Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 8369362, 17 pages
https://doi.org/10.1155/2022/8369362

Research Article

Multicriteria Model for Shared Parking and Parking Route Recommender Systems

Pengfei Zhao[1] **Lingxiang Wei,**[2,3] **Dong Pan,**[4] **and Shuai Dong**[3]

[1]*School of Civil and Transportation Engineering, Beijing University of Civil Engineering and Architecture, Beijing 102616, China*
[2]*School of Defense Engineering, Army Engineering University of PLA, Nanjing 210007, China*
[3]*School of Materials Science and Engineering, Yancheng Institute of Technology, Yancheng 224051, China*
[4]*School of Automobile and Transportation and Engineering, Hefei University of Technology, Hefei 230009, China*

Correspondence should be addressed to Pengfei Zhao; 18810926166@163.com

Received 22 April 2022; Accepted 6 August 2022; Published 29 August 2022

Academic Editor: Socrates Basbas

In many congested areas, shared parking has gotten increasing attention because of its potential to alleviate parking resource shortages. However, managing parking resources remains a challenge when simultaneously considering multiple decision-making criteria of public travelers in allocating parking spaces and recommending optimal parking routes. To fill this gap, from four perspectives, i.e., driving, among shared parking lots, at a shared parking lot, between shared parking spaces and destinations, we proposed nine criteria for shared parking space allocations and parking route recommendations, and we also gave the quantitative models for different criteria. Furthermore, an analytic hierarchy process Entropy-TOPSIS grey relational analysis (AHP-Entropy-TOPSIS-GRA) method and an improved ant colony algorithm were proposed to solve the proposed allocation of parking spaces and recommend optimal parking routes, respectively. Finally, the validity of our proposed models and algorithms was tested by empirical parking data and road traffic data collected in Huai'an City, Jiangsu province, China. The research helps provide a theoretical foundation for implementing shared parking initiatives and improving public travelers' parking satisfaction.

1. Introduction

Parking has received much-deserved attention in the last decade as an essential component of urban transportation systems. Considering its convenience and comfort, people in cities prefer to drive to work rather than use public transport to some extent. In addition, during the COVID-19 epidemic, travelling by private cars can reduce the risk of COVID-19 infections and help slow the virus's spread in commuter traffic. However, as the number and the usage of vehicles increases, finding parking near self-driving destinations may become difficult. As a result, for travelers, urban planners, as well as traffic management agencies, urban parking problems motivated by urbanization and modernization have become one of the hottest issues, especially in crowded megalopolis cities, like Hong Kong [1], Beijing [2], and New York [3], etc. One of the most important reasons is the imbalance between parking supply and demand [4]. Meanwhile, a fact is that the utilization rate of existing parking resources is relatively low due to the lack of prompt information communication between owners and public travelers and the exclusive use right [5].

In the center of the city, it is impractical to build numerous new parking facilities, which are affected by the shortage of land resources and the financial difficulties caused by the long payback period. Therefore, improving existing parking resources' utilization efficiency is critical to alleviating the urban parking problem [6, 7].

Given that the differences in urban land use bring different spatial and temporal parking requirements for travelers, shared parking can potentially improve the utilization efficiency of parking resources. The primary connotation of shared parking is to rationalize the use of regional parking resources based on the different peak hours of different types of land use [8], as well as improve the revenue of parking space owners due to parking problems, thus rationalizing the use of regional parking resources [4, 6].

In addition, the development of mobile Internet, Radio Frequency Identification, and other technologies have laid a physical foundation for the practical application of shared parking resource management [9]. In the wave accompanying the construction of smart cities, some city management departments or enterprises in China, the USA, Australia, England, etc., have launched various smart parking apps or websites to search for reserved parking spaces quickly. However, most of the existing platforms and algorithms mainly focus on maximizing the revenue of parking resource management platforms for a single parking lot [6, 10–13] but without comprehensive sophisticated consideration of influencing factors of travelers parking space choice among several parking lots in an area, especially some metrics that are difficult to quantify linearly, such as location preferences, parking safety, etc.

In addition, facing the complexity of transportation infrastructure and the urban environment, travelers increasingly depend on parking guidance systems. Although some studies have dealt with parking route guidance, these studies mainly considered parking routes on urban road sections, and few studies integrated three phases of their travels, i.e., choice of shared parking spaces, assignment, traveling from origins to parking spaces, and traveling from parking spaces to destination, as a whole.

However, most of the existing related research focuses on traffic guidance services only on urban roads [14–16]. In fact, some other factors, especially some subjective factors, such as parking safety and parking convenience, are also critical for travelers; there is relatively little research that considers these factors together in the route recommendation method involving parking in travel.

To solve the problems mentioned above, we focus on the whole trip process, i.e., before travel, during driving, and after parking, and consider public travelers' multi-dimensional preferences, e.g., driving time, parking fee, parking convenience, so that they enjoy all services from departures to destinations. Under this context, we construct an integrated model of parking space allocation and parking route recommendation based on multiple criteria. Furthermore, the corresponding algorithms are designed, and the models and algorithms are tested based on the empirical parking survey data.

This work makes the following contributions: (a) We propose the concept of Parking as a Service (PaaS) to meet the parking requirements that involve multi-dimensional criteria of public travelers with the help of advanced communication technology; (b) We propose nine criteria on parking space allocations and parking route recommendations from four aspects, i.e., on driving, among parking lots, inner a shared parking lot, between shared parking spaces and destinations, and give the corresponding models; (c) We propose an analytic hierarchy process Entropy-TOPSIS grey relational analysis (AHP-Entropy-TOPSIS-GRA) method to solve the parking space allocation problem and apply the improved ant colony algorithm to solve the optimal parking route problem; (d) Through empirical survey data, the model and algorithm are tested to verify the feasibility of the proposed models and algorithms.

The remainder of this paper is organized as follows: Section 2 reviews the previous studies of influencing factors of parking behavior, shared parking space allocation, and parking route guidance. Section 3 presents the methodology of shared parking space allocation and parking route recommendation problems, including assumptions, models, and solution algorithms. In Section 4, the analysis of the validity and applicability of the proposed models and algorithms are presented. This analysis is carried out with the empirical data on parking behaviors collected in the city of Huai'an, Jiangsu province, China. In Section 5, we draw some conclusions and point out future research directions.

2. Literature Review

The goal of this paper was to take into account various influencing factors when travelers reserve shared parking spaces to better recommend appropriate parking spaces for them. To that end, in this section, we first identify the relevant influencing factors of parking behavior, then review existing research on the allocation of shared parking space resources, as well as parking route recommendations, and summarize the shortcomings of the existing research.

2.1. Influencing Factors of Parking Behavior. Understanding parking behavior, specifically identifying relevant influencing factors, is the foundation of parking resource management [17]. The factors that affect the choice of parking spaces influencing travelers' parking decisions can be roughly divided into personal attribute factors and external factors.

Personal attribute factors include genders, ages, education levels, parking facility preferences, and so on [18]. However, the data of these personal factors are difficult for parking resource managers to collect and utilize to guide parking space allocations due to privacy protection and information security [19].

Collecting data on external factors that affect parking behavior, such as parking fee and acceptable walking distance, can avoid the abovementioned problems [20]. As a result, determining which factors are related to parking behaviors and how these factors effect parking behaviors have been widely studied by many scholars. As early as 1991, it has been found that parking space locations and parking facility types influence travelers' choice behavior [21]. Later, Bonsall and Palmar [22] found that different travel purposes have a significant impact on the choice of parking lots. Furthermore, Amott and Rowse found that not only travel purposes but also parking, driving, and stationary conditions impact the choice of parking space for travelers [23]. Chaniotakis and Pel [24] concluded that the availability of parking spaces and the walking distance to the destination have a great influence on the choice of parking spaces through the stated preference experiment. Based on questionnaire data, Zong et al. [25] found that parking space choice behaviors are closely related to parking charges. Based on the empirical parking data, Mo et al. [26] found that adjusting the price of parking fees can effectively change the parking behavior of travelers. Zeng et al. [27] considered three factors, i.e., occupancy, weather conditions, and holiday, to achieve higher-precision parking space occupancy prediction than previous models.

As a type of parking facility, parking and ride (P&R) facilities have also attracted the attention of academics. He et al. found that several external factors had a significant impact on the choice of P&R facilities. These factors include but are not limited to trip purpose, road traffic, the distance between parking spaces and destinations, and parking fees [20, 28]. Based on parking behavioral survey data, Clayton et al. [29] stated that the size of the group of people traveling together also impacts travelers' choice behavior of P&R facilities. Based on scenarios with different modes of transportation, Kono et al. [30] found that the cost of transportation trips and travel time have a significant impact on the choice of P&R facilities. Very recently, several studies have been conducted on the choice behavior of demanders in shared parking. For example, Ardeshiri et al. [31] found that the adjustment of the parking fee changed the possibility of choosing shared parking spaces. Using the combined technology acceptance model and theory of planned behavior, Ning et al. [32] proved that the three factors of perceived network externality, cost risk, and safety risk affect travelers' choice of shared parking spaces.

It can be found from the above study that travelers' parking behaviors are influenced by various external factors, such as parking fees, the surrounding environment of parking lots, walking distance between parking spaces, and desalination. Thus, integrating these factors into the parking allocation process is vital for improving traveler satisfaction.

