Article

Game-Based Demand Feedback Reservation Parking Pricing

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Featured Application: This article develops a viable reservation parking pricing plan and corresponding parking strategy for parking lots that use reservations in commercial areas.

Abstract: Reservation parking is a new type of parking that allows users to obtain a parking space for an appropriate time slot by reservation. This paper pioneers a high-degree-of-freedom reservation strategy and rules for commercial districts in which users can arbitrarily select parking time slots. The nested logit is applied to build a parking revenue model by analyzing the cost, demand, and price factors sequentially according to the user’s choice behavior. The parking lot price game in the region is dissected and a nonlinear pricing model is proposed for maximizing regional returns. A model validation of a parking lot in an actual commercial area shows that compared to the traditional parking method, the parking lot revenue increased by 69.63% upon the application of this reservation strategy and pricing scheme, while the parking lot traffic increased by 22.4%. This model can provide strong support for reservation parking pricing in commercial areas. In the comparison of scenarios, the scientific validity of this model using dynamic pricing and regional game competition is verified. In the application, a reasonable price scheme can be formulated based on the parking lot traffic, cost, and surrounding parking strategies, which can result in higher parking revenue while providing users with great parking convenience.

Keywords: reserve parking; dynamic pricing; optimization model; selective behavior; game

1. Introduction

In recent years, with the rapid growth in the number of private cars, per capita motor vehicle ownership has become saturated. This has given rise to a few concomitant problems, such as road congestion, parking difficulties, and so on. Alongside these problems, people spend an excessive amount of time on finding and waiting for parking, and these ineffective hours in traveling greatly increase trip delays. Based on empirical data from several cities (e.g., Chicago, San Francisco), 30% of traffic is due to drivers looking for vacant parking spaces. Finding a parking space in the center of a big city can be a daunting task for commuters [1]. How to solve parking difficulties and shorten parking times have gradually become hotspot topics for researchers and has entered the cutting-edge vision of scholars. In recent years, many platforms have tried to open up new types of parking, such as shared parking lots, reserved parking, and smart parking [2–4]. Among them, reserved parking stands out with its features of advance booking and staggered parking, and has achieved remarkable results in practical application.

Parking reservations are usually made online by the user selecting a parking time in advance. After the reservation is completed, the parking lot reserves a parking space for the user for a specified period of time, waits for the user to arrive and provides parking services for him. After the user drives away, the whole parking reservation process is completed. The advantage of this method is that during the reservation process, drivers can easily obtain the availability of parking spaces and parking prices at the specified time,
and by reasonably choosing the time to make trip planning, it greatly reduces the cruising time and queuing time in search of parking spaces during the trip [5].

2. Literature Review

The reservation parking model, pioneered by scholars Mouskos et al. [6], establishes a fixed-fee parking reservation system through integer linear programming. Subsequently, Inaba K. et al. [7] developed a framework for an intelligent parking reservation system via the Internet and proposed the concept of time-sharing and real-time for parking. So far, parking reservation has begun to enter the public eye. After this, an increasing number of scholars began to study the parking reservation model. Teodorovic et al. [8] controlled the inventory of the car park through reservation decision making and rationally allocated the parking spaces to achieve the goal of maximizing the profit of the car park, which was the first time that revenue management was introduced into the reservation mechanism. In order to better validate the science of reservation, Kurauchi et al. [9] verified the positive effects of reservation parking in reducing users’ cruising time and controlling the flow during peak periods with an analog simulation. In addition, Mei et al. [10] found that the use of reservation for parking can not only suspend traffic congestion, but also improve the utilization rate of parking spaces, thus providing full play to the time cost of the car park and improving the effectiveness of parking in addition to establishing a positive role in improving parking revenue. Further, Tsai and Chu [11] added an appointment handling fee to the fee model to study the changes it brings. The simulation results show that the surcharge induces a further increase in the revenue of the parking lot while users spend less time searching for a parking space. Hashimoto et al. [12] extended the surcharge study by proposing a time-varying parking base fee, where the actual fee is determined through an auction to the users, which is a cumbersome process but realizes dynamic charging under the reservation mechanism, linking the user’s demand to the reservation price. In this context, the research direction in the field of reserved parking is more extensive; Caicedo et al. [13] builds a parking space allocation decision model based on the user’s demand prediction results, and allocates parking spaces from a prediction point of view. Ibeas et al. [14] analyzed from the user’s psychological point of view and proposed a model for the user’s choice of reservation parking. Lei et al. [15] analyzed the relationship between reservation demand and price and modeled the reservation request decision with system optimality. Ye et al. [16] analyzed users’ behaviors and influencing factors in choosing reserved parking, shared parking, traditional car parks, and other travel modes by building a multinomial logit model, and the study showed that the parking fee, available parking spaces, and the distance of the user to reach the destination were the main factors affecting the user’s travel choices. Hanzl et al. [17] focused on the application of reserved parking, where a coil senses whether a parking space is free or not, and thus assigns a reserved parking space with a reserved parking space.

As shown in Table 1, in recent years, the research directions included in the relevant research articles are indicated with “√”. It can be found that basic research on reserved parking has become increasingly sophisticated, and the relationship between demand, price, and other elements has become clearer. Parking reservation research has focused on user selection, demand forecasting, space allocation, garage decision-making, and price management. Among them, the price management direction has more methods, and more mixed research from the price attributes can be divided into dynamic price, real-time price, and fixed price. Dynamic pricing is more suitable for a parking reservation mechanism from the objectives of garage revenue, user cost, and other dynamic characteristics, but there are fewer existing studies, and dynamic pricing is more complicated. As the pricing method can be categorized into occupancy pricing, demand pricing, game pricing, etc., the bases of several pricing methods are their rationality and scientific foundations, which are different from the scope of application and considerations. In the existing research results on reserved parking, pricing is relatively rarely combined and linked to other reservation factors, and a systematic and comprehensive approach to pricing is lacking. In terms of
booking strategies, a large percentage of existing studies use a fixed booking time window with a single service period selection, where the user is required to select a service period within a specified time window. This strategy provides convenience in berth management, but reduces reservation flexibility, with users having a limited choice of time while having a small choice set. In addition, another mainstream research strategy is the rolling booking, i.e., short-term booking, where users can book a berth in the current service period for the next service period. Decision-making and space allocation under this strategy are relatively convenient but suffer from the same drawback of limited user reservations. Existing strategy studies lack a user-friendly high-degree-of-freedom reservation strategy applicable to commercial areas.

