of residential and employment locations, as well as accessibility, directly influence bus travel demand (Zhong and Sun, 2022). These findings not only clarify how optimizing charging station locations affects bus travel demand but also highlight the necessity and importance of studying the electric bus charging station location problem from the integrated land-use and transportation perspective.

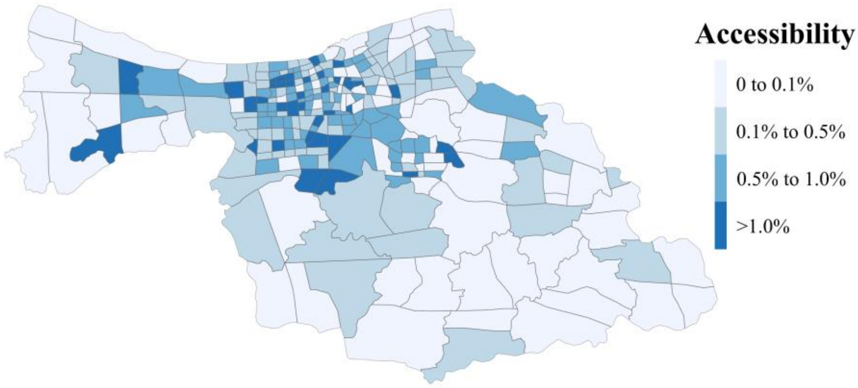

Fig. 9 The effect of the optimal location strategy on regional accessibility relative to the initial strategy. The legend displays the difference rate between the two strategies.

4.3 Transportation impact analysis

To illustrate the impact of the optimal charging station location strategy on urban transportation system, Table 4 and Supplementary Fig. 3(d) presents the change in the share of passenger kilometers traveled (PKT) by different modes, highlighting a shift toward more sustainable and environmentally friendly modes. Under the optimal strategy, the PKT share of buses increases from 19.9% to 20.5%, and walking increases as well, while the shares of private cars and bicycles decline compared to the initial strategy. The reasons for these changes are as follows: (1) Optimizing charging station locations boosts the efficiency and appeal of electric buses, encouraging more residents to choose them over other modes. This results in a higher PKT share of buses. Since walking is a primary way to access bus stops, increased bus usage also drives up walking demand, a connection well-documented in previous studies (Morency et al., 2011). (2) The improved electric bus system provides low-cost, reliable, and efficient services, attracting users who would otherwise drive or bike. This transition contributes to the decline in the PKT shares of private cars and bicycles.

Table 4 Comparison between the initial strategy and the optimal location strategy

Performance indicator	The initial strategy	The optimal location strategy
Total bus travel demand (passenger trips)	272,021	284,170
Average passenger waiting time (minute)	4.37	4.30
Population density (people/km^2)	5,113.97	5,117.42
Employment density (count/km^2)	3,794.68	3,794.87
Accessibility	31.19	31.31
PKT share of bus	19.9%	20.5%
PKT share of walking	25.4%	26.0%
PKT share of private car	30.9%	30.4%
PKT share of bicycle	23.7%	23.0%
Delay ratio	0.37	0.36
Vehicle carbon emission (kiloton)	2.90	2.87

Fig. 10 and Supplementary Fig. 3(e) illustrates the impact of the optimal strategy on traffic congestion. The delay ratio, defined as the ratio of delayed travel time to free-flow travel time, serves as a congestion metric. Compared with the initial strategy, the optimal strategy alleviates traffic congestion on most road links, with the greatest improvements along bus routes in the urban center. This result demonstrates that location optimization can reduce traffic loads by improving the efficiency of the bus services. Beaudoin et al. (2015), Romero et al. (2020), and Lu et al. (2021) have also demonstrated that the promotion of public transportation development is a crucial strategy for alleviating urban traffic congestion and promoting sustainable urban development.

Fig. 10 The effect of the optimal location strategy on traffic congestion relative to the initial strategy. The legend displays the difference rate between the two strategies.

Furthermore, this study estimates the impact of the optimal location strategy on vehicle CO_2

emissions using MOVES5, the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator (U.S. EPA, 2024). The model accounts for (i) traffic flow characteristic, including traffic volume and speed, (ii) meteorological conditions obtained from the China Meteorological Data Service Center, (iii) fuel properties conforming to the Chinese national gasoline standard GB 17930-2016, and (iv) vehicle age vehicle age distribution data derived from the Jiangyin Statistical Yearbook. Simulation results demonstrate that the optimal strategy can reduce vehicle carbon emissions from 2.90 kilotons to 2.87 kilotons, with a decrease of approximately 1.1%, by improving road network efficiency and reshaping travel mode choices (Table 4 and Supplementary Fig. 3). This finding highlights the strategy's potential to advance transportation sector decarbonization and foster sustainable urban development.

