Hindawi
Journal of Advanced Transportation
Volume 2022, Article ID 5977168, 13 pages
https://doi.org/10.1155/2022/5977168

Research Article

Parking Resource Allocation Optimization Framework Based on a Two-Level Grid Model

Haonan Guo ,[1] Yun Wang ,[1] Xuedong Yan ,[1] Yunlin Guan,[1] and Yu Zhou[2]

[1]*MOT Key Laboratory of Transport Industry of Big Data Application Technologies for Comprehensive Transport, School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China*
[2]*Department of Civil and Environmental Engineering, National University of Singapore 117576, Singapore*

Correspondence should be addressed to Yun Wang; wang.yun@bjtu.edu.cn

Received 28 December 2021; Revised 1 March 2022; Accepted 29 April 2022; Published 26 May 2022

Academic Editor: Ruimin Ke

With the rapid increase in vehicle population, solving difficult-to-park and inconvenient-to-park problems has become a necessity for sustainable transportation in major cities. This study investigated the parking resource allocation optimization problem based on a two-level grid model. To address this problem, first users' travel data were matched to the map to obtain the distribution of both parking resources and demands. Second, key demand-supply imbalanced grids were identified. Subsequently, the parking resource allocation optimization problem was formulated as an integer linear programming (ILP) problem aiming to minimize the total cost, including the parking facility construction cost, users' total walking distance, and the penalty for unserved users. Finally, a case study based on real-world data in Cangzhou was conducted to verify the feasibility and effectiveness of the proposed method. The results show that the imbalance between the supply and demand of parking resources can be effectively alleviated.

1. Introduction

For large and medium-sized cities, traffic problems caused by the rapid growth of motor vehicle ownership, such as traffic congestion, environment pollution, traffic safety, and parking inconvenience, are becoming increasingly serious. Previous research [1, 2] has mainly focused on traffic congestion, energy consumption, and traffic safety problems. However, with economic development, urban expansion, and the rapid increase of vehicle population, the difficult-to-park and inconvenient-to-park problem has become a bottleneck restricting sustainable transportation in major cities. Shoup [3] found that the 35% of cars in traffic were cruising for parking. According to a report by a transportation data company, drivers in the United States waste $73 billion each year in terms of time, fuel, and emissions costs when searching for a parking space [4]. Moreover, a significant share of the total amount of energy consumption and CO_2 emissions originates from cruising for parking [5, 6]. Therefore, providing high-quality parking services is crucial to easing congestion and reducing emissions.

In recent years, research on parking problems has received considerable attention. Previous research [7–11] on the parking problem has mainly focused on parking pricing, parking behavior analysis, and parking reservation. Motivated by the sharing economy model, the parking space sharing problem has received more and more attention [12–14]. Although both parking pricing and shared parking spaces are effective means of allocating parking resources, regardless of the type of management measures, it is necessary to ensure that parking spaces are available in the area. Therefore, reasonable parking planning and construction of parking facilities is a prerequisite. Owing to the less effort being devoted to parking planning at present, the unreasonable layout of urban parking spaces has exacerbated the above-mentioned difficult-to-park and inconvenient-to-park problems. The parking planning problem cannot be solved simply by continuously building new parking facilities, particularly in urbanized areas with high traffic density and limited land resources. Therefore, in the early stages of urban planning, reasonable planning of parking facilities should be formulated considering a macro-perspective;

otherwise, there are possibilities of no land availability or expensive reconstruction costs.

This study focused on the parking resource allocation optimization problem during the early stages of urban planning, when land resources are abundant. An optimized parking resource allocation scheme should provide sufficient parking space and reasonable spatial distribution of parking resources. Otherwise, when approaching a destination, drivers always need to cruise to find an available parking space, and consequently certain people may choose to park disorderly. Moreover, drivers may still need to walk a long distance to reach their destination even after parking the car. This is because there are always distances between the origin/destination and parking spaces. As shown in Figure 1, for a trip, users must depart from their origins, walk to parking lots, drive cars, park cars, and finally walk to their destination. Two parking spaces are required for each trip: the trip origin and destination. Thus, the spatial distribution of parking resources determines whether it is convenient for drivers to park and further influences their driving behaviors.