Table 1. Modeling factors comparison [15–17].

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<tr>
<td>Possible reservation strategies</td>
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<td>Demand-led prices</td>
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<td>User selection behavior</td>
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<td>Dynamic pricing</td>
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<td>Gaming with neighboring parking lots</td>
<td>√</td>
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<td>Feasible pricing model</td>
<td>√</td>
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3. Application and Innovation

Based on the above research directions, in recent years, many researchers have applied novel approaches to solving parking problems in specific contexts. Currently, the main directions of existing parking research and the review of applied models are summarized as follows.

In Table 2, the typical approaches and main contexts of various parking strategy and pricing studies in recent years are listed. In terms of research objectives, most of the research mainly focuses on on-street parking spaces and ancillary parking spaces, and there is insufficient research on parking in specific areas such as commercial districts, hospitals, schools, office areas, etc., which ignores the characteristics of the area and the characteristics of the user’s needs. In terms of research direction, the main directions are pricing, policy, behavioral choices, and demand, and the relationship between the factors should be considered comprehensively in the research process. In terms of research methodology, more researchers have chosen MNL modeling, nonlinear programming, game modeling, and machine learning methods. From their studies, it can be found that the main optimization objectives tend to be travel costs, parking profits, parking occupancy, and parking patronage.

This study will focus primarily on the pricing of reserved parking in commercial areas. Under this study, we assume a scenario in which one of the various commercial facility parking lots in a business district pioneers a relatively new reservation method of parking allocation. Accordingly, we assume that parking in commercial areas is sufficient to accommodate demand. In this case, how can the most reasonable booking price be adopted by the management of a parking lot, with the potential to increase profit and at the same time not lose customer flow to the commercial property as a result of adopting the new method?

We first considered the characteristics and user needs of the commercial area and proposed a set of user-friendly reservation policies that could be adopted for this parking lot. Afterward, in this scenario, we sequentially analyzed the user’s choice behavior with the responses of other parking lots in the business district and formulated the price adopted by the reservation parking lot based on the user’s demand and the subsequent price adjustment strategies of other parking lots.
Among the methods and models, we adopted the research experience and chose the logit model and Stackberg game model. For a more refined research direction, we further innovatively used a nested logit model to predict users’ travel modes and booking durations. Based on the two models, the objective function of maximizing the profit of the parking lot and increasing the passenger flow is proposed, and the optimal price for each hour is solved using nonlinear programming.

By summarizing and generalizing the research results, we conclude this paper by proposing a parking reservation strategy where the reservation time is free, and the user can choose a combination of multiple reservation periods. We develop a peak parking pricing model for commercial areas that considers the main parties of the garage and the user, and the demand feedback, and dynamically formulate the reservation price by analyzing the game psychology of the parties, the change of the user’s choice of service period, and the demand forecast.

### 4. Reservation Strategy and Rules

#### 4.1. Reservation Strategy

In the parking reservation, the following reservation platform and user parking rules are established:

In Figure 1, the reservation strategy divides the operating time into multiple service periods (the total number in the figure is denoted by N and the number of cycles omitted from the graph is h). Assume that the user can freely choose the number of reservation periods in advance, obtain pricing information, and cannot withdraw the reservation after confirming the reservation application.

<table>
<thead>
<tr>
<th>Researcher</th>
<th>Type of Parking</th>
<th>Field</th>
<th>Applicable Situation</th>
<th>Methodology/Model</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qian et al. (2014) [18]</td>
<td>commuter parking</td>
<td>dynamic pricing of parking</td>
<td>time-varying parking demand under commuting hours</td>
<td>variational inequalities, linear programming</td>
<td>reduced travel costs</td>
</tr>
<tr>
<td>Mackowski et al. (2015)</td>
<td>off-street parking</td>
<td>dynamic pricing of parking</td>
<td>finding parking in congested areas</td>
<td>Stackberg game model</td>
<td>increased occupancy and parking lot profitability</td>
</tr>
<tr>
<td>He et al. (2015) [20]</td>
<td>universal parking</td>
<td>dynamic pricing of parking</td>
<td>competition for parking spaces in anarchy</td>
<td>nonlinear programming</td>
<td>reduced parking lot costs</td>
</tr>
<tr>
<td>Sowmya et al. (2023) [21]</td>
<td>parking attached to the facility</td>
<td>dynamic pricing of parking</td>
<td>the facility parking lot and external parking lot based on price and demand</td>
<td>intensive learning</td>
<td>improved parking lot profitability and increased occupancy</td>
</tr>
<tr>
<td>Luis et al. (2023) [22]</td>
<td>off-street parking</td>
<td>reservation parking requirements</td>
<td>allow multi-region selection under booking travel with a clear itinerary time</td>
<td>user behavioral choice model</td>
<td>increased parking patronage</td>
</tr>
<tr>
<td>Hu et al. (2023) [23]</td>
<td>universal parking</td>
<td>dynamic pricing under reservation</td>
<td>on-street, indoor, and underground parking available</td>
<td>nonlinear programming</td>
<td>increased parking occupancy</td>
</tr>
<tr>
<td>Rakha et al. (2022) [24]</td>
<td>universal parking</td>
<td>user parking options</td>
<td>the time of entry and exit from the parking lot is known</td>
<td>MNL model</td>
<td>increased cruise times and increased occupancy rates</td>
</tr>
<tr>
<td>Li et al. (2022) [25]</td>
<td>universal parking</td>
<td>parking fees and behavior</td>
<td>observations after the implementation of the charging strategy</td>
<td>observations after the implementation of multiple pricing policies</td>
<td>increased parking occupancy</td>
</tr>
<tr>
<td>Mingardo et al. (2022) [26]</td>
<td>parking attached to the facility</td>
<td>parking pricing and policy</td>
<td>cities targeted by the study</td>
<td>post-implementation observation of multiple pricing policies</td>
<td>concluded the inelasticity of demand and the validity of limiting the length of parking hours</td>
</tr>
<tr>
<td>Vidovic et al. (2022) [27]</td>
<td>parking attached to the facility</td>
<td>parking pricing and behavioral choices</td>
<td>travel with no available off-street parking</td>
<td>field survey, MNL model</td>
<td>the conclusion that the price of parking significantly affects the mode of travel was obtained</td>
</tr>
</tbody>
</table>
A parking process is divided into a reservation period and a service period. The service period is a fixed window of time; the length of each period is fixed at 1 h. After the reservation, the user must enter the car park 15 min before the start of the service period up to 15 min after the opening of the car park to choose their vacant berths for parking. After the service has ended, the user is required to remove the vehicle from the parking lot within 15 min of the opening of the next service period. The reservation period is not binding; the user can reserve any period and number of service periods. The earliest reservation service period is the next service period at the current moment, and the latest reservation can be made to the last service period within the operation period; see Figure 2 for a schematic diagram.

