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Research Article

Prospect Theory-Based Two-Sided Satisfied and Stable Matching Mechanism for the Shared Parking Slots Problem

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The contradiction between the dramatic increase in the aggregate number of automobiles and the short supply of parking spaces leads to parking difficulties. Sharing mode helps improve the efficiency of existing parking spaces, increase resource utilization, and alleviate the difficulty of parking. This paper focuses on the matching mechanism in the shared parking slots problem, which involves three agents: shared parking suppliers, shared parking demanders, and shared parking platform. We propose a prospect theory-based two-sided satisfied and stable matching model (PT-TSSM) with two objectives to maximize the satisfaction degree of both shared parking demanders and shared parking suppliers. Numerical experiments are illustrated to demonstrate the efficiency of the proposed model. Moreover, the PT-TSSM model is compared with the other two shared parking mechanisms. The proposed model considers the satisfaction degrees of both shared parking demanders and suppliers, while first book first serve (FBFS) cares only one side of the participants. And compared with deferred acceptance (DA), our model not only takes two-sided stable matching into account but also considers the satisfaction degree of all the demand and supply participants, which obtain a two-sided satisfied and stable matching scheme.

1. Introduction

The reconstruction and expansion speed of parking spaces cannot keep up with the growth rate of car ownership, which leads to parking difficulty, energy consumption, environmental pollution, and other issues [1]. As a worldwide problem, scholars have studied how to alleviate parking difficulties from various angles. Increasing parking spaces is the first choice to ease parking difficulties. However, in large cities with scarce land resources, expanding the parking lot is unrealistic. Therefore, ways of parking management are proposed to alleviate the parking difficulty, such as car ownership control policies [2], traffic congestion charging [3], and regional restrictions [4]. These approaches aim at reducing the usage of private car and encouraging travelers to take the public transportation. Another part of parking management is to allocate parking resources and release the parking difficulty based on the development of mobile technology and data processing technique [5].

With the promotion of the sharing economy concept, a new approach of parking management—shared parking—draws wide attention, which helps revitalize stock resources. Shared parking refers to the common use of parking spaces between parking attraction points with different land use properties by using the peak parking characteristics at different periods of the day in a certain area [6]. In this paper, shared parking slots mainly include public parking lots (e.g., those owned by large shopping malls or cinemas) and private parking slots. The usage time utilization rate is less than 50% in some Chinese cities. There is a lot of potential for us to make full use of the existing parking spaces and improve the parking space utilization rate. Although the market potential of shared parking is unlimited, its market share is lower than expectation. Relevant scholars have conducted research on the use intention and acceptance of shared parking. Niu et al. [7] analysed the influencing factors that affect the transformation of users from traditional parking modes to shared parking modes. They concluded that the key to the transformation of mode is to control the user's perceived risk of shared parking and improve the user's perception level at the same time, so as to increase the user's reputation and repurchase.

At present, there is much optimization literature that focuses on the user experience in the process of shared parking [8, 9]. These papers are mainly from the perspective of the platform or the demand side of shared parking spaces, such as increasing platform revenue and reducing parking walking distance. However, less attention is paid to the perception of the shared parking suppliers. In fact, a major feature that makes shared parking different from traditional parking is that the suppliers of shared parking can easily enter and exit the market. Therefore, the shared parking platform cannot just care about the user experience of the shared parking demanders but also consider the user experiences of both the suppliers and the demanders to improve the user experience of the whole shared parking market. For shared parking, the platform is only an intermediary. Both the suppliers and the demanders are people entering this market. Under the condition of parking sharing, it is unreasonable to treat the suppliers and the platform as the same items. It is necessary to regard the parking space supplier and demander as both important bilateral partners to match so as to improve the user experience in the market. For example, private parking spaces have the characteristic of going out early and returning late. The supplier will have parking demands after work. If the user, who parked in the private parking space, still has not left at this time, the supplier's parking will be affected, resulting in a poor user experience and the risk of leaving the market in the future. Therefore, it is necessary to consider the user experience on both sides. Xu et al. [10] and Xiao et al. [11] both considered the bilateral situation and established a matching mechanism with the shared parking suppliers and demanders. However, they assumed that the parking spaces were homogeneous and did not consider the influencing factors such as parking walking distance and integrity. These influencing factors will easily affect the user experience of both suppliers and demanders. Therefore, we should take these factors that affect the matching between supply and demand into account when considering the two-sided matching mechanism.

Many scholars have studied the key factors affecting the user experience of both the shared parking supplier and the shared parking demander. Parking walking time, parking safety, and comfort are factors affecting the user experience of the shared parking supplier; parking price and integrity are factors affecting the user experience of the shared parking demander [12, 13]. These indices have different dimensions and units. Therefore, we standardize these indices to 0-1, and the value indicates the degree of satisfaction. Satisfaction refers to the comparison between the effect of the product after use and the cognition before use. That is, for each index, there is a reference point. It indicates satisfaction when the value of the index is higher than the reference point, and it indicates dissatisfaction when it is lower than the reference point. At the same time, the perception of equal gains and losses is asymmetric. In fact, people tend to be more sensitive to losses than gains. Therefore, we need to start with the user's psychologically perceived value when considering satisfaction. And the prospect theory can well reflect the user's attitude towards gains and losses.

In this paper, we propose a prospect theory-based two-sided satisfied and stable matching (PT-TSSM) model for the shared parking slots problem to help the shared parking platform better allocate the parking resources and increase the satisfaction degree of the participants. In the proposed model, biobjective is used to simultaneously maximize the satisfaction degree of both shared parking demanders and shared parking suppliers on the basis of a stable match. Moreover, the prospect theory is used to integrate the value function into the traditional two-sided satisfied and stable matching (TSSM) mechanism to consider the fact that losses loom larger than gains.

The main contribution of this work is as follows: (1) Due to the uniqueness of shared parking, both the supplier and the demander can enter and exit the market at will. In order to make the user experience in the market better and more willing to stay in the market, we regard the supplier and the demander of shared parking as matching parties and consider the user experience of both the suppliers and the demanders. (2) Ffor various indices that affect the supply and demand sides, due to their different dimensions and different units, we normalize them and introduce the concept of satisfaction to quantify the user experience. The higher they are than the reference point, the more satisfied they are, and the lower they are than the reference point, the more dissatisfied they are. At the same time, we consider the perceived value of the matching parties to measure the user's perception of gain and loss, reflecting that users are often more sensitive to loss than gain. (3) Iin the process of matching, we not only consider the satisfaction of the matching parties but the stability of the matching is also considered to make the matching result of the successful matching pairs more stable.

The paper is organized as follows: a literature review is given in Section 2; Section 3 describes the shared parking slots matching problem; Section 4 is the illustration of the notations, followed by a prospect theory-based two-sided satisfied matching model and a prospect theory based two-sided satisfied and stable matching model for the shared parking slots matching problem. The proposed models are solved after transforming the original biobjective programming into the single-objective one in Section 5. Numerical experiments with sensitive analysis are performed in Section 6. Conclusions and further research directions are given in Section 7.

2. Literature Review

Compared with the traditional parking mode, the shared parking mode can reduce the idle time of parking spaces and reduce the waste of resources, which is indisputable [14]. The authority needs to help users accept the new sharing mode. Using public parking lots for sharing has been widely used. Different from public parking lot, private parking lot sharing faces some challenges. There are two main gaps between private parking slots and sharable private parking slots: (1) the housing estates in China have been mostly gated in the past, and drivers who do not live in the communities are unable to enter; (2) the usage rights and ownership of the private parking slots cannot be separated, and the owner has no access to lease the private parking slot. Recently, the Chinese government released some files about the suggestions on the city planning management, which suggested building open housing estates instead of building the closed ones [15]. And with the development of mobile applications, the owner can easily offer their private parking slots to the platform. Therefore, since private parking slots can be shared, we consider private parking slot sharing to expand the range of shared parking spaces.

People in communities in the city always have the feature of “going out at dawn and coming back at dusk” [11]. Private parking slots owners drive to work in the morning and go back after being off duty, which means that the private parking slots are usually used in the night and they are in the idle state in the daytime. Hence, the private parking slots have the potential to be shared in the daytime. In fact, the commercial areas are more eager for parking spaces in the daytime. If the private parking slots in the nearby communities can be shared, it will relieve the parking pressure in commercial areas (e.g., the Central Business District). Moreover, Chen et al. [16] analyzed the shared parking feasibility of appertaining parking facilities to buildings in cities. The scholars explored the feasibility of using adjacent accessory parking facilities for parking when the building was oversaturated during a certain period, such as commercial areas, residential areas, and hospitals [17]. Duan et al. [18] analyzed the available characteristics of parking spaces and proposed a shared parking service capacity assessment model. The example results show that residential shared parking can provide parking for about fifty-five percent of its adjacent buildings.

Xu et al. [10] raised a price-compatible top trading cycles and chains (PC-TTCC) mechanism, widely used on the indivisible good matching problem, to help better the allocation of private shared parking slots resources. In the proposed PC-TTCC mechanism, the utility relies on parking fees and fixed walking distances. Shao et al. [19] proposed a simple reservation and allocation model for shared parking lots to maximize the use of private resources to benefit the community. Based on the model proposed by Shao et al. [19], Ning et al. [20] studied this model with the goal of maximizing the satisfaction of demanders. Zhang et al. [21] proposed a two-objective programming model based on shared parking with a time window, aiming at the balanced utilization of parking resources and the minimum walking distance of the demander. In addition, some scholars studied the uncertainty in the shared parking problem. Yan et al. [22] established a two-stage matching and scheduling algorithm for real-time private parking sharing programs to obtain appropriately matching demands and supplies in an uncertain setting. However, the previous research considered that there exist two agents traditionally: shared parking platform and private shared parking slots demanders. They regard the private parking slots provided by the private parking slot owners as a tradeable item rather than taking the private parking slot owners as agents in the matching mechanism. Different with parking lots sharing, we attach great importance to the preference of private parking slots owners, since the shared parking suppliers are made up of individuals, who have low cost to get in and out of the market. The owners of private parking slots have the potential to quit the shared parking market, if their slots are seldom chosen or often matched with drivers with poor performances (e.g., default). Thus, taking both sides into account in the shared parking problem can keep the shared parking suppliers in the market, although in reality, single-sided matching is easier than two-sided matching. Xiao and Xu [23] conducted a novel, truthful double auction mechanism approach in which price, parking units, and parking times are taken into consideration to deal with the shared parking matching problem. However, they did not consider how the spatial allocation of private shared parking slots affects the preferences of shared parking demanders.