The travel origin and destination information of the driver plays an important role in the parking resource allocation optimization problem, as it directly determines the walking distance. However, the above-mentioned information in most previous research on parking planning problems has been primarily obtained through questionnaire surveys or manual records, which is time-consuming and costly. Moreover, the accuracy of the data collected from traditional traffic surveys or records cannot be guaranteed. Fortunately, the rapid development of big data and machine learning technologies has provided new opportunities for innovation in transport modelling and has been increasingly applied in solving various transportation problems. Big data is superior to traditional survey data in terms of data volume, velocity, variety, and veracity [16]. Furthermore, it can reveal a wealth of hidden travel information using special tools for processing and crawling. In recent years, big data and machine learning methods have been applied to forecast traffic demand and speed, assess traffic congestion and safety, etc. [17–20]. However, studies on parking problems that have applied big data methods are scarce. In fact, introducing the big data method to obtain accurate travel origin and destination information can bring revolutionary changes to parking planning research.

In this study, a two-level grid-based area division method was proposed to process travel OD big data and study the parking resource allocation optimization problem by considering the differences between parking demand and current parking spaces. First, a two-level grid model was designed to divide the study area and process drivers' travel OD data. The proposed area division method can significantly improve computational efficiency while preserving the properties of each grid. Second, key demand-supply imbalanced grids were identified by calculating the gap between parking demand and parking spaces in each grid. Subsequently, the parking resource allocation optimization problem was formulated as an integer linear programming (ILP) problem, simultaneously optimizing three competing objectives: minimizing construction costs of parking facilities, minimizing drivers' walking distances after parking, and maximizing the number of served drivers. Finally, a case study based on parking planning in Cangzhou was conducted to demonstrate the practical significance of the proposed method.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 develops a framework for parking resource allocation optimization, including data processing, key imbalanced grid identification, and an optimization model. In Section 4, a case study based on Cangzhou parking planning is presented to illustrate the application of the method. Finally, Section 5 provides conclusions and suggests future research directions.

2. Literature Review

Parking problems have attracted considerable attention in the past decade and can be generally classified into three types: parking planning, parking operations, and parking management. Existing studies have overwhelmingly focused on operations and management, such as parking pricing and behavior analysis [7–10, 21–23], parking reservation [11, 24–29], and shared parking [12–14].

As stated in the Parking Guidelines [30, 31], optimal parking pricing can significantly balance parking demand and supply based on existing parking facilities. Therefore, a large amount of literature on the parking problem is devoted to investigating ways to use parking pricing as the main policy strategy to influence drivers' parking behavior, such as the hourly or daily periodic adjustments of parking pricing policy and the completely dynamic pricing scheme. Nourinejad and Roorda [10] studied the impact of hourly parking pricing on travel demand and found that parking pricing policies should be devised with sufficient knowledge of dwell-time elasticities. Fei [22] analyzed changes in travel behavior after eliminating the free parking policy and found that increasing parking pricing can increase the utilization rate of public transportation. He et al. [9] presented an uncooperative static atomic parking game with complete information to address parking competition issues. They discussed optimal pricing schemes that steer parking competition in a system that optimally assigns parking spaces. Considering the impact of parking pricing on the use of private cars, Tezcan [21] used data obtained from a questionnaire to propose a mode choice model to analyze travelers' willingness to pay for different parking pricing. Qian and Rajagopal [7] proposed a dynamic pricing scheme wherein parking prices were adjusted in real time to achieve an optimal flow pattern for demand and travelers' heterogeneity. They also studied a similar problem for parking pricing under stochastic demand [8].

