Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 1905526, 19 pages
https://doi.org/10.1155/2022/1905526

Research Article

A Long-Term Shared Autonomous Vehicle System Design Problem considering Relocation and Pricing

Jingjing Tian,[1] **Hongfei Jia**,[1] **Guanfeng Wang**,[1] **Yu Lin**,[2] **Ruiyi Wu**,[1] **and Ao Lv**[1]

[1]*College of Transportation, Jilin University, Changchun 130022, China*
[2]*Faculty of Maritime and Transportation, Ningbo University, Ningbo 315211, China*

Correspondence should be addressed to Hongfei Jia; jiahf@jlu.edu.cn

Received 6 March 2022; Revised 19 May 2022; Accepted 25 May 2022; Published 15 June 2022

Academic Editor: Nirajan Shiwakoti

Compared to conventional private vehicles (CPVs), shared autonomous vehicles (SAVs) provide users the potential for the reduced value of time (VoT), improved mobility experience, and less traffic congestion. In the presence of the SAV system, numerous studies have mainly concentrated on the strategic planning and operational decision problem separately while ignoring the complicated interaction between them and the distinct features of autonomous vehicles. It is imperative to determine the relocation and pricing strategies at the operational level. In this study, in terms of the pricing strategy, we formalize a logit model to capture the mode choice behavior in a multimodal network, where the reduced VoT is considered simultaneously. A time-space network is employed to capture the daily operation problem based on the elastic demand. The minimum customer service rate is regarded as a constraint to ensure the system's reliability. Moreover, a mixed-integer nonlinear programming (MINLP) model is formulated to jointly determine the number of stations and parking spaces, fleet size, relocation, and pricing strategies to maximize the total profit. Then, we integrate the Particle Swarm Optimization (PSO) algorithm with the optimization solver Gurobi to address the complex problem. Numerical experiments and comparative analyses are conducted to demonstrate the feasibility and efficiency of the proposed model.

1. Introduction

In recent years, the urban transportation system has faced unprecedented challenges such as severe traffic congestion, environmental degradation, and a shortage of land resources. Federal Highway Administration [1] has proved that private vehicles only work for 90 minutes a day but are idle and parked the rest of the time, which is an immense waste of resources. With reference to these issues, the shared autonomous vehicles (SAVs) emerge as a flexible modality to provide a seamless door-to-door transport service for passengers and have the potential to improve mobility and sustainability. Compared with traditional shared vehicles, SAVs have no necessity for human involvement and comply with instructions from the control center. It can pick up passengers and relocate empty vehicles according to advanced reservation information [2], raising the opportunity to manage the fleet easily. Moreover, there is literature demonstrating that it is easier to implement ride-pooling in a connected environment, which can improve air quality and alleviate congestion [3]. However, various factors are involved in designing a financially sustainable SAV system, not only strategic planning decisions, but also the daily operation decisions that should be considered.

There are three sets of decisions to be optimized at the operational level: vehicle-trip assignment, relocation, and trip pricing. Vehicle-trip assignment is that when travelers submit their request in advance, the control platform decides to assign SAVs to pick up passengers or not. According to Narayanan et al. [4] and Chen et al. [5], the most notable type is the one-way station-based SAV system, which is flexible but faces the imbalance problem due to the spatial and temporal distribution variation in demand. In order to address the issue, relocation is proposed as a primary technique to dispatch empty vehicles to stations where there is a lack of vehicles [6, 7]. Another critical element that must be considered is pricing strategies for SAVs [8]. In the mixed market of SAVs and conventional private vehicles (CPVs), the induced travel demand for SAVs is determined by the trip pricing strategies and the value of time (VoT) consumed during the trip. As a side note, compared to CPVs, SAVs have the potential to enable users to travel with higher comfort and flexibility, thereby decreasing the VoT of users. Childress et al. [9] proposed that the VoT is envisioned to reduce by 30–35%. Besides, the customer service rate is always used to evaluate the performance of the SAV system [10, 11]. Although there are studies that have investigated the daily operation from various aspects separately, few studies have considered relocation, pricing, the reduced VoT, and customer service rate simultaneously to delineate the daily operation problem.

At the strategic planning level, similar to other transport infrastructures, the design of an SAV system is a long-term process and has to accommodate the continuously changing traffic environment [12]. Predictably, the SAV services will hopefully be extensively used as the technology develops. Namely, the travel demand for SAVs in daily operation is unavoidable to increase in the future, which requires more optimal decision-making on infrastructures, such as the establishment of stations and parking spaces, and fleet size over a long period.

Besides, there exists a complicated association between daily operational and strategic planning decisions [13]. On the one hand, efficient distributions of stations and parking spaces benefit the vehicle-trip assignment and reduce the mileage of empty SAVs. Also, large fleet size can decrease the waiting time and schedule delays, which improves the customer service rate. However, a greater cost is required to purchase vehicles and establish more parking spaces. On the other hand, existing research demonstrates that relocation is beneficial for reducing fleet size and improving vehicle utilization [14, 15]. At the same time, the automated technology is envisioned to park the idle SAVs at distant stations where the land resource is adequate and inexpensive [16, 17]. Therefore, it is of great essence for the operator to design the SAV systems considering the strategic planning and daily operation decisions simultaneously, which maximizes the total profit and provides a high customer service rate.

Noticing the above challenges, this paper proposes a holistic optimization framework to describe the SAV system design problem. The main contributions of this study are as follows. (1) To accommodate for the stochastic characteristic of travelers' mode choice, we formalized a logit model that captures the nonlinear relationship between the elastic demand and its attributes, such as reduced VoT and the pricing for SAV trips. (2) Incorporating the elastic demand, a time-space network flow is proposed to capture the vehicle-trip assignment and relocation decisions in the daily operation problem. What is worth mentioning is that a minimum customer service rate is proposed as a constraint to ensure the reliability of an SAV system. (3) A mixed-integer nonlinear programming (MINLP) model is developed to delineate the long-term design problem by simultaneously integrating daily operation and long-term strategic planning. (4) To effectively address the MINLP optimization model, we implement a hybrid computation procedure combing the Particle Swarm Optimization (PSO) algorithm with the optimization solver Gurobi. Note that the problem formulated in this paper is not desired to acquire actual, detailed operation decisions, which only serve as a benchmark for long-term planning for the SAV system. As far as we know, this study is the first attempt to address these problems simultaneously.

The remainder of this paper is structured as follows: Section 2 reviews previous literature on the SAV system design problem and identifies the research gap. Next, the discrete choice model and the time-space network flow model are developed to formulate the daily operation problem. Then, a MINLP model for the long-term design of the SAV system is delineated in Section 3. Numerical experiments are conducted, and results are analyzed in Section 4. Besides, several practical implications and insights are discussed in Section 5. Furthermore, we draw the conclusions and raise the future research direction in Section 6.

2. Literature Review

As a trending topic in the last few years, there exist numerous studies in the context of SAV system design. Owning to this study concentrating on the combinatorial optimization problem, thereby we provide a comprehensive review related to relocation, pricing, system design, and other relevant studies of the SAV system.

2.1. Relocation and Pricing of the SAV System. For the relocation analysis of shared vehicle systems, two main classes of methods are categorized: optimization-based methods [18, 19] and simulation-based methods [14, 20]. Optimization-based methods are typically formulated as a mixed-integer programming (MIP) problem or bilevel optimization problem to address predefined decision-making objectives. For instance, Li and Liao [2] creatively introduce a bilevel model to determine the optimal fleet size and hub location while considering the SAV relocations, the dynamic interaction between supply and demand, multimodal mode choice, and dynamic user equilibrium. The previous studies conclude that the time-space network is the most frequently used model to investigate the relocation strategies [21]. A mixed-integer linear programming model is developed by Correia [22] to determine the depot location so that the cost of the shared vehicle system is minimized. As for the simulation methods, microscopic traffic simulations are commonly utilized to simulate the supply-demand interaction. A simulation-based method is employed by Martínez et al. [23] to mimic relocation operations and indicate that vehicle-trip assignment is crucial to the performance of the vehicle sharing system. Besides, Hyland and Mahmassani [24] develop an agent-based simulation tool to describe six relocation strategies and demonstrate that they benefit operational efficiency and vehicle utilization. Although simulation methods efficiently respond to various scenarios with distinct approaches, the lack of historical data because of the limited penetration of SAVs in the current traffic system results in the difficulties of calibrating the numerous parameters. In addition, the optimization-based methods are more transparent and tractable with clearly specified objective functions and constraints. Therefore, we develop an optimization-based method to formulate and design the SAV system.

In terms of trip pricing for SAVs, relevant studies have been conducted to capture the stochastic nature of travelers in mixed traffic. Optimal price-setting strategies for SAVs and private vehicles are studied by Kaddoura et al. [25] to avoid excessive use of transport resources. Liu et al. [26] discuss how travelers react to mode choice under different price-setting conditions. Similarly, Hörl et al. [27] carry out stated-choice experiments to study SAV cost structures and mode choice reactions through simulation. Concerning the impact of pricing on the mode choice, Liu et al. [28] formulate a unified framework to optimize supply-side parameters such as fleet size and fare by Bayesian optimization and simulation method simultaneously.

2.2. The SAV System Design Problem. One stream of literature on the SAV system design problem is optimization-based methods. Various mathematical models are developed in this context. For instance, Lu et al. [29] incorporate the pricing and relocation into the car-sharing system and formulate a bilevel nonlinear mathematical programming model to optimize the fleet size. Nair and Miller-Hooks [30] propose an equilibrium network design model to determine the deployment of a vehicle sharing system, including station locations, vehicle inventories, and parking capacities. Besides, Hu and Liu [31] develop a mixed queueing network model to decide the fleet size and station capacities with the objective of profit-maximization. Similarly, Seo and Asakura [13] propose a multiobjective optimization model to determine the strategic planning of the SAV system while considering passenger pickup/delivery and ridesharing. Li et al. [12] propose a link transmission model to describe the dynamic routing for SAVs, and a MILP model was developed to investigate the time-dependent SAV system design problem.

Another common framework is integrating optimization-based with the simulation-based methods to investigate the combined strategic planning with operational decisions. Deng and Cardin [32] formulate an optimization model to design a vehicle-sharing system to minimize the overall cost. A discrete event simulator is adopted to describe the stochasticity of demand and the relocation operations. Furthermore, Dandl et al. [33] develop a trilevel mathematical model to capture the interrelation among the public sector, operators, and travelers. At the same time, an agent-based transportation model is adopted to capture mode choice and mobility services provided by operators.

2.3. Metaheuristic Approach for SAV System Design. The optimization-based models with vast constraints and variables are hard to solve, and researchers are inclined to employ metaheuristic methods to reduce the computational complexity. For instance, Shun Su et al. [34] adopt a metaheuristic tabu search method to address the optimization problem of reservation-based autonomous car-sharing systems, and the performance of the metaheuristic is evaluated. In addition, the tabu search heuristic is used for the SAVs congestion-aware routing problem [35]. Lu et al. introduce a combination of genetic algorithm (GA) and KKT conditions to address the bilevel model for relocation and pricing problems of shared vehicles. The GA algorithm significantly raises the infer efficiency [29].