A two-sided matching mechanism is proposed to solve this problem, in which the spatial factors that affect the matching consequence can be considered. A two-sided matching mechanism was first proposed by Gale and Shapley in 1962 to solve the marriage matching problem. Nowadays, the research on two-sided matching mainly focuses on the matching activities of different participants in different scenarios in reality. Janssen and Verbraeck [24] conducted a qualitative analysis of the potential advantages of two-sided matching in the market and established a real-time supply and demand matching system, which was supported by e-commerce intermediaries. Wan and Li [25] explored the two-sided matching problem between venture capitalists and investment enterprises in real life. Jiang and Yuan [26] studied the one-to-many two-sided matching problem between applicants and positions with tenants. And, in some two-sided matching mechanism such as deferred acceptance mechanism, the participants need to give the complete preference ordering information. However, in shared parking matching problems, it is difficult for the shared parking slot demanders and shared parking slot suppliers to give the complete preference ordering information. And, we want to take the satisfaction degree of the participants into account. Many scholars in the field of transportation conducted studies regarding the satisfaction-loyalty model, and they found that higher satisfaction is an important factor of repeated patronage intention and a customer’s continuous loyalty will also promote users’ clear behavioral intentions [7, 27, 28]. Therefore, we propose a two-sided satisfied and stable matching (TSSM) model to overcome this difficulty. In the proposed model, the shared parking platform can obtain the matching results by constructing the two-sided matching after calculating the satisfaction degree according to the information of the departure place, the destination and the parking unit from the demander, and the location information of the parking lots from the suppliers.

Bendoly et al. [29] summarized 52 articles on operation management and found that the management mode based on user behavior was necessary. From the perspective of the platform (manager), only by improving users' perceived value can we win the market. Therefore, when measuring the satisfaction of both parties, we need to start from the perspective of the users' perceived value. In traditional TSSM, the rational theory of choice is used to assume description invariance, which states that equivalent formulations of a choice problem should give rise to the same preference order [30]. In fact, there is much evidence that losses loom larger than gains [31]. That is, the same gains and losses yield systematically different preferences [32]. Losses may hurt the decision-makers more than the same profits would satisfy them. Moreover, they care more about the change in satisfaction degree than the exact value. In the shared parking matching process, agents' attitudes toward gains and losses are also asymmetric. Thus, we take the value function into account and propose the prospect theory-based TSSM (PT-TSSM) model to consider the phenomena that losses loom larger than gains when treating both risk and uncertainty, which can well describe the psychologically perceived value of users. Kahneman and Tversky [33] proposed the well-known prospect theory based on the reference system. The theory points out that when faced with future risks, individuals use an S-shaped value function to evaluate utility. This function has three properties, namely, reference dependence, loss aversion, and diminishing sensitivity [34]. As prospect theory indicates, the same gains and losses yield systematically different preferences [32]. The theoretical research and practical application of prospect theory have been discussed a lot in recent years in transportation management, such as travel mode choice [35, 36], traffic network planning [37], traffic demand management [38], and route choice modelling [39]. Several empirical research studies conducted on aspects of shared parking indicate the impact of perceived value on the transaction between the supplier and the demander of shared parking. Wang et al. [40] confirmed that psychological factors affect the choice of shared parking participants and the intention of private parking space owners in different levels of cities to participate in shared parking, and the mechanism of action of the psychological factors is different and not all psychological factors have a direct impact on the intention to share. Niu et al. [7] emphasized that users may turn to conventional parking mode because of concerns about the performance of shared parking modes, and the perceived risk is the key variable leading to a change in parking mode. Li et al. [41] raised a prospect theory-based random regret minimization model that was applied to study parking mode choice behavior.

Therefore, we add the prospect theory to the model to consider the psychological activities of shared parking participants.

3. The Description of the Shared Parking Two-Sided Satisfied and Stable Matching Problem

In this paper, the two-sided satisfied and stable matching problem of shared parking is approached by the proposed bi-objective programming model. As illustrated in Figure 1, three agents, i.e., shared parking suppliers, shared parking demanders, and a shared parking platform, are involved in the scenario. We focus on how the shared parking platform allocates the parking slots to match the shared parking suppliers and shared parking demanders. The allocated scheme given by the shared parking platform will return to suppliers and demanders, which maximizes simultaneously the satisfaction degree of both according to the received information.

3.1. Assumptions. Before we begin the modelling approach to the problem, we have the following assumptions:

(1) Shared parking suppliers and shared parking demanders are assumed to be self-interested, and they have a strict preference for matching partners.

(2) The shared parking platform is assumed to be a nonprofit organization, aiming at reducing real-time matching pressure and increasing matching efficiency.

(3) The submitted information is assumed to be true and effective. In the process of submitting information, no shared parking demanders or suppliers have displayed deceptive behavior, but the parking time may not be precisely controlled by the shared parking demanders, which will lead to an early (or delayed) departure.

(4) The price of shared parking slots is determined according to the bidding price of the shared parking demanders, since there is no price difference between the shared parking slots and other parking lots. The parking lot demanders are willing to reserve a shared parking lot to reduce the time spent cruising for a parking slot, because the situation will not get worse if the matching fails.

(5) The suppliers of shared parking lots have the feature of "go out at dawn and come back at dusk" [18]. They do not use the private parking slots in a specific time window in daily life (e.g., 8.00 am to 6.00 pm). The private parking slots can be shared based on this situation. In large commercial areas (e.g., Central Business District), the need of parking lots is in tension in daytime. Thus, one private parking slot can meet the parking need of the demander according to the feature, considering that the time of parking is not out of the time window.

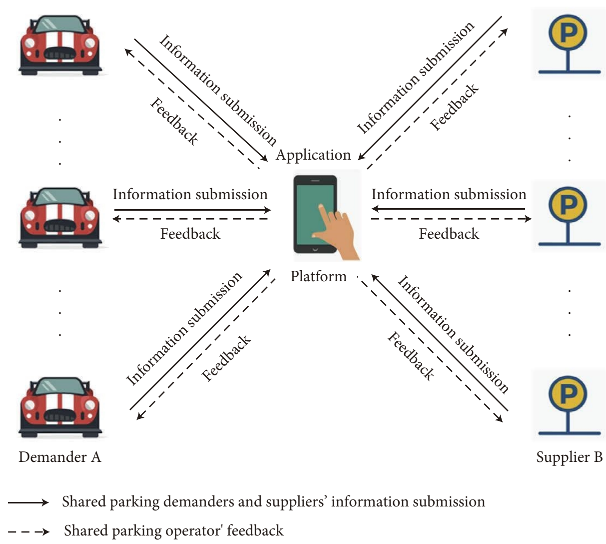

Figure 1: Shared parking scenario of the two-sided satisfied and stable matching problem.

(6) "One-to-one" principle is assumed for suppliers and demanders. One private parking lot can only be occupied by one shared parking demander. The number of shared parking suppliers is calculated according to the number of private parking slots only by separating the slots from the same owners if they own more than one private parking slot.

On the premise of the assumption, a period T can be divided into three parts: 0 to $(t-1)$, $(t-1)$ to t, and t to $(t+1)$. On the 0 to $(t-1)$ period, the shared parking demanders and suppliers submit the information through the application provided by the platform. The shared parking demanders provide the shared parking platform with information of the departure place, the destination, and parking unit, etc. The suppliers of shared parking provide the shared parking platform with the location information of the parking lots, bidding price, etc. On the $(t-1)$ to t period, the shared parking platform uses the information given by the shared parking demanders and shared parking suppliers to calculate the satisfaction, constructs the two-sided matching, and returns the matching results. On the t to $(t+1)$ period, the shared parking demanders implement the parking behavior. Thus, we research how the platform obtains the matching results satisfied by both the shared parking demanders and the shared parking suppliers using the biobjective programming model.

3.2. Problem Extension. From these assumptions, we only consider the typical case of the parking slots problem. In fact, the proposed shared parking two-sided satisfied and stable matching model can address the general parking slot problem via transformation from the following extensions:

(1) A profitable shared parking platform is used. The shared parking platform can be a profit organization or nonprofit organization. The profit organization earns commissions from shared parking demanders and shared parking suppliers in a certain proportion, while the nonprofit organization does not get any reward from shared parking suppliers and shared parking suppliers; the operational expenses come from the government or self-financing.

(2) "One to many" principle is used. The "one to one" principle is a specific situation that all the parking slots are in the identical available time gaps. In fact, the parking slots have different available time gaps, and the supplier of the parking slots can serve more than one demander if he has enough available time. Thus, the "one to many" principle can be considered by dividing the available time windows of parking slots into several equidistantly ones. Then, each time window of the same parking slot can be recognized as one private parking slot, which can be solved with the "one to one" principle.

(3) Dynamic matching is performed. In the above shared parking matching problem, we consider a one-time matching situation. Shared parking suppliers and shared parking demanders submit information on Day 1, and the transaction takes place on Day 2. It is a static matching process. If we shorten the time interval of matching (e.g., the matching process is conducted every ten minutes), the static shared parking matching problem will become a real-time dynamic shared parking matching problem.

4. Model Formulations

4.1. Notations

4.1.1. Sets. $A=\{a_1,a_2,\ldots,a_M\}$ is the set of shared parking slot demanders, where a_i represents the i-th shared parking demander, $i=1,2,\ldots,M$.

$B=\{b_1,b_2,\ldots,b_N\}$ is the set of shared parking slot suppliers, where b_j represents the j-th shared parking supplier, $j=1,2,\ldots,N$.