The above price strategy is a typical market-oriented allocation model, wherein resources are allocated to users with stronger demand and willingness to pay for price adjustment. Conversely, the reservation mechanism is a nonmarket allocation model that can ensure fairness in parking resource allocation [29]. Certain reservation

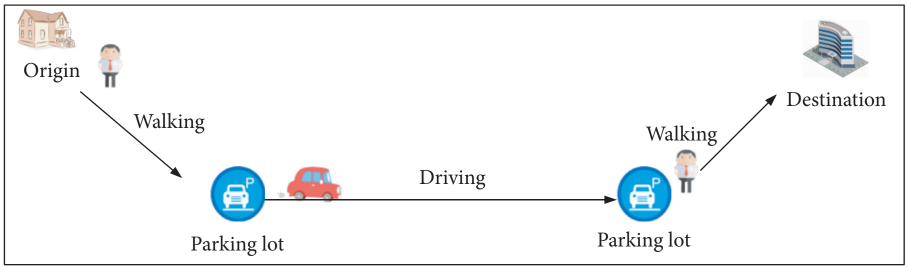


Figure 1: Illustration of a vehicle driving trip.

strategies have been proposed for improving parking space usage efficiency. Zhang et al. [26] and Yang et al. [32] found that parking reservations with parking permit distribution and trading are efficient parking management methods. Ferreira and Silva [11] proposed an optimal parking-lot selection model based on a reservation system. Lei and Ouyang [28] used dynamic location-dependent parking pricing and reservation to determine the spatial and temporal distribution of parking prices, with the goal of system-wide optimization. Moreover, Mei et al. [29] analyzed and compared the benefits of parking charges and reservation mechanisms and provided operational suggestions for urban parking managers. They established a parking simulation model based on agents and discussed two parking allocation mechanisms. The results showed that parking charges and reservations could remarkably improve comprehensive benefits.

Shared parking has recently emerged as a more efficient method for using parking facilities. Most research on shared parking is devoted to solving the reservation and allocation of existing parking spaces in the period when the owner does not use it. Shao et al. [12] addressed the allocation problem in a parking-reservation environment by proposing a binary integer linear programming model to solve the allocation of shared parking spaces based on an e-parking platform. The aim was to maximize parking space utilization and accommodate maximum requests possible under strict parking space and time constraints. However, their work is limited to the case of a one-sided market and constant parking fares, and the approach they used was not an auction mechanism. Xiao et al. [13] proposed two truthful double auction mechanisms for shared parking problems concerning space allocation and transaction payment rules, wherein parking time assignment was fully considered. However, they did not explicitly consider the spatial nature of parking spaces for the demanders. In addition, the authors also proposed a novel mechanism for optimizing shared parking management [14]. Li et al [15]. proposed a shared parking space optimization model by considering travelers' credit value and used the modified ant colony algorithm to solve the problem.

However, compared to parking operations and management, less research has been dedicated to optimizing parking systems at the planning stage. Representative studies include Kazemi et al. [33]; Nourinejad et al. [34]; and Du et al. [35]. Du et al. [35] proposed a method to optimize the location of street parking facilities to serve commuters. Recently, with the rapid advancement in electric vehicle (EV) and autonomous vehicle (AV) technologies, EVs and AVs are expected to occupy the market in the next decade. An increasing number of studies are exploring the design and allocation of parking resources. Kazemi et al. [33] presented a new approach for determining the optimal number, location, and capacity of EV parking lots. Nourinejad et al. [34] found that AV car parks could reduce the need for parking space. Furthermore, they proposed an optimal AV car-park layout design with minimum relocations for the blocked vehicle to find a clear pathway when exiting the parking lot.

Although a comprehensive body of literature on the parking problem is available, there are still certain limitations and gaps in previous studies, particularly in the parking planning issue. Most existing research predetermines candidate parking space locations and then treats this problem as a facility location problem. Yet, whether a parking space needs to be allocated is determined by the differences between demand and supply. However, none of the previous studies have treated the gap between parking demand and supply as a key indicator for determining the allocation of parking resources. One of the primary reasons is that obtaining accurate parking demand is challenging. In traditional transportation planning, there are mainly two types of demand forecasting methods: the "four-stage" model based on the trip-based forecasting method and the activity-based forecasting method. The trip-based demand forecasting method usually divides the study area into traffic zones and then forecasts the zone demand based on population, car ownership, land use, etc. [36, 37]. The activity-based forecasting method focuses on travel purposes [38] and requires a large volume and high veracity of private information data, which are difficult to collect based on traditional data acquisition and processing methods [39]. Fortunately, in recent years, there have been new trends in the field of demand forecasting owing to the development of big data technologies, which significantly increase the number of forecasting samples and improve the accuracy of forecasting results [17]. Moreover, compared with the traditional parking demand forecasting method that uses land use and traffic community information to estimate travel attraction, the travel origin and destination information is hidden in the big travel data, which can be extracted accurately and directly reflects the potential parking demand.