Particle Swarm Optimization (PSO) is another widely used metaheuristic algorithm, a population-based optimization technique proposed by Eberhart [36]. Because PSO is easy to implement and applicable to a vast array of problems, it has been applied to various fields, such as communication networks, control, and robotics. Numerous studies have demonstrated that the PSO is successful in addressing transportation problems [37]. In addition, the convergence of this algorithm was theoretically studied and explained by Clerc and Kennedy [38]. Recently, PSO has been used to solve the path planning problem of autonomous vehicles [39], transportation network design [40], autonomous vehicle navigation, and obstacles avoidance [41]. Considering the excellence of PSO, a valid metaheuristic approach is presented to cope with the SAV system design problem.

2.4. Summary. Based on the literature review, three challenges need to be addressed in the SAV system design problem. (1) Considering the automated nature of SAVs, the reduced VoT for SAVs needs to be integrated with trip pricing in the mode choice model to capture the stochastic characteristic of travelers. (2) Accommodating operational and strategic planning decisions into a holistic traffic model are still a challenge, specifically the customer service rate, relocation, pricing decisions, and infrastructure deployment. (3) Only very few works have been done for the long-term design of the SAV system, which ignores the continuously growing demand and is not economically sufficient. To solve the abovementioned problems, we formulate a MINLP model to study the long-term SAV design problem. To the authors' knowledge, this is the first time to incorporate customer service rate, relocation, pricing, and ride pooling into a unified framework to determine the number of stations and parking spaces, fleet size, and operational decisions.

3. Mathematical Model

The long-term SAV system design problem involves two categories of decisions: the daily operation and the long-term strategic planning decisions. In this section, the first step we carry out is modeling the mode choice in the mixed traffic of SAVs and CPVs. A discrete choice model considering the various utilities is introduced to determine the number of travelers who intend to employ SAVs. And then secondly, a nonlinear programming (NLP) model is proposed for the daily operation problem to optimize the pricing, relocation, and vehicle-trip assignment to satisfy the travel demand. Finally, we consider the increasing demand, the daily operation problem, and strategic planning

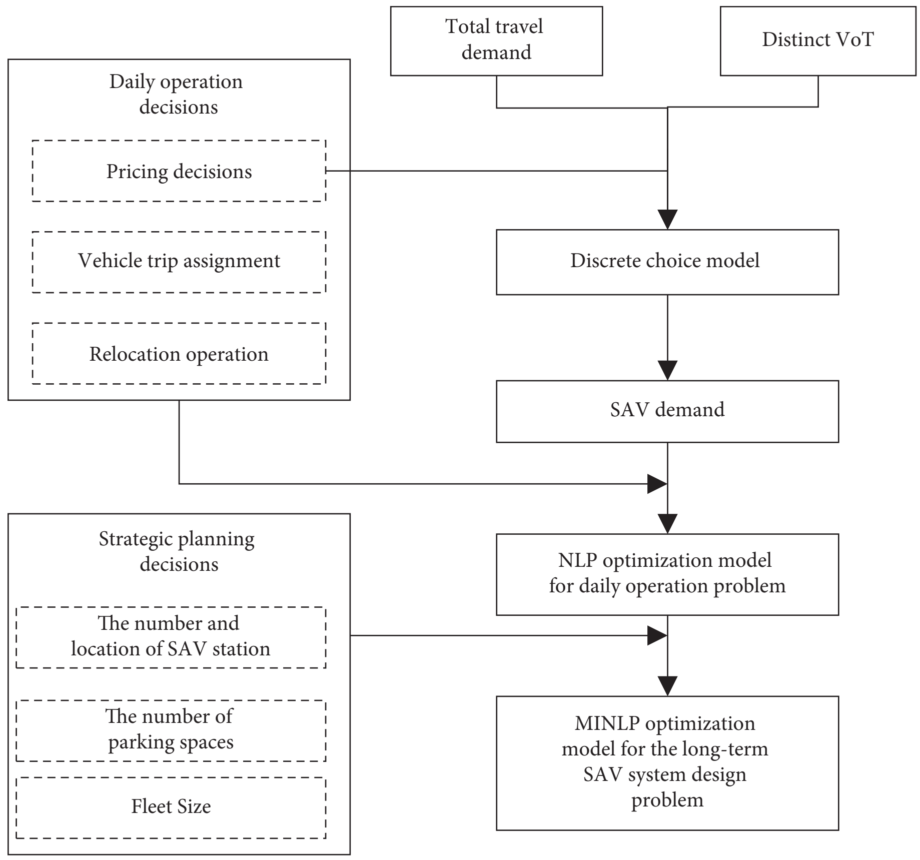


Figure 1: Flowchart of the modeling process.

decisions into a unified framework and develop a MINLP model to holistically describe the SAV system design problem. And the complex modeling process in this paper is delineated in Figure 1.

3.1. Network Presentation. We consider a one-way station-based SAV system to provide on-demand mobility services. In the daily operation problem, several assumptions are made as follows:

(1) The total travel demand is known prior based on historical data or through the online reservation system
(2) Only two travel modes are considered, including SAVs and CPVs
(3) We assume that the relocation of SAVs only occurs at the beginning of the time steps
(4) We simplistically assume that SAV users will choose ride-pooling only if they have the same origin and destination at the same departure time
(5) All the SAVs studied in this paper are regular internal combustion vehicles, and electric SAVs are out of the investigation scope

The study area is partitioned into multiple zones $\mathbf{N} = \{1, 2, \ldots, \overline{N}\}$, where $\overline{N}$ represents the total number of zones. Define $\mathbf{A} = \{(i, j)\}$, which is a set for arcs linking zones, in which $i \in \mathbf{N}$, $j \in \mathbf{N}$. Besides, the operation time is divided into multiple time steps $\mathbf{T} = \{1, 2, \ldots, t, \ldots, \overline{T}\}$ and Δ is the duration of one-time step. And we denote $\gamma_{i,j}^{t}$ to represent the shortest travel time from zone i to zone j departure at time t. As a side note, the travel time is negligible when the SAVs depart from stations to pick up travelers in the same zone. In the traffic network, travelers will determine to use SAVs and CPVs according to their travel cost (Figure 2). If the traveler chooses a SAV, he/she will send the origin, destination, and departure time to the SAV platform. Then, the central controller will determine if an available vehicle can be assigned to finish this task. Once the request is accepted, a SAV will drive to pick up the passenger and deliver them to the destination. On the other hand, if a traveler is rejected by the SAV platform or chooses a CPV, he will drive himself to the destination and park.

We delineate the SAV system as a time-space network (Figure 3), which is applied in the existing studies [29, 42]. Each node in the time-space network comprises time and location information. There are three kinds of arcs for SAVs: relocation arcs, delivery arcs, and waiting arcs. Relocation arcs indicate that the system dispatch surplus empties SAVs to service more travel demand. Delivery arcs represent that SAVs s occupied with passengers to their destinations. The waiting arcs for SAVs are designed to allow stopovers at regular parking regions. We let Q_{ij}^{t} describe the number of occupied vehicles with passengers from zone i to zone j and R_{ij}^{t} represent the number of empty vehicles relocate from

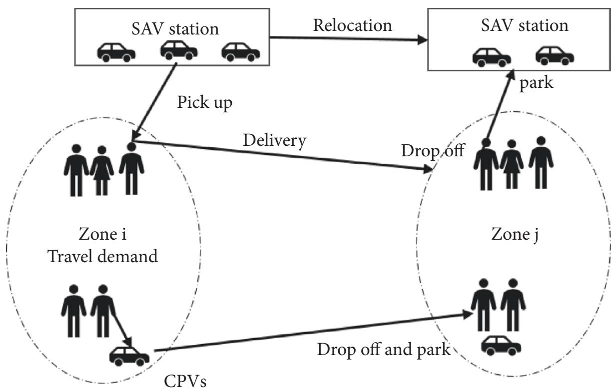


Figure 2: Representation of discrete mode choice.

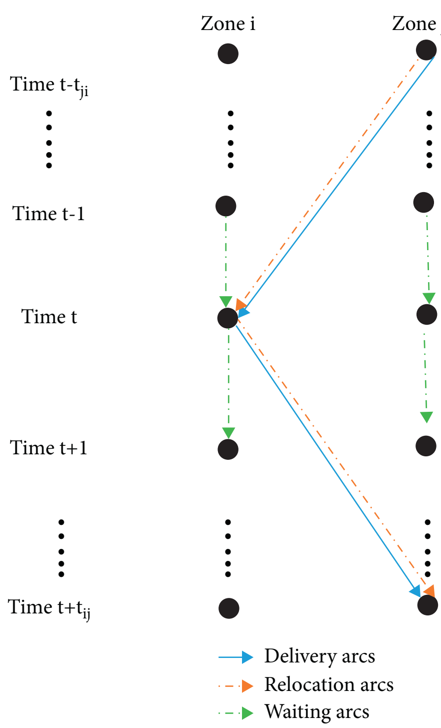


Figure 3: SAV flow conservation in time-space network.

zone i to zone j at time t. Furtherly, we employ V_i^t to indicate the number of vehicles waiting at zone i at time t. At each node, the SAVs obey the rule of flow conservation and satisfy the travel demand as much as possible.

3.2. The NLP Model on the Daily Operation Problem. This section introduces a NLP optimization model to describe the daily operation problem with discrete mode choice based on the time-space network. The premise assumes that the infrastructure deployment is determined initially, which will be discussed together in Section 3.3. Specifications on variables and parameters used in the daily operation problem are shown in Table 1.

3.2.1. Discrete Mode Choice. Random utility maximization (RUM) theory is extensively used to portray the mode choice behavior [33, 43], which assumes that each traveler tries to maximize the utility related to their trip. We define D_{ij}^t to represent the total travel demand from zone i to zone j at time t. Besides, we consider that the fare paid for the SAVs consists of the base price and the time-related price. In this paper, the base price δ_f for an SAV trip is introduced as a decision variable to affect the induced demand. For SAV trips from zone i to zone j departing at time t, the generalized cost $C_{sav}^{i,j,t}$ is formulated in (1), where the first term is the travel time $\gamma_{i,j}^t$ weighted by the unit VoT c_{sav}^{vot}, and the second term in the bracket is the fare paid for an SAV trip, which includes the base price δ_f for an SAV trip and the travel time $\gamma_{i,j}^t$ weighted by the time-related price δ_t.

$$C_{sav}^{i,j,t} = c_{sav}^{vot} \cdot \gamma_{i,j}^t + \left(\delta_f + \delta_t \cdot \gamma_{i,j}^t\right), \quad \forall i, j \in \mathbf{N}, t \in \mathbf{T}. \tag{1}$$

For CPVs travelers from zone i to zone j departing at time t, the generalized cost $C_{cpv}^{i,j,t}$ is developed in

$$C_{cpv}^{i,j,t} = c_{cpv}^{vot} \cdot \gamma_{i,j}^t + \beta \cdot \gamma_{i,j}^t + c_p, \quad \forall i, j \in \mathbf{N}, t \in \mathbf{T}. \tag{2}$$

where the first attribute is the travel time $\gamma_{i,j}^t$ weighted by the unit VoT c_{cpv}^{vot}, the second attribute is the travel time $\gamma_{i,j}^t$ weighted by the unit fuel consumption cost β, and the third attribute is the average parking cost c_p for a CPV trip.