$C^A=\{c_1^A,c_2^A,\ldots,c_L^A\}$ is the set of all the indices that affect the satisfaction of shared parking demanders, where c_k^A represents the k-th index, $k=1,2,\ldots,L$.

$C^B=\{c_1^B,c_2^B,\ldots,c_T^B\}$ is the set of all the indices which affect the satisfaction of shared parking suppliers, where c_q^B represents the q-th index, $q=1,2,\ldots,T$.

4.1.2. Parameters. $\mathbf{w}=\{w_1,w_2,\ldots,w_L\}$ is the weight set of selected indices C^A, where w_k is the weight of the k-th index c_k^A, $w_k\in[0,1]\,(k=1,2,\ldots,L)$, and $\sum_{k=1}^{L}w_k=1$.

$\theta=\{\theta_1,\theta_2,\ldots,\theta_T\}$ is the weight set of selected indices C^B, where θ_q is the weight of the q-th index c_q^B, $\theta_q\in[0,1]q=1,2,\ldots,T$, and $\sum_{q=1}^{T}\theta_q=1$.

α,β is the curvature of the value function; λ is the loss aversion parameter; $D^{A,k}=[d_{ij}^{A,k}]_{M\times N}=$

$\begin{bmatrix} d_{11}^{A,k} & \cdots & d_{1N}^{A,k} \\ \vdots & \ddots & \vdots \\ d_{M1}^{A,k} & \cdots & d_{MN}^{A,k} \end{bmatrix}(k = 1, 2, \ldots, L)$ is the matrix of the selected index c_k^A which affect the satisfaction degree of shared parking demanders, where $d_{ij}^{A,k}$ is the preference value of shared parking demander a_i to shared parking supplier b_j when considering the index c_k^A, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L$.

$D^{B,q} = [d_{ij}^{B,q}]_{M\times N} = \begin{bmatrix} d_{11}^{B,q} & \cdots & d_{1N}^{B,q} \\ \vdots & \ddots & \vdots \\ d_{M1}^{B,q} & \cdots & d_{MN}^{B,q} \end{bmatrix}(q = 1, 2, \ldots, T)$ is the matrix of the selected index c_q^B which affect the satisfaction degree of shared parking suppliers, where $d_{ij}^{B,q}$ is the preference value of shared parking supplier b_j to shared parking demander a_i when considering the index c_q^B, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$.

$D^A = \sum_{k=1}^{L} D^{A,k} * w_k = [d_{ij}^A]_{M\times N} = \begin{bmatrix} d_{11}^{A} & \cdots & d_{1N}^{A} \\ \vdots & \ddots & \vdots \\ d_{M1}^{A} & \cdots & d_{MN}^{A} \end{bmatrix}$ is the matrix of selected indices C^A which affect the satisfaction degree of shared parking demanders, where $d_{ij}^A = \sum_{k=1}^{L} d_{ij}^{A,k} * w_k$ is the preference value of shared parking demander a_i to shared parking supplier b_j and $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N$.

$D^B = \sum_{q=1}^{T} D^{B,q} * \theta_q = [d_{ij}^B]_{M\times N} = \begin{bmatrix} d_{11}^{B} & \cdots & d_{1N}^{B} \\ \vdots & \ddots & \vdots \\ d_{M1}^{B} & \cdots & d_{MN}^{B} \end{bmatrix}$ is the matrix of selected indices C^B which affect the satisfaction degree of shared parking suppliers, where $d_{ij}^B = \sum_{q=1}^{T} d_{ij}^{B,q} * \theta_q$ is the preference value of shared parking supplier b_j to shared parking demander a_i and $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N$.

$\overline{d_i^{A,k}}$ is the reference point of shared parking demander a_i for index c_k^A, $i = 1, 2, \ldots, M, k = 1, 2, \ldots, L$.

$\overline{d_j^{B,q}}$ is the reference point of shared parking supplier b_j for index c_q^B, $j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$.

$\widetilde{D^{A,k}} = [\widetilde{d_{ij}^{A,k}}]_{M\times N} = \begin{bmatrix} \widetilde{d_{11}^{A,k}} & \cdots & \widetilde{d_{1N}^{A,k}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{M1}^{A,k}} & \cdots & \widetilde{d_{MN}^{A,k}} \end{bmatrix}$ is the normalized form of decision matrix $D^{A,k}$, $k = 1, 2, \ldots, L$;

$\widetilde{D^{B,q}} = [\widetilde{d_{ij}^{B,q}}]_{M\times N} = \begin{bmatrix} \widetilde{d_{11}^{B,q}} & \cdots & \widetilde{d_{1N}^{B,q}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{M1}^{B,q}} & \cdots & \widetilde{d_{MN}^{B,q}} \end{bmatrix}$ is the normalized form of decision matrix $D^{B,q}$, $q = 1, 2, \ldots, T$.

$\widetilde{D^A} = \sum_{k=1}^{L} \widetilde{D^{A,k}} * w_k = [\widetilde{d_{ij}^A}]_{M\times N} = \begin{bmatrix} \widetilde{d_{11}^{A}} & \cdots & \widetilde{d_{1N}^{A}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{M1}^{A}} & \cdots & \widetilde{d_{MN}^{A}} \end{bmatrix}$ is the normalized form of decision matrix D^A.

$\widetilde{D^B} = \sum_{q=1}^{T} \widetilde{D^{B,q}} * \theta_q = [\widetilde{d_{ij}^B}]_{M\times N} = \begin{bmatrix} \widetilde{d_{11}^{B}} & \cdots & \widetilde{d_{1N}^{B}} \\ \vdots & \ddots & \vdots \\ \widetilde{d_{M1}^{B}} & \cdots & \widetilde{d_{MN}^{B}} \end{bmatrix}$ is the normalized form of decision matrix D^B.

$\widetilde{V^{A,k}}$ is the matrix $\widetilde{D^{A,k}}$ with prospect theory added, where $\widetilde{v_{ij}^{A,k}}$ is the normalized preference value of shared parking demander a_i to shared parking supplier b_j when considering the index C_k^A with prospect theory added, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L$.

$\widetilde{V^{B,q}}$ is the matrix $\widetilde{D^{B,q}}$ with prospect theory added, where $\widetilde{v_{ij}^{B,q}}$ is the normalized preference value of shared parking supplier b_j to shared parking demander a_i when considering the index C_q^B with prospect theory added, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$.

$\widetilde{V^A} = \sum_{k=1}^{L} \widetilde{V^{A,k}} * w_k$ is the matrix $\widetilde{D^{A,k}}$ with prospect theory added, where $v_{ij}^A = \sum_{k=1}^{L} v_{ij}^{A,k} * w_k$ is the normalized preference value of shared parking demander a_i to shared parking supplier b_j with prospect theory added, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L$.

$\widetilde{V^B} = \sum_{q=1}^{T} \widetilde{V^{B,q}} * \theta_q$ is the matrix $\widetilde{D^{B,q}}$ with prospect theory added, where $v_{ij}^B = \sum_{q=1}^{T} v_{ij}^{B,q} * \theta_q$ is the normalized preference value of shared parking supplier b_j to shared parking demander a_i with prospect theory added, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$.

η is the weight of Z_1; $1 - \eta$ is the weight of Z_2; l_{ij} is the walking distance after parking; $\max L_{\text{walking}}$ is the maximum walking distance that can be accepted by the demander of shared parking space; t_{ij}^{arrive} is the arrival time of shared parking demanders; t_{ij}^{leave} is the departure time of shared parking demanders; T_{ij}^{start} is the time of the parking space starts to be rented; T_{ij}^{end} is the time of the parking space ends to be rented. (Note: when we define the matrix, we consider the fixed form of i as a row and j as a column to facilitate subsequent matrix operations.)

4.1.3. Decision Variables. $x_{ij} = \begin{cases} 1, & \text{if } a_i \text{ and } b_j \text{ are matched} \\ 0, & \text{otherwise} \end{cases}$ is the binary decision variable that indicates whether the shared parking demander a_i and the shared parking supplier b_j are matched, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N.$, $X = [x_{ij}]_{M\times N} = \begin{bmatrix} x_{11} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots \\ x_{M1} & \cdots & x_{MN} \end{bmatrix}$ is the matrix composed of decision variable x_{ij}, $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N$.

Z_1 is the satisfaction degree of shared parking demanders; Z_2 is the satisfaction degree of shared parking suppliers; Z is the total satisfaction degree of shared parking demanders and shared parking suppliers, and it is the weighted sum of Z_1 and Z_2.

4.2. Normalization. The indices that affect the satisfaction of shared parking demanders and shared parking suppliers include parking fees and walking distance after parking. And these indices have different dimensions and measurements. Some indices can be converted into each other. For example, time can be converted to money by using the value of time (VOT), or vice versa. However, some indices are not convertible because how to complete the mutual conversion between these indices is unknown or not authoritative in the current research. The two-sided matching of shared parking is likely to involve these indices, which are difficult to transform with each other, such as parking comfort and participants' credit scores. So, we consider using normalization to eliminate the gap between the dimensions and units of each indicator.

Normalization can be done to make sure all the indices are additive and avoid the problems resulting from the dimension and order of magnitude [42]. Indices are divided into profit attributes and cost attributes. Profit attributes mean that the larger the index value is, the better the evaluation is. Cost attributes mean that the smaller the index value is, the better the evaluation is.

Normalization method is given as follows:

When c_k^A is a positive index, $\widetilde{d_{ij}^{A,k}} = d_{ij}^{A,k} - \min_j (d_{ij}^{A,k}) / \max_j (d_{ij}^{A,k}) - \min_j (d_{ij}^{A,k})$, where $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L$

When c_k^A is an inverse index, $\widetilde{d_{ij}^{A,k}} = \max_j (d_{ij}^{A,k}) - d_{ij}^{A,k} / \max_j (d_{ij}^{A,k}) - \min_j (d_{ij}^{A,k})$, where $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L$

Decision matrix of selected index C_q^B can be normalized in the same way as follows:

When c_q^B is a positive index, $\widetilde{d_{ij}^{B,q}} = d_{ij}^{B,q} - \min_i (d_{ij}^{B,q}) / \max_i (d_{ij}^{B,q}) - \min_i (d_{ij}^{B,q})$, where $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$

When c_q^B is an inverse index, $\widetilde{d_{ij}^{B,q}} = \max_i (d_{ij}^{B,q}) - d_{ij}^{B,q} / \max_i (d_{ij}^{B,q}) - \min_i (d_{ij}^{B,q})$, where $i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, T$

4.3. Prospect Theory. Based on prospect theory, the marginal cost of a loss is greater than that of an equivalent unit of gain. That is, people are inclined to gamble (risk preference) when they are faced with the loss prospect with equal conditions, while they are inclined to realize the deterministic profit (risk aversion) when they are faced with the profit prospect with equal conditions.