Through the real-time monitoring of the number of vacant parking spaces and the implementation of the control of vehicle entrances and exits to ensure that the vehicles arriving at the reserved parking lot on time can enter the parking lot smoothly, an electronic screen set up at the entrance displays the location of vacant parking spaces in real time.

4.2. Rules for Reservation Service

Under the corresponding policy, it is assumed that the user and the platform obey the following rules:

1. Rule 1: The hours of operation of a parking lot attached to a commercial facility shall be used as the total hours of service.
2. Rule 2: Individual periods of service shall be of one hour in length, with adjacent periods of service succeeding each other.
3. Rule 3: Users who have made a reservation must enter the garage and park in the available parking space of their choice between 15 min before and 15 min after the start of the reserved service period. The first service period entry is 30 min after the opening.
4. Rule 4: After the service has ended, the user is required to remove the vehicle from the parking lot within 15 min of the start of the next unreserved service period. Exceeding the time limit is considered a default, and defaulting vehicles exceeding the time limit will be placed in the reserved garage.
5. Rule 5: Users may only book the next service period from the current moment to the last service period within the operating session.
6. Rule 6: Users can only operate reservations for one vehicle at a time, and no withdrawal is allowed after payment.
7. Rule 7: Reservation of parking spaces is on a first-come-first-served basis, and when “the number of occupied parking spaces + the number of reservations ≤ the total number of parking spaces in the car park”, the reservation of parking spaces for that period is no longer allowed.

8. Rule 8: When a user makes a request for parking unreservedly, it is considered a “reservation from the next nearest service period” and the parking lot manager quotes a price for the user, who agrees to the service and then enters the reserved garage and waits for the opening of the available parking slot.

5. Nested Logit and Game Modeling Proposed

5.1. User Behavioral Choices

A nested logit model is used to analyze the user’s reservation slot selection behavior. As the first choice layer, in making appointment choices, users make the following choices based on travel costs [28–30]:

Option 1: Select reservation parking.
Option 2: Choose other parking lots in the neighborhood.
Option 3: Choosing other modes of travel.

This paper focuses on the analysis of the probability of the user’s choice of time slot in the first case, and other parking lots and travel modes will not be categorized and analyzed in detail. Therefore, the second-choice tier unfolds under the first choice option of the first-choice tier (choosing reserved parking), including the choice of the combination j for the operation period, where \( J = \{ \text{any combination of consecutive numbers contained in the maximum number of reservation periods} \} \), \( j \in J \). The overall nested logit tree structure is shown in Figure 3.

![Nested logit selection tree](image-url)

The factors affecting the user’s choice by considering the travel utility, perceived utility.

The main subjective factors considered in the travel costs are the distance (km), cost (CNY), and time (min) required by the user to park. The parking time in the parking lot is categorized into peak and flat, and users weigh the time metrics according to their needs.

The factors to be considered for the perceived cost of user trips were categorized into the convenience of parking, dependability of the garage, and user behavioral habits for trips to commercial areas. These factors were categorized in our questionnaire into five levels according to the degree of intensity, e.g., very convenient, relatively convenient, average, relatively inconvenient, and very inconvenient.

In the process of travel parking behavior selection, among the inherent attributes of the user itself, the user’s age (years), income (CNY), and purpose of travel are mainly considered.
Based on the above factors, the user’s travel utility function that considers their own preference habits is established as follows:

\[
V_i = \alpha_1 \text{distance} + \alpha_2 \text{cost} + \alpha_3 \text{travel time} + \beta_1 \text{preferences} + \beta_2 \text{dependability} + \beta_3 \text{convenience} + \gamma_1 \text{age} + \gamma_2 \text{purpose} + \gamma_3 \text{income}
\]

(1)

where \(\alpha\) is the parameter corresponding to travel utility; \(\beta\) is the parameter corresponding to perceived utility; and \(\gamma\) is the parameter corresponding to attribute utility.

The utility functions in the last two choice branches of the first tier (choosing another parking lot vs. choosing another mode of travel) are all the above forms.

Since the choice tree of the logit model is constructed in the form of a nested logit, the utility of the first choice branch of the first level (choosing to book a parking reservation) is affected by the utility of its nested branch, whose utility function is:

\[
V_a = V_i(a) + \beta_{\text{logsum}} \logsum_a
\]

(2)

\[
\logsum_a = \ln\left(\sum_{l=1}^{n!} e^{V_l}\right)
\]

(3)

where \(V_a\) is the utility function of the user who chooses to reserve parking; \(V_i(a)\) is the corresponding basic utility function of the user in the same form as \(V_i\) where \(V_a\) is the user utility function for choosing reservation parking; \(V_i(a)\) is the corresponding user basic utility function in the same form as \(V_i\); \(\beta_{\text{logsum}}\) is a dissimilarity parameter reflecting the degree of correlation among the lower choice branches; \(\logsum\) is the nested additional utility; and \(V_i\) is the utility function for selecting each reservation period in the same form as \(V_i\).

Under the assumption that the number of reservation periods is \(n\), in the first level of choice branches, the user has a total of three choices. In the second level of choice branches, the user has a total of \((n!)\) choices. Then, the selection probability that the user chooses the \(i\)-th parking option \((i \in 1, 3)\) is:

\[
p_i = \frac{\exp(V_i)}{\sum_{k=1}^{3} \exp(V_k)}
\]

(4)

The probability that the user chooses the reservation period as combination \(j\) is:

\[
p_{ja} = p_a \cdot \frac{\exp(V_j)}{\sum_{j=1}^{n!} \exp(V_j)}
\]

(5)

The user’s global travel cost minimization objective can be expressed as follows:

\[
\min V = \sum_{k=1}^{3} V_k
\]

(6)

The above is an analysis of user travel in terms of user’s travel factors, travel utility, and choice probability in turn. A choice nested model of user travel is proposed. Subsequently, the parking demand is projected based on the choice probability proposed in this part, and the price analysis of parking lots is carried out.