2.2. Shared Parking Space Allocation. The issue of shared parking space allocation has received considerable attention. In terms of the goals of relevant research, it can be divided into two main branches: maximizing the utilization of parking resources and maximizing the revenue of parking management. For example, Chen et al. [11] studied the optimal allocation of on-street parking spaces, considering the cost of parking search time and the cost of walking time from the parking space to the destination. Shao et al. [6] established a simple parking space reservation, allocation, and charging model with the objective of maximizing management revenue considering parking price. Aiming at the problem of online parking reservation, considering the influence of travelers' location information and dynamic parking price on parking choice behavior, Lei and Ouyang [33] designed a dynamic parking space allocation model to improve the performance of intelligent parking system. The model was solved by a nonmyopia approximate dynamic programming (ADP) method. Mirheli and Hajibabai [12] proposed a stochastic dynamic parking management model based on a user-agent competition relationship to study the parking management problem, taking into account user demand and uncertainty in parking utilization. Hassija et al. [13] constructed an adaptive parking pricing model that ensures maximum revenue for managers and optimal comfort for users of parking spaces. Shao et al. [34] studied a parking reservation problem using auction theory and analyzed the impact of parking time uncertainty on management revenue. Very recently, in view of the complexity of solving the parking space allocation problem and the time window constraints, Zhao et al. [35] designed six meta-heuristic algorithms to achieve an efficient solution to the large-scale parking space allocation problem.

Considering the uncertainty of parking demanders and parking suppliers, Zhao et al. [4] constructed a research framework to guarantee that parking spaces are always available for parking space providers and designed a solution algorithm based on simulation techniques. To assure the most parking profit and the least negative impact on residents simultaneously, Huang et al. [36] constructed a stochastic optimization model taking the overtime parking behavior of parking customers into consideration. Based on real-time parking location information, Lu and Liao [37] constructed a parking space occupancy model to predict the availability of parking spaces to achieve more efficient use of parking resources.

To sum up, it can be seen that the existing mathematical and simulation models have achieved rich results in the allocation of parking resources under specific scenarios. However, few studies have addressed the compound influence of multiple factors in the choice of parking spaces by public travelers. As a result, even if a traveler has reserved a shared parking space, his/her travel experience might be greatly reduced due to extra time spent on finding parking spaces during trips, the impact of parking surroundings, too long walking distance, etc.

2.3. Parking Route Recommendations. Numerous studies have been conducted to increase the search effectiveness of available parking spaces because cruising for parking has a substantial impact on travel time, traffic, and even air pollution [38, 39].

The development of parking guidance systems can be roughly divided into two categories: parking guidance systems based on traffic information signs and parking guidance systems based on mobile Internet.

For the former, they provide drivers with rough directions and the number of available parking spaces through roadside information signage. The relevant research focuses on optimizing the location and content of the message signs, as well as their forms. For example, Thompson et al. [40] investigated what is the optimal display mode of parking information signage and how parking information affects travelers' parking decision-making.

With the increasing complexity of structures of urban roads and parking lots, traditional parking guidance systems can hardly meet the rising demand for parking due to the lack of real-time accurate traveler location information and parking lot location information. Waterson et al. [15] analyzed the effectiveness of parking guidance and informational signage in reducing cruising for parking.

Moreover, it also has been found that the best place to attempt to reserve a parking space depends on the driver's location in the road network [41]. Without considering the accurate location information, it will be difficult to utilize the optimal performance of parking guidance systems.

With the development of mobile information technology, modern parking guidance systems based on mobile platforms continue to become essential aids for accurate parking services. These parking guidance systems can adjust driving routes in time to reach parking lots around travelers' destinations as soon as possible through real-time road traffic conditions and the location of vehicles. Chai et al. [42] designed an efficient system that can update parking destinations based on real-time road condition information to maximize the utility of travelers.

Similar to the parking behavior discussed earlier, how to choose a parking guidance is also affected by a variety of factors. Li et al. [16] stated that walking time from parking spaces to destinations, parking fee, the availability of parking spaces, and travelers' preferences proposed an intelligent parking guidance algorithm that takes into account three typical decision influences of travelers, i.e., walking time, parking fee, and number of vacant parking spaces, and the heterogeneity of drivers' preferences. Considering both travel cost and parking fee, Gao et al. [43] developed a multi-criteria parking route guidance optimization model, and the validity of the proposed model was verified by the data of parking behaviors.

In summary, we can find that a comprehensive consideration of multiple influencing factors of parking behavior when allocating shared parking spaces and parking guidance is necessary to improve travelers' satisfaction, the reputation of parking management platforms, as well as the utilization of parking resources and road resources.

3. Modeling for Shared Parking Allocation and Parking Route Recommendations

In this section, we propose the concept of Parking as a Service (PaaS): Access and manage parking-related services before travel, during driving, and after parking until to destinations, through an electronic interface to meet the parking requirements that involve multi-dimensional criteria of public travelers.

3.1. Problem Description. Considering the advantages of global optimization offered by centralized parking resource management [44], a centralized shared parking management system (CSPMS) is introduced. It connects the parking supply side and parking demand side, and enables public travelers to plan, book, and pay for parking services.

For the parking supply side, owners of shared parking spaces submit their shared periods and the location of parking spaces to CSPMS in advance. For the parking demand side, public travelers need to make a reservation for shared parking spaces via mobile phone app or web, and parking routes will be recommended for them when their reservations are approved, as shown in Figure 1.

3.2. Criteria for Shared Parking Allocations and Parking Route Recommendations. Below we divide these criteria for shared parking resource management into four aspects, i.e., on driving, among parking lots, inner a shared parking lot, between shared parking spaces and destinations, see Figure 2.

For presentation convenience of shared parking modeling, the symbols and notations involved in this paper are given in Table 1.

In order to facilitate the construction of the shared parking model, we further propose two assumptions: (1) The public travelers provide their real parking information on the CSPMS, and they can access the right shared parking spaces with successful reservations; (2) The public travelers accept shared parking allocation, and they will not cancel their orders.

3.2.1. Criteria on Driving

(1) **Driving time:** the expected driving time of a recommended parking route is crucial for public travelers to choose the recommended parking route or not. The expected driving time DT_{m_i} of a public traveler m_i includes two parts: the expected driving time $DT_{m_i}^{ur}$ on urban roads and the expected driving time $DT_{m_i}^{nur}$ on nonurban roads. The urban road refers to expressways, main roads, sub-main roads, and branch roads. Usually, $DT_{m_i}^{ur}$ depends on two important parameters, namely, traffic volume and traffic capacity. It can be calculated as follows:

$$DT_{m_i}^{ur} = \sum_{r=1}^{R_{m_i}} t_{m_i}^{r} \left[1 + \phi \left(\frac{q_{m_i}^{r}}{c_{m_i}^{r}} \right)^{\varsigma} \right], \tag{1}$$

where $DTur/m_i$ represents the expected driving time of public traveler m_i on urban road sections; R_{m_i} is the total number of road sections included in a recommended parking route for public traveler m_i; $t_{m_i}^{r}$ indicates the driving time on urban road section r under the free traffic flow condition; $q_{m_i}^{r}$ shows the traffic volume of urban road section r within the recommended parking route; and $c_{m_i}^{r}$ indicates the actual capacity of urban road section r within the recommended parking route; ϕ and ς represent regression parameter, respectively, which can be determined by least square method, here taking $\phi = 0.15$, $\varsigma = 4$ [45].

The nonurban roads refer to internal roads of residential areas, shopping malls, and shared parking lots. When driving on these road sections, limited by space and environmental conditions, the speed is generally relatively slow. $DT_{m_i}^{ur}$ can be simply calculated as follows:

$$DT_{m_i}^{nur} = \frac{d_{m_i}^{h_j}}{\overline{v^{nur}}}, \tag{2}$$

where $d_{j}^{h_j}$ represents the shortest distance between shared parking space h_j to the access of urban road sections; and $\overline{v^{nur}}$ represents the average travel speed on nonurban road sections. According to the speed

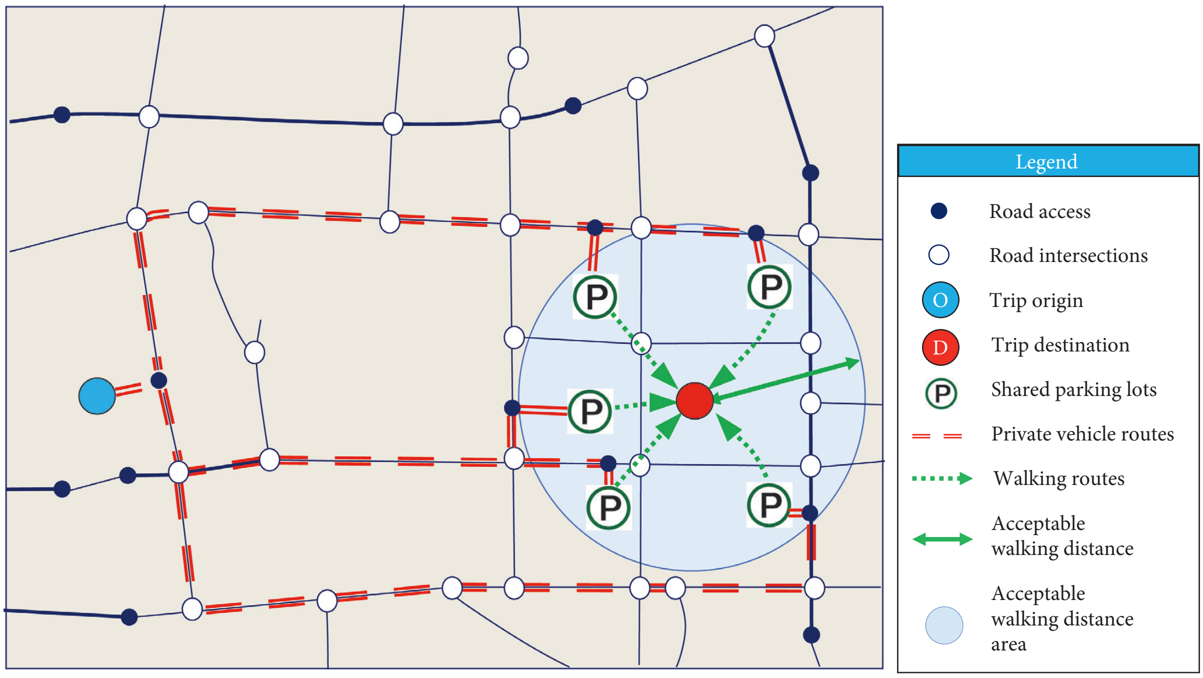

FIGURE 1: Schematic diagram of shared parking space reservation and recommended parking routes.