5 Conclusion

This study develops a bi-level programming model to determine the electric bus charging station location while initially taking into account an integrated land-use and transportation model to capture the long-term impacts on transportation and land-use systems. Using Jiangyin City as the case study, the following key conclusions are drawn:

Firstly, optimizing electric bus charging station locations from the integrated land-use and transportation perspective is crucial for the development of an effective electric bus system. Our findings demonstrate that the optimal location strategy considering the feedback effects can reduce user waiting time and improve service level compared with the initial location strategy. Consequently, bus travel demand increases from 272,021 to 284,170 passenger trips, and the PKT share of buses rises from 19.9% to 20.5%. These results suggest that in promoting the development of electric buses, policymakers should not only allocate more financial resources to charging infrastructure but also incorporate the feedback mechanism of charging stations on transportation and land-use systems (Szeto et al., 2015). Therefore, effective planning requires close collaboration between transportation planning departments and land management agencies to strategically determine charging station locations from an integrated land use and transportation perspective. Such coordination ensures that the charging infrastructure not only meets current demand but also stimulates further bus ridership by guiding land-use and transportation development. Meanwhile, policymakers should apply the integrated models, such as the modeling framework proposed in this study, during the planning stage to take into account how proposed station location strategies influence travel demand. Such analyses are essential for devising location strategies that more effectively accommodate evolving travel demands and urban development patterns, fostering a more adaptive and efficient electric bus charging infrastructure (Suzuki et al., 2013).

Secondly, the optimal location strategy improves accessibility by reshaping urban employment distribution, increasing population density, and enhancing road network efficiency, leading to a 0.4% increase in average accessibility, from 31.19 to 31.31. The strategy also reinforces the role of electric buses in reducing car dependence, promoting sustainable travel behaviors, alleviating traffic congestion, and providing a more efficient and convenient travel environment for residents (Morency et al., 2011; Kuo et al., 2023). Furthermore, it is expected to decrease vehicle carbon emissions from 2.90 kilotons to 2.87 kilotons, thereby accelerating the decarbonization of the transportation sector. Our findings suggest that transportation planning departments should comprehensively analyze the impacts of charging station location strategies on both land-use and transportation systems. Specifically, policymakers should consider not only bus operational indicators (such as operational costs, passenger ridership, and service level) but also broader impacts such as accessibility, traffic congestion, and vehicle carbon emissions. This supports informed decision-making among multiple location strategies, ensuring alignment with urban development goals and contributing to long-term urban sustainability (Tan et al., 2022; Giagnorio et al., 2024). Moreover, coordinating with land management agencies to promote transit-oriented development around optimized electric bus routes and charging stations can amplify these benefits, creating positive feedback between improved electric bus service and sustainable urban development (Ibraeva et al., 2020).

Several directions are worthy of future investigation. First, this study focuses on the strategic planning of the most popular conventional charging stations. With the advancement in battery and charging technologies, alternative methods such as battery swapping and wireless lane-based charging are gradually being introduced to the market (Jang, 2018; Tan et al., 2022; Cui et al., 2023; Zeng & Qu, 2023; Qu et al., 2024). In future studies, it is necessary to extend the modeling framework proposed in this study to optimize the locations of these emerging types of charging infrastructure. Second, to facilitate the model development while maintaining practical relevance, this study adopts a set of electric bus fleet and operational assumptions that are commonly applied in the previous studies and mirror current conditions in the study area. Future studies could relax these assumptions to further enhance the adaptability and realism. For instance, incorporating mixed fleets with heterogeneous vehicle types and battery capacities would enable investigation of how fleet diversity influences optimal station locations (Hu et al., 2022). The framework could also be extended by introducing decision variables that determine both the timing and location of en-route charging events, thereby allowing opportunity charging at intermediate stops (Rogge et al., 2018; Liu & Ceder, 2020). Third, the widespread adoption of electric buses will influence power grid loads. Future studies could explore the impact of charging station deployment on grid load balancing and examine the integration of charging infrastructure with renewable energy sources, such as solar and wind energy (Deng et al., 2019; Jia et al., 2024b). This would involve investigating the interactive relationship between electric bus charging demand and grid loads and optimizing charging station locations to minimize stress on the power grid (Alamatsaz et al., 2022). Fourth, although the iterative solution method proposed in this study is effective for solving the bi-level programming model, its computational cost may become prohibitive when applied to large-scale transit networks. Future studies could explore more efficient solution approaches. Promising directions include: problem decomposition techniques (e.g., by region or decision layer) to reduce problem size (Arslan & Karaşan, 2016); acceleration heuristics or metaheuristic algorithms that quickly generate high-quality solutions without requiring full optimization at each iteration (Wen et al., 2016); and surrogate models that approximate the lower-level simulation, thereby decreasing the number of expensive calls to the low-level model and improving overall computational efficiency (Liu et al., 2024).