5.2. Parking Pricing Analysis

It is assumed that the target garage is the first “leader” in the commercial parking management industry to adopt reservation parking fees. The remaining garages continue to use the traditional parking pricing model, adjusting their own strategies based on the target garages’ fee pricing strategies. The subsequent pricing analysis is conducted separately for both [31,32].
5.2.1. Reservation Parking Lot Pricing

The costs of car parks with reserved parking are mainly divided into fixed costs ($C_b$) and variable costs ($C_v$). The fixed costs include the costs of operation, management, maintenance, and mall rentals of the car parks, which are fixed costs using an average of the daily operations of the car parks and which do not vary with user demand or with the pricing of the remaining car parks. Variable costs refer to the fees paid by the garage for parking inspection, guidance information provided to users, etc., which vary with the volume of users entering the garage for parking and are variable values. Similarly, the variable cost is taken as the average cost per vehicle trip served per unit service cycle during the operating period of the garage (billed per vehicle trip per cycle). The cost of the garage for a single operating period is then:

$$C_x = C_b + q_x C_v$$ (7)

where $C_x$ is the total cost of the xth operating period; $C_b$ is the fixed cost of the garage; $q_x$ is the total number of passengers entering the garage for parking in the x-th operating period (person trips); and $C_v$ is the variable cost of the garage.

Assuming that the maximum number of reservation periods/operating periods of the parking lot is $n$, the total cost of the operating period of the parking lot is:

$$C = \sum_{x=1}^{n} C_x = \sum_{x=1}^{n} (C_b + q_x C_v)$$ (8)

where $C$ is the total cost of reserving the parking lot.

The demand for a single operating period of the car park is:

$$q_x = q \left( \sum_{j=1}^{n_x} (P_{a,x}) \right) = q \left( \sum_{j=1}^{n_x} \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \cdot \frac{\exp(V_{jx})}{\sum_{l=1}^{n} \exp(V_l)} \right)$$ (9)

where $q_x$ is the total parking demand (person-times) in the x-th operation period of the car park; $P_{a,x}$ is the probability that the user chooses to reserve parking.

The total parking demand in the surrounding mall area during the operating hours of the car park $Q$ (person trips) according to the above equation enables us to calculate the total demand of the reserved parking lot, as:

$$q = Q \cdot p_a = Q \cdot \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)}$$ (10)

where $p_a$ is the probability that the user chooses to reserve parking.

The total profit during the operation of the reserved parking lot is:

$$Z = \sum_{x=1}^{n} (w_x q_x - C_x) = \sum_{x=1}^{n} (q_x (w_x - C_v) - C_b)$$ (11)

$$= \sum_{x=1}^{n} \left( Q \cdot \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \cdot \frac{\exp(V_{jx})}{\sum_{l=1}^{n} \exp(V_l)} \right) (w_x - C_v) - C_b$$

where $w_x$ is the parking lot pricing for the x-th operating period.

The goal of maximizing revenue from reservation parking can be expressed as follows:

$$\max Z = \sum_{x=1}^{n} \left( Q \cdot \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \cdot \frac{\exp(V_{jx})}{\sum_{l=1}^{n} \exp(V_l)} \right) (w_x - C_v) - C_b$$ (12)
The independent variables in the above profit function are the reservation parking lot price \( w_x \) and the traditional parking lot price \( w' \). In this case, the reservation parking lot manager as the decision maker can only decide on the price \( w \) corresponding to each operation period, i.e., in the objective function of the reservation parking lot party, the decision maker independent variable is only \( w_x \). In addition, the utility function in the objective function also has non-decidable parking prices of traditional car parks as well as users’ choices. Reservation car parks cannot maximize revenue by unilaterally setting the optimal price \( (w_x) \) and need to play a game with traditional car parks to find the equilibrium point as well as consider the user’s choice behavior to make their own optimal pricing decisions.

5.2.2. Neighborhood Traditional Garage Pricing

The total cost of the parking lot with traditional parking is:

\[
C' = C'_b + q' C'_v
\]  

(13)

The total demand for traditional car parks is:

\[
q' = Q \cdot p_b = Q \exp(V_b) \sum_{k=1}^{3} \exp(V_k)
\]  

(14)

where \( p_b \) is the probability that the user chooses a traditional parking lot and \( V_b \) is the travel cost of the user choosing a traditional parking lot.

The total profit during the operation of a traditional parking lot is:

\[
Z = w' q' - C' = q' (w' - C'_v) - C'_b = Q \exp(V_b) \left( \sum_{k=1}^{3} \exp(V_k) \right) (w' - C'_v) - C'_b
\]  

(15)

The revenue maximization goal for traditional parking lots can be expressed as follows:

\[
\max Z = Q \left( \frac{\exp(V_b)}{\sum_{k=1}^{3} \exp(V_k)} \right) (w' - C'_v) - C'_b
\]  

(16)

In the above model, the traditional parking lot manager, who is the decision maker, can only decide on the pricing \( (w') \) for each operation period, i.e., in the objective function of the traditional parking lot party, the decisive independent variable is only \( w' \). Similarly, to maximize its own revenue, the decision maker needs to take into account the pricing decisions of the booking garage and the user’s choice behavior to formulate the parking price so as to maximize the revenue.

5.3. Stackberg Gaming between Parking Lots

It can be found that the two types of car parks analyzed above are not able to independently set prices to find an optimal solution, and need to formulate their own prices based on each other’s decisions, constituting a game relationship. In this section, the Stackberg game model is applied to solve the pricing objective function of the car park. Among them, the industry’s priority is to implement the reservation mechanism of the target parking lot as a pricing autonomy priority, i.e., as a “leader”, while surrounded by another traditional parking lot, according to its price decision-making process as a “follower”.