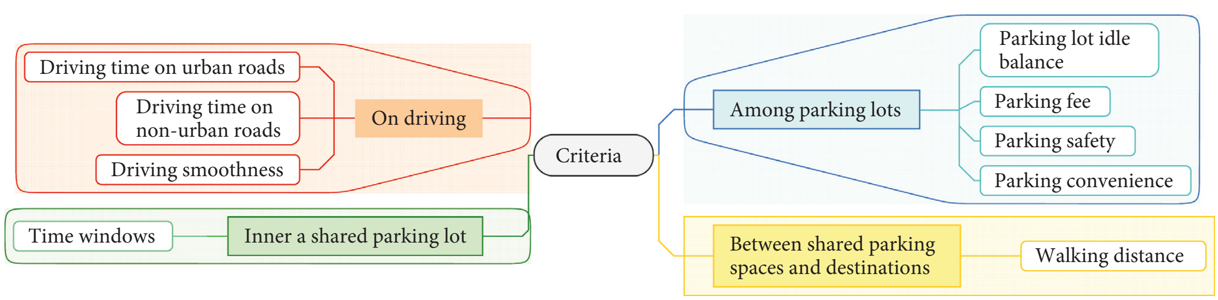

FIGURE 2: Multi-criteria for shared parking and parking route recommendations.

TABLE 1: Nomenclature list of shared parking problem.

Variables	Interpretation
S	The total number of shared parking lots
M	The total number of public travelers that reserve for shared parking spaces
H_j	The total number of parking spaces of shared parking lot j
$Hi\ dl\ e/j, k$	The total number of idle shared parking spaces of shared parking lot j at time k
$T^s_{h_j}$	The starting time of sharing of parking space h_j
$T^e_{h_j}$	The end time of sharing of parking space h_j
T_{h_j}	The available parking duration of shared parking space h_j
$Tlea/m_i$	The departure time of public traveler m_i
$Tarr/m_i$	The arrival time of public traveler m_i
T_{m_i}	The parking duration of public traveler m_i
T^s_r	The starting time of rush hours within a day
T^e_r	The end time of rush hours within a day
$P\ Fm_i$	The total parking fee of parking traveler m_i
DT_{m_i}	The total driving time for public traveler m_i
$DTur/m_i$	The driving time on urban road for public traveler m_i
$DTnur/m_i$	The driving time on nonurban road for public traveler m_i
DS_{m_i}	The driving smoothness for public traveler m_i
R_{m_i}	The total number of urban road sections for public traveler m_i

limit of some parking lots and residential areas, $\overline{v^{nur}}$ can be taken as 5 km/h.

Under these criteria, the total driving time for public traveler m_i is

$$DT_{m_i} = DT^{ur}_{m_i} + DT^{nur}_{m_i}. \tag{3}$$

(2) **Driving smoothness:** another important indicator is the driving smoothness DS_{m_i} of public traveler m_i; it refers to the proportion of the congestion distance to the total road length between the origin and the destination, which can be written as follows:

$$DS_{m_i} = \frac{\sum_{r=1}^{R_{m_i}} d^r_{m_i,c} + d^{h_j}_{m_i,c}}{\sum_{r=1}^{R_{m_i}} d^r_{m_i} + d^{h_j}_{m_i}}, \tag{4}$$

where $d^r_{m_i,c}$ and $d^r_{m_i}$ represent the congested distance and the total distance of the parking route on urban road section r, respectively; $d^{h_j}_{m_i,c}$ and $d^{h_j}_{m_i}$ represent the congested distance and the total distance of the parking route on nonurban road sections, respectively.

These two criteria will be considered in the parking route recommendation, see Subsection 4.2.

3.2.2. Criteria among Shared Parking Lots.

(1) **Parking lot idle balance:** without loss of generality, we assume that there are $S\,(S\geqslant 2)$ shared parking lots in a large enough area; a shared parking lot $j\,(j \in [S], [S]:\ = \{1, 2, \ldots, S\})$. has H_j shared parking spaces. Let $Hi\ dl\ e/j,k$ be the total number of idle shared parking spaces in shared parking lot j at the time point of k, then we define parking lot idle index $(PI)PI_{j,k}$ of shared parking lot j, which can be written as follows:

$$PI_{j,k} = \frac{H^{i\ dl\ e}_{j,k}}{H_j}. \tag{5}$$

In order to avoid the local traffic congestion, the availability of shared parking spaces from multiple parking lots should be considered. One of the management objectives is to equalize the idle rate of parking resources in multiple parking lots. The objective function can be written as:

$$\min \sum_{j=1}^{S} \left(PI_{j,k} - \min PI_{j,k}\right) \forall k. \tag{6}$$

(2) **Parking fee:** we firstly define the parking duration of public travelers. Let $T^{arr}_{m_i}$ and $T^{lea}_{m_i}$ be the arrival time and the departure time of public traveler m_i, respectively, so the parking demand duration is $T_{m_i} = Tlea/m_i - Tarr/m_i$ $(m_i \in [M], [M]:\ = \{1, 2, \ldots, M\}$, M is the total number of public travelers).

In order to differentiate parking prices during parking rush hours and other hours, two types of parking prices are set for each shared parking lot. Let Ts/r and Te/r denote the starting time and ending time of parking rush hours, respectively, and let cj/r and cj/nr denote the parking price during parking rush hours and the parking price during other hours in shared parking lot j, then the parking fee PFm_i of public traveler m_i at share parking lot j can be calculated as follows:

$$PFm_i = \begin{cases} T_{m_i} c^j_{nr}, T^{lea}_{m_i} < T^s_r \cup T^{arr}_{m_i} > T^e_r \\ T_{m_i} c^j_r, T^s_r \leq T^{arr}_{m_i} < T^{arr}_{m_i} \leq T^e_r \\ \left(T^s_r - T^{arr}_{m_i}\right) c^j_{nr} + \left(T^{lea}_{m_i} - T^s_r\right) c^j_r, T^{arr}_{m_i} < T^s_r \cap T^s_r \leq T^{lea}_{m_i} \leq T^e_r. \\ \left(T^e_r - T^{arr}_{m_i}\right) c^j_r + \left(T^{lea}_{m_i} - T^e_r c^j_{nr}\right), T^s_r \leq T^{arr}_{m_i} \leq T^e_r \cap T^{lea}_{m_i} > T^e_r \\ \left(T^s_r - T^{arr}_{m_i} + T^{lea}_{m_i} - T^e_r\right) c^j_{nr} + \left(T^e_r - T^s_r\right) c^j_r, T^{arr}_{m_i} < T^s_r \cap T^{lea}_{m_i} > T^e_r \end{cases} \tag{7}$$

Under the above criteria, the management objective of CSPMS is to minimize the parking fee for each public traveler.

(3) **Parking safety:** different types of parking lots, like indoor parking lots, ground parking lots, are exposed to the different external environments, which will lead to differentiated safety of vehicles and public travelers. In order to consider the above effects in the allocation of shared parking spaces, here, we introduce the parking safety indexes (PSIs). To quantitatively evaluate this fuzzy index, a linear coordinate system is introduced, see Table 2.

Under the above criteria, the management objective of CSPMS is to maximize the PI for each public traveler.

(4) **Parking convenience:** affected by the spatial structure of its parking spaces, the difficulty of parking in different types of parking lots is different. Here, we introduce the parking convenience indexes (PIs), it can be quantified by Table 3.

Under the above criteria, the management objective of CSPMS is to maximize the PI for each public traveler.

3.2.3. Criteria Inner A Shared Parking Lot. (1) Time Windows. As shared parking spaces are provided by the owners of private parking spaces, these parking spaces can be used for public travelers only during shared periods. Let Ts/h_j and Te/h_j be the starting time and the end time of sharing period of the h_j shared parking space, respectively. When parking demand period of public traveler m_i is not in the shared period of shared parking space h_j, the following Equation (8) holds:

$$\left(T^{arr}_{m_i}, T^{lea}_{m_i}\right) \notsubset \left(T^s_{h_j}, T^e_{h_j}\right). \tag{8}$$

Let $y^{h_j}_{m_i}$ denote whether the parking demand period of public traveler m_i is in the shared period of the shared

Table 2: PSIs of different types of parking lots.

Types	Outdoor	Underground	Mechanical	Residential
PSIs	3–5	7–9	7–9	5–7

Table 3: PCIs of different types of parking lots.