In the shared parking slot two-sided matching problem, the participants have more unhappiness when the loss is equal to the gain, and when the gain is more than their reference point, they are not so sensitive to acquisition, but when they lose, they are sensitive to loss. As the choice behavior of shared parking demanders and suppliers adheres to prospect theory, the value function should be taken into consideration [43–45].

Under the present theory, assuming value $v(x_j)$ is the outcome of x_j, the form of the value function in prospect theory [30] is $v(x_j) = \begin{cases} x_j^\alpha & x_j > 0 \\ 0 & x_j = 0 \\ -\lambda(-x_j)^\beta & x_j < 0 \end{cases}$, where $x_j > 0$ implies gain, $x_j < 0$ implies loss, and α and β are the risk preference coefficients that satisfy $0 \le \alpha, \beta \le 1$; the higher the value of α and β, the more likely the decision-makers are to take risks. λ is the loss aversion coefficient, and $\lambda > 1$ means the decision-makers are sensitive to the risk of loss, and Figure 2 shows the tendency of the value function.

According to Tversky and Kahneman's present theory, the value function in shared parking two-sided matching problem can be described as follows:

$$\widetilde{v_{ij}^{A,k}} = v\left(\widetilde{d_{ij}^{A,k}} - \overline{d_i^{A,k}}\right) = \begin{cases} \left(\widetilde{d_{ij}^{A,k}} - \overline{d_i^{A,k}}\right)^\alpha, & \widetilde{d_{ij}^{A,k}} > \overline{d_i^{A,k}}, \\ 0, & \widetilde{d_{ij}^{A,k}} = \overline{d_i^{A,k}}, \mathrm{i} = 1, 2, \ldots, \mathrm{M}, \mathrm{j} = 1, 2, \ldots, \mathrm{N}, \mathrm{k} = 1, 2, \ldots, \mathrm{L}, \\ -\lambda\left(\overline{d_i^{A,k}} - \widetilde{d_{ij}^{A,k}}\right)^\beta, & \widetilde{d_{ij}^{A,k}} < \overline{d_i^{A,k}}. \end{cases} \quad (1)$$

$\overline{d_i^{A,k}}$ denotes the reference point of $d_{ij}^{A,k}$. And the value function $v_{ij}^{B,q}$ can be obtained in the same way as follows:

$$\widetilde{v_{ij}^{B,q}} = v\left(\widetilde{d_{ij}^{B,q}} - \overline{d_j^{B,q}}\right) = \begin{cases} \left(\widetilde{d_{ij}^{B,q}} - \overline{d_j^{B,q}}\right)^\alpha, & \widetilde{d_{ij}^{B,q}} > \overline{d_j^{B,q}}, \\ 0, & \widetilde{d_{ij}^{B,q}} = \overline{d_j^{B,q}}, i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, q = 1, 2, \ldots, L, \\ -\lambda\left(\overline{d_{ij}^{B,q}} - \widetilde{d_j^{B,q}}\right)^\beta, & \widetilde{d_{ij}^{B,q}} < \overline{d_j^{B,q}}. \end{cases} \quad (2)$$

$\overline{d_j^{B,q}}$ denotes the reference point of $d_{ij}^{B,q}$.

4.4. The Two-Sided Satisfied and Stable Match of Shared Parking Slots Problem. Suppose there is a set A of shared parking demander and a set B of shared parking supplier. (a_i, b_j) means that a_i and b_j are willing to be matched. A feasible matching μ is a set of compatible pairs (a, b) such that each a and each b occur in at most one pair. If (a_i, b_j) is in μ, then $\mu(a_i) = b_j$ and $\mu(b_j) = a_i$. Assuming that the demand for shared parking is greater than the number of

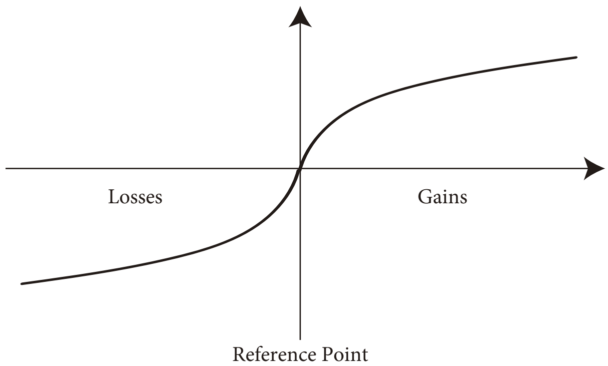

Figure 2: A value function in prospect theory.

shared parking suppliers, for each shared parking supplier b_j, there exists a compatible matching pair a_i. Shared parking two-sided matching is to combine the shared parking demanders and shared parking suppliers in a specific matching rule.

In shared parking two-sided matching problem, $R = [r_{ij}]_{M\times N}$ denotes the preference degree of shared parking demanders and $T = [t_{ij}]_{M\times N}$ denotes the preference degree of shared parking suppliers. For the feasible matching μ, we have the following:

(1) $\exists a_i, a_l \in A, b_j, b_k \in B, \mu(a_i) = b_k, \mu(a_l) = b_j$, and $r_{ij} > r_{ik}, t_{ij} > t_{lj}$

(2) $\exists a_i \in A, b_j \in B$, $\mu(a_i) = b_k$, b_j failed the matching, and $r_{ij} > r_{ik}$, if Equation (3) works, a_i has higher preference degree to b_j than b_k and b_j has higher preference degree to a_i than a_l

So a_i has the potential to give up the current matching results to get a new matching pair $\mu(a_i) = b_j$, as condition (2). And if (1) and (2) neither work, μ is a stable match.

To maximize the total satisfaction degree of share parking demanders and suppliers and to achieve the stability of the matching model, the two-sided satisfied and stable matching model for shared parking slots problem can be established as follows:

$$\max(Z_1, Z_2) = \left(\sum_{i=1}^{M}\sum_{j=1}^{N}\tilde{v}_{ij}^{A}\bullet x_{ij}, \sum_{i=1}^{M}\sum_{j=1}^{N}\tilde{v}_{ij}^{B}\bullet x_{ij}\right),$$
$$\text{s.t.} \sum_{i=1}^{M} x_{ij} \le 1, j = 1, 2, \ldots, N, \tag{3a}$$

$$\sum_{j=1}^{N} x_{ij} = 1, i = 1, 2, \ldots, M, \tag{3b}$$

$$x_{ij} + \sum_{r:\tilde{v}_{ir}^{A} > \tilde{v}_{ij}^{A}} x_{ir} + \sum_{s:\tilde{v}_{sj}^{B} > \tilde{v}_{ij}^{B}} x_{sj} \ge 1, i, r = 1, 2, \ldots, M, j, s = 1, 2, \ldots, N, \tag{3c}$$

$$x_{ij} = \begin{cases} 1, & \mu(a_i) = b_j \\ 0, & \mu(a_i) \ne b_j \end{cases}, i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, \tag{3d}$$

$$l_{ij} \le \max L_{\text{walking}}, i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, \tag{3e}$$

$$\left(t_{ij}^{\text{arrive}}, t_{ij}^{\text{leave}}\right) \subseteq \left(T_{ij}^{\text{start}}, T_{ij}^{\text{end}}\right), i = 1, 2, \ldots, M, j = 1, 2, \ldots, N. \tag{3f}$$

Equation (3a) denotes to simultaneously maximize the satisfaction degree of both all shared parking slot demanders and all shared parking slot suppliers. Constraints (3a) and (3b) imply that shared parking slot demanders and shared parking slot suppliers follow "one to one" principle, which is proposed in Section 2. Here is the case where supply is less than demand. If supply is greater than demand, equations (3a) and (3b) should be changed to $\sum_{i=1}^{M} x_{ij} = 1, j = 1, 2, \ldots, N$, $\sum_{j=1}^{N} x_{ij} \le 1, i = 1, 2, \ldots, M$. Constraint (3c) guarantees the stable match. According to constraint (3c), $\sum_{r:\tilde{v}_{ir}^{A} > \tilde{v}_{ij}^{A}} x_{ir} = 1$ means a_i and b_r has a higher preference than b_j; otherwise, $\sum_{r:\tilde{v}_{ir}^{A} > \tilde{v}_{ij}^{A}} x_{ir} = 0$; $\sum_{s:\tilde{v}_{sj}^{B} > \tilde{v}_{ij}^{B}} x_{sj} = 1$ means b_j and a_s has a higher preference than a_i; otherwise, $\sum_{s:\tilde{v}_{sj}^{B} > \tilde{v}_{ij}^{B}} x_{sj} = 0$. If constraint (3c) works on the condition that $x_{ij} = 0$, at least one of $\sum_{r:\tilde{v}_{ir}^{A} > \tilde{v}_{ij}^{A}} x_{ir}$ and $\sum_{s:\tilde{v}_{sj}^{B} > \tilde{v}_{ij}^{B}} x_{sj}$ equal to 1. Then, there exist $\mu(a_i) = b_r$ and $\mu(a_s) = b_j$, which means a_i and b_j do not represent a blocking pair, which ensures the solution of the match is stable. Constraint (3d) indicates that the shared parking slot demanders and suppliers' matching follow the principle of "all or nothing" if the shared parking demander is matched. Constraint (3e) is the walking distance after parking limitation, and it shall not exceed the maximum acceptable walking distance. Constraint (3f) means $T_{ij}^{\text{start}} \leq t_{ij}^{arrive} \leq t_{ij}^{leave} \leq T_{ij}^{end}$ $(i = 1, 2, \ldots, M,\ j = 1, 2, \ldots, N)$. The start time of shared parking supply is earlier than the arrival time of the demander, and the end time is later than the departure time of the demander.