In the price analysis of the previous subsection, the profit functions of both car parks contain their own decision variables and those of the other party, and the response functions of both parties can be derived.
Reservation garages, as leaders, are priced with a known response function \( F \) for traditional garages, i.e., their profit function is derived for decision pricing \( (w') \), which is derived as follows:

\[
F(w') = \frac{\partial Z}{\partial w'} = Q \left( (w' - C'_v) \frac{\partial \left( \frac{\exp(V_b)}{\sum_{k=1}^3 \exp(V_k)} \right)}{\partial w'} + \frac{\exp(V_b)}{\sum_{k=1}^3 \exp(V_k)} \right)
\]

\[
= Q \left( (w' - C'_v) \frac{(a_2 \exp(V_b)(\exp(V_a) + \exp(V_c)))}{(\sum_{k=1}^3 \exp(V_k))^2} + \frac{\exp(V_b)}{\sum_{k=1}^3 \exp(V_k)} \right)
\]

(17)

From the game model, it can be seen that when the corresponding reaction function of both parties is zero, the profits of both parties reach equilibrium, and the prices are all optimally priced. Therefore, in the above Stackberg game model, the leader reservation parking lot needs to consider the equilibrium pricing of the follower traditional parking lots in their pricing decision to set its own price. That is, let the above reaction function \( (F) \) be zero and derive the equilibrium price \( (w') \) as follows:

\[
F(w') = 0,
\]

(18)

\[
\exp(V_b) + (a_2(w' - C'_v) + 1)(\exp(V_a) + \exp(V_c)) = 0
\]

(19)

Highlighting the variables for simplicity, \( \exp(V_b) \) here is written in the form of \( \exp(a_2 w' + \epsilon) \), where \( \epsilon \) is the parameter in the traditional parking lot choice utility other than price, which is a constant, and simplicity is performed to obtain:

\[
\frac{\exp \left( \epsilon + C'_v - \frac{1}{a_2} \right)}{\exp(V_a) + \exp(V_c)} = -a_2w'e^{-a_2w'}
\]

(20)

Here, \( (-a_2w') \) is set to \( x \) and simplified by applying the Lambert W function [33]:

\[
\frac{\exp \left( \epsilon + C'_v - \frac{1}{a_2} \right)}{\exp(V_a) + \exp(V_c)} = xe^x
\]

(21)

\[
x = W \left( \frac{\exp \left( \epsilon + C'_v - \frac{1}{a_2} \right)}{\exp(V_a) + \exp(V_c)} \right)
\]

(22)

Reducing \( x \) solves for the equilibrium price \( (w') \) of the surrounding conventional parking lot:

\[
w' = \frac{W \left( \frac{\exp \left( \epsilon + C'_v - \frac{1}{a_2} \right)}{\exp(V_a) + \exp(V_c)} \right)}{a_2}
\]

(23)

Subsequent prices surrounding conventional parking lots are expressed in the form \( f(w_x) \), i.e.,:

\[
w' = f(w_x)
\]

(24)

Therefore, the objective function of reservation parking lot is converted from \( Z(w_x, w') \) to \( g(w_x) \); at this time, the game with the traditional parking lot is considered in the objective function, and the equilibrium price is used as a decision variable to re-construct the objective function of the reservation parking lot, as follows:

\[
\max Z = g(w_x)
\]

(25)

Up to this point, the above model takes into account the user’s behavioral choices and the price game of the surrounding parking lots, and the equilibrium price of the reserved
parking lot under the feedback of the user’s demand can be directly obtained through the collated simplified form.

In the above Stackberg game, the optimal price of the reserved parking lot is obtained by substituting the response function of the traditional parking lot into the reserved parking lot, combined with the introduction of the Burrang W-function to solve for the optimal price of the reserved parking lot. Similarly, the optimal price of a conventional parking lot can theoretically be obtained and solved by substitution again. However, this part of the mathematical calculation is very large and complicated to derive. In addition, the specific pricing of traditional parking lots does not impact the subsequent process of solving for patronage and profitability in reserved parking lots, so this part of the solution is ignored in this study. It is expected that future research related to the pricing of traditional parking lots can continue to extend this part of the application.

6. Instance Validation

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

6.1. User Choice Behavior Fitting

Based on the utility function proposed in Section 4.1, a questionnaire survey is conducted to investigate the users’ travel choice behavior according to the variable parameters contained in it. A total of 500 questionnaires were distributed in this experiment, and the respondent population was randomly selected from the Xi’an Road business district in Dalian, Liaoning Province, China. The questionnaire included the respondents’ gender, age, income, purpose of travel, distance from the business district, and perceived comfort and reliability of the various modes of travel, as well as the travel choices made in the corresponding scenarios. According to the survey results, a total of 41.8% of the respondents’ travel intentions were concentrated between 17:00 and 22:00 h, which was used as the peak parking lot period, with a subsequent formulation of prices for this peak period.

The results of the questionnaire were analyzed to develop a nested logit model, and the parameters of the variables in the model were fitted and calibrated based on the results of 500 user business district travel surveys.

The parameters for each option are listed in Table 3.

<table>
<thead>
<tr>
<th>Variant</th>
<th>Coefficient</th>
<th>Standard Deviation</th>
<th>p-Value Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>age</td>
<td>0.149</td>
<td>0.169</td>
<td>0.038</td>
</tr>
<tr>
<td>income</td>
<td>0.121</td>
<td>0.166</td>
<td>0.047</td>
</tr>
<tr>
<td>purpose</td>
<td>0.021</td>
<td>0.130</td>
<td>0.047</td>
</tr>
<tr>
<td>distance</td>
<td>0.085</td>
<td>0.147</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Each of the above four attributes is a personal user attribute, an attribute that does not change with each selected branch. It can be seen that among the four user personal attributes, age and income attributes have a higher degree of influence on travel mode choice.

Table 4 shows the parameters corresponding to each attribute for each travel mode. In the model, the variables’ dependability, convenience, and travel time are varied with each mode of transportation, i.e., the utility attributes of each mode of transportation for the user. From the above table, it can be seen that dependability, as well as convenience, are positively correlated with the probability of choice in reserved parking, traditional parking, as well as other modes of travel, with a positive impact. And in all three ways, travel time is negatively correlated with the selection result. In the fitting results, the most influential weights are the dependability and convenience factors for choosing other modes of travel and the travel time factor for choosing parking reservations, respectively, which are in line with the actual logic.
Table 4. Travel mode attribute parameters.