Types	Outdoor	Underground	Mechanical	Residential
PCIs	7–9	4–7	1–3	7–9

parking space h_j. If yes, $y_{m_i}^{h_j} = 1$, otherwise, $y_{m_i}^{h_j} = 0$, see Equation (9).

$$y_{m_i}^{h_j} = \begin{cases} 0, & \left(T_{m_i}^{arr}, T_{m_i}^{lea}\right) \subseteq \left(T_{h_j}^{s}, T_{h_j}^{e}\right), \\ 1, & \left(T_{m_i}^{arr}, T_{m_i}^{lea}\right) \nsubseteq \left(T_{h_j}^{s}, T_{h_j}^{e}\right). \end{cases} \quad (9)$$

For any two public travelers m_i and m_l, if there is a parking time conflict, Equation (10) holds.

$$\left(T_{m_i}^{arr}, T_{m_i}^{lea}\right) \cap \left(T_{m_l}^{arr}, T_{m_l}^{lea}\right) \neq \varnothing. \quad (10)$$

When Eq. (10) holds, two public travelers m_i and m_l cannot be simultaneously assigned to one parking space at the same parking period and Equation (11) holds.

$$q_{m_i}^{m_l} = \begin{cases} 0, & \left(T_{m_i}^{arr}, T_{m_i}^{lea}\right) \cap \left(T_{m_l}^{arr}, T_{m_l}^{lea}\right) \neq \varnothing, \\ 1, & \left(T_{m_i}^{arr}, T_{m_i}^{lea}\right) \cap \left(T_{m_l}^{arr}, T_{m_l}^{lea}\right) = \varnothing. \end{cases} \quad (11)$$

In order to make the best use of shared parking spaces, the management objective of CSPMS can be to maximize the utilization of shared parking spaces (UPS), which can be expressed as follows:

$$\max UPS = \frac{\sum_{m_i=1}^{M} \sum_{h_j=1}^{H_j} T_{m_i} x_{m_i}^{h_j}}{T_{h_j}}. \quad (12)$$

The constraints are as follows:

$$\text{s.t} \begin{cases} x_{m_i}^{h_j} - q_{m_i}^{m_l} + x_{m_l}^{h_j} \leq 1, m_i, m_l \in [M], m_i \neq m_l, h_j \in \left[H_j\right] (a), \\ y_{m_i}^{h_j} x_{m_i}^{h_j} = 0 m_i \in [M], h_j \in \left[H_j\right] (b), \\ \sum_{h_j=1}^{H_j} x_{m_i}^{h_j} \leq 1 m_i \in [M], h_j \in \left[H_j\right] (c), \end{cases} \quad (13)$$

where Equation (13) ensures that two public travelers m_i and m_l cannot be assigned to the same parking space simultaneously with time conflicts; Equation (13) ensures that parking demand period should be within the shared period; Equation (13) checks that each parking demand is allocated to one shared parking space; $xh_j/m_i \in \{0, 1\} (m_i \in [M], h_j \in [H_j])$. is a binary decision variable.

3.2.4. Criteria between Shared Parking Spaces and Destinations. After having parked their vehicles, public travelers need to walk for a certain distance from shared parking spaces to their destinations; therefore, the walking distance is also a very important indicator that affects public travelers.

Here, we can simply calculate the walking distance from the latitude and longitude coordinates of a parking lot and a destination. Let $llat/h_j$ and $llon/h_j$ represent latitude and longitude of shared parking space h_j, respectively. Let $llat/m_i$ and $llon/m_i$ represent latitude and longitude of destination of public traveler m_i, respectively.

Furthermore, let $C = \sin(llat/\ h_j)\sin(l\ \ lat/m_i) + \cos(llat/h_j)\cos(llat/m_i)\cos(llon/h_j - llon/m_i)$. Then, the round trip walking distance $d_{m_i}^{h_j}$ for public traveler m_i between the shared parking lot and his/her destination can be written as

$$d_{m_i}^{h_j} = \pi \arccos(C) \frac{R}{180}, \quad (14)$$

where $\pi \approx 3.14$; R is the radius of the Earth, $R \approx 6378.137$km.

Let $d^{\max_{m_i}}$ and d_{total} be the maximum acceptable distance and the total walking distance from shared parking lots to their destinations; we have the following criteria for all public travelers to choose shared parking spaces:

$$\min d_{total} = \sum_{m_i}^{h_j} d_{m_i}^{h_j} x_{m_i}^{h_j} \text{s.t} d_{m_i}^{h_j} \leq d_{m_i}^{\max} \forall m_i \in [M], \forall h_j \in \left[H_j\right]. \quad (15)$$

4. Solution Method

The shared parking problem is a two-stage multi-objective optimization problem. For convenience, we divide this problem into two sub-problems. One is the problem of matching parking supply and parking demand, and the other is the problem of optimal parking route. In this section, we introduce algorithms for solving these two sub-problems.

4.1. AHP-Entropy-TOPSIS-GRA Method for Optimal Parking Allocations. The technique for order of preference by similarity to optimal solution (TOPSIS), as a common evaluation method for multi-objective decision-making of limited scheme, can treat the original data in the same direction and normalization, eliminate the influence of different index dimensions, and make full use of the original data information to reflect the real and objective reality. In addition, it has no special requirements for data and sample data [46]. To avoid problems such as difficulty in the analysis due to small differences in indexes, an analytic hierarchy process (AHP)-TOPSIS [47] and Entropy-TOPSIS [48] methods were proposed to accurately reflect the information in these indexes, and improve the contrast and resolution between the indexes. In order to combine the advantages of these two approaches, in this paper, an AHP-Entropy weight method is adopted to quantitatively weight these indexes [49].

4.1.1. Determining Subjective Weights Based on the AHP Method. The main steps of determining the weight of the scheme based on the AHP method are as follows:

Step 1 Assuming that n subjective indicators are related to the choice of shared parking spaces in the AHP method, we can construct an evaluation matrix $\mathbf{D}_{n\times n}$ according to n evaluation indexes

Step 2 Calculate the relative weight of each index according to Equation (16).

$$d'_{ij} = \frac{d_{ij}}{\sum_{i=1}^{n} d_{ij}}. \quad (16)$$

Step 3 Obtain the eigenvector $\mathbf{w}^A$ of the evaluation matrix $\mathbf{D}_{n\times n}$ by Equation (17)

$$w_i^A = \frac{\sum_{i=1}^{n} d'_{ij}}{\sum_{i=1}^{n}\sum_{i=1}^{n} d'_{ij}}. \quad (17)$$

Step 4 Calculate the maximum eigenroot $\lambda_{\max}$ of $\mathbf{D}_{n\times n}$

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(\mathbf{D}\mathbf{w}^A\right)_i}{w_i^A}. \quad (18)$$

Step 5 Calculate the consistency index (CI)

$$CI = \frac{\lambda_{\max} - n}{n-1}. \quad (19)$$

Step 6 Calculate the consistency ratio (CR) according to the average random consistency index (RI)

$$CR = \frac{CI}{RI}. \quad (20)$$

When $CR < 0.1$, the scheme passed the consistency test.

4.1.2. Determining Objective Weights Based on the Entropy Weight Method. The main steps of determining the weight of the scheme based on the entropy weight method are as follows:

Step 1 Build the initial decision matrix.

Assuming that there are m share parking lots to choose for travelers and each share parking lot has n evaluation criteria, the initial decision matrix $\mathbf{D}'$ is:

$$\mathbf{D}' = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix}. \quad (21)$$

Step 2 Obtain a normalized matrix $\mathbf{Y}$ by transforming $\mathbf{D}'$.

The profitable indexes and the cost indexes can be processed according to Equation (22)-a and Equation (22)-b, respectively.

$$\begin{cases} y_{ij} = \dfrac{d_{ij} - \min d_{ij}}{\max d_{ij} - \min d_{ij}} \text{ (a)}, \\ \\ y_{ij} = \dfrac{\min d_{ij} - d_{ij}}{\max d_{ij} - \min d_{ij}} \text{ (b)}. \end{cases} \quad (22)$$

The normalized matrix $\mathbf{Y}$ obtained after normalizing $\mathbf{D}$ can be written as:

$$\mathbf{Y} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix}. \quad (23)$$

Step 3 Normalization of the normalized matrix $\mathbf{Y}$.

In order to solve the problem of different dimensions among different criteria, it is necessary to normalize the normalized matrix $\mathbf{Y}$, then we can get the matrix $\mathbf{P}$ by (24):

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}. \quad (24)$$

Therefore, the entropy value e_j, the difference coefficient g_j, and the entropy weight β_j of index j can be expressed by Equation (25)–(27).

$$e_i = -k\sum_{i=1}^{m} p_{ij}\ln p_{ij}\left(k \geq 0;\ e_i \geq 0\right), \quad (25)$$

$$g_i = 1 - e_i\ \left(j \in [n]\right), \quad (26)$$

$$w_i^E = \frac{g_i}{\sum_{j=1}^{n} g_i}\left(\beta_{ij} \in [0,1]; i \in [m]; j \in [n]\right). \quad (27)$$

4.1.3. Determining the Combined Weights. The comprehensive weight $\mathbf{w}^C$ of index i is obtained by combining $\mathbf{w}^A$ and $\mathbf{w}^A$, which can be written as follows:

$$w_i = \frac{\sqrt{w_i^A w_i^E}}{\sum_{i=1}^{m}\sqrt{w_i^A w_i^E}}. \quad (28)$$

4.1.4. TOPSIS Grey Relational Analysis.

Step 1 Give the weight to the dimensionless gauge matrix.

The weighted decision matrix $\mathbf{Z}$ can be calculated by:

$$\mathbf{Z} = \begin{bmatrix} \omega_1 y_{11} & \omega_2 y_{12} & \cdots & \omega_n y_{1n} \\ \omega_1 y_{21} & \omega_2 y_{22} & \cdots & \omega_n y_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ \omega_1 y_{m1} & \omega_2 y_{m2} & \cdots & \omega_n y_{mn} \end{bmatrix}. \quad (29)$$

It should be noted that the reference sequence $z_0 = \left\{z_{0j} \mid j \in [n]\right\}$, and z_0 is the optimal value of each evaluation index.

Step 2 Determine the positive scheme and negative optimal one.

The positive and negative optimal schemes can be expressed as follows:

$$\begin{cases} \mathbf{z}^+ = \left\{z_1^+, z_2^+, \ldots, z_j^+, \ldots, z_n^+\right\} \\ \mathbf{z}^- = \left\{z_1^-, z_2^-, \ldots, z_j^-, \ldots, z_n^-\right\} \end{cases}, \tag{30}$$

where $z+/j = \max z_{ij} = w_j$.; $z_j^- = \min z_{ij} = 0$.

Step 3 Calculate the distance from the evaluation object to the positive and negative optimal solutions.

By calculating the n-dimensional Euclidean distance, the distances from each feasible parking path to the positive optimal solution and the negative optimal solution can be obtained, respectively, see Equation (31)(a and b).

$$\begin{cases} d_i^+ = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^+\right)^2} \text{ (a)}, \\ d_i^- = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^-\right)^2} \text{ (b)}. \end{cases} \tag{31}$$

Step 4 Determine the grey correlation coefficient.