Based on the utility function, the probability of travelers intending to choose SAVs $p_{i,j}^t$ is defined by

$$p_{i,j}^t = \frac{\exp\left(-b \cdot C_{sav}^{i,j,t}\right)}{exp\left(-bC_{sav}^{i,j,t}\right) + exp\left(-bC_{cpv}^{i,j,t}\right)}, \quad \forall i, j \in \mathbf{N}, t \in \mathbf{T}. \tag{3}$$

Therefore, the number of users who are inclined to SAVs $d_{i,j}^t$ is determined by the choosing probability and is formulated as the following constraint:

$$d_{i,j}^t = D_{i,j}^t \cdot p_{i,j}^t \quad \forall i, j \in \mathbf{N},\ t \in \mathbf{T}. \tag{4}$$

3.2.2. The NLP Optimization Model. Our objective for the daily operation problem is to acquire the most efficient operational decisions, including relocation and pricing strategies to maximize the daily operation profit (DOP), which is formulated in

$$\begin{aligned}\max Z = {} & \sum_{t\in\mathbf{T}}\sum_{i\in\mathbf{N}}\sum_{j\in\mathbf{N}}\left(\delta_f + \delta_t\gamma_{i,j}^t\right)\cdot s_{i,j}^t \\ & - \left\{\beta\cdot\left(\sum_{t\in\mathbf{T}}\sum_{i\in\mathbf{N}}\sum_{j\in\mathbf{N}} Q_{i,j}^t\cdot\gamma_{i,j}^t + \sum_{t\in\mathbf{T}}\sum_{i\in\mathbf{N}}\sum_{j\in\mathbf{N}} R_{i,j}^t\cdot\gamma_{i,j}^t\right)\right. \\ & \left. + \eta\cdot\sum_{i\in\mathbf{N}} V_i^1 + \sum_{t\in\mathbf{T}}\sum_{i\in\mathbf{N}}\sum_{j\in\mathbf{N}}\left(d_{i,j}^t - s_{i,j}^t\right)\cdot\varphi\right\}.\end{aligned} \tag{5}$$

In (5), the first term represents the revenue charges from the served SAV users, and the second term in the curly brace is the daily operation cost (DOC). Here, we marked the DOC as H. The DOC includes the fuel consumption cost for occupied and relocated vehicles, the fixed cost for daily maintenance of all SAVs, and the penalty cost for unserved

Table 1: Variables and parameters used in the daily operation problem model.

Notations	Description
Parameters	
N	Set of zones, indexed as i and j
T	Set of time periods, indexed as t
δ_t	The unit time-related price for SAV users
c_{sav}^{vot}	The unit value of time for SAV users
c_{cpv}^{vot}	The unit value of time for CPV users
c_p	The parking cost for a CPV trip
η	Daily maintenance cost for an SAV
D_{ij}^t	The total travel demand for SAVs and CPVs from origin i to destination j departure at time t
α	The minimum customer service rate
m	The capacity of an SAV, which allows ride-pooling
φ	The unit penalty cost for one unserved SAV demand
β	The unit fuel consumption cost
$\gamma_{i,j}^t$	The shortest travel time from zone i to zone j at time t in k-th period
f	The total fleet size
y_i	The number of parking spaces at zone i
Decisions variables	
δ_f	The base price for a SAV trip
$Q_{i,j}^t$	The number of occupied vehicles with passengers from zone i to zone j departure at time t
$R_{i,j}^t$	The number of empty vehicles relocating from zone i to zone j at departure time t
Auxiliary variables	
V_i^t	The number of SAVs waiting at zone i at the beginning of time t
$p_{i,j}^t$	The probability of travelers choosing SAVs from zone i to zone j at time t
$d_{i,j}^t$	The number of travelers who intend to employ SAVs from zone i to zone j at time t
$s_{i,j}^t$	The number of travelers served actually by SAVs from zone i to zone j at time t

SAV demand. The objective function is subject to the customer service rate, flow conservation, parking, and definitional constraints.

Given the spatial-temporal imbalance between available SAVs and travel requests, it is inevitable to lose some travelers. Thus, constraint (6) is proposed to ensure that the served demand $s_{i,j}^t$ is no more than the total SAV demand $d_{i,j}^t$ from zone i to zone j at time t.

$$s_{i,j}^t \le d_{i,j}^t, \quad \forall i, j \in \mathbf{N}, t \in \mathbf{T}. \tag{6}$$

Besides, to guarantee the reliability of the SAV system, constraint (7) is provided to satisfy the minimum customer service rate α. Here, the customer service rate is expressed as the number of served demands divided by the total SAV demand.

$$\frac{\sum_{t\in T}\sum_{i\in N}\sum_{j\in N} s_{i,j}^t}{\sum_{t\in T}\sum_{i\in N}\sum_{j\in N} d_{i,j}^t} \ge \alpha. \tag{7}$$

In addition, the number of occupied vehicles is no more than the served travel demand, which can be expressed as the following formula:

$$Q_{i,j}^t \le s_{i,j}^t, \quad \forall i, j \in \mathbf{N}, t \in \mathbf{T}. \tag{8}$$

Ride-pooling is simplistically considered in this study. We denote the average number seat of SAVs is m . Hence, the served travel demand is subject to the total capacity of employed SAVs, which is described as follows:

$$s_{i,j}^t \le m \cdot Q_{i,j}^t, \quad \forall i, j \in \mathbf{N},\ t \in \mathbf{T}. \tag{9}$$

The number of SAVs waiting at zone i at time $t+1$ equals the number of SAVs waiting at time t plus the occupied and relocated SAVs, which arrive at zones i during time t and $t+1$, minus the occupied and relocated SAVs, which depart from zone i at time $t+1$, which is shown in constraint (10). As a side note, subscript u describes the time instant at which SAVs depart from zone j and exactly arrive at zone i during time constant t and $t+1$.

$$\begin{gathered} V_i^{t+1} = V_i^t + \sum_{j\in N} Q_{j,i}^u + \sum_{j\in N} R_{j,i}^u - \sum_{j\in N} Q_{i,j}^{t+1} - \sum_{j\in N} R_{i,j}^{t+1}, \\ \forall i \in N, \quad t = 1, 2, \ldots, \overline{T}-1, u = \max\left\{0, t+1-\gamma_{j,i}^t\right\}. \end{gathered} \tag{10}$$

Further, we assume that the SAV system will recover to the initial level at the end of the day in order to serve the demand the next day, which requires that $V_i^{\overline{T}+1} = V_i^1$. Thus, we have the constraint (11). The right hand in equation (11) is the number of vehicles waiting at zones i at the end of the day, that is, $V_i^{\overline{T}+1}$.

$$\begin{gathered} V_i^1 = V_i^{\overline{T}} + \sum_{j\in \mathbf{N}} Q_{j,i}^u + \sum_{j\in \mathbf{N}} R_{j,i}^u - \sum_{j\in \mathbf{N}} Q_{i,j}^{\overline{T}+1} - \sum_{j\in \mathbf{N}} R_{i,j}^{\overline{T}+1}, \\ \forall i \in \mathbf{N}, u = \max\left\{0, \overline{T}+1-\gamma_{j,i}^{\overline{T}}\right\}. \end{gathered} \tag{11}$$

By definition, the number of vehicles waiting at zone i at any time t is no more than the number of parking spaces in zone i.

$$V_i^t \le y_i, \quad \forall i \in \mathbf{N}, t \in \mathbf{T}. \tag{12}$$

Table 2: Variables and parameters used in the long-term planning of the SAV system.

Notations	Description
Parameters	
$\boldsymbol{K}$	Set of the planning periods, indexed as k
c_i^s	Unit construction cost for a station at zone i
c_i^p	Unit construction cost for a parking space at zone i
c_k^v	Unit purchase cost for an SAV in k-th periods
ε	Interest rate
θ_k	Discount factor in the k-th planning period
ϑ	The total number of operational days in a year
$p_i^{\max}$	The maximum number of parking spaces at zone i
Decision variables	
x_i^k	If there is a station built at zone i at the beginning of k-th period
y_i^k	The number of parking spaces at zone i at the beginning of k-th period
f_k	The total fleet size at zone i at the beginning of k-th period

Moreover, the sum of vehicles waiting at all zone i at the beginning of the initial time equals the total fleet size.

$$\sum_{i \in N} V_i^1 = f. \tag{13}$$

Finally, the nonnegative constraints for decision variables are described in

$$Q_{i,j}^t \geq 0, \quad \forall i, j \in \mathbf{N}, \forall t \in \mathbf{T}. \tag{14}$$

$$R_{i,j}^t \geq 0, \quad \forall i, j \in \mathbf{N}, \forall t \in \mathbf{T}. \tag{15}$$

$$V_i^t \geq 0, \quad \forall i \in \mathbf{N}, \forall t \in \mathbf{T}. \tag{16}$$

3.3. The MINLP Model on the SAV Design Problem. Given the continuously growing demand and complicated interaction between strategic planning and daily operation decisions, there exists a necessity for the planner to design the SAV system over a long planning horizon. The long-term strategic planning horizon is divided into multiple periods, and we assume that one year is one period. Define the set $\mathbf{K} = \{1, 2, \ldots, \overline{K}\}$ to represent the planning periods. Sequential strategic planning decisions include where and when to establish stations, how many parking spaces to deploy at stations, and the fleet size. During each planning period, we let $\mathbf{X} = \{x_i^k\}$ be the binary variables. If $x_i^k = 1$, then there is a station built at zone i at the beginning of k-th period; otherwise, we define $x_i^k = 0$. Denote $\mathbf{Y} = \{y_i^k\}$ to indicate the number of parking spaces at station i at the beginning of k-th period. Moreover, we define $\mathbf{F} = \{f_k\}$ to represent the total fleet size at the beginning of the k-th period. These strategic decisions are determined at the beginning of each period, and the daily operation problem in Section 3.2 is according to the responding infrastructure deployment in k-th period. The decision variables and parameters in the long-term planning horizon are listed in Table 2.

The total capital cost (TCC) for the long-term infrastructure deployment consists of three components: the construction cost for stations $W_1(X)$, the construction cost for parking spaces $W_2(Y)$, and the purchasing cost for SAVs $W_3(F)$. And we assume that once stations and parking spaces are established, they will continue working until the final planning period. Moreover, the parking spaces at stations are expanded year by year. We define the initial value $x_i^0 = 0$, $y_i^0 = 0$, and then the numbers of newly established stations and parking spaces at zone i are represented as $x_i^k - x_i^{k-1}$, $y_i^k - y_i^{k-1}$ in the k-th period, respectively. Similarly, we assume the initial fleet size is 0, that is, $f_0 = 0$. The number of SAVs purchased at the k-th period is $f_k - f_{k-1}$. Thus, $W_1(X)$, $W_2(Y)$, $W_3(F)$ can be described as

$$W_1(\mathbf{X}) = \sum_{k \in \mathbf{K}} \sum_{i \in \mathbf{N}} \theta_k c_i^s \left(x_i^k - x_i^{k-1}\right). \tag{17}$$

$$W_2(\mathbf{Y}) = \sum_{k \in \mathbf{K}} \sum_{i \in \mathbf{N}} \theta_k c_i^p \left(y_i^k - y_i^{k-1}\right). \tag{18}$$

$$W_3(\mathbf{F}) = \sum_{k \in \mathbf{K}} \theta_k c_k^v \left(f_k - f_{k-1}\right), \tag{19}$$

where θ_k is the money discounted factor, which is a decreasing function of interest rate ε, and we define $\theta_k = 1/(1+\varepsilon)^{k-1}$.