<table>
<thead>
<tr>
<th>Travel Mode</th>
<th>Variant</th>
<th>Coefficient</th>
<th>Standard Deviation</th>
<th>p-Value Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking Reservation</td>
<td>dependability</td>
<td>0.036</td>
<td>0.347</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>convenience</td>
<td>1.275</td>
<td>0.451</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>travel time</td>
<td>−2.336</td>
<td>0.680</td>
<td>0.010</td>
</tr>
<tr>
<td>Conventional Parking</td>
<td>dependability</td>
<td>0.495</td>
<td>0.481</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>convenience</td>
<td>1.453</td>
<td>0.575</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>travel time</td>
<td>−2.287</td>
<td>0.615</td>
<td>0</td>
</tr>
<tr>
<td>Other Travel Modes</td>
<td>dependability</td>
<td>1.807</td>
<td>0.935</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>convenience</td>
<td>1.957</td>
<td>0.863</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>travel time</td>
<td>−0.883</td>
<td>0.772</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Table 5 shows the cost, preferences factor weights and the constant term for each choice branch. Among them, cost and preferences variables that vary with each choice branch are choice branch attributes. In the above table, the weights of the cost factors for each travel mode and reservation option are negative, i.e., they are negatively correlated with the probability of choice. In contrast, the weights of the preferences factors, which represent user habits, are all positive and positively correlated with the probability of selection. The cost has a slightly smaller impact weighting overall, with the largest impact being the travel option that selects a reservation time slot of 20:00–21:00. The weighting of the preferences varies considerably, with the most influential option being “Choose to book a parking slot between 17:00 and 22:00”. The dissimilarity parameter for each choice branch in the above fitted appointment time scenario is 0.593. Based on the fitting results for this parking lot, the utility function for each travel mode is as follows.

Table 5. Attribute parameters of each selected branch.

<table>
<thead>
<tr>
<th>Selection</th>
<th>Reservation Time</th>
<th>Cost</th>
<th>Preferences</th>
<th>Constant Term</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional Parking</td>
<td></td>
<td>−0.428</td>
<td>2.220</td>
<td>−3.447</td>
</tr>
<tr>
<td>Other Travel Modes</td>
<td></td>
<td>−0.278</td>
<td>2.639</td>
<td>−15.06</td>
</tr>
<tr>
<td>Parking Reservation</td>
<td>17:00–18:00</td>
<td>−0.637</td>
<td>1.910</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>18:00–19:00</td>
<td>−0.626</td>
<td>2.057</td>
<td>−1.006</td>
</tr>
<tr>
<td></td>
<td>19:00–20:00</td>
<td>−0.541</td>
<td>1.920</td>
<td>−1.809</td>
</tr>
<tr>
<td></td>
<td>20:00–21:00</td>
<td>−0.719</td>
<td>2.210</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>21:00–22:00</td>
<td>−0.341</td>
<td>1.914</td>
<td>−5.730</td>
</tr>
<tr>
<td></td>
<td>17:00–19:00</td>
<td>−0.422</td>
<td>2.340</td>
<td>0.127</td>
</tr>
<tr>
<td></td>
<td>18:00–20:00</td>
<td>−0.392</td>
<td>2.357</td>
<td>−0.521</td>
</tr>
<tr>
<td></td>
<td>19:00–21:00</td>
<td>−0.444</td>
<td>2.118</td>
<td>0.130</td>
</tr>
<tr>
<td></td>
<td>20:00–22:00</td>
<td>−0.240</td>
<td>2.052</td>
<td>−4.016</td>
</tr>
<tr>
<td></td>
<td>17:00–20:00</td>
<td>−0.383</td>
<td>1.059</td>
<td>1.902</td>
</tr>
<tr>
<td></td>
<td>18:00–21:00</td>
<td>−0.264</td>
<td>1.509</td>
<td>−1.373</td>
</tr>
<tr>
<td></td>
<td>19:00–22:00</td>
<td>−0.330</td>
<td>1.765</td>
<td>−0.289</td>
</tr>
<tr>
<td></td>
<td>17:00–21:00</td>
<td>−0.425</td>
<td>1.459</td>
<td>3.869</td>
</tr>
<tr>
<td></td>
<td>18:00–22:00</td>
<td>−0.425</td>
<td>2.147</td>
<td>0.970</td>
</tr>
</tbody>
</table>
|                       | 17:00–22:00      | −0.667 | 20.754      | −26.157
1. Parking reservations

The calibrated utility model for a user choosing to travel by reserved parking is:

\[ V_{i(u)} = 0.149(\text{age}) + 0.121(\text{income}) + 0.021(\text{purpose}) + 0.085(\text{distance}) \]
\[ + 0.036(\text{dependability}) + 1.275(\text{convenience}) \]
\[ - 2.336(\text{travel time}) \] (26)

Similarly, the probability of a user choosing a specific appointment time slot can be calculated. The utility of the appointment time layer selection branch is taken as an example for the 18:00–19:00 time slot:

\[ V_l = -0.626(\text{cost}) + 2.057(\text{preferences}) - 1.006 \] (27)

Based on the pooled attributes of the user group for this mode of travel, estimated for age, income, trip purpose, and distance, the pooled utility function for users who choose to reserve a parking lot for parking is as follows:

\[
V_1 = -1.826 + 0.593 \ln (\exp (2.057 - 0.637w_1) + \exp (1.736 - 0.626w_2) + \exp (0.495 - 0.541w_3) + \exp (3.036 - 0.719w_4) + \exp (-3.179 - 0.341w_5) + \exp (3.328 - 0.422w_{12}) + \exp (2.694 - 0.392w_{23}) + \exp (2.778 - 0.444w_{34}) + \exp (-1.671 - 0.24w_{45}) + \exp (2.961 - 0.383w_{123}) + \exp (0.702 - 0.264w_{234}) + \exp (2.359 - 0.33w_{345}) + \exp (6.301 - 0.425w_{1234}) + \exp (4.835 - 0.425w_{2345}) + \exp (15.351 - 0.667w_{12345}) ) \] (28)

2. Traditional parking in the neighborhood

The probabilistic utility of a user choosing to park in the traditional way in a neighboring parking lot is calculated. The calibrated user utility model is:

\[ V_2 = 0.149(\text{age}) + 0.121(\text{income}) + 0.021(\text{purpose}) + 0.085(\text{distance}) \]
\[ + 0.495(\text{dependability}) + 1.453(\text{convenience}) \]
\[ - 2.287(\text{travel time}) + 2.22(\text{preferences}) - 0.428(\text{fee}) \]
\[ - 3.447 \] (29)

Based on the pooled attributes of the user group of this travel mode, age, income, gender, nature of work, and distance are estimated, and the pooled utility function of the users who choose the surrounding traditional parking lots for parking in the experimental parking lot is as follows:

\[ V_2 = -0.606 - 0.082w \] (30)

3. Other modes of travel

According to the survey data on the probability utility of the user travel to choose other travel modes such as bus, subway, walking, etc., the calibrated user utility model is:

\[ V_3 = 0.149(\text{age}) + 0.121(\text{income}) + 0.021(\text{purpose}) + 0.085(\text{distance}) \]
\[ + 1.807(\text{dependability}) + 1.957(\text{convenience}) \]
\[ - 0.883(\text{travel time}) + 2.639(\text{preferences}) - 0.278(\text{fee}) \]
\[ - 15.06 \] (31)
Based on the pooled attributes of the user group for this travel mode, age, income, gender, nature of work, and distance are estimated, and the pooled utility function of the users who chose the traditional parking lots in the neighborhood for parking is as follows:

\[ V_3 = -1.0951 \]  

(32)

In summary, the corresponding utility function of each choice branch in the nested behavioral choice model is determined, and using it as a basis, the behavioral probability calculation of each choice branch can be carried out so as to clarify the profit optimization model of the reservation parking method and solve the optimal pricing scheme.