Calculate the absolute differences between the reference sequence and other comparison sequences, and use the absolute difference matrix to calculate the grey correlation coefficient matrices R^+ and R^- between each feasible parking route and the positive and negative optimal solutions:

$$\begin{cases} R^+ = \left(r_{ij}^+\right)_{m\times n}, \\ R^- = \left(r_{ij}^-\right)_{m\times n}, \\ r_{ij}^+ = \dfrac{\min_i \min_j \left|z_j^+ - z_{ij}\right| + \lambda \max_i \max_j \left|z_j^+ - z_{ij}\right|}{\left|z_j^+ - z_{ij}\right| + \lambda \max_i \max_j \left|z_j^+ - z_{ij}\right|}, \\ r_{ij}^- = \dfrac{\min_i \min_j \left|z_j^- - z_{ij}\right| + \lambda \max_i \max_j \left|z_j^- - z_{ij}\right|}{\left|z_j^- - z_{ij}\right| + \lambda \max_i \max_j \left|z_j^- - z_{ij}\right|}, \end{cases} \tag{32}$$

where $\lambda \in [0, 1]$ is the resolution coefficient. The smaller the value, the greater the resolution. Here, it is set as 0.5 [48].

As a result, the grey correlation between each feasible parking route and the positive and negative optimal solutions can be calculated as follows:

$$\begin{cases} r_i^+ = \dfrac{1}{n} \sum_{j=1}^{n} r_{ij}^+, \\ r_i^- = \dfrac{1}{n} \sum_{j=1}^{n} r_{ij}^-. \end{cases} \tag{33}$$

Step 5. Calculate multi-dimensional comprehensive applicability.

Based on the results of the Euclidean distances d_i^+ and d_i^- and the grey correlations r_i^+ and d_i^-, the dimensionless processes can be done as follows:

$$\begin{cases} D_{\mathrm{i}}^+ = \dfrac{d_i^+}{\max d_i^+} \\ D_{\mathrm{i}}^- = \dfrac{d_i^-}{\max d_i^-} \\ R_{\mathrm{i}}^+ = \dfrac{r_i^+}{\max r_i^+} \\ R_{\mathrm{i}}^- = \dfrac{r_i^-}{\max r_i^-} \end{cases} \tag{34}$$

The larger values of $D-/i$ and R_i^+ indicate that the scheme is closer to the positive optimal solution, while the larger values of $D+/i$ and $R-/i$ indicate that the scheme is farther away from the positive optimal solution, so the formula can be further written as:

$$\begin{cases} S_i^+ = \theta_1 D_i^- + \theta_2 R_i^+ \\ S_i^- = \theta_1 D_i^+ + \theta_2 R_i^- \end{cases}, \tag{35}$$

where $\theta_1 = \theta_2 = 0.5$, S_i^- and S_i^+ comprehensively reflect the distance between the current scheme and the optimal value.

Therefore, the comprehensive applicability degree of scheme evaluation c^+ can be obtained by (36). The greater the c_i^+, the better the solution are; otherwise, the worse the solutions are.

$$c_i^+ = \frac{S_i^+}{S_i^+ + S_{\mathrm{i}}^-}. \tag{36}$$

4.2. Improved Ant Colony Algorithm. In this paper, a heuristic ant colony algorithm was chosen to find the optimal parking route, mainly because of its good robustness, high flexibility, and fast convergence speeds [50]. However, it is necessary to make corresponding improvements in the selection of transition states in order to have better rationality and adaptability, as well as avoid falling into local optimum, in parking route planning.

Here, we mainly optimized two aspects: the probability selection and the pheromone update mode.

4.2.1. Improvement of the Probability Selection. Since the heuristic function of the traditional ant colony algorithm only considers the distance relationship between two adjacent nodes, it only reflects the relationship between the current node and its neighbors but lacks the relationship between the current node and the destination. For this reason, it is difficult to jump out of the local optimal solution region and lose the ability to search for the global optimum solution.

Therefore, the linear distance between the next node j and the destination g can be considered to be added to the heuristic function, which enhances the purpose of ant search and accelerates the convergence speed of the algorithm. The expression is as follows:

$$\eta_{ij}(t) = \frac{1}{l_{ij} + 1_{jg}}, \tag{37}$$

where l_{ij} is the distance from current node i to next node j, and l_{jg} is the distance from next node j to the destination g; it can be solved by Euclidean distance.

If $l_{jg} \leq l_{ij}$, specify that node j is a distant node, otherwise, specify that node j is a near node. Furthermore, the improved probability selection can be calculated as follows:

$$p_{ij}^{k}(t) = \begin{cases} \tau_{ij}^{\alpha}(t)\left[\dfrac{1}{l_{ij} + l_{jg}}\right]^{\beta}, \\ \\ \displaystyle\sum_{s\in \mathbf{A}_x} \tau_{is}^{\alpha}(t)\left[\dfrac{1}{l_{ij} + l_{jg}}\right]^{\beta}, j \in \mathbf{A}_k, 0, j \notin \mathbf{A}_k, \end{cases} \tag{38}$$

where $pk/ij(t)$. represents the state transition probability of ant k from node i to node j at time t, α is the pheromone factor, β is the expected heuristic factor, $\mathbf{A}_k$ represents the set of nodes that ant k has not yet visited. Note that if a node has been visited, it will be put into a tabu table $\mathbf{TB}_k$ that can no longer be accessed.

4.2.2. Improvement of the Pheromone Update Rule. In order to obtain the optimal solution faster, the influence of various factors on the parking route choice is taken into account in the pheromone update rule. The selection of the optimal parking route mainly considers the driving time and the average smoothness of road sections. For the driving time DT_{m_i} of public traveler m_i, it can be calculated by Equation (3).

In order to weaken parking routes with poor driving environments, a penalty factor can be added to reduce the selected probability. The pheromone update rules are improved as follows:

$$\tau_{ij}^{t+1} = \begin{cases} \varphi \dfrac{\tau_{ij}(t)}{DS_{m_i} DF_{m_i}} + \xi\left(\left|D_w\right| - \left|D_b\right|\right), & i, j \in D_b, \\ \\ \varphi \dfrac{\tau_{ij}(t)}{DS_{m_i} DF_{m_i}} - \xi\left(\left|D_w\right| - \left|D_b\right|\right), & i, j \in D_w, \\ \\ 0, & \text{other}, \end{cases} \tag{39}$$

where D_b and $|D_b|$ represent the best searched path and its length, respectively. D_w and $|D_w|$ represent the worst searched path and its length, respectively. φ is the pheromone volatility coefficient, which ranges from $[0, 1]$. ξ is the pheromone enhancement factor of the improved ant colony algorithm.

In order to prevent the unlimited accumulation of path pheromone concentrations in the process of improving the ant colony algorithm, it must be restricted by Equation (40):

$$\tau_{ij} = \begin{cases} \tau_{\max}, & \tau_{ij} \geq \tau_{\max}, \\ \tau_{ij}, & \tau_{\min} < \tau_{ij} < \tau_{\max}, \\ 0, & \tau_{ij} \leq \tau_{\min}, \end{cases} \tag{40}$$

where $\tau_{\max}$ and $\tau_{\min}$ are the maximum and the minimum value of pheromones.

5. Case Study

5.1. Study Area and Data Collection. Huai'an Xinya International Business Circle (HXIBC) is one of the most prosperous CBDs in Huai'an city, Jiangsu, China. Because of the limitation of parking facilities, public travelers often spend extra time cruising for parking, which not only causes great inconvenience to public travelers but also leads to frequent traffic congestion. HXIBC and its surrounding communities are selected as the study area, see Figure 3.

For ease of presentation, we have abbreviated place names, see Table 4.

Here, we assume that a public traveler whose max acceptable walking distance is 500 m reserves a parking space from 9:00–11:00 and the destination is GEISC. Taking GEISC as the center, we surveyed the surrounding shared parking lots. The results of the number of parking spaces, shared periods, and walking distance between GEISC and shared parking lots are shown in Table 5.

It can be found that there are five shared parking lots (namely, SDS, NPY, HFC, ASB, and HHG-B) meeting the public traveler's requirements in terms of the max acceptable walking distance and shared periods.

Next, we analyze the indexes of parking fee, parking safety, and parking convenience; the assignments of different

Figure 3: The location of HXIBC and its surrounding residential areas.

Table 4: List of place name Abbreviations.

Place names	Abbreviation
Huaian Xinya International Business Circle	HXIBC
Golden Eagle International Shopping Center	GEISC
Shidai Square	SDS
Nanping Yuan	NPY
Huaihai First City	HFC
Chengde Mountain Villa	CMV
Anshe Bridge	ASB
Huaihai Garden-Zone A	HHG-A
Huaihai Garden-Zone B	HHG-B

Table 5: Sharing periods of shared parking lots.

ID	Communities	Sharing periods	Number of parking spaces	Walking distance (m)
1	SDS	8:00–17:30	60	242
2	NPY	9:00–12:00; 14:00–18:00	54	138
3	HFC	8:30–17:30	414	127
4	CMV	12:00–18:00	55	347
5	ASB	8:00–17:00	70	400
6	HHG-A	8:00–18:00	128	587
7	HHG-B	8:00–18:00	104	293

Table 6: Assignments of PF, PSIs, and PCIs of shared parking lots.

Communities	SDS	NPY	HFC	ASB	HHG
PF (Yuan)	8	8	6	4	6
PSIs	3	4	2.5	2.5	3
PCIs	6	7	7	6	7

criteria are shown in Table 6. It should be noted that the temporary charging standard for commercial parking lots in XIB is 5 Yuan/hour, and free for half an hour.