5. Solution Algorithm

The proposed shared parking two-sided satisfied and stable matching problem is a special assignment problem with two linear objective functions, which can solved by biobjective programming (BOP) as one kind of multi-objective programming (MOP). The assignment problem is a standard combinatorial optimization problem [46]. And, it is NP-hard since the min-max regret assignment problem, as a special case of the assignment problem, is known to be NP-hard [47]. As one of the most-studied, well-known, and important problems of discrete optimization, the assignment problem has been well studied, and many algorithms have been designed to solve it, including single-objective and multiobjective cases [48–50].

The weighted sum method, goal programming method, and sequential optimization method can be used for solving MOP. In this paper, we choose the weighted sum method to solve the proposed shared parking two-sided satisfied and stable matching model with two objectives because it is easy and especially directly used due to the normalization of indices in Section 3.2, for the fact that these two objective functions are additive after all the indices are normalized.

The shared parking platform determines the appropriate weights $[\eta, (1-\eta)]^T$ according to the importance of the shared parking slots demanders and suppliers' satisfaction degree. Thus, biobjective programming for the prospect theory-based two-sided satisfied and stable matching model for the shared parking slots problem can be transformed into the following single-objective form:

$$\max Z = \eta Z_1 + (1-\eta) Z_2, \tag{4}$$

where η and 1-η denote the weight of Z_1 and Z_2. And $\in [0, 1]$.

The transformed single-objective model is an assignment problem with a nonlinear objective function, which is a mixed 0-1 integer nonlinear programming model. There are generally two kinds of methods to solve mixed-integer linear programming: exact algorithm and heuristic algorithms. In this paper, we consider the branch and cut plane method (exact algorithm) to solve this mixed integer programming problem. The branch cut plane method is often used to solve mixed integer programming problems [51]. The optimization goal is sought by solving a series of prior relaxation problems of integer programming problems. In the process of solving, the cut-plane method cuts the feasible region of the advance relaxation problem, which makes the advance relaxation problem closer to the hospital integer programming problem. The branch and cut method solves the original integer programming problem by precise branching and pruning methods:

Step 1: (delete infeasible solutions): Delete the paths which do not meet the maximum walking limitation condition: $l_{ij} \leq \max L_{\text{walking}}$ and time window condition: $(t_{ij}^{\text{arrive}}, t_{ij}^{\text{leave}}) \subseteq (T_{ij}^{\text{start}}, T_{ij}^{\text{end}})$.

Step 2: Initialize the optimal solution to the problem $Z^* = +\infty$.

Step 3: The original problem is decomposed into a main problem and subproblem; relax the subcycle constraints and integer constraints of the main problem, and the relaxed main problem is put into a specific list T.

Step 4: If there is no problem to be solved in the list T, the algorithm stops. Otherwise, select a problem from the list according to the priority rule.

Step 5: Solve the relaxation problem and find the value of the objective function $Z = Z_0^*$; if $Z \leq Z_0^*$, then go to step 4; otherwise, go to the next step.

Step 6: Add the subcycle condition as the cutting plane to the relaxation problem to verify the solution. If it passes the verification, go to the next step. Otherwise, add these cutting planes as new constraints to the relaxation problem, and then go to step 5 to continue solving.

Step 7: If the solution value of the relaxation problem is an integer, go to step 4; otherwise, go to the next step.

Step 8: Select one of the fractional variables to branch into two new constraints, drive these two conditions to the relaxation problem, form two new problems, add them to the list T, and then go to step 4.

The flowchart of the proposed algorithm is demonstrated in Figure 3.

6. Numerical Experiments

6.1. Index Selection. Some researchers found that driving distance, parking fee, and walking distance after parking were closely related to parking choice [12, 13] as mentioned in Section 1. At the same time, Zhou et al. [52] pointed out that the credit of participants in the auction directly affects the success of the transaction. Xie et al. [53] also found that residential safety and privacy should be strengthened by a supervision mechanism from governmental and operational parties. If the residents' safety and privacy were invaded by the outside parking vehicles, punishments like restriction of parking and violations of personal credit records should be carried out. The relevant policies of punishments and rewards should be regulated by the government. Some other indices also involved parking comfort, safety, and service [54]. Based on this, we selected four indices in the numerical experiment, such as traffic impedance of the road and walking distance after parking for shared parking demanders and revenue and credit score for shared parking suppliers. If the satisfaction degree increases with the rise of the index value, it is a positive

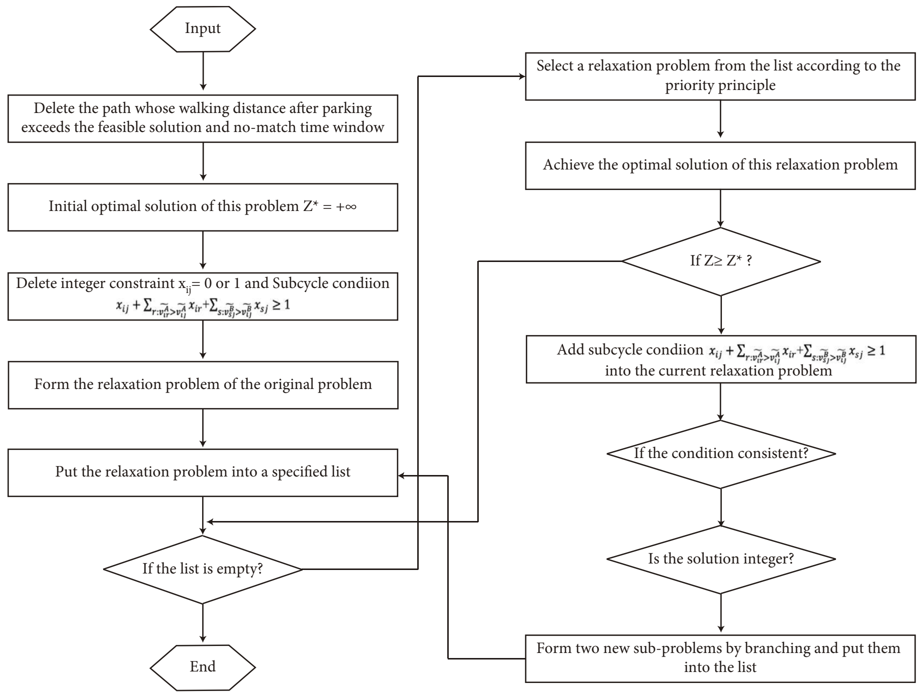

Figure 3: Flowchart of the branch and cut method.

index; otherwise, it is an inverse index. These indices are demonstrated as follows:

(1) Traffic impedance of road (inverse index): The average travel time of vehicle passing the road, which indicates the level of difficulty to pass the road.

(2) Walking distance after parking (inverse index): The distance required for a shared parking demander to walk from the shared parking lot to the destination.

(3) Revenue (positive index): We calculate the revenue of shared parking suppliers with the bidding price of suppliers themselves minus the bidding price of shared parking demanders and multiply the parking hours. Although the income of shared parking suppliers comes from the bidding price of shared parking demanders, which multiplies the parking hours, now that we have introduced the auction mechanism, the gain of shared parking spaces should be measured by their psychological expectations.

(4) Credit score (positive index): The credit of the shared parking demanders comes from historical data, similar to the score of drivers on taxi service software.

Suppose that all the shared parking demanders have the same value of time (VOT) and all the shared parking demanders have the same value of money (VOM).

6.2. A Small Example. We use a small example to demonstrate the practical application of this model. We choose the district that contains two top hospitals in Wuhan to conduct the experiment to verify the effectiveness of the model and solution algorithm. The average number of outpatient visits in these two hospitals is more than 5000 vehicles per day, with a huge demand for parking spaces. However, the number of parking spaces in both hospitals is less than 400, which makes it difficult to meet the parking demand. It is necessary to implement shared parking in such areas to reduce cruising time.

In Figure 4, I and II are hospital; $b_i\,(i = 1, \ldots, 8)$ are parking spaces, where $b_i\,(i = 1, \ldots, 6)$ are commercial parking lots and b_7, b_8 are private parking slots. On weekdays, it always takes more than half an hour to find a parking space in hospitals I and II. Nearby the hospital, there are many commercial areas and residential community, with abundant idle parking slots. So, we can consider shared parking to be involved in commercial areas and residential communities in this district.

The shared parking platform offers a shared parking application to shared parking demanders and shared parking suppliers for their submitting information. In light of the requirements of the platform, on the previous day, ten shared parking demanders $a_i\,(i = 1, \ldots, 10)$ uploaded the information of the parking unit (per hour as a unit), departure place, and destination, and eight shared parking suppliers $b_i\,(i = 1, \ldots, 8)$ uploaded the information of the location of the parking slots.

6.2.1. Data. The data on parking units could be obtained via the information uploaded and the credit score information could be obtained from the historical data in reality. We conduct the numerical experiments with simulated data. The parking units is random discrete distribution in [2, 8]. And, the credit score is random discrete distribution in [0, 5]. Table 1 lists the parking units and credit score of shared parking demanders.

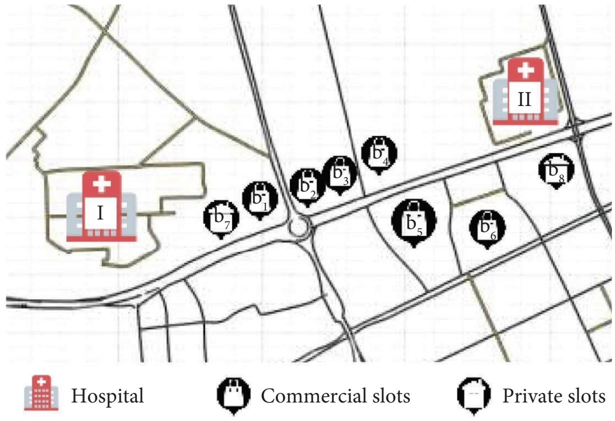

FIGURE 4: The research area in experiments.