6.2. Solving the Game Pricing Model

Based on the pricing function of the reservation parking lot proposed in Section 5.3, the actual situation of the parking lot is taken into account. To ensure profitability, the minimum price per reservation period is set as a variable cost, and no additional constraints need to be added because the objective function contains the dual constraints of real-time user choice and the surrounding parking lot pricing game. Therefore, after adding the minimum cost constraint, the pricing model for the reservation parking lot is developed and the pricing model is as follows:

\[
\text{objective function : } \max Z = g(w_x) = \sum_{x=1}^{n} \left( Q_1 \sum_{k=1}^{n} \exp(V_k) \right) \frac{\sum_{j=1}^{n} \exp(V_j)}{\sum_{j=1}^{n} \exp(V_j)} \left( w_x - C_v - C_b \right)
\]

(33)

condition binding : \( w_x > C_b \)

(34)

According to the survey of the parking lot and passenger flow in the commercial area of Xi’an Road, which is the subject of the experiment, the price of parking in this commercial area is 4 yuan/h, the variable cost is about 2 yuan/(car-hour), and the fixed cost is about 50 yuan/h. During the 16–18 July traffic survey, the average number of trips in the business district between 17:00 and 22:00 p.m. was 642 trips. Substituting this price and patronage parameter into the model, all parameters in the model are now explicit except for the independent variable (reservation price \( w_x \) for each reservation period) and the dependent variable (profit \( z \)). In this study, nonlinear optimization combined with a genetic algorithm is used to iteratively calculate the global optimal solution of this model and the results of the solution after 100 iterations are shown in Figure 4.

![Figure 4. The iterative process corresponding to model pricing.](image-url)
The optimal profit and pricing scheme for reserved parking is shown in Table 6.

**Table 6. The pricing scheme of the optimize model.**

<table>
<thead>
<tr>
<th>Parking Period</th>
<th>17:00–18:00</th>
<th>18:00–19:00</th>
<th>19:00–20:00</th>
<th>20:00–21:00</th>
<th>21:00–22:00</th>
<th>Peak Period Total Profit</th>
<th>User Choice Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (CNY)</td>
<td>3.2</td>
<td>4.1</td>
<td>2.9</td>
<td>4.2</td>
<td>2.0</td>
<td>2357.8</td>
<td>81.54%</td>
</tr>
</tbody>
</table>

The price plan for each hour of reserved parking, calculated on the basis of the existing parking price of CNY 4/h, is shown above.

Under the parking lot’s status quo scenario, the status quo profit was CNY 1390, and dynamic pricing with a reservation mechanism resulted in a 69.63% increase in the lot’s profit. The probability of user selection in the commercial area under the original traditional parking scheme was 59.08%, and under the pricing scheme developed by this optimization model, the probability of user selection increased to 81.54%, and the target parking lot traffic in this commercial area increased by 144 visits. In addition, this game pricing model develops an implementable pricing scheme for reservation car parks based on patronage.

6.3. Comparative Analysis of Pricing Strategy Returns

In this section, parking prices are analyzed in terms of traditional uniform pricing schemes and autonomous pricing schemes without gaming with neighboring parking lots, respectively, for the target parking lots.

6.3.1. Traditional Flat-Rate Pricing

In this scenario, instead of using dynamic pricing where the price varies from one reservation period to the next, the parking lot draws up the reservation period price in a uniform pricing manner. The pricing process also takes into account the user’s choice behavior while gaming prices with neighboring parking lots.

Under this pricing strategy, the objective function is:

$$
\max Z = \sum_{x=1}^{n} \left( Q \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \left( \frac{\exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \cdot \frac{\exp(V_k)}{\sum_{l=1}^{n + 1} \exp(V_l)} \right) (w - C_v) - C_b \right)
$$

where $w$ is a fixed parking price that is consistent across cycles. The form of the profit function of the neighboring parking lots remains unchanged, and after substituting their reaction functions, the objective function of the reservation garage can be expressed as follows:

$$
\max Z = g(w)
$$

The price model is solved for this price model and the iterative solution process is shown in Figure 5.

Under this strategy, the optimal profit and pricing scheme for reserved parking is as shown in Table 7.

**Table 7. Correspondence program under fixed price.**

<table>
<thead>
<tr>
<th>Parking Period</th>
<th>17:00–18:00</th>
<th>18:00–19:00</th>
<th>19:00–20:00</th>
<th>20:00–21:00</th>
<th>21:00–22:00</th>
<th>Peak Period Total Profit</th>
<th>User Choice Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (CNY)</td>
<td>3.3</td>
<td>3.3</td>
<td>3.3</td>
<td>3.3</td>
<td>3.3</td>
<td>2313.4</td>
<td>81.27%</td>
</tr>
</tbody>
</table>

In the optimal results obtained through the model, the price of reserved parking is priced at CNY 3.3 for all peaks. The total profit corresponding to the parking lot under this scenario is CNY 2323.1. The predicted traveler choice probability for the parking lot under this scenario is 81.27%, with a patronage of 521.
The expected profit function of the reservation car park is:

$$
\max Z = \sum_{x=1}^{n} \left( \frac{Q \exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \left( \sum_{j=1}^{n_x} \frac{\exp(V_{a_j})}{\sum_{l=1}^{n_{a,j+1}} \exp(V_l)} \right) (w - C_v) - C_b \right) 
$$

(37)

The form of the price component is the same as in the original model, with the difference being that the conventional garage price $w'$ in the utility function is a fixed constant.