5.2. Optimal Shared Parking Allocation. According to the AHP method, the importance of parking fees, parking safety, and parking convenience are comparatively evaluated by $\mathbf{D}$, and we can get the $\mathbf{w}^A$:

$$\mathbf{D} = \begin{bmatrix} 1 & 0.1429 & 0.3333 \\ 7 & 1 & 5 \\ 3 & 0.2 & 1 \end{bmatrix}, \quad \mathbf{w}^A = (0.0671, 0.5445, 0.1140). \tag{41}$$

According to the entropy weight method, we can obtain $\mathbf{D}'$, $\mathbf{Y}$, and $\mathbf{P}$, respectively:

Table 7: Sorting of recommended shared parking spaces.

Communities	SDS	NPY	HFC	ASB	HHG
c^{+}	0.357	0.37	0.503	0.595	0.36
Sorting	5	3	2	1	4

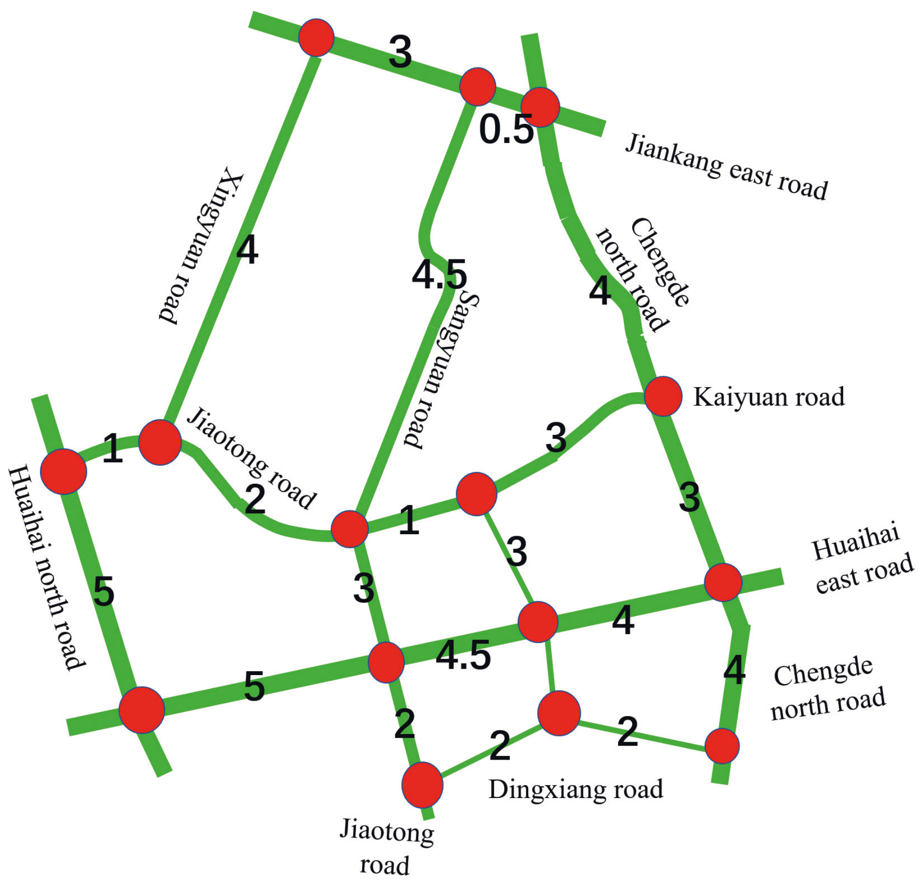

Figure 4: Road network with travel time (Unit: minutes).

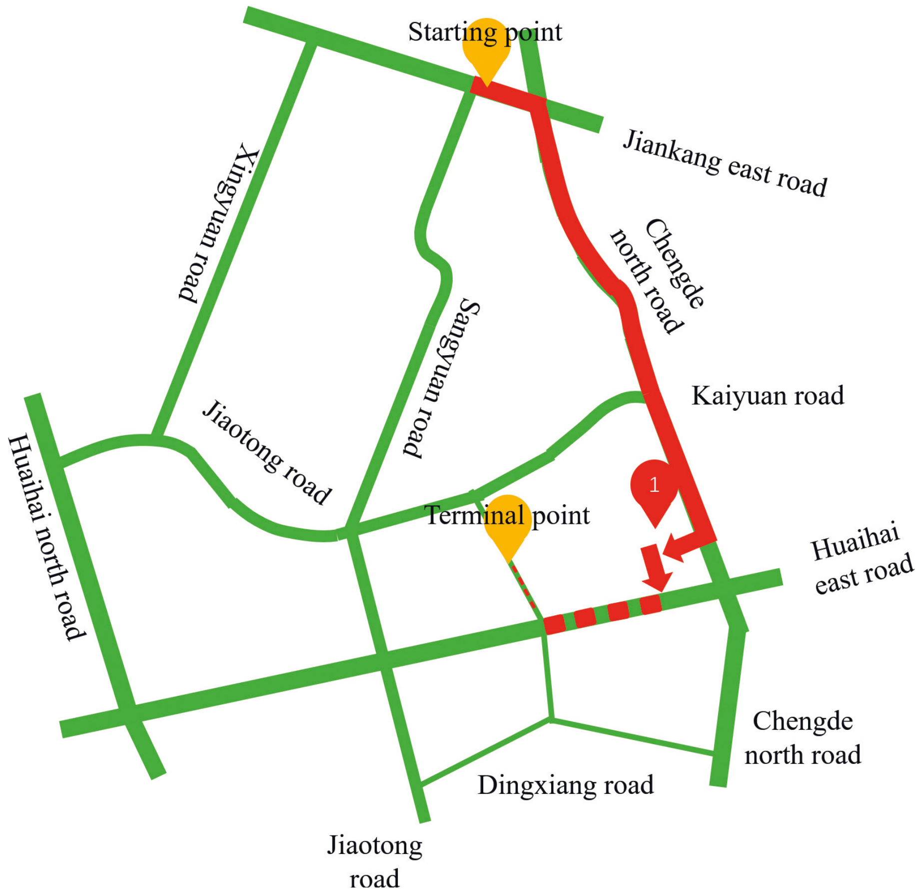

Figure 5: The optimal recommended parking route in the road network.

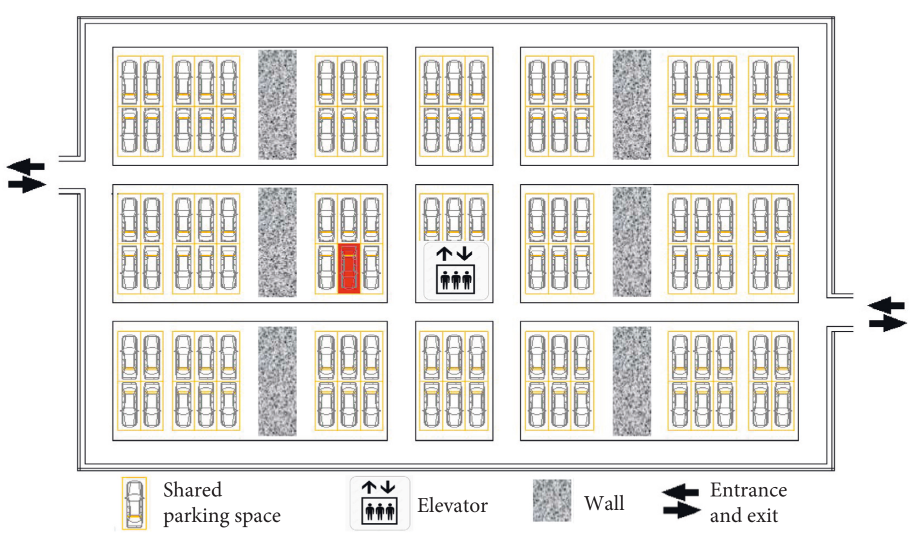

Figure 6: Layout of parking spaces and the optimal allocation of parking space.

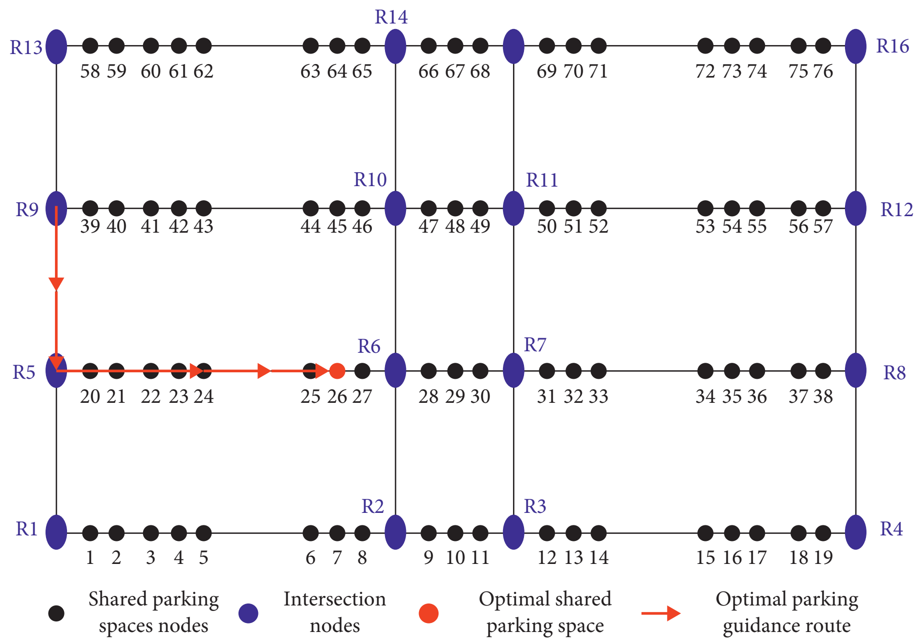

FIGURE 7: Topological network of shared parking spaces and the optimal parking route in the parking lot.