TABLE 1: The parking units and credit score of shared parking demanders.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}
Parking unit (hour)	3	6	4	3	7	2.5	3	2	6	5
Credit score	4.3	3.7	5	3	4.9	4.6	4.1	4.5	3.8	4.2

Based on the information given by shared parking suppliers and demanders, the destination of $a_1, a_2, a_4, a_8,$ and a_9 is hospital I and the destination of $a_3, a, a_6, a_7,$ anda_{10} is hospital II, so the driving cost (min) matrix is calculated as follows which was obtained by Google Map, and the driving cost matrix is shown in Table 2.

According to the destination, we can get the walking distance of parking space demanders through Google Maps, since the parking space here is meager, we set the maximum acceptable parking walking distance as one kilometer. The walking distance is in Table 3.

The shared parking suppliers and demanders will give their bidding time and price information separately, which is listed in Table 4.

6.2.2. Parameter. In this example, we use the mean value as the reference point. And, we choose the parameters of the prospect theory $\alpha = \beta = 0.88$ and $\lambda = 2.25$. Under circumstances of homogeneous preference, according to the research of Kahneman and Tversky [31], the value function is as follows:

$$\widetilde{v_{ij}^{A,k}} = v\left(\widetilde{d_{ij}^{A,k}} - \overline{d_i^{A,k}}\right) = \begin{cases} \left(\widetilde{d_{ij}^{A,k}} - \overline{d_i^{A,k}}\right)^{0.88}, & \widetilde{d_{ij}^{A,k}} > \overline{d_i^{A,k}}, \\ 0, & \widetilde{d_{ij}^{A,k}} = \overline{d_i^{A,k}}, i = 1, 2, \ldots, M, j = 1, 2, \ldots, N, k = 1, 2, \ldots, L, \\ -2.25\left(\overline{d_i^{A,k}} - \widetilde{d_{ij}^{A,k}}\right)^{0.88}, & \widetilde{d_{ij}^{A,k}} < \overline{d_i^{A,k}}, \end{cases} \quad (5)$$

where $\overline{d_i^{A,k}} = \sum_{i=1}^{M} d_i^{A,k}/M$ is the mean value of $d_{ij}^{A,k}$ to be selected as the reference point in the two-sided satisfied and stable matching problem. $\widetilde{v_{ij}^{B,q}}$ can be obtained in the same way as $\widetilde{v_{ij}^{A,k}}$.

As the indices are normalized, they are additive; we simply suppose that all the weight of the index is the same, $\omega_1 = \omega_2 = 0.5$, and $\theta_1 = \theta_2 = 0.5$. In reality, the weight of each index can be calculated by the experts grading method, the analytic hierarchy process (AHP),

Table 2: The driving cost matrix of shared parking demanders (min).

	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8
a_1	8	12	10	11	8	9	8	9
a_2	13	15	15	16	14	13	13	14
a_3	8	8	8	7	9	9	8	10
a_4	14	18	18	18	15	15	14	16
a_5	16	21	22	22	18	18	16	19
a_6	22	22	22	21	23	23	23	24
a_7	47	52	52	51	48	48	47	49
a_8	25	24	24	24	26	26	25	27
a_9	72	84	84	80	83	79	81	83
a_{10}	27	29	30	28	26	26	25	28

Table 3: Distance matrix from the parking slots to the hospital (m).

	Commercial slots						Private slots	
	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8
Distance from parking slots to hospital I	500	600	750	900	1000	700	300	1000
Distance from parking slots to hospital II	950	850	650	550	520	350	1200	150

Table 4: The bidding information of shared parking suppliers and demanders.

Demanders	Arrive	Leave	Using price (¥)	Supplier	Start	End	Letting price (¥)
a_1	9:00	12:00	8	b_1	8:00	17:00	8
a_2	8:00	14:00	7	b_2	9:00	16:00	6
a_3	11:00	15:00	9	b_3	7:00	17:00	6
a_4	11:00	14:00	10	b_4	8:30	17:30	7
a_5	9:00	16:00	8	b_5	6:00	18:00	6
a_6	12:00	14:30	6	b_6	8:00	19:00	9
a_7	9:00	12:00	8	b_7	9:00	17:00	8
a_8	13:00	15:00	10	b_8	6:30	16:00	6
a_9	10:00	16:00	7				
a_{10}	9:00	14:00	6				

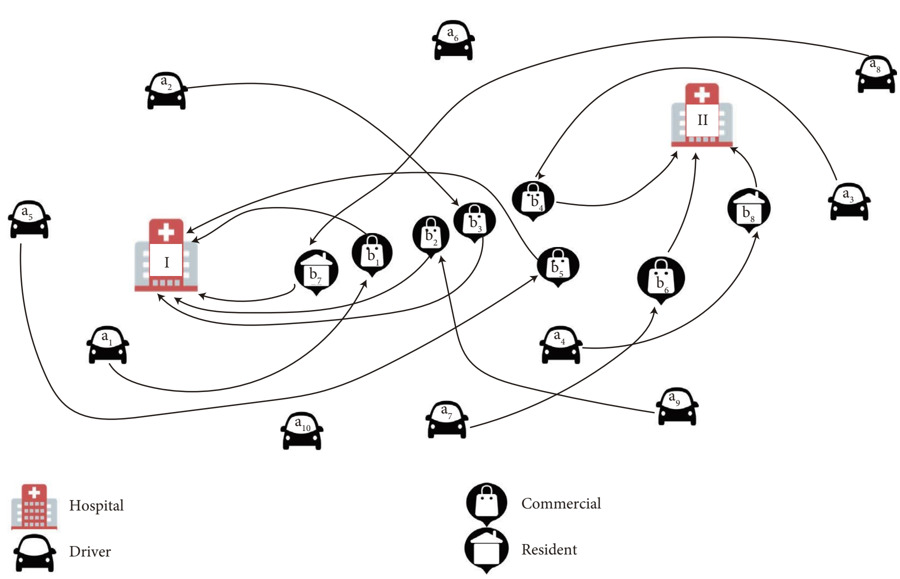

Figure 5: The matching results of the PT-TSSM model.

Table 5: Parameters setting.

Variable name	Symbol	Value
Number of demanders	m	60
Number of suppliers	n	50
Bidding price of demander	p_i	Discrete uniform distribution in [5, 10]
Bidding price of supplier	p_j	Discrete uniform distribution in [5, 10]
Parking time	T	Discrete uniform distribution in [2, 8]
Traffic impendence of road	t_d	Discrete uniform distribution in [1, 100]
Walking time after parking	r^j_{start}	Discrete uniform distribution in [1, 1000]
Credit score	r^j_{end}	Discrete uniform distribution in [1, 5]

etc. The decision matrix of value function $\widetilde{V^A}, \widetilde{V^B}$ is as follows:

$$\widetilde{V^A} = \begin{bmatrix} 0.38 & -0.67 & -0.29 & -0.85 & -0.31 & 0.08 & 0.51 & -0.44 \\ 0.39 & -0.28 & -0.45 & -1.09 & -0.47 & 0.23 & 0.53 & -0.47 \\ -0.29 & -0.18 & 0.08 & 0.32 & -0.20 & -0.12 & -0.55 & -0.39 \\ -0.18 & -1.04 & -0.77 & -0.71 & 0.14 & 0.23 & -0.44 & 0.04 \\ -0.60 & -0.50 & -0.85 & -1.12 & -0.50 & 0.03 & 0.51 & -0.72 \\ -0.36 & -0.25 & 0.01 & 0.26 & -0.34 & -0.25 & -1.05 & -0.52 \\ -0.18 & -1.04 & -0.77 & 0.50 & 0.17 & 0.26 & -0.44 & 0.17 \\ 0.19 & 0.30 & 0.12 & -0.15 & -0.92 & -0.40 & 0.33 & -1.28 \\ 0.49 & -0.42 & -0.59 & -0.19 & -0.84 & 0.25 & 0.37 & -0.84 \\ -0.32 & -0.68 & -0.64 & -0.12 & 0.24 & 0.33 & -0.37 & 0.08 \end{bmatrix}$$

$$\widetilde{V^B} = \begin{bmatrix} -0.01 & -0.17 & -0.17 & -0.10 & -0.17 & 0.05 & -0.01 & -0.17 \\ -0.84 & -0.54 & -0.54 & -0.73 & -0.54 & -0.92 & -0.84 & -0.54 \\ 0.36 & 0.39 & 0.39 & 0.38 & 0.39 & 0.34 & 0.36 & 0.39 \\ -0.52 & -0.56 & -0.56 & -0.53 & -0.56 & -0.52 & -0.52 & -0.56 \\ 0.15 & 0.43 & 0.43 & 0.32 & 0.43 & -0.07 & 0.15 & 0.43 \\ -0.31 & -0.57 & -0.57 & -0.47 & -0.57 & -0.18 & -0.31 & -0.57 \\ -0.13 & -0.29 & -0.29 & -0.22 & -0.29 & -0.07 & -0.13 & -0.29 \\ 0.23 & 0.09 & 0.09 & 0.17 & 0.09 & 0.27 & 0.23 & 0.09 \\ -0.78 & -0.48 & -0.48 & -0.67 & -0.48 & -0.86 & -0.78 & -0.48 \\ -0.78 & -0.70 & -0.70 & -0.79 & -0.70 & -0.77 & -0.78 & -0.70 \end{bmatrix}. \quad (6)$$

The weighted sum method is chosen to solve the shared parking two-sided satisfied and stable matching problem, as η and $(1-\eta)$ represent the importance of shared parking suppliers and shared parking demanders, respectively. In our numerical experiment, we assume that the shared parking operator thinks the shared parking suppliers have the same importance as shared parking demanders; in this situation, $\eta = 0.5$.