Besides, the numbers of stations and parking spaces at each station and the fleet size during the entire planning period are monotonically nondecreasing, which are described as

$$x_i^{k-1} \leq x_i^k \quad \forall i \in \mathbf{N}, k \in \mathbf{K}. \tag{20}$$

$$y_i^{k-1} \leq y_i^k \quad \forall i \in \mathbf{N}, k \in \mathbf{K}. \tag{21}$$

$$f_{k-1} \leq f_k \quad \forall k \in \mathbf{K}. \tag{22}$$

Constraint (23) limits the number of parking spaces established at station i and cannot exceed the maximum number of parking spaces p_i^{max}.

$$0 \leq y_i^k \leq p_i^{\max} x_i^k \quad \forall i \in \mathbf{N}, k \in \mathbf{K}. \tag{23}$$

Finally, constraints (24)–(26) denote the feasible solution domain of decision variables.

Table 3: The statistical number of variables in the proposed model.

Variables	x_i^k	y_i^k	f_k	δ_f	$R_{i,j}^t$	$Q_{i,j}^t$
The number of variables	$\overline{N}\cdot\overline{K}$	$\overline{N}\cdot\overline{K}$	$\overline{K}$	1	$\overline{N}\cdot(\overline{N}-1)\cdot\overline{T}\cdot\overline{K}$	$\overline{N}\cdot(\overline{N}-1)\cdot\overline{T}\cdot\overline{K}$

$$x_i^k \in \{0,1\} \quad \forall i \in \mathbf{N},\ k \in \mathbf{K}. \tag{24}$$

$$y_i^k \text{ Integer} \geq 0 \quad \forall i \in \mathbf{N},\ k \in \mathbf{K}. \tag{25}$$

$$f_k \text{Integer} \geq 0 \quad \forall k \in \mathbf{K}. \tag{26}$$

In terms of the given x_i^k , y_i^k , f_k in the *k-th* period, the operation decisions can be acquired from the optimization model in Section 3.2. Here, we consider the set $\mathbf{Z} = \{Z_1, Z_2, Z_3, \ldots, Z_{\overline{K}}\}$ to represent the daily operation profit (DOP) in different periods. We assumed that daily demand is similar; namely, DOP in the specific planning period is identical every day. The assumption can be held because the demand variation has a negligible impact on the optimization objective. The total operational profit (TOP) in a long period is the sum of DOP in all the planning periods. Hence, TOP is formulated as follows:

$$\overline{Z}\left(Q, R, \delta_f\right) = \sum_{k\in\mathbf{K}} \theta_k \vartheta Z_k. \tag{27}$$

In (27), ϑ is employed to denote the total number of operation days in a year. In this paper, we assume that SAVs are of use throughout the year, that is to say, $\vartheta = 365$. As a side note, the base price is only considered in the discrete mode choice, and we have not considered the varying base price in long-term planning, which will be studied in the future. Hence, the discount factor is applied to the TOP integrally, not affecting the base price separately in this paper. According to the thorough analysis of the daily operation problem and the long-term strategic planning, we can formulate the long-term SAV system design problem as a MINLP model as follows:

$$\max P\left(Q, R, \delta_f, \mathbf{X}, \mathbf{Y}, \mathbf{F}\right) = \overline{Z}\left(Q, R, \delta_f\right) - W_1(\mathbf{X}) - W_2(\mathbf{Y}) - W_3(\mathbf{F}), \tag{28}$$

subject to (1)–(27), where P represents the total profit in the SAV system and is defined as the difference between TOP and TCC.

3.4. Solution Approach. As stated in Section 3.3, the long-term SAV system design problem is formulated as a MINLP model, which involves a large number of decision variables. Specifically, seven sets of decision variables are included. The number of each decision variable is, respectively, listed in Table 3.

According to Table 3, the total number of decision variables is equal to $(2\cdot\overline{N} + 2\cdot\overline{N}\cdot(\overline{N}-1)\cdot\overline{T}+1)\cdot\overline{K}+1$, which is determined by the number of study areas, operation time steps, and planning periods. With the exception of the

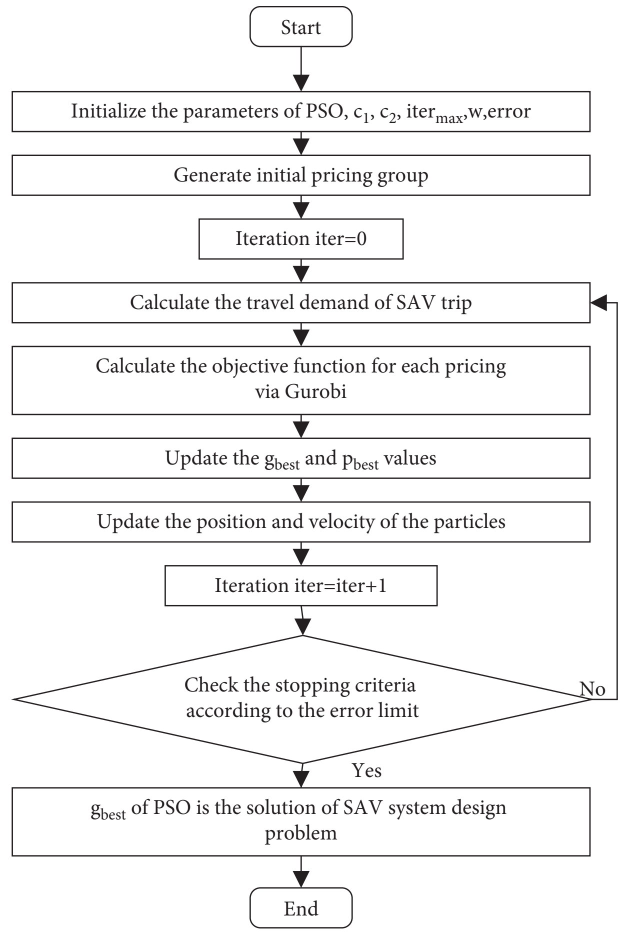


Figure 4: Flowchart of the solution algorithm.

logit mode choice model in constraint (3), the objective and other constraints are linear. Considering the solving complexity of the NINLP model, this study integrates Particle Swarm Optimization (PSO) algorithm [36] and the Gurobi solver [44]to address the problem effectively. In such a case, PSO is envisioned to generate the initial solution for the base price; constraint (3) will be a known probability parameter once particles are generated. Further, the MINLP model is converted into a MILP model, which can be solved by optimization solvers Gurobi. The modified computation procedure is as follows (Figure 4).

The parameters of PSO are defined with constriction factors of 2 and inertial weights of 0.6. The number of particles in a swarm is set to 50, and the maximum number of iterations is set to 100. The solution of the MILP model is obtained using the interior point method by Gurobi, which is installed with Python 3.8 and runs on a personal computer with Intel Core i5-CPU of 3.2 GHz and 16 GB RAM. A maximum time limit of 10 thousand seconds is to find an optimal solution. Besides, we set the gap as 0.001, and if an optimal solution cannot be found in the limited time, we regard the current best feasible solution as the objective value.

4. Numerical Experiments

4.1. Model Validation Framework. Two numerical experiments are conducted to validate the performance of the proposed MINLP model and the solution method. We first perform numerical experiments on the Four-Node [45] network to illustrate the optimal results and analyze how the parameters influence the system's performance. In Section 4.2, we set the basic parameters in the test case. Then, we continuously explore the distribution of relocation activities, deployment of parking spaces, and fleet size in Section 4.3 to validate the solvability and efficiency of the proposed model. Furtherly, sensitivity analysis experiments are carried out to validate the robustness of the proposed model in Section 4.4. Finally, a large-scale case in the Sioux Falls network is conducted in Section 4.5, which aims to validate that the model is applicable to more complex networks.

4.2. Test Case Setting. We first select a small example to manifest that the model can determine the infrastructure deployment and operational decisions. The example concerns a Four-Node Network (Figure 5), in which zone 1 and zone 2 are defined as home zone and work zone, and there are travel demands between the two zones to conduct work activity. Additionally, zones 3 and 4 are set as leisure areas with zero demand and are designed to achieve relocation when there are no available vehicles at zones 1 and 2. In this problem, we assume that the SAV system operates from 6:30 to 20:30 in a day and is divided into 28 time steps, that is to say, $\Delta = 0.5h$. We supposed that the travel demands departing from zones 1 and 2 are randomly generated and are depicted in Figure 6.

We assume that the free-flow travel time along each link is one-time step. However, travel time is associated with the actual traffic situation. Thus, a correction factor is put forward in Table 4 to describe the congestion characteristic of traffic flow.

This study attempts to integrate the increasing demand over the next 10 years to design the SAV systems. Furthermore, it is reasonable to assume that the total travel demand is gradually growing at a rate of $\tau = 1.05$ per year. Also, the monetary discount factor is set as $\varepsilon = 0.05$. According to Huang et al. [42] and Li et al. [12], daily operational parameters are set as follows: the VoT for SAV users $c_{sav}^{vot} = 5\$/\text{time step}$, for CPV users $c_{cpv}^{vot} = 8\$/\text{time step}$, and the parking cost for a CPV trip $c_p = 2\$$. The unit fuel consumption cost for vehicles $\beta = 3\$/\text{time step}$, the unit time-related price for SAV travelers $\delta_t = 1\$/\text{time step}$, and the maintenance cost for an SAV in a day$\eta = 1\$/day$. The feasible region for the base price of an SAV trip $\delta_f \in [6, 12]\$$. Similarly, we define the infrastructure construction cost as follows: the unit construction cost for a station and a parking space is $c_i^s = 15000\$$, $c_i^p = 150\$$ for home and work zones,

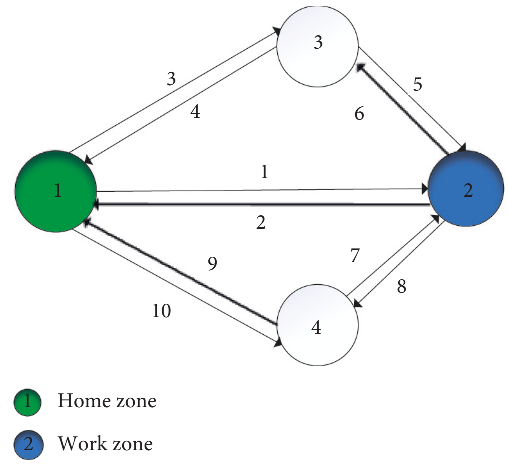


Figure 5: Four-node network example.