Thus, in this study, the aim was to investigate the parking resource allocation optimization problem by considering the differences between parking demand and current supply. The major innovations and contributions of this study are as follows. A grid-based parking resource allocation method was proposed. The drivers' actual travel data based on the grid model were processed, and subsequently, key demand-supply imbalanced grids were identified. Thereafter, the parking resource allocation optimization problem was formulated as an ILP problem coupling the information of imbalanced grids. The proposed method can support operators in simultaneously optimizing three competing objectives: minimizing the construction costs of parking facilities, minimizing drivers' walking distances, and maximizing the number of served drivers.

3. A Framework for Parking Resource Allocation Optimization

This section presents a detailed description of the parking resource allocation optimization problem. The section is organized as follows: first, the grid model is introduced to split a study area into smaller cells; second, the key demand-supply imbalanced grids are identified based on the collected big data; third, a traditional parking resource allocation model is proposed; finally, the key imbalanced grids and traditional parking resource allocation are integrated to subsequently formulate the parking resource allocation optimization model as an ILP.

3.1. Grid Mapping and Size Identification. Traditional parking planning research usually divides the study area into several traffic communities or predetermines certain candidate parking space locations, which may lead to the following two problems: the lack of high-quality vector GIS maps may influence the accuracy of the matching between parking supply and demand, and an unreasonable candidate location set can hardly obtain an optimal resource allocation scheme. Thus, in this study, the traffic grid model derived from the theory of city management grid model was applied to process multisource traffic data, which is very effective for solving the parking problem [40].

When dividing the study area into multiple meshes using a traffic grid model, among the most important issues is choosing an appropriate grid size. The grid size should be adjustable for different management purposes, and the grid attributes should be classified to improve management effectiveness. Parking resource allocation involves two sequential parts: first, the parking facility location should be determined, and then drivers should be assigned to a parking location. Moreover, when dealing with parking facility location issues, the grid size cannot be too small; else, it would result in a multitude of grids with no data value, and the scale of the optimization problem will explode dramatically. Conversely, the grid size cannot be too large when dealing with the location assignment issue because the drivers' walking distance between parking facilities and trip origin/destination should be calculated more accurately. Therefore, in this study, a two-level grid model was proposed, as shown in Figure 2.

Specifically, the grid size concerning the key demand-supply imbalanced grid identification issue must be relatively larger than that of the resource allocation issue. However, it cannot be too large because certain important grid attributes may be hidden. Here, the maximum acceptable walking distance [41] was adopted, that is, 200 m, as the grid size for parking when identifying the key demand-supply imbalanced grids. Further, considering that the drivers' trips and origins/destinations are heterogeneous, each trip in the travel big data has latitude and longitude coordinates. Thus, to simplify such a travel big data problem, the origin/destination information was mapped onto the grids. Moreover, each upper lever grid was further divided into 6×6 smaller lower-level grids when assigning drivers to parking facilities.

3.2. Key Demand-Supply Imbalanced Grid Identification. The identification of key demand-supply imbalanced grids is crucial to determining the locations of parking resource shortages. Based on this, parking resources can be allocated much more reasonably and efficiently, avoiding either over or under-allocation. Information regarding the parking resource supply and parking demand of each grid should be obtained. Generally, parking resource supply information can be collected from urban land-use documents or by conducting field surveys. However, compared to parking resource supply information, parking demand information is much more difficult to obtain. The parking demand for each grid should be forecasted. Methods, such as regression analysis and machine learning, have been proven to effectively predict parking demand. Further details can be found in Chen et al. [42] and Hensher and King [43] wherein comprehensive reviews have been presented. Guan et al. [44] proposed a parking demand prediction method based on big data of trip origin/destination information and proved that parking demand has a significant correlation with travel demand.