$$\mathbf{D}' = \begin{bmatrix} 242 & 3 & 6 \\ 138 & 4 & 7 \\ 127 & 2.5 & 7 \\ 400 & 2.5 & 6 \\ 293 & 3 & 7 \end{bmatrix},$$

$$\mathbf{Y} = \begin{bmatrix} 0.5788 & 0.3344 & 1 \\ 0.9579 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0.3913 & 0.3334 & 0 \end{bmatrix}, \quad (42)$$

$$\mathbf{P} = \begin{bmatrix} 0.1975 & 0.2 & 0.5 \\ 0.3275 & 0.5999 & 0 \\ 0.3413 & 0 & 0 \\ 0 & 0 & 0.5 \\ 0.1337 & 0.2 & 0 \end{bmatrix}.$$

Using (27), we obtain $\mathbf{w}^E$:

$$\mathbf{w}^E = (0.0174, 0.0195, 0.085). \quad (43)$$

Using (28), we obtain $\mathbf{w}^C$:

$$\mathbf{w}^C = (0.0174, 0.0195, 0.085). \quad (44)$$

For the weighting of the dimensionless norm matrix, the weighted decision matrix $\mathbf{Z}$ is obtained according to Equation (29):

$$\mathbf{Z} = \begin{bmatrix} 0.010 & 0.007 & 0.085 \\ 0.017 & 0.020 & 0 \\ 0.017 & 0 & 0 \\ 0 & 0 & 0.085 \\ 0.006 & 0.007 & 0 \end{bmatrix}. \quad (45)$$

Therefore, the positive optimal solution and the negative optimal solution can be determined:

$$\begin{cases} \overset{+}{\mathbf{z}} = (0.017, 0.020, 0.085), \\ \overset{-}{\mathbf{z}} = (0, 0, 0). \end{cases} \quad (46)$$

By calculating the walking distance, the distances from each feasible parking space to the positive optimal solution and the negative optimal solutions are obtained, respectively. The distance from each standby parking space to the positive and negative optimal solutions is:

$$\begin{cases} \mathbf{d}^+ = (0.480, 0.459, 0.300, 0.197, 0.471), \\ \mathbf{d}^- = (0.138, 0.155, 0.310, 0.425, 0.14). \end{cases} \quad (47)$$

Calculate the absolute difference between the reference sequence and other comparison sequences, use the absolute difference matrix to get the grey correlation coefficient matrix and between the positive and negative optimal solutions of each feasible parking space, and then calculate the grey correlation and between the positive and negative optimal solutions of each feasible parking space as follows:

$$\begin{cases} \mathbf{r}^+ = (0.956, 0.965, 0.944, 1.055, 0.966), \\ \mathbf{r}^- = (0.920, 0.919, 0.989, 1.086, 0.924). \end{cases} \quad (48)$$

Based on the calculation of the Euclidean distances and the grey correlation, the comprehensive closeness of scheme evaluation is finally obtained as follows:

$$\mathbf{c}^{+} = (0.357, 0.370, 0.503, 0.595, 0.360). \quad (49)$$

According to the comprehensive progress of each feasible parking space, it is recommended and sorted, see Table 7.

According to Table 7, the comprehensive approach degree of ASB Community is 0.595, which is the largest among the five shared parking lots, indicating that it is the optimal shared parking lot for this traveler.

5.3. Optimal Parking Route Recommendation

5.3.1. Parking Route of Road Sections. Based on the intelligent navigation app of Gaode Map, we can query the estimated travel time of a specific path within a certain period of time. Figure 4 represents expected driving time of all road sections between 8:00 am and 9:00 am, which is the most likely time period for the public traveler to choose in terms of the parking demand.

Based on the proposed improved ant colony algorithm, we can solve the optimal parking route recommendation. The parameters are given as follows: the number of ants is 100, $\alpha = 0.15$ [45], $\beta = 4$ [45], $\varphi = 0.5$, $\xi = 0.33$.

Based on the above parameter settings, we can get the optimal recommended parking route from the origin to the optimal shared parking lot, see Figure 5.

5.3.2. Inner Parking Route of a Shared Parking Lot. The environmental layout assumption of the underground parking lot in ASB Community is shown in Figure 6, in which the parking spaces marked in red are the optimal allocated parking space.

Figure 7 shows the topological network of shared parking spaces and the optimal parking route in the parking lot. The intersection nodes of each road section are represented as R1-R16, and the circles filled in blue represent important points of parking routes. The shared parking spaces are represented by numbers 1–76, and according to the symmetry of parking spaces, the upper and lower parking spaces on the road section are summed up as one node, to fit the realistic car-seeking scene.

According to the improved ant colony algorithm, the optimal parking route from the entrance of the shared parking lot to the optimal shared parking space is R9-R5-20-24-25-26, as shown in Figure 7.

6. Conclusions and Future Research Directions

In this paper, the shared parking space resource allocation and parking route guidance problem are studied. Our innovations and conclusions are as follows:

(1) Considering the interests of both parking space managers and public travelers, we construct a multi-criteria approach to shared parking resource management. For the parking space manager, we simultaneously aim to maximize the utilization of shared parking spaces and minimize the average idle index of multiple parking lots in a given region. For public travelers, we simultaneously aim to minimize each public traveler's parking fee, and maximize parking safety, and maximize parking convenience. As a result, the shared parking space management is a multi-objective and multi-attribute decision-making problem based on time window constraints. In order to solve this problem, we design an AHP-Entropy-TOPSIS-GRA method.

(2) We also study the optimal parking route guidance problem for public travelers, where the travel time and the travel comfort are considered from the starting point to the optimal shared parking space and from the optimal shared parking space to the destination. In order to solve this problem, we improve the traditional ant colony algorithm.

(3) Finally, taking Huai'an Xinya International Business Circle as an example, the proposed models and algorithms are validated and analyzed by the empirical parking data, road traffic data.

Nevertheless, in the future, there also are rich research directions that can be extended based on this research framework and results:

(1) Under more realistic conditions, due to the influence of many factors like weather, road conditions, etc., both the public travelers and the owners of shared parking spaces may change their time [4, 36, 51].

(2) In the follow-up study, a demand-responsive parking pricing mechanism can be developed through the real-time utilization of parking spaces to maximize the utilization of parking spaces and social welfare [12, 52]. Under ambiguous parking sharing and parking demand time situations, the challenge of allocating shared parking spaces can be taken into consideration in future research.

(3) Cruising for parking can result in a huge waste of time and energy [3]. With the support of advanced Internet of things (IoT) [53], fog computing [54], etc., reserve parking and shared parking will be implemented, which will ease operating pressure from cruising and road traffic. A highly significant subject is figuring out how to calculate the societal benefits of shared parking, such as time, energy, and pollution reduction [7].

(4) For cities with different development levels and urban residents with different attributes, it is also critical to study their sharing willingness, as well as relevant influencing factors, to improve the implementation of shared parking policies and schedules [55, 56].

(5) Although the development of information and communication technology has provided travelers with convenient booking services, in the travel

management system, the privacy and security of travelers are also worthy of attention [19].

Data Availability

All data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by National Natural Science Foundation of China (No. 71971005), Beijing Municipal Natural Science Foundation (No. 8202003), Young Teachers' Research Ability Enhancement Program Grant of Beijing University of Civil Engineering and Architecture (No. X21066), and Beijing Postdoctoral Research Foundation (No. 2021-zz-111).

References

[1] W. Yang, P. T. Lam, and I. Lam, "Evaluation of drivers' benefits accruing from an intelligent parking information system," *Journal of Cleaner Production*, vol. 231, pp. 783–793, 2019.

[2] W. Yan-ling, W. Xin, and Z. Ming-chun, "Current situation and analysis of parking problem in beijing," *Procedia Engineering*, vol. 137, pp. 777–785, 2016.

[3] D. Shoup, *The High Cost of Free Parking*, Routledge, Oxfordshire, England, UK, 2017.

[4] P. Zhao, H. Guan, and P. Wang, "Data-driven robust optimal allocation of shared parking spaces strategy considering uncertainty of public users' and owners' arrival and departure: an agent-based approach," *IEEE Access*, vol. 8, pp. 24182–24195, 2020.

[5] J.-K. Liang, T. Eccarius, and C.-C. Lu, "Investigating factors that affect the intention to use shared parking: a case study of taipei city," *Transportation Research Part A: Policy and Practice*, vol. 130, pp. 799–812, 2019.

[6] C. Y. Shao, H. Yang, Y. Zhang, and J. T. Ke, "A simple reservation and allocation model of shared parking lots," *Transportation Research Part C: Emerging Technologies*, vol. 71, pp. 303–312, 2016.

[7] P. Zhao, H. Guan, P. Wang, and H. Yan, "Evaluation of environmental benefits caused by reservation-based shared parking: a case study of Beijing, China," *IEEE Access*, vol. 9, pp. 3744–3751, 2021.

[8] M. S. Smith, *Shared Parking Design & Management*, Urban Land Institute, USA, 1984.

[9] J. Lin, S.-Y. Chen, C.-Y. Chang, and G. Chen, "SPA: smart parking algorithm based on driver behavior and parking traffic predictions," *IEEE Access*, vol. 7, pp. 34275–34288, 2019.

[10] J. van Ommeren, J. de Groote, and G. Mingardo, "Residential parking permits and parking supply," *Regional Science and Urban Economics*, vol. 45, pp. 33–44, https://doi.org/10.1016mar 2014. [Online]. Available:.

[11] Z. Chen, Y. Yin, F. He, and J. L. Lin, "Parking reservation for managing downtown curbside parking," *Transportation Research Record*, vol. 2498, no. 1, pp. 12–18, 2015.

[12] A. Mirheli and L. Hajibabai, "Utilization management and pricing of parking facilities under uncertain demand and user decisions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 5, pp. 2167–2179, 2020.