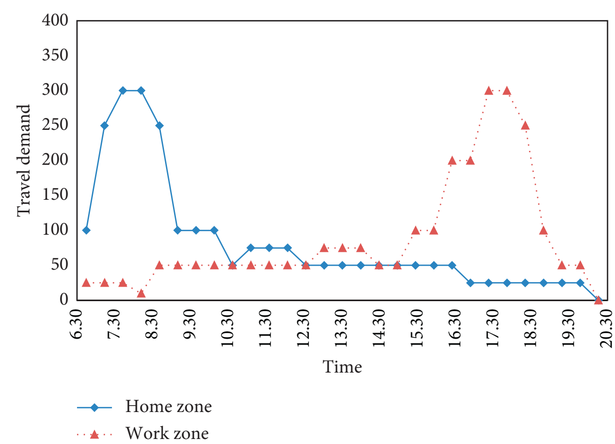


Figure 6: Distribution of travel demand from zones 1 and 2.

and $c_i^s = 10000\$$, $c_i^p = 100\$$ for other zones. And the maximum number of park space at zone i is defined as $p_i^{\max} = 100$. The unit purchase cost for an SAV in the initial year is $c_1^v = 15000\$$ and will decrease by 150\$ per year. In addition to these system parameters, to better balance the quality of service and total profit, in what follows in this paper, we define the minimum customer service rate as $\alpha = 0.9$.

The following indicators are collected to evaluate the performance of the proposed model:

(1) The total profit for the SAV system $P(Q, R, \delta_f, \mathbf{X}, \mathbf{Y}, \mathbf{F})$.

(2) The total capital cost (TCC). $W = W_1(\mathbf{X}) + W_2(\mathbf{Y}) + W_3(F)$

(3) The total operational cost (TOC). Similar to TOP, we consider the set $\mathbf{H} = \{H_1, H_2, H_3, \ldots, H_{\overline{K}}\}$ to represent the DOC in different periods. We calculate the TOC as $H(Q, R, \delta_f) = \sum_{k\in\mathbf{K}} \theta_k \vartheta H_k$.

(4) The strategic planning decisions, such as the number of parking spaces y_i^k at zones i and the total fleet size f_k at the beginning of the k-*th* period.

Table 4: The growth factor of travel time departure at different time periods.

Time	6:30–7:29	7:30–9:29	9:30–10:59	11:00–13:29	13:30–14:29
Growth factor	1	1.5	1.3	1	1.2
Time	14:30–16:29	16:30–18:29	18:30–19:29	19:30–20:00	—
Growth factor	1	1.5	1.3	1	—

4.3. Optimal Results

4.3.1. The Optimal Trip Pricing. According to the above-mentioned parameters, a preliminary experiment is conducted to determine the optimal base price in order to achieve the total profit maximized. In the benchmark case, ride pooling is not taken into account, that is, m = 1. According to the iterative process by PSO-Gurobi, the optimal solution of the base price is determined as δ_f = 8.61\$ with the maximized profit $P = 24365598.85\,\$$. The MILP solved by Gurobi can obtain the optimal solution through an average of 7317 simplex iterations. The average computation time for each optimization run is 5940s, which indicates that the model and algorithm are efficient.

The variation tendency of total profit and fleet size is delineated in Figure 3 under the varying base price. As expected, the fleet size in the SAV system is decreasing with the upward base price, owing to the reduced demand. However, the total profit has a transfer point; that is, although the demand for SAVs decreases with the growing base price, the incremental revenue allows the total profit to grow. Once the base price is exorbitantly high, fewer travelers are likely to choose SAVs to travel, resulting in less revenue. Therefore, the total profit tends to rise first and then fall, and the solid red dot in Figure 7 represents the optimal base price.

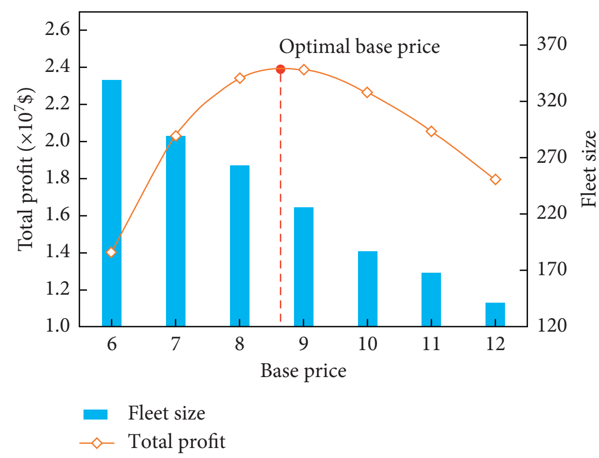


Figure 7: The effect of the base price on the system performance.

the demand is more unbalanced. For instance, at the beginning of the day, few vehicles arrive at the home zone, but a large number of vehicles leave. Accordingly, more relocation activities are carried out from other zones to zone1. Summarily, these findings demonstrate that relocation is beneficial to unbalanced demand, which is meaningful in reducing fleet size and improving the utilization rate of SAVs.

4.3.2. The Optimal Distribution of SAV Relocation Activities. According to the mentioned analysis, we define the base price δ_f = 8.61 to analyze the optimal results of the SAV system design. The total profit of the SAV system is 2.44 × 10^7\$ with a gap of 0.0788%. In the final planning year, the SAV system employs 245 vehicles to serve 2474 trips in a day, in which one vehicle can deliver 10 trips due to relocation. The distributions of relocation activities from or to each zone are described in Figures 8(a) and 8(b). There are 1731 relocation activities in the small network, with an average of 15 per zone per time step.

We can obviously observe that relocation activities frequently happen in two time periods, which are 6:30–9:00 and 16:30–18:30, respectively. At 6:30–9:00, a considerable volume of empty vehicles relocates from zone 2 or zone 3 and 4 to home zone 1. Because numerous traveling demands originate from the home zone, there are no sufficient available vehicles constrained to the parking spaces. Similarly, at 16:30–18:30, empty vehicles relocate from the home zone and leisure areas to the work zone to carry out the travel activities for home. Simultaneously, it is necessary to relocate vehicles from the work zone to the home zone to recover the SAV system for the initial distribution. Another interesting observation is that relocation activities are more intense when

4.3.3. The Optimal Strategic Planning Decisions. With respect to the long-term design of the SAV system, Figure 9 depicts the distribution of parking spaces and fleet size at each zone at the beginning of each planning period. We can observe from Figure 9(a) that, in zones 1 and 2, the number of parking spaces equals the maximum number due to high travel demand and limited parking spaces. However, the number of parking spaces in zone 3 is growing consistently. Even though no travel demand originates from zone 3 in the hypothetical network, more parking spaces are constructed for the growing demand from other zones, which is achieved through relocation. Moreover, at zone 4, there are hardly any changed parking spaces established from beginning to end. One possible explanation for that may be that the number of parking spaces is enough for relocation through zone 4 in the initial year. Figure 9(b) furtherly summarizes the distribution of fleet size at the beginning of the *k-th* period. Figure 9(b) shows an apparent growing tendency in the first six years, and then the fleet size has been sustained. The trend is that it is more economically viable to carry out relocation to serve travel demands than to purchase more vehicles. Results of the strategic planning decisions have demonstrated that the varying demand deeply influences infrastructure deployment to achieve the total profit maximized.

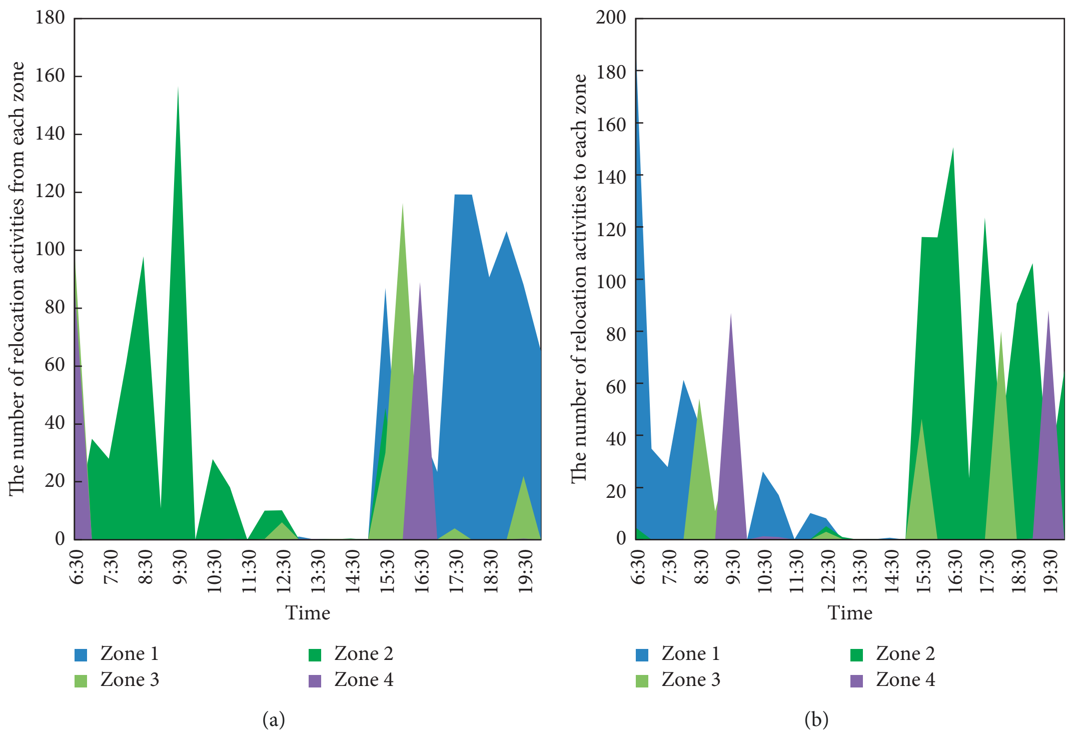


Figure 8: The distribution of relocation activities in a small network.