Thus, based on the grid model, this study mapped the obtained spatial and quantity distribution information of the essential parking resources and parking demand onto each upper-level grid. Let G represent finite sets of upper-level grids. For grid i in G, let $\overline{s}_i$ and $\overline{p}_i$ represent existing parking resource supply and predicted parking demand, respectively. Here, as shown in Figure 3, parking demand in grid $i \in G$ is served by parking resources in its surrounding grids within the maximal walking distance threshold. In a similar manner, parking resources in grid $i \in G$ can also serve the parking demands in the surrounding grids. Therefore, to identify the gap between the actual demand and supply in each grid, the actual number of parking resources and parking demand in grid $i \in G$ can be represented as $\widetilde{s}_i$ and $\widetilde{p}_i$, respectively. Let $\overline{G}_i$ represent the finite sets of grids surrounding the upper-level grid $i \in G$ and the grid itself. Equations (1) and (2) represent the relationship between $\overline{s}_i$ and $\widetilde{s}_i$ and $\overline{p}_i$ and $\widetilde{p}_i$.

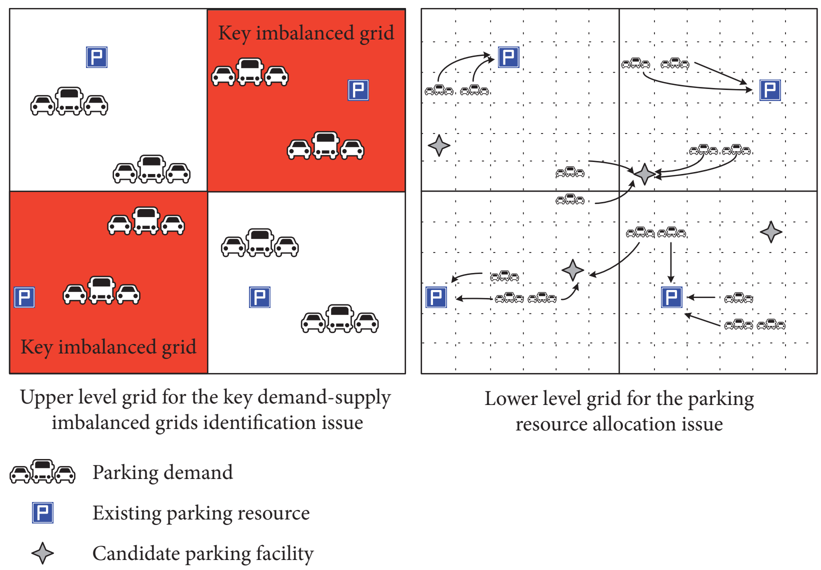


Figure 2: Two-level grid model.

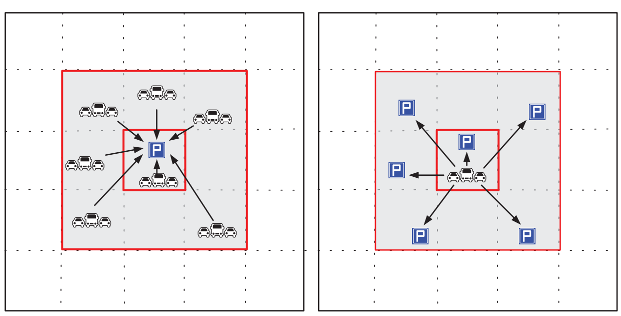


Figure 3: Sets of grids, $\overline{G}_i$, surrounding upper-level grid $i \in G$.

$$\tilde{s}_i = \sum_{j \in \overline{G}_i} \overline{s}_j \forall i \in G, \tag{1}$$

$$\tilde{p}_i = \sum_{j \in \overline{G}_i} \overline{p}_j \forall i \in G. \tag{2}$$

Based on $\tilde{s}_i$ and $\tilde{p}_i$, the gap between the actual parking resource supply and parking demand in each upper-level grid $i \in G$ can be calculated. As shown in Figure 4, the relationship between $\tilde{s}_i$ and $\tilde{p}_i$ is classified into the following five situations: $\tilde{s}_i$ is approximately equal to $\tilde{p}_i$; $\tilde{s}_i$ is larger than $\tilde{p}_i$; $\tilde{s}_i$ is much larger than $\tilde{p}_i$; $\tilde{s}_i$ is less than $\tilde{p}_i$; and finally $\tilde{s}_i$ is much less than $\tilde{p}_i$. Further, different thresholds can be set to identify the key supply-demand imbalanced grids according to various real-world planning scenarios. Let $\widehat{G}$ represent finite sets of the above-obtained key demand-supply imbalanced grids, where $\widehat{G} \subset G$.