6.2.3. Matching Result. By using branch and cut method to solve this model, the optimal solution is as follows:

$$X = \begin{bmatrix} 1&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1 \\ 0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&1&0 \\ 0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0 \end{bmatrix}. \quad (7)$$

The matching result is (a_1, b_1), (a_2, b_3), (a_3, b_4), (a_4, b_8), (a_5, b_5), $(a_6, \varnothing)$, (a_7, b_6), (a_8, b_7), (a_9, b_2), and $(a_{10}, \varnothing)$ shown in Figure 5, and $Z_1 = -0.04$, $Z_2 = -0.62$, $Z = -0.33$.

6.3. Scheme Analysis. We conducted the numerical experiments with 60 shared parking demanders and 50 shared parking suppliers to test the practicability of the PT-TSSM model. In addition, we do sensitive analysis of the parameters in prospect theory and stable match and then compare our model with first come first serve and deferred acceptance mechanism.

6.3.1. Parameter Setting. Table 5 lists the parameter setting.

6.3.2. Reference Point of Prospect Theory. The reference point value plays an important role in the studies of prospect theory, which can affect the matching result in shared parking matching. Three approaches for the setting of a value to the reference point are suggested as follows: (a) setting a value to the reference point based on the mean or median travel time, (b) using a direct way to set a value to the reference point, or (c) deriving the parameter value from stated or revealed preferences [55]. We use the first method in the numerical experiment.

6.3.3. Parameter Setting of Prospect Theory. In prospect theory, $\alpha/\beta < 1$ shows that when the value of index gets higher, the sensitivity decreases. In the study of traffic routing and parking problems, we adopt the situation $\alpha/\beta < 1$. We searched the relevant literature of prospect theory; the value of α and β is different in the literature, where α equals to 0.37 [56], 0.52 [57], and 0.88 [31] and β equals to 0.60 [58], 0.74 [57] and 0.88[31]. We pairwise combine the parameters in the literature and obtain the three combinations (0.37, 0.6), (0.52, 0.74), and (0.88, 0.88) to explore the influence of different parameters on the results.

About the value of λ in the travel choice context, Van de Kaa [59] found that setting λ equal to 2.0 provides an explanation for more than 55% of the responses. We consider λ= 2 as the experiment group, and λ=2.25, which is proposed by Kahneman and Tversky [31] as the control group, to see whether the value of λ has influence on our PT-TSSM model.

6.3.4. Results and Analysis. We respectively considered whether to use prospect theory and whether to use stable matching constraint conditions. And, we solved the model using the data and parameters mentioned in Section 6.3.2. We obtained statistics on the solution results and calculated the values of Z, Z_1, and Z_2 and four indices A: traffic impedance of the road, B: walking distance after parking, C: revenue, and D: credit score. The statistical results are shown in Table 6. As can be seen from Table 6, in our case, when the value of λ changes from 2 to 2.25, the results are the same, but with changing the value of (α, β), the difference has an impact on the matching results. At the same time, different reference points also affect the matching results.

In this paper, we consider the use or nonuse of prospect theory. From Table 6, we can see the results of using prospect theory or not using it are different. Therefore, we consider to specifically analyze the advantages and disadvantages of using prospect theory and not using prospect theory. Since the results of using $\lambda = 2$ and $\lambda = 2.25$ are the same, we counted the cases of using prospect theory and not using prospect theory when using $\lambda = 2$. We calculated the number of each index higher than the reference point in the matching results obtained in these two cases, and the statistical results are shown in Figure 6.

It can be seen from Figure 6 that the number of indices higher than the reference point in the three different parameter scenarios using the prospect theory is higher than that without the prospect theory, whether we use the mean or the median as the reference point. In the process of matching, we consider that the prospect theory can reduce the number of indicators that affect the satisfaction of matching lower than the reference point. Although this may cause the overall satisfaction decline, they can ensure that most of the matching results are higher than their reference point.

From Table 6, we find that the satisfaction of the solution results obtained with stable matching conditions is lower than that obtained without stable matching conditions. Based on the result analysis, we sacrifice a part of total satisfaction degree, when we get high stability of the model. However, in fact, there is no need to get a strictly stable match, so we relax the stable match constraint to achieve a higher total satisfaction degree. Constraints (2) and (3) $x_{ij} + \sum_{r: \tilde{v}_{ir}^A > \tilde{v}_{ij}^A} x_{ir} + \sum_{s: \tilde{v}_{sj}^B > \tilde{v}_{ij}^B} x_{sj} \geq 1$ are changed to $x_{ij} + \sum_{r: \tilde{v}_{ir}^A - \tilde{v}_{ij}^A > \varepsilon} x_{ir} + \sum_{s: \tilde{v}_{sj}^B - \tilde{v}_{ij}^B > \varepsilon} x_{sj} \geq 1$, where ε denotes the relaxation parameter of the stable match constraint. With the decreasing value of ε, the strictly stable match condition gets less and less strict. Taking the reference point (average), $\lambda = 2, \alpha = 0.37, \beta = 0.6$, and $\eta = 0.5$ as an example, we progressively relax the stability constraint. The matching results of the total satisfaction degree are shown in Figure 7.

Table 6: Matching results.

			λ	α, β	Z	Z_1	Z_2	A	B	C	D
No prospect theory		Stable			74.18	31.18	42.99	1728	26716	802	241
		No stable			79.80	40.26	39.55	999	18723	579	222
Prospect theory	Mean	Stable	2	0.37, 0.6	40.87	8.00	32.87	1966	26199	869	233
				0.52, 0.74	32.51	4.11	28.40	2072	27294	944	231
				0.88, 0.88	20.80	0.80	20.01	2087	26948	910	234
		No stable		0.37, 0.6	59.14	29.72	29.42	1075	19390	661	215
				0.52, 0.74	49.24	25.24	24.00	1078	18818	622	216
				0.88, 0.88	32.83	17.34	15.49	1026	18414	569	218
		Stable	2.25	0.37, 0.6	39.32	6.45	32.87	1966	26199	869	233
				0.52, 0.74	31.16	2.76	28.40	2072	27294	944	231
				0.88, 0.88	20.19	0.72	19.47	1866	27343	805	240
		No stable		0.37, 0.6	59.08	29.67	29.42	1075	19390	661	215
				0.52, 0.74	49.19	25.19	24.00	1078	18818	622	216
				0.88, 0.88	32.78	17.30	15.47	1026	18414	569	218
	Median	Stable	2	0.37, 0.6	38.05	5.29	32.76	1993	27548	837	237
				0.52, 0.74	33.00	5.47	27.58	1927	27155	804	237
				0.88, 0.88	21.21	1.75	19.47	1866	27343	805	240
		No stable		0.37, 0.6	57.89	29.92	27.97	1161	18304	592	217
				0.52, 0.74	48.30	25.63	22.67	1137	17814	573	217
				0.88, 0.88	32.47	17.13	15.33	989	18914	573	220
		Stable	2.25	0.37, 0.6	36.32	3.55	32.76	1993	27548	837	237
				0.52, 0.74	30.92	3.03	27.89	1950	27504	833	237
				0.88, 0.88	20.19	0.72	19.47	1866	27343	805	240
		No stable		0.37, 0.6	57.84	29.88	27.96	1161	18304	592	217
				0.52, 0.74	48.24	25.47	22.77	1121	18066	596	214
				0.88, 0.88	32.39	17.08	15.31	989	18914	573	220

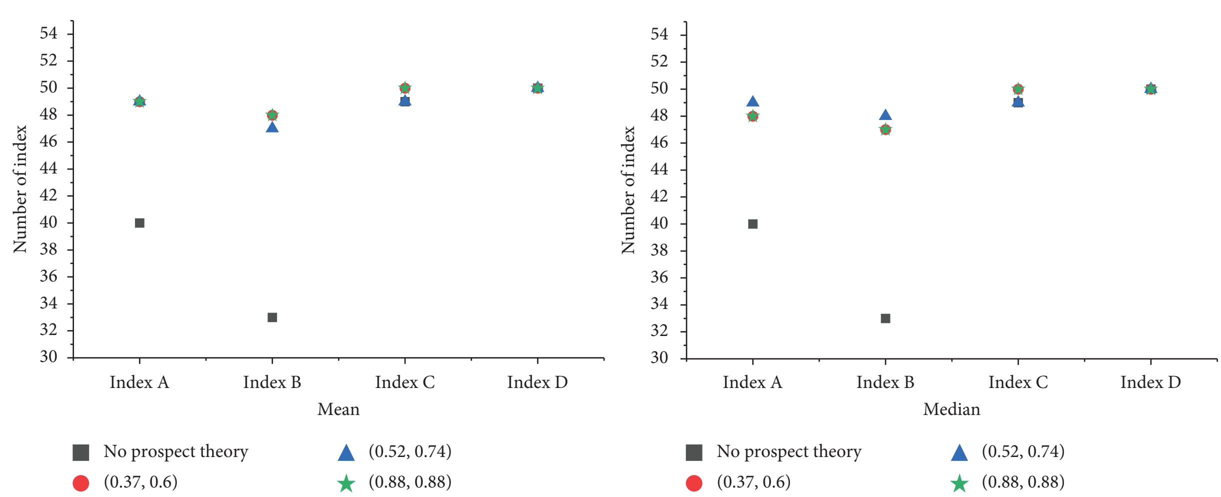

Figure 6: The number of index higher than the reference point (mean or the median as the reference point).

As can be seen in Figure 7, the value of total satisfaction degree Z increases and gradually approaches two-sided satisfied matching, when the value of ε increases. In real life, decision makers could be set reasonable ε and sacrifice a part of stability to get higher satisfaction degree.

In addition, we also calculated the impact of the change of ε on each index, as shown in Figure 8.

From Figure 8, we can see that with the increase of the value of ε, the values of the four indicators under stable matching tend to be the same as under no stable matching. However, the traffic impact of the road and walking distance after parking becomes better with the increase of the value of ε, while revenue and credit score become worse.

6.3.5. Comparison with Other Mechanisms. The model we proposed has two characteristics: (1) two-sided satisfaction and (2) two-sided stability; so we compare it with two models that are widely used: FCFS model (one-sided satisfaction) model and DA model (two-sided stability) model to reflect the advantages and disadvantages of our model.