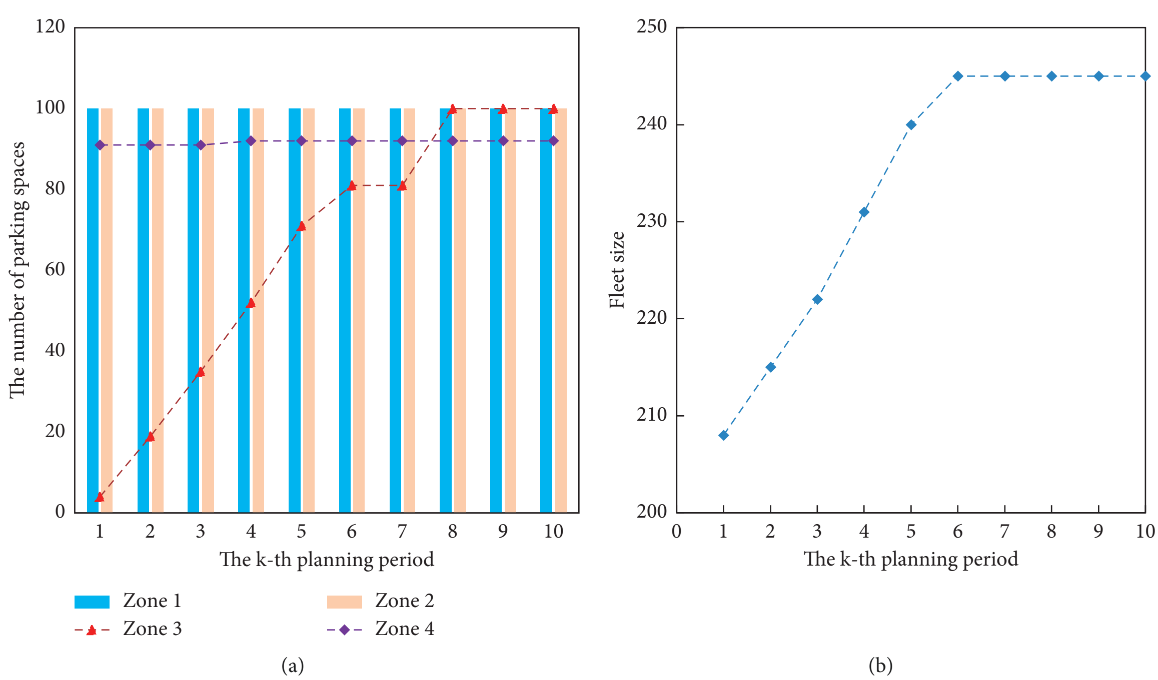
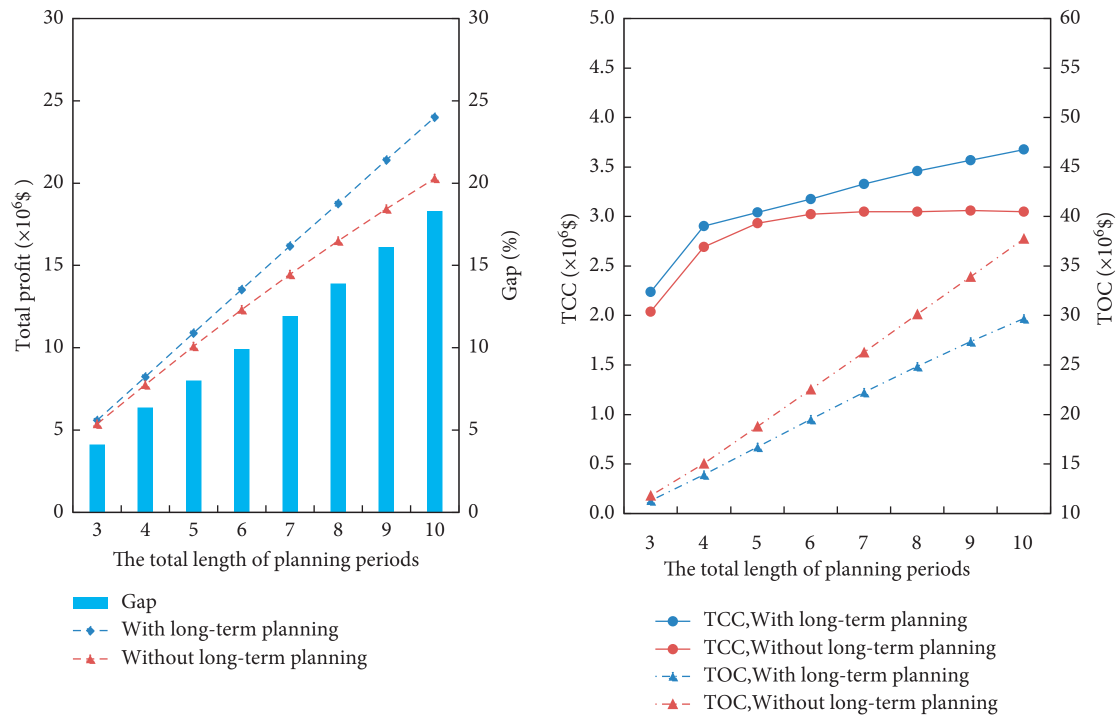


Figure 9: The number of parking spaces at each zone (a) and fleet size (b) at the beginning of *k-th* period.

4.4. Sensitivity Analysis

4.4.1. Comparison with and without Long-Term Strategic Planning. To investigate the impact of long-term strategic planning on the SAV system, in this subsection, this study dives into the optimal solutions obtained using the MINLP model with long-term planning and its counterpart without long-term planning, as seen in Figure 10. We set several scenarios in that the total length of planning periods k change from 3 to 10, respectively. Regarding the scenarios without long-term planning, we design the SAV system only considering travel demand in the current year.



(a) (b)

Figure 10: System performance with and without long-term planning.

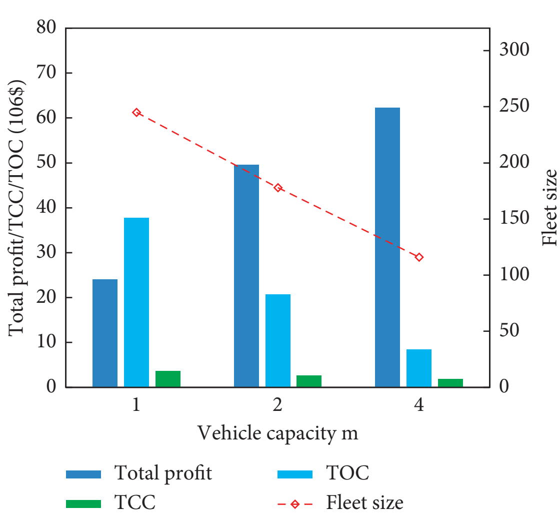


Figure 11: Impact of ride-pooling on system performance.

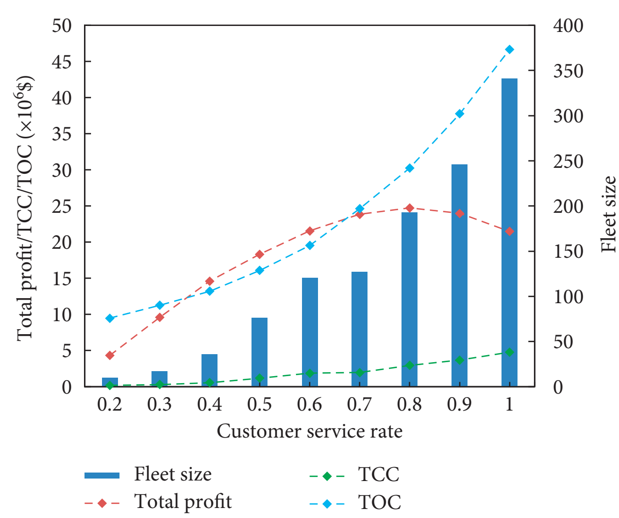


Figure 12: The effect of customer service rate on the system performance.

As seen in Figure 10(a), the optimal total profit with long-term planning is significantly increased versus the scenarios without long-term planning. An interesting observation we can find is that the range of improvement in total profit gradually increases with the growth of planning years; even the gap reached 18% when the entire planning year is up to 10. We carry out two comparative analyses to portray the connection between TCC and TOC. Figure 10(b) shows that the TCC with long-term planning is always higher than that without long-term planning, no matter how long the entire planning year is. Inversely, the TOC with long-term planning will remain lower than that without long-term planning. This is because the increasing demand in the future year is considered in the scenarios with long-term planning, which will need to invest more budget to purchase vehicles and building stations or parking spaces instead of the cost for relocation in daily operation. Similarly, the gaps of TOC and TCC with and without long-term planning in Figure 10(b) are positively associated with the total planning years, which indicates that the effect is more

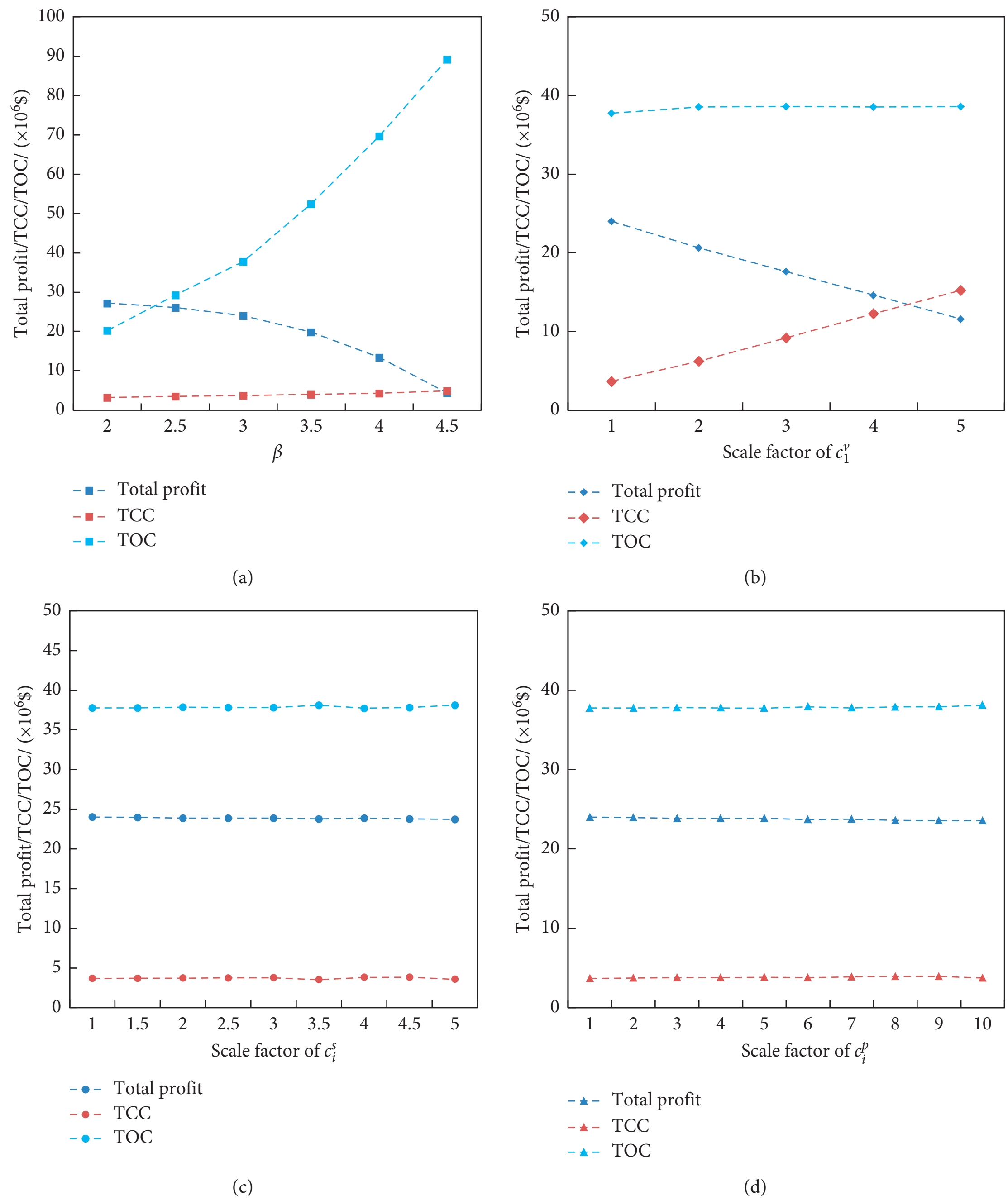


Figure 13: Sensitivity of model parameters on system performance.

remarkable when the whole length of planning years is longer. With respect to these phenomena, we can conclude that long-term planning is beneficial to achieving total profit maximization and a trade-off between the TCC and TOC.