Appendix A

Symbols	Description
The upper-level electric bus charging station location model	
Set	
$I=\{i\}$	Set of bus terminals, which are the charging demand generation points.
$J=\{j\}$	Set of candidate electric bus charging stations.
$T=\{t\}$	Set of time intervals.
T_{day}, T_{night}	Set of time intervals in bus operation and non-operation hours. An operation day is divided into operation periods T_{day} and non-operation periods T_{night}.
Decision variables	
x_j	= 1 if a charging station is constructed at $j \in J$, otherwise 0.
y_{ij}	= 1 if bus terminal $i \in I$ is assigned to charging station $j \in J$, otherwise 0.
s_j	Number of charging piles installed at charging station $j \in J$.
f_{it}	Frequency of buses from bus terminal $i \in I$ within time interval $t \in T$.
w_{ijt}	Number of electric buses charging at station $j \in J$ from bus terminal $i \in I$ during time interval $t \in T$.
z_i	Fleet size of electric buses at bus terminal $i \in I$.
Auxiliary variables	
e_{it}	Energy consumption of a whole trip on bus route departing from terminal i during time interval t, output from the lower-level model.

cec_{it}	Cumulative energy consumption at bus terminal i till time interval t.
q_{it}	Cumulative charging demand at bus terminal i till time interval t.
α_{it}	Auxiliary variable for capturing (or calculating) the cumulative charging demand q_{it} at bus terminal $i \in I$ till time interval $t \in T$.
d_{it}, β_{itk}, l_{ijh}	Auxiliary variables used in the linearization.
Parameters	
G^{sta}	Fixed construction cost per charging station.
G^{chg}	Installation cost per charging pile.
G^{bus}	Purchase cost per electric bus.
G^{dis}	Unit travel cost for an electric bus to a charging station.
D_{ij}	Distance from bus terminal $i \in I$ to charging station $j \in J$.
C_t	Electricity price within time interval $t \in T$.
P_{it}	Passenger travel demand at bus terminal i during time interval t.
$\mathrm{Cap}^{\mathrm{bus}}$	Bus capacity.
Vowt	Value of waiting time.
$\mathrm{Chg}^{\max}$	Maximum number of charging piles allowable at a charging station.
$\mathrm{Chg}^{\min}$	Minimum number of charging piles required at a charging station.
$\mathrm{Wt}^{\max}$	Maximum acceptable waiting time for bus passengers.
Q	Charging efficiency of a charging pile.
σ	Number of hours required to fully recharge a depleted electric bus.
M	A sufficiently large positive constant.
The lower-level integrated land-use and transportation model	
Set	
$V = \{o\}$	Set of decision options.
$H = \{a,b\}$	Set of zones.
$B = \{m\}$	Set of basic employment types.
$N = \{n\}$	Set of induced activity types.
$R = \{r\}$	Set of travel modes.
$Z = \{p\}$	Set of travel routes.
$L = \{c\}$	Set of road links.

Functions	
$u_{go}(\cdot)$	Random utility function for the individual g choosing decision option o.
$v_{go}(\cdot)$	Deterministic part of the random utility function $u_{go}(\cdot)$.
Variables	
prob_{go}	Probability of the individual g choosing decision option o.
$\mathrm{be}_a^{m,\tau}$	Number of basic employment of type m in zone a at time τ.
$\mathrm{ia}_{ab}^{mn,\tau}$	Number of induced activity n in zone b generated by basic employment m in zone a at time τ.
ldsup_a^{τ}	Available land area in zone a at time τ.
ldval_a^{τ}	Land-rent value of zone a at time τ.
$\mathrm{tvol}_{ab}^{\tau}$	Travel volume from zone a to zone b at time τ.
tc_{ab}^{τ}	Travel cost from zone a to zone b at time τ.
tt_{ab}^{τ}	Travel time from zone a to zone b at time τ.
wt_{ab}^{τ}	Waiting time from zone a to zone b at time τ.
ec^{rc}	Energy consumption per vehicle per unit distance for travel mode r on link c.
ts^{rc}	Travel speed of travel mode r on link c.
Parameters	
ϵ_g	Random part of the random utility function $u_{go}(\cdot)$.
W_o	Measurable characteristics associated with decision option o.
τ	Modeling time slot.
Tp	Total number of time slots.
$L^{mn,\tau}$	Coefficient matrix, indicating the number of induced activity n generated by basic employment m at time τ.
$\mathrm{Attr}_a^{n,\tau}$	Attraction coefficient of zone a for induced activity n at time τ.
$\delta^{n,\tau}$	Aggregation tendency parameter for induced activity n at time τ.
χ^n, ϑ^n	Spatial location decision function parameters for induced activity n.
ω^{τ}, θ^{τ}	Trip-generation elasticity parameters at time τ.
γ^{τ}	Mode choice parameter at time τ.
$\mathrm{Rcap}^{rp,\tau}$	Bottleneck capacity for travel mode r on route p at time τ.
$\mu^{r,\tau}$	Route assignment parameter at time τ.

$\mathrm{Fare}^{\mathrm{bus},\tau}$	Bus fare parameter at time τ
Vott^{τ}	Value of travel time at time τ
$\mathrm{Ec}^{\max}$	Maximum energy consumption per unit distance at congested speed.
$\mathrm{Ec}^{\min}$	Minimum energy consumption per unit distance at free-flow speed.
ϖ^{r}	Parameter regulating the steepness of the energy consumption curve of travel mode r .

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Replication and data sharing

The dataset used in this research is partially available upon request by emailing the corresponding author.

Declaration of competing interest

The authors declare no competing interests.

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