3.3. Grid-Based Parking Resource Allocation Optimization Model. In the traditional facility location problem, candidate facility locations and demands are provided directly, and decision variables (etc., x_{ij}) are defined to represent the assignment relationships between demand and facilities (demand i is assigned to facility j). This study proposed a framework for allocating grid-based parking resources. By introducing the grid model, integration of essential information onto a single grid, such as existing parking resource supply, parking demand, parking facility construction conditions, is possible.

As defined above, G represents finite sets of upper-level grids, and each upper-level grid $i \in G$ can be divided into 6×6 lower-level grids. Let G_i represent finite sets of all lower-level grids of the upper-level grid $i \in G$. For grid $j \in G_i$ in upper-level grid $i \in G$, let s_j and p_j represent existing parking resource supply and predicted parking demand, respectively. Let $T = \{t | t = t_1, t_2\}$ denote a finite set of parking facility types. Type t_1 and type t_2 are the parking space and curbside parking space, respectively. Further, let a non-negative integer variable $\delta(j, t)$ represent the maximum capacity of new parking spaces that can be constructed in grid $j \in G_i$, $i \in G$. Specifically, $\delta(j, t)$=0 implies that the parking facility of type t can not be constructed in grid $j \in G_i$, $i \in G$.

As mentioned previously, drivers are not willing to walk a long way to reach their destination after parking. Thus, when assigning drivers to parking facilities, the walking distance should be considered. Owing to the mapping of parking resources and trip destination information onto grids, a parameter d_{jk} can be defined to represent the walking distance between the lower-level grid $j \in G_i$ and $k \in G_{i'}$ in upper-level grid $i, i' \in G$. Let $d_{\max}$ represent the walking distance threshold.

The parking resource allocation optimization problem must solve the following three issues: construction of parking facilities, facility capacity setting, and vehicle-to-resource assignment. Thus, three decision variables were introduced: x_j^t, y_j^t, and z_{jk}. Specifically, the binary decision variable $x_j^t = 1$ represents that a parking facility of type t is constructed in grid $j \in G_i$, $i \in G$, and otherwise not. Further, the nonnegative integer decision variable y_j^t represents