4.4.2. Impacts of the Ride Pooling. Ride-pooling is envisioned to alleviate traffic congestion and reduce carbon emissions. To discuss how ride-pooling influences the design of the SAV system, the parameter of vehicle capacity changes in this section. Regarding ride-pooling, we design three comparative experiments, no ride-pooling (m = 1), two-person ride-pooling ($m = 2$), and four-person ride-pooling ($m = 4$), and the result is delineated in Figure 11. As shown in Figure 11, the fleet size, the TCC, and the TOC of the SAV system have a clear downward tendency. Contrarily, there exists a significant increase in total profit. All these results demonstrate that ride-pooling is beneficial in reducing fleet size and the number of relocation activities. Thus, some subsidy policies are essential to be conducted to encourage passengers to ride together, which will be investigated in our future research.

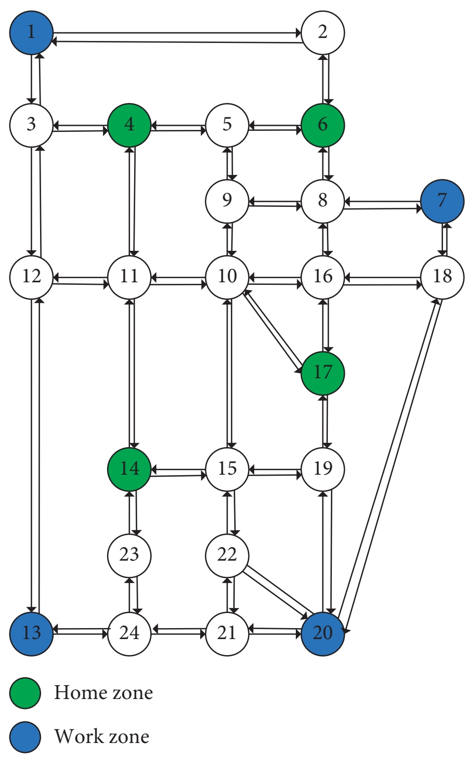


FIGURE 14: The Sioux Falls network.

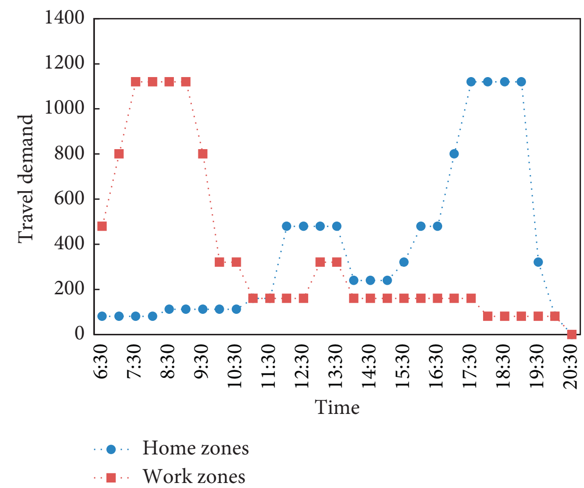


FIGURE 15: Distribution of travel demand from home and work zones.

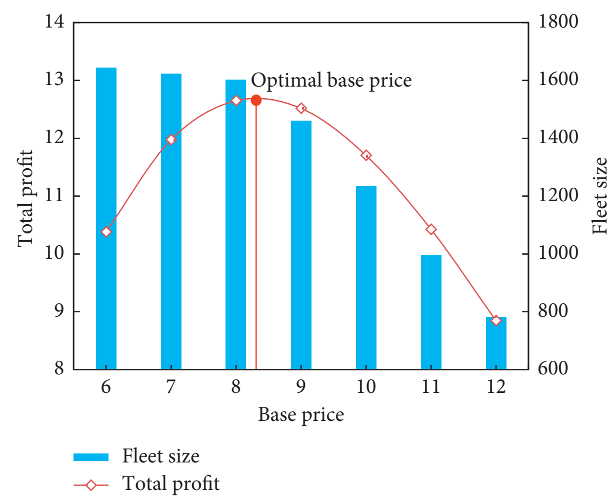


FIGURE 16: The optimal base price for the Sioux Falls network.

4.4.3. Impacts of the Customer Service Rate. The constraint of the minimum customer service rate strictly limits the system reliability, forcing the operator to satisfy travel demands. In order to discuss how the customer service rate influences the SAV system, we carry out sensitive experiments when the customer service rate is precisely equal to [0.1, 0.2, . . ., 0.9,1]. Figure 12 delineates the SAV system performance under different scenarios based on the statistical data. We can observe a noticeable increase in the fleet size and TOC with the variation in customer service rate. This is due to the higher customer level requiring more vehicles to carry out more travel activities to pick up passengers and relocation. Moreover, the TCC also grows because of more fleet size and parking infrastructures. Thus, the total profit tends to go up first and then down. We can conclude that the SAV system design is tightly associated with the customer service rate, and the optimization results can be distinct due to different reliability constraints.

4.4.4. Impacts of Model Parameters. To further analyze the effects of crucial model parameters on the performance of the SAV system, four parameters in the MINLP model, namely, unit fuel consumption cost for an SAV β, unit purchase cost for an SAV c_1^v, unit construction cost for a station c_i^s, and unit construction cost for a parking space c_i^p, are changed in a specific rule. This section investigates how the total profit, TOC, and TCC change correspondingly to different scenarios. The relative changing tendencies are displayed in Figure 13.

As seen in Figure 13(a), the sensitivity analysis of unit fuel consumption cost for an SAV β changes from 2\$ to 4.5\$ at step size 0.5\$. When β increases, the total profit declines, while the TOC goes up. That is due to the constraint on the customer service rate so that the cost for passengers occupied vehicles and relocated empty vehicles inevitably increases. Another observation is that the TCC then barely changes. One reason might be that the fleet size is subject to the customer service rate and is hardly changed. Therefore, there is less influence on the infrastructure construction cost.

Meanwhile, a scale factor from 1 to 5 is utilized to multiply the unit purchase cost for an SAV c_1^v and the effect on the system is shown in Figure 13(b). We can see the total profit is decreased by about 51.72%. But the TCC increases in number threefold. As c_1^v increasing, fewer vehicles are put into the SAV systems; still, concerning the constraint of the customer service rate, the number of SAVs is incapable of reducing overtime. Therefore, the decline in fleet size would hardly influence the total daily operation, indicating small changes in the TOC. Further, the TCC increases in terms of the unit purchase cost for an SAV growing, thus a tiny reduction in the total profit.

Table 5: Performance of the optimal solution.

Total profit ($\times 10^8$)	Total capital cost ($\times 10^7$)	Total operation cost ($\times 10^8$)	Customer service rate	Gap (%)
1.29	2.37	3.59	0.94	0.39

More importantly, a scale factor from 1 to 5 is multiplied by the unit construction cost for a station c_i^s to investigate the effect on the SAV system. As displayed in Figure 13(c), the variation of c_i^s leads to the total profit, the TCC, and the TOC are rarely changing. Resemble results are graphically shown in Figure 13(d), in which sensitivity analyses are conducted regarding unit construction cost for a parking space c_i^p that is multiplied by the scale factor changes from 1 to 10. Therefore, the conclusion can be drawn that unit construction cost for a station or parking space has few impacts on the total system performance.

Broadly speaking, the SAV system is more sensitive to the unit fuel consumption cost and purchase cost for a SAV than the unit construction cost for a station and a parking space.

4.5. Large-Scale Network Application

4.5.1. Sioux Falls Network Case Setting. To investigate the efficiency and flexibility of the proposed MINLP model and the solution method, this section explores a larger transport network (Figure 14) concerning the long-term SAV system design in the Sioux Falls network, one of the most frequently used in the transportation area. The study network consists of 24 zones and 76 links. We divide the network into four home zones, four work zones, and other zones for entertainment or medical. Similarly, the travel demand is randomly generated, as displayed in Figure 15. We assume the travel cost at links 12–13 and 18–20 as two-time steps, but all the remaining links are one-time step. For the sake of consistency, these basic parameters are set the same as in the Four-Node network.

4.5.2. Optimization Results. According to the assumption, the SAV system of the Sioux Falls network is designed over the next ten years, considering the fluctuating demand and the minimum customer service rate required. We display the first result of the favorable base price for SAV trips in the Sioux Falls network obtained by the proposed method. By repeatedly iterative calculation using the proposed method, we can observe that the optimal base price is 8.33$, as described in Figure 16. Moreover, we can draw the conclusion that the variation tendencies of total profit and fleet size comply with the results in the Four-Node network referred to in Figure 7. Thereby, it is believed that favorable pricing is essential for the performance of different SAV systems.

We design the SAV system with the optimal base price in the following. Based on the optimal solutions, the system's performances are depicted in Table 5. Besides, the accumulated fleet size deployed during the design period is portrayed in Figure 17. Regarding the continuously growing demand in the future years, the number of SAVs remarkably increases before the first six years and then is nearly constant. Indeed, in the initial year, 1235 vehicles are needed to serve 10355 demands at a customer service rate beyond 0.9.

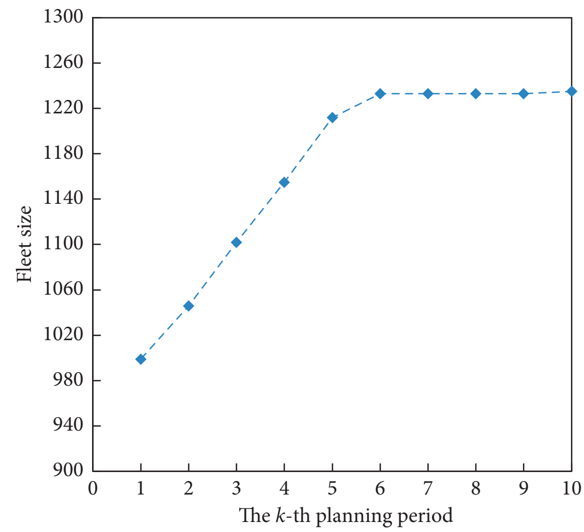


Figure 17: Fleet size at each planning period.

Another strategic decision we should pay attention to is the parking space construction in the Sioux Falls network. A stacked bar chart is shown in Figure 18, which delineates the newly built parking spaces during the different planning periods. At the beginning of the planning period, the number of parking spaces will arrive at the maximum capacity at the zones, which are origins, destinations, and zones near them. According to the growing demand in the long-term planning periods, the number of parking spaces will grow gradually in other zones. Hence, we can conclude that designing the SAV system from a long-term perspective is of great essence, and the strategic planning decisions are closely associated with the travel demand.

To further depict the distribution of relocation activities in a large network, a heat map is displayed in Figures 19(a) and 19(b), representing the number of relocation activities conducted from and to each zone at different time steps. The relocation activities are distributed mainly at 6:30–7:30, 15:30–17:30, and 19:30–20:00. At the morning peak, relocation activities always originate from work and entertainment zones to the home zones, contrarily, from home and other zones to work zones at the evening peak. The number of relocation activities reaches 9841 in one day of the initial year, with an average of 14 per zone per time step.