Therefore, the price decision function made by the traditional car park for this strategy is:

$$
\max Z = Q \left( \frac{\exp(V_b)}{\sum_{k=1}^{3} \exp(V_k)} \right) (w' - C_v') - C_b' 
$$

(38)

With this as the reaction function, the reservation parking lot sets the corresponding optimal price. The difference in the price part of the model is that the price $w_x$ of the reservation car park in the utility function is a fixed constant.

Therefore, the actual profit of the subsequent reservation of the car park is:

$$
Z = \sum_{x=1}^{n} \left( \frac{Q \exp(V_a)}{\sum_{k=1}^{3} \exp(V_k)} \left( \sum_{j=1}^{n_x} \frac{\exp(V_{a_j})}{\sum_{l=1}^{n_{a,j+1}} \exp(V_l)} \right) (w - C_v) - C_b \right) 
$$

(39)
Since the objective is to maximize the constraint, the solution is minimized by taking negative values. The iterative solution process to solve the above model is shown in Figure 6.

![Function-valued curves, ending at iteration number = 50](image)

**Figure 6.** The iterative process corresponding to no-game pricing.

The pricing scheme and actual profit of the reserved parking lot without considering the pricing strategy and gaming competition of the neighboring parking lots are as in Table 8.

**Table 8.** Autonomous pricing under gaming competition not considered.

<table>
<thead>
<tr>
<th>Parking Period</th>
<th>17:00–18:00</th>
<th>18:00–19:00</th>
<th>19:00–20:00</th>
<th>20:00–21:00</th>
<th>21:00–22:00</th>
<th>Expected Profit</th>
<th>Actual Profit</th>
<th>User Choice Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (CNY)</td>
<td>2.0</td>
<td>4.9</td>
<td>2.8</td>
<td>4.2</td>
<td>2.0</td>
<td>2320.8</td>
<td>2046.2</td>
<td>79.49%</td>
</tr>
</tbody>
</table>

The optimal pricing scheme under this scenario is shown in the table above. Under this pricing scheme, the projected profit for the reservation parking party is CNY 2320.8. After price adjustments for neighboring parking lots, the actual profit earned by the reserved parking lot is CNY 2046.20. Traveler choice probability and parking lot traffic were also lower than expected, at 79.49% and 510 trips, respectively.

6.3.3. Comparative Analysis of Program Results

The corresponding benefits of adopting status quo pricing, optimized pricing for reserved parking, traditional uniform pricing, and self-pricing strategy without gaming are compared for the target car parks, respectively.

Figure 7 above summarizes the price attributes of the original parking lot price plan and each of the optimized price plans. In the pricing of the optimization model, prices are higher for hours with a higher peak demand and are lower than the original prices for other hours. It can be found that under the game competition, the price of reservation parking lots tends to be lower while obtaining greater traffic and revenue at lower prices.

Figure 8 above shows the corresponding parking lot revenue for each scenario. The dynamic pricing scheme that employs user choice and parking lot price gaming leads the other schemes with a profit of CNY 2357.8. In addition to verifying the validity of the optimization model under comparison with the original scheme, the usefulness of dynamic pricing and consideration of gaming competition for real parking revenue is demonstrated. The rationality of the model is proven.
Table 8. Autonomous pricing under gaming competition not considered.

<table>
<thead>
<tr>
<th>Parking Period</th>
<th>17:00–18:00</th>
<th>18:00–19:00</th>
<th>19:00–20:00</th>
<th>20:00–21:00</th>
<th>21:00–22:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected Profit</td>
<td>2.0</td>
<td>4.9</td>
<td>2.8</td>
<td>4.2</td>
<td>2.0</td>
</tr>
<tr>
<td>Actual Profit</td>
<td>2320.8</td>
<td>2046.2</td>
<td>79.49%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Choice Probability</td>
<td>510 trips</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The optimal pricing scheme under this scenario is shown in the table above. Under this pricing scheme, the projected profit for the reservation parking party is CNY 2320.8. After price adjustments for neighboring parking lots, the actual profit earned by the reserved parking lot is CNY 2046.20. Traveler choice probability and parking lot traffic were also lower than expected, at 79.49% and 510 trips, respectively.

6.3.3. Comparative analysis of program results

The corresponding benefits of adopting status quo pricing, optimized pricing for reserved parking, traditional uniform pricing, and self-pricing strategy without gaming are compared for the target car parks, respectively. Figure 7 above summarizes the price attributes of the original parking lot price plan and each of the optimized price plans. In the pricing of the optimization model, prices are higher for hours with a higher peak demand and are lower than the original prices for other hours. It can be found that under the game competition, the price of reservation parking lots tends to be lower while obtaining greater traffic and revenue at lower prices.

Figure 7. Price comparison of the four options.

Figure 8 above shows the corresponding parking lot revenue for each scenario. The dynamic pricing scheme that employs user choice and parking lot price gaming leads the other schemes with a profit of CNY 2357.8. In addition to verifying the validity of the optimization model under comparison with the original scheme, the usefulness of dynamic pricing and consideration of gaming competition for real parking revenue is demonstrated. The rationality of the model is proven.

Figure 8. Comparison of parking lot benefits for four scenarios.

Figure 9 below shows a chart that provides statistics on the patronage of users who chose the reserved parking option under each scenario. In the data, it can be found that the strategy of gaming competition and dynamic pricing is effective under the model, and the passenger flow is more substantial than in other scenarios. Using this optimization model, travelers are more willing to choose reserved parking.

Figure 9. Comparison of parking lot traffic for four scenarios.
Figure 9. Comparison of parking lot traffic for four scenarios.

7. Conclusions

From the study in this paper, the following conclusions can be drawn:

1. In this paper, we propose a new reservation parking strategy for commercial districts where users can freely choose the combination of reservation time slots. In addition, based on the nested logit model and Stackberg model, the derivation process of the profit of a reservation parking lot is given more systematically. From the example experiments, it can be seen that the model demands fewer and easily accessible independent variables, while specific price schemes can be obtained with a high degree of applicability.

2. The feasibility of using nested logit for the user selection of specific time slots in the parking reservation mechanism is partially verified by an example. This paper is also the first time that nested logit is introduced into the direction of passenger flow analysis for reserved parking, which can provide some ideas for subsequent research on reserved parking pricing.

3. Parking lots can dynamically adjust their own prices by using the attributes of the traffic flow and the strategies of neighboring parking lots to develop a reasonable pricing scheme. Lower prices for several time slots may mean a higher traffic attraction and higher profits.

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References


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