[13] V. Hassija, V. Saxena, V. Chamola, and F. R. Yu, "A parking slot allocation framework based on virtual voting and adaptive pricing algorithm," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 6, pp. 5945–5957, 2020.

[14] R. G. Thompson, K. Takada, and S. Kobayakawa, "Optimisation of parking guidance and information systems display configurations," *Transportation Research Part C: Emerging Technologies*, vol. 9, no. 1, pp. 69–85, feb 2001, https://doi.org/10.1016[Online]. Available:.

[15] B. J. Waterson, N. B. Hounsell, and K. Chatterjee, "Quantifying the potential savings in travel time resulting from parking guidance systems: a simulation case study," *Journal of the Operational Research Society*, vol. 52, no. 10, pp. 1067–1077, 2001.

[16] B. Li, Y. Pei, H. Wu, and D. Huang, "MADM-based smart parking guidance algorithm," *PLoS One*, vol. 12, no. 12, Article ID e0188283, 2017.

[17] M. Jelokhani-Niaraki and J. Malczewski, "A group multicriteria spatial decision support system for parking site selection problem: a case study," *Land Use Policy*, vol. 42, pp. 492–508, 2015.

[18] P. Van der Waerden, H. Timmermans, and A. N. R. da Silva, "The influence of personal and trip characteristics on habitual parking behavior," *Case Studies on Transport Policy*, vol. 3, no. 1, pp. 33–36, 2015, 33–36.

[19] M. M. Badr, W. A. Amiri, M. M. Fouda, M. M. E. A. Mahmoud, A. J. Aljohani, and W. Alasmary, "Smart parking system with privacy preservation and reputation management using blockchain," *IEEE Access*, vol. 8, pp. 150823–150843, 2020.

[20] T. Campisi, M. Ignaccolo, Giuseppe Inturri, G. Tesoriere, and V. Torrisi, "The growing urban accessibility: a model to measure the car sharing effectiveness based on parking distances," in *Proceddings of the International Conference on Computational Science and its Applications*, pp. 629–644, Italy, July, July2020.

[21] K. W. Axhausen and J. W. Polak, "Choice of parking: stated preference approach," *Transportation*, vol. 18, no. 1, pp. 59–81, 1991, 59–81.

[22] P. Bonsall and I. Palmer, "Modelling drivers' car parking behaviour using data from a travel choice simulator," *Transportation Research Part C: Emerging Technologies*, vol. 12, no. 5, pp. 321–347, 2004.

[23] R. Arnott and J. Rowse, "Modeling parking," *Journal of Urban Economics*, vol. 45, no. 1, pp. 97–124, 1999.

[24] E. Chaniotakis and A. J. Pel, "Drivers' parking location choice under uncertain parking availability and search times: a stated preference experiment," *Transportation Research Part A: Policy and Practice*, vol. 82, pp. 228–239, 2015.

[25] F. Zong, P. Yu, J. Tang, and X. Sun, "Understanding parking decisions with structural equation modeling," *Physica A: Statistical Mechanics and Its Applications*, vol. 523, pp. 408–417, 2019.

[26] B. Mo, H. Kong, H. Wang, X. C. Wang, and R. Li, "Impact of pricing policy change on on-street parking demand and user

satisfaction: a case study in nanning, China," *Transportation Research Part A: Policy and Practice*, vol. 148, pp. 445–469, 2021, https://www.sciencedirect.com/science/article/pii/S0965856421001117.

[27] C. Zeng, C. Ma, Ke Wang, and Z. Cui, "Parking occupancy prediction method based on multi factors and stacked gru-lstm," *IEEE Access*, vol. 10, pp. 47361–47370, 2022.

[28] B. He, W. He, and M. He, "The attitude and preference of traveler to the park & ride facilities: a case study in nanjing, China," *Procedia-Social and Behavioral Sciences*, vol. 43, pp. 294–301, 2012.

[29] W. Clayton, E. Ben-Elia, G. Parkhurst, and M. Ricci, "Where to park? a behavioural comparison of bus park and ride and city centre car park usage in bath, UK," *Journal of Transport Geography*, vol. 36, pp. 124–133, 2014.

[30] Y. Kono, K. Uchida, and K. Andrade, "Economical welfare maximisation analysis: assessing the use of existing park-and-ride services," *Transportation*, vol. 41, no. 4, pp. 839–854, 2014.

[31] A. Ardeshiri, F. Safarighouzhdi, and T. Hossein Rashidi, "Measuring willingness to pay for shared parking," *Transportation Research Part A: Policy and Practice*, vol. 152, pp. 186–202, 2021.

[32] Yu Ning, M. Yan, S. X. Xu, Y. Li, and L. Li, "Shared parking acceptance under perceived network externality and risks: theory and evidence," *Transportation Research Part A: Policy and Practice*, vol. 150, no. 2, pp. 1–15, 2021.

[33] C. Lei and Y. Ouyang, "Dynamic pricing and reservation for intelligent urban parking management," *Transportation Research Part C: Emerging Technologies*, vol. 77, pp. 226–244, 2017.

[34] S. Shao, S. X. Xu, H. Yang, and G. Q. Huang, "Parking reservation disturbances," *Transportation Research Part B: Methodological*, vol. 135, pp. 83–97, 2020.

[35] P. Zhao, H. Guan, H. Wei, and S. Liu, "Mathematical modeling and heuristic approaches to optimize shared parking resources: a case study of beijing, China," *Transportation Research Interdisciplinary Perspectives*, vol. 9, no. 4, Article ID 100317, 2021.

[36] X. Huang, X. Long, J. Wang, and L. He, "Research on parking sharing strategies considering user overtime parking," *PLoS One*, vol. 15, no. 6, Article ID e0233772, 2020.

[37] E. H. C. Lu and C. H. Liao, "Prediction-based parking allocation framework in urban environments," *International Journal of Geographical Information Science*, vol. 34, no. 9, pp. 1873–1901, 2020.

[38] D. C. Shoup, "Cruising for parking," *Transport Policy*, vol. 13, no. 6, pp. 479–486, 2006.

[39] C. Di Napoli, D. Di Nocera, and S. Rossi, "Using negotiation for parking selection in smart cities," in *Proceedings of the International Conference on Practical Applications of Agents and Multi-Agent Systems*, pp. 331–334, Salamanca, Spain, June2014.

[40] R. G. Thompson, K. Takada, S. Kobayakawa, and B. Saturo Kobayakawa, "Optimisation of parking guidance and information systems display configurations," *Transportation Research Part C: Emerging Technologies*, vol. 9, no. 1, pp. 69–85, 2001.

[41] M. W. Levin and S. D. Boyles, "Optimal guidance algorithms for parking search with reservations," *Networks and Spatial Economics*, vol. 20, no. 1, pp. 19–45, 2020.

[42] H. Chai, R. Ma, and H. M. Zhang, "Search for parking: a dynamic parking and route guidance system for efficient parking and traffic management," *Journal of Intelligent Transportation Systems*, vol. 23, no. 6, pp. 541–556, 2019.

[43] H. Gao, Q. Yun, R. Ran, and J. Ma, "Smartphone-based parking guidance algorithm and implementation," *Journal of Intelligent Transportation Systems*, vol. 25, no. 4, pp. 412–422, 2021.

[44] A. Chatterjee, D. Raha, F. Joseph, and S. Cohn-Sfetcu, "Parking system with centralized reservation, payment and enforcement," *US Patent App*, vol. 10/463, p. 321, April 8 2004.

[45] D. Nobel and S. Yagi, "Network assignment calibration of BPR function: a case study of Metro Manila, the Philippines," *Journal of the Eastern Asia Society for Transportation Studies*, vol. 12, pp. 598–615, 2017.

[46] B. Roy and R. Słowiński, "Questions guiding the choice of a multicriteria decision aiding method," *EURO Journal on Decision Processes*, vol. 1, no. 69–97, pp. 69–97, 2013.

[47] M. Tavana and A. Hatamimarbini, "A group AHP-TOPSIS framework for human spaceflight mission planning at NASA," *Expert Systems with Applications*, vol. 38, no. 11, pp. 13588–13603, 2011.

[48] X. Li, K. Wang, L. Liu, J. Xin, H. Yang, and C. Gao, "Application of the entropy weight and TOPSIS method in safety evaluation of coal mines," *Procedia Engineering*, vol. 26, pp. 2085–2091, 2011.

[49] J. Freeman and T. Chen, "Green supplier selection using an AHP-Entropy-TOPSIS framework," *Supply Chain Management: International Journal*, vol. 20, no. 3, pp. 327–340, 2015.

[50] M. Dorigo, M. Birattari, and T. Stutzle, "Ant colony optimization," *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28–39, 2006, 28–39.

[51] S. X. Xu, M. Cheng, X. T. R. Kong, H. Yang, and G. Q. Huang, "Private parking slot sharing," *Transportation Research Part B: Methodological*, vol. 93, pp. 596–617, 2016.

[52] M. Friesen and G. Mingardo, "Is parking in europe ready for dynamic pricing? a reality check for the private sector," *Sustainability*, vol. 12, no. 7, p. 2732, 2020.

[53] F. Al-Turjman and A. Malekloo, "Smart parking in IoT-enabled cities: a survey," *Sustainable Cities and Society*, vol. 49, Article ID 101608, 2019.

[54] C. Tang, X. Wei, C. Zhu, W. Chen, and J. J. P. C. Rodrigues, "Towards smart parking based on fog computing," *IEEE Access*, vol. 6, pp. 70172–70185, 2018.

[55] C. Zhang, J. Chen, Z. Li, and Y. Wu, "Predicting owners' willingness to share private residential parking spots," *Transportation Research Record*, vol. 2672, no. 8, pp. 930–941, 2018.

[56] Z. Guo and S. McDonnell, "Curb parking pricing for local residents: an exploration in New York city based on willingness to pay," *Transport Policy*, vol. 30, pp. 186–198, 2013.