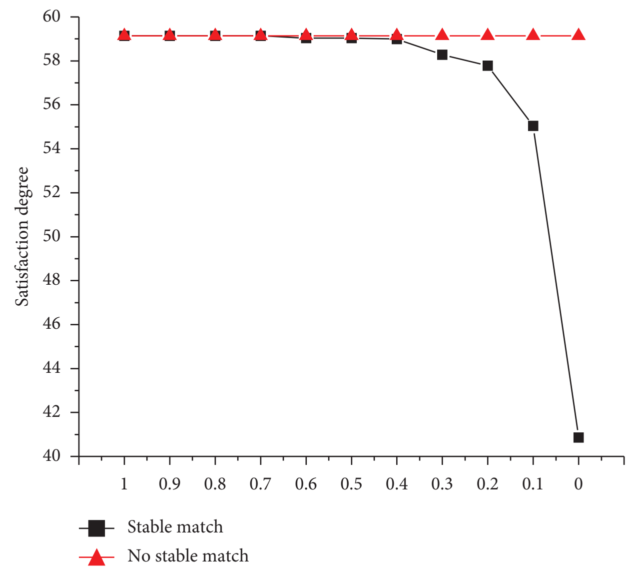

Figure 7: The satisfaction degree of stable or nonstable match when ε changes.

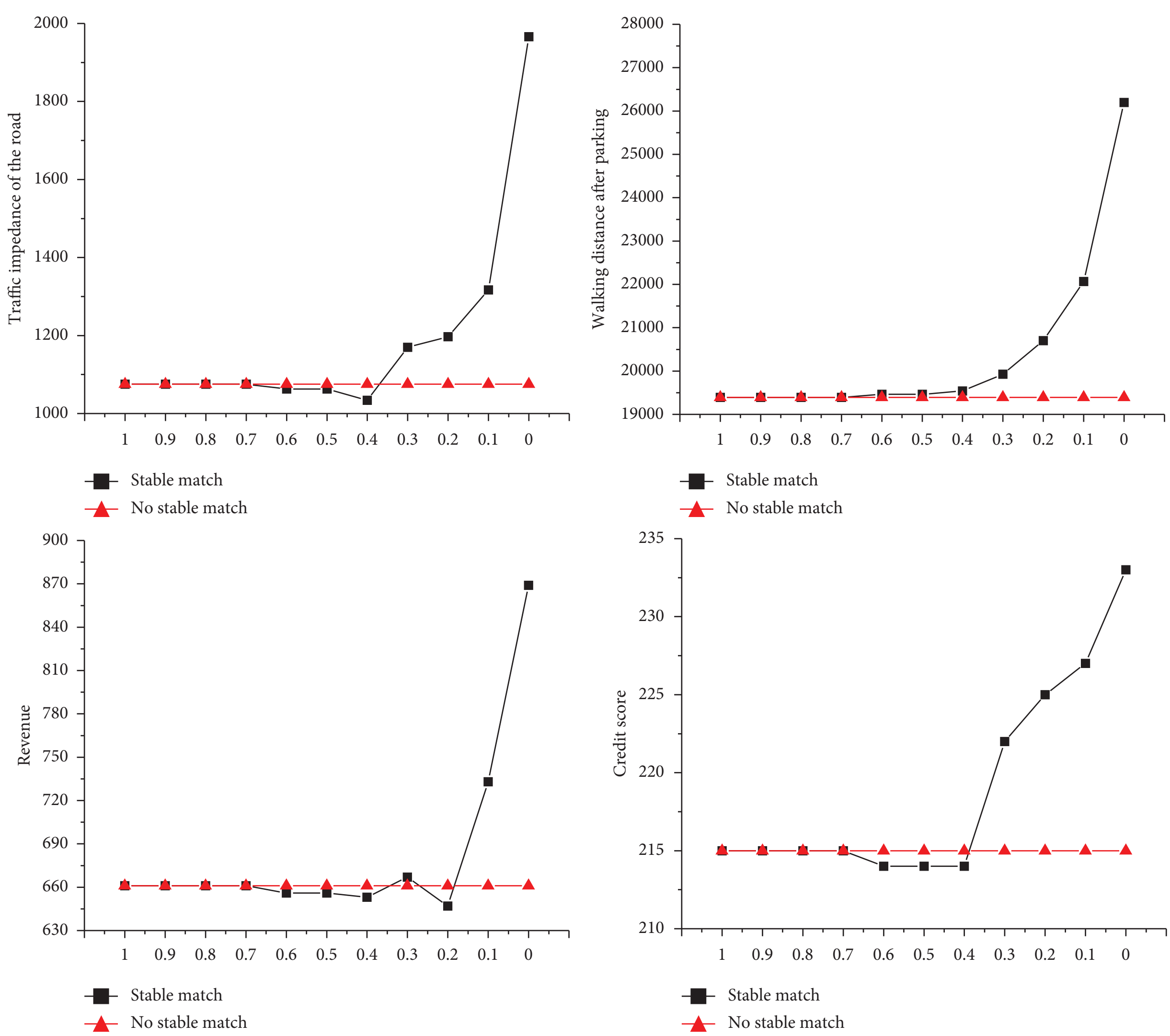

Figure 8: Value of four indices when ε changes.

Table 7: Matching results of FBFC and two-sided matching mechanism.

Model	Z	Z_1	Z_2	Index A	Index B	Index C	Index D
FBFS	59.13	36.06	−6.15	542	14012	−125	132
Two-sided matching	72.12	29.72	29.41	1075	19390	661	215

(1) Comparison with First Book First Serve (FBFS) Mechanism. For real-time parking resource management, the first come first serve (FCFS) mechanism is widely used and in parking reservation cases and it is called FBFS [19]. The shared parking matching problem involves two-sided agents, shared parking demanders a_i and suppliers b_j. Supposing that the information submission is in the order of $a_1, a_2, a_3 \ldots$, the idea of FBFS is to help the agent a_1 who submit information firstly to get the highest satisfaction degree matching pair and then pair the second one a_2 until the last agent is matched.

We use the FBFS mechanism to solve the $60 * 50$ scenario, and the results are presented in Table 7.

As can be seen in Table 7, as the FBFS mechanism is a single-sided matching essentially; it only focuses on the satisfaction degree of shared parking demanders and ignores the satisfaction degree of shared parking suppliers, which makes a worse preference on the satisfaction degree of shared parking suppliers. At the same time, in the FBFS mechanism, the one who comes early has the superiority of choosing the best shared parking slots, and it may not be a system optimization matching.

It can be seen from Table 7 that the satisfaction of shared parking demanders is higher in FBFS than in two-sided matching. However, FBFS does not pay attention to the satisfaction of shared parking suppliers, which makes the satisfaction of the suppliers very low, and the overall satisfaction is also lower with two-sided matching.

(2) Comparison with Deferred Acceptance. In the two-sided matching problem where price mechanisms are not applicable, the deferred acceptance (DA) mechanism is widely used because it can consolidate information effectively, improve resource allocation [60], and achieve stable matching results.

In the matching process, each shared parking supplier a_i sends out invitations to the first-rank preference shared parking demander of themselves. Shared parking demanders keep the highest rank preference supplier among all the invitations received and reject other invitations. Then, shared parking suppliers a_i who is rejected send out invitations to the second-rank preference shared parking demanders of themselves, the and steps are repeated until all the shared parking suppliers are matched. It is a stable matching mechanism.

There are two main differences between the DA mechanism and the PT-TSSM mechanism during the matching process. (1) In the DA mechanism, the matching process is based on preference order. For example, supposing that the satisfaction of shared parking space demander a_1 to shared parking space suppliers $b_1, b_2, \text{and}\, b_3$ is $(2.1, 1.4, 3)$, then the preference order is $(2, 3, 1)$, indicating that the demander prefers b_3 most, b_1 next, and b_2 last. This linear representation can only reflect people's preference order, but not how much they prefer. However, the PT-TSSM mechanism can reflect the quantity of satisfaction. (2) As the DA mechanism is based on ordinal values, the change of reference point will not affect the results of using the DA mechanism. However, the PT-TSSM mechanism can obtain different matching results according to different reference points.

Overall, we compare our PT-TSSM model with the FCFS model (single-sided matching model) and the DA model (stable matching model). Compared with the FCFS model, our model focuses on the satisfaction degree of both sides in the matching, which will not lead to a high satisfaction degree on one side and a lower satisfaction degree on the other side. The DA model assumes that there is an inverse linear relationship between the satisfaction degree and the preference order, but in the PT-TSSM model, we take the satisfaction degree and reference point into account, which is more in line with reality.

7. Conclusion and Future Research Directions

This study focuses on the parking challenge caused by the shortage of parking lots. To alleviate the difficulty of parking, we address the parking slot sharing problem. We propose a two-sided satisfied and stable matching model to achieve a stable and satisfactory matching result of both shared parking suppliers and shared parking demanders. We use a small example to demonstrate the feasibility of our proposed method and verify that the change of different parameters will affect the matching results. In addition, we use a large-scale case to simulate the two-sided matching problem of shared parking. The simulation results show that using the prospect theory can reduce the number of matching pairs that deviate from the reference point. We also compare this with the first-come-first-serve and deferred acceptance mechanisms and conclude that our model can consider the satisfaction of both the supplier and the demander of shared parking at the same time and can also get a stable matching result.

For future research directions, we have the following considerations:

(1) In this paper, we suppose all the shared parking demanders have the same value of time (VOT) and value of money (VOM). Commuters may be more sensitive to the travel time after parking. Thus, some new results will be obtained when considering shared parking demanders with different VOT and VOM [61].

(2) We assume that all the participants are honest and submit complete information. In practice, there exists cheating behavior, so study on incomplete information shared in parking matching could be conducted.
(3) An empirical study should be conducted to obtain the parameter settings in a real-life situation and validate the effectiveness of the model on this basis.
(4) We consider a reservation situation, and the real-time matching could be considered at the same time to make full use of the parking spaces.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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