Meanwhile, a comparative trial is conducted in the context of TOC and TCC, considering the scenarios with the long-term planning or not. We suppose the design period changes from 3 to 10, and the corresponding relations under the varying scenarios are presented in Figure 20. Analogous to Figure 10, an apparent increase in total profit in scenarios with long-term

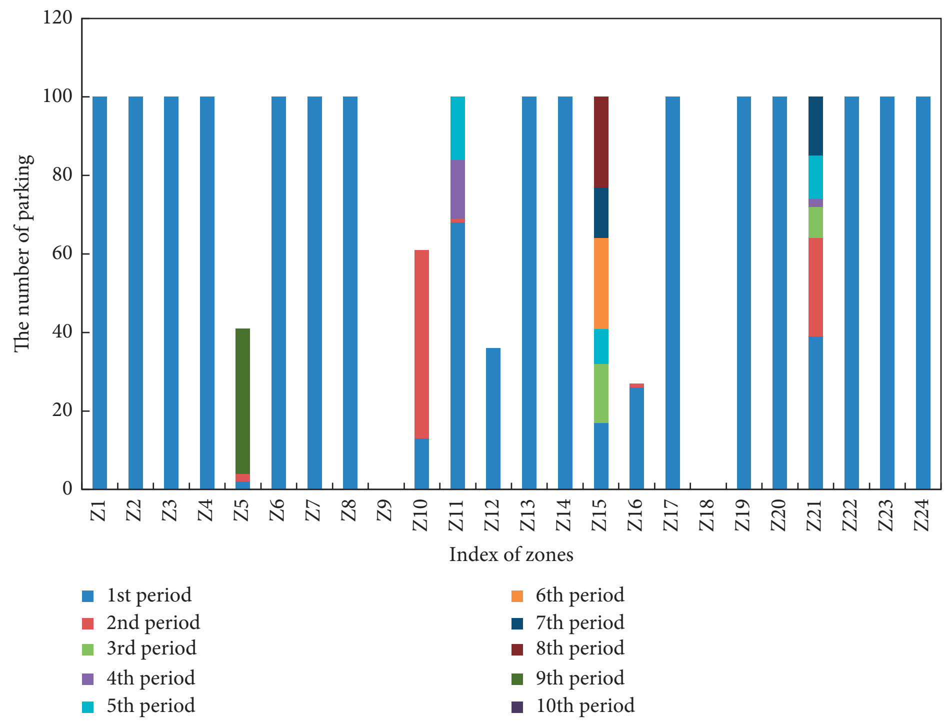


Figure 18: The number of new building parking spaces each period in each zone.

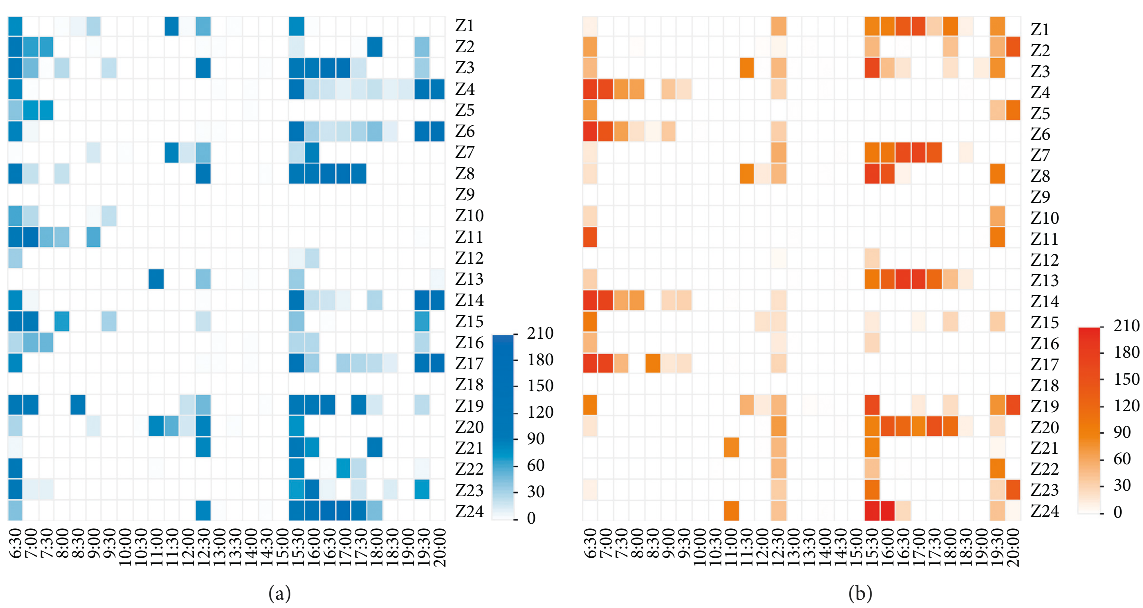


Figure 19: The distribution of relocation in the Sioux Falls network. (a) The number of relocation activities from each zone. (b) The number of relocation activities to each zone.

planning is indicated in Figure 20(a), and a trade-off relation between TOC and TCC can be concluded in Figure 20(b).

These thorough analyses of the Sioux Falls network demonstrate the flexibility and applicability of the MINLP model. In addition, these results confirm that integrating long-term strategic planning and daily operation decisions is of great significance for designing the SAV system while considering relocation and pricing.

5. Discussion

This paper develops a MINLP model to deal with the SAV design problem with long-term planning periods. The objective of the model is to maximize the operator's profit during the whole planning horizon. The proposed model provides an effective decision tool for the SAV system configuration considering the balance of SAV strategic planning and total daily operation cost.

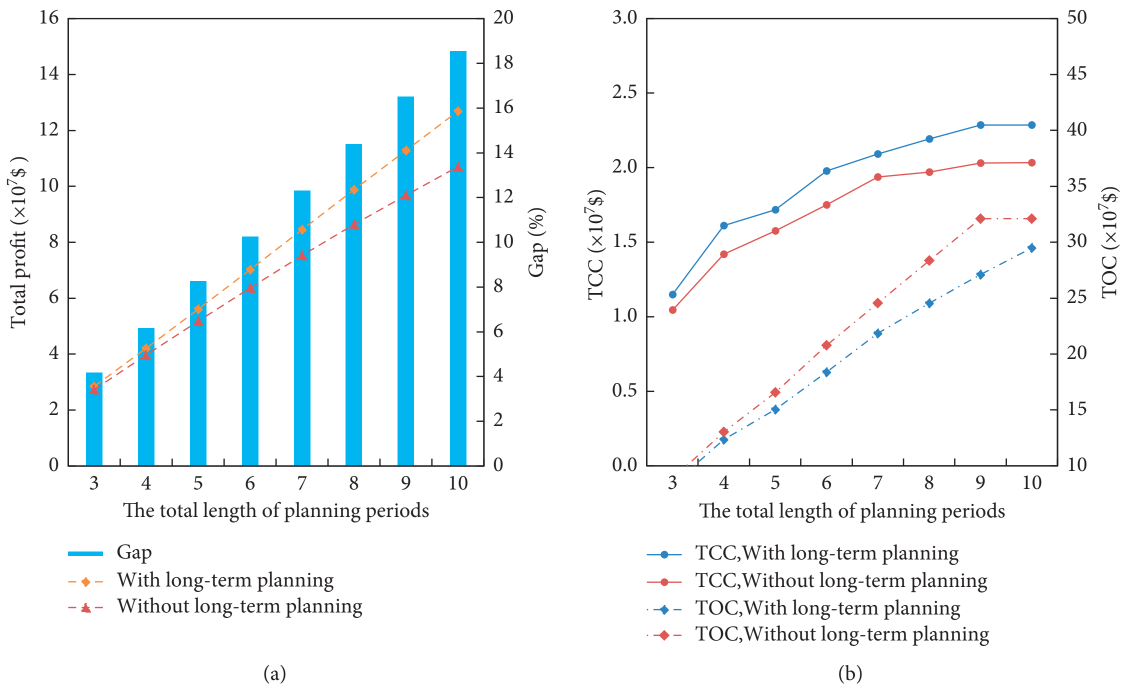


Figure 20: System performance with and without long-term planning in the Sioux Falls network.

Based on the above numerical analysis, we can have the following practical implications and insights on the SAV system design problem. (1) Firstly, the model and method proposed in this paper provide suggestions to the SAV operator on the optimal infrastructure deployment scheme and operation strategies of the SAV system. Considering the unbalanced demand, this model determines the initial fleet deployment to reduce the relocation and improve mobility efficiency. (2) Secondly, compared to the time-depend SAV design problem in Li et al. [12], we consider the pricing decision sufficiently and discuss the mode choice in a multimode traffic network. Our results show that the total profit is tightly associated with the base price for SAVs. The total profit will be maximized when the base price is 8.61$ and 8.33$ for the Four-ode and Sioux Falls networks. Hence, the decision-maker can employ our proposed model to make reasonable pricing to maximize their earnings. (3) Moreover, Lu et al. [29] have studied in detail the performance of one-way car-sharing systems under the combined strategy of pricing and relocations. Referring to this literature, we investigated the long-term SAV design problem and indicated that the average total profit increased by nearly 18% when the planning period was ten years. The analysis also shows that growing demand in the future has a higher impact on the SAV system design, which the policymaker should take into account. (4) Finally, the additional service level constraints compared to Huang et al. [42]strictly limit the reliability of the SAV system, which can also be relaxed for other objectives by the decision-makers.

The model we developed has strong flexibility, versatility, and scalability, which can be applied to other shared mobility scenarios. This paper only considers CPVs and SAVs, but the traffic network is more complex. Therefore, our model can easily extend to discuss more travel modes, such as public transit, taxi, and micro-mobility. In addition, our model is expected to be applied in the interurban SAV system, which will significantly improve the availability and quality of public transport. With the maturity of electric vehicle technology, it has the potential to deploy electric vehicles in the SAV system, and it is convenient to integrate the profile of electric vehicles to investigate the electric SAV system design problem.

6. Conclusions

6.1. Summary. This research investigates the long-term SAV system design problem while considering relocation and pricing strategies, which is novel in this context. To solve the sophisticated system design problem, a novel MINLP model based on the time-space network is devised to tackle the strategic and operational decisions in the SAV system. This model originally contains new factors that AVs bring to the shared system, such as reduced VoT and central dispatching. Simultaneously, we have taken the minimum customer service rate into account to guarantee the reliability of the SAV system. Moreover, a novel PSO-Gurobi method is proposed to address the complicated problem and acquire joint pricing, relocation, fleet size, and infrastructure deployment scheme to maximize the total profit. The empirical results demonstrate the effectiveness and efficiency of the proposed solution scheme. Managerial insights are summarized using the proposed framework, including the decision guide for the deployment of stations, parking spaces, fleet size, and operational decisions.

6.2. Limitations. While this study proves that it is feasible to design the SAV system integrating operational decisions into the long-term strategic planning, the proposed model has a few limitations that we would like to emphasize on for future research. Firstly, the demand in each planning period we employ is of a deterministic value, ignoring the stochastic characteristic on a particular day. Although this assumption is reasonable, it may be more efficient to propose a robust optimization method to represent the uncertainty. Secondly, there exists a necessity to investigate dynamic pricing and real-time vehicle-trip matching. Thirdly, the actual traffic conditions (i.e., congestion) are not considered in the current research. If these factors can be taken into consideration, the overall framework will be more realistic. Finally, the popularity of electric vehicles is an irreversible trend in the traffic system. Thus, integrating the charging station siting and the charging characteristic will become another stream of the focal point.

Data Availability

All data and program files included in this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the National Natural Science Foundation of China (grant no. 52072143).

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