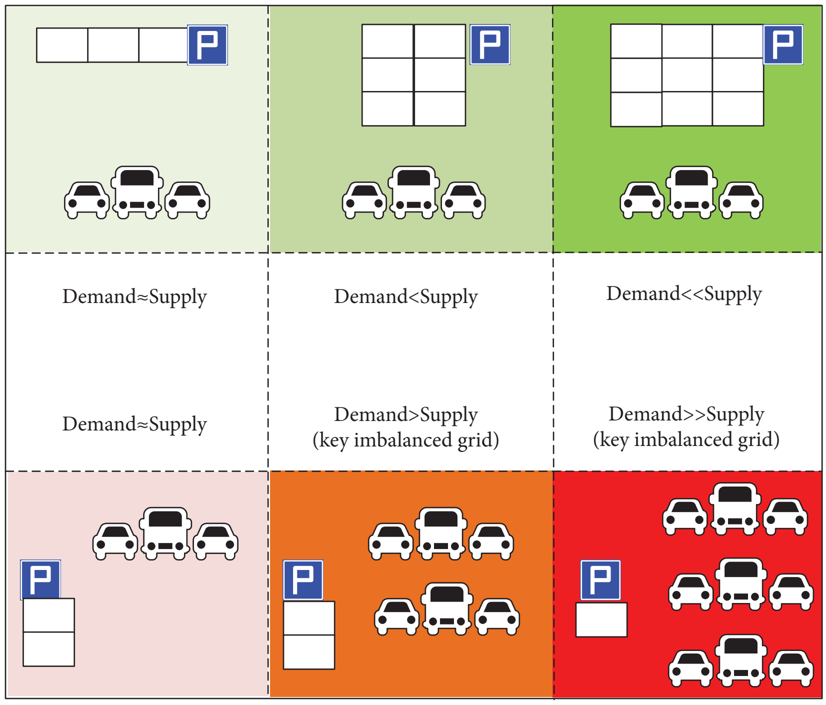


Figure 4: Classification of the relationship between $\hat{s}_i$ and $\hat{p}_i$.

the parking facility capacity of type t constructed in the grid $j \in G_i, i \in G$. Finally, the nonnegative integer decision variable z_{jk} represents the number of drivers in the lower-level grid $j \in G_i$ assigned to parking resources in grid $k \in G_{i'}$ of upper-level grid $i, i' \in G$.

The parking resource allocation problem involves two types of stakeholders: operators and users. There exists an obvious trade-off between operating costs and user benefits. Although adequate parking resources should be provided to ensure drivers can find a place to park with shorter walking distance, operators may seek to spend less money on parking facility construction. However, fewer parking resources can exacerbate difficult-to-park and inconvenience-to-park problems. To best address this trade-off, the total operating cost, drivers' travel cost, and number of unserved parking demands were simultaneously minimized. Herein, an ILP method for determining the optimal parking resource allocation scheme is presented. The combined model was formulated as follows:

$$\min \alpha \sum_{t\in T}\sum_{i\in G}\sum_{j\in G_i} c_i^t y_j^t + \beta c_a \sum_{i,i_\prime\in G}\sum_{j\in G_i}\sum_{k\in G_{i_\prime}} d_{jk} z_{jk} + \chi c_b \left(\sum_{i\in G}\sum_{j\in G_i} p_j - \sum_{i,i_\prime\in G}\sum_{j\in G_i}\sum_{k\in G_{i_\prime}} z_{jk} \right), \tag{3}$$

$$s.t. \sum_{j\in G_i} z_{jk} \le \sum_{t\in T} y_j^t + s_j \forall k \in G_i, i \in G, \tag{4}$$

$$\sum_k z_{jk} \le p_j \forall j \in G_i, i \in G, \tag{5}$$

$$y_j^t \le \delta_j^t \forall t \in T, j \in G_i, i \in G, \tag{6}$$

$$z_{jk}\left(d_{jk} - d_{\max}\right) \le 0 \forall j \in G_i, k \in G_{i'}, i, i' \in G, \tag{7}$$

$$M x_j^t - y_j^t \ge 0 \forall t \in T, j \in G_i, i \in G, \tag{8}$$

$$\left(\sum_{t\in T}\sum_{j\in G_i} x_j^t - \varepsilon \right)\left(\sum_{t\in T}\sum_{j\in G_i} \delta_j^t - \varepsilon \right) \ge 0 \forall i \in \widehat{G}, \tag{9}$$

$$x_j^t \in \{0, 1\} \forall t \in T, j \in G_i, i \in G, \tag{10}$$

$$y_j^t \ge 0 \forall t \in T, j \in G_i, i \in G, \tag{11}$$

$$z_{jk} \ge 0 \forall j, k \in G_i, i \in G. \tag{12}$$

As shown in equation (3), the objective function includes three parts: the total construction cost, drivers' total walking cost after parking, and the plenty of unserved drivers, where c_i^t is the fixed construction cost of parking spaces type $t \in T$ in grid $i \in G$, c_a is the average walking cost of the drivers, and c_b is the average penalty cost of each unserved driver. A convex combination of these three parts was used with three weighting factors α, β, and χ respectively, where $\alpha, \beta, \chi \ge 0$ and $\alpha + \beta + \chi = 1$. Constraint (4) limits the total number of drivers served that do not exceed the parking capacity provided by both new construction facilities and existing parking resources. Further, constraint (5) limits the total number of served drivers in each lower-level grid to less than the parking demand. Constraint (6) implies that new parking facilities can only be constructed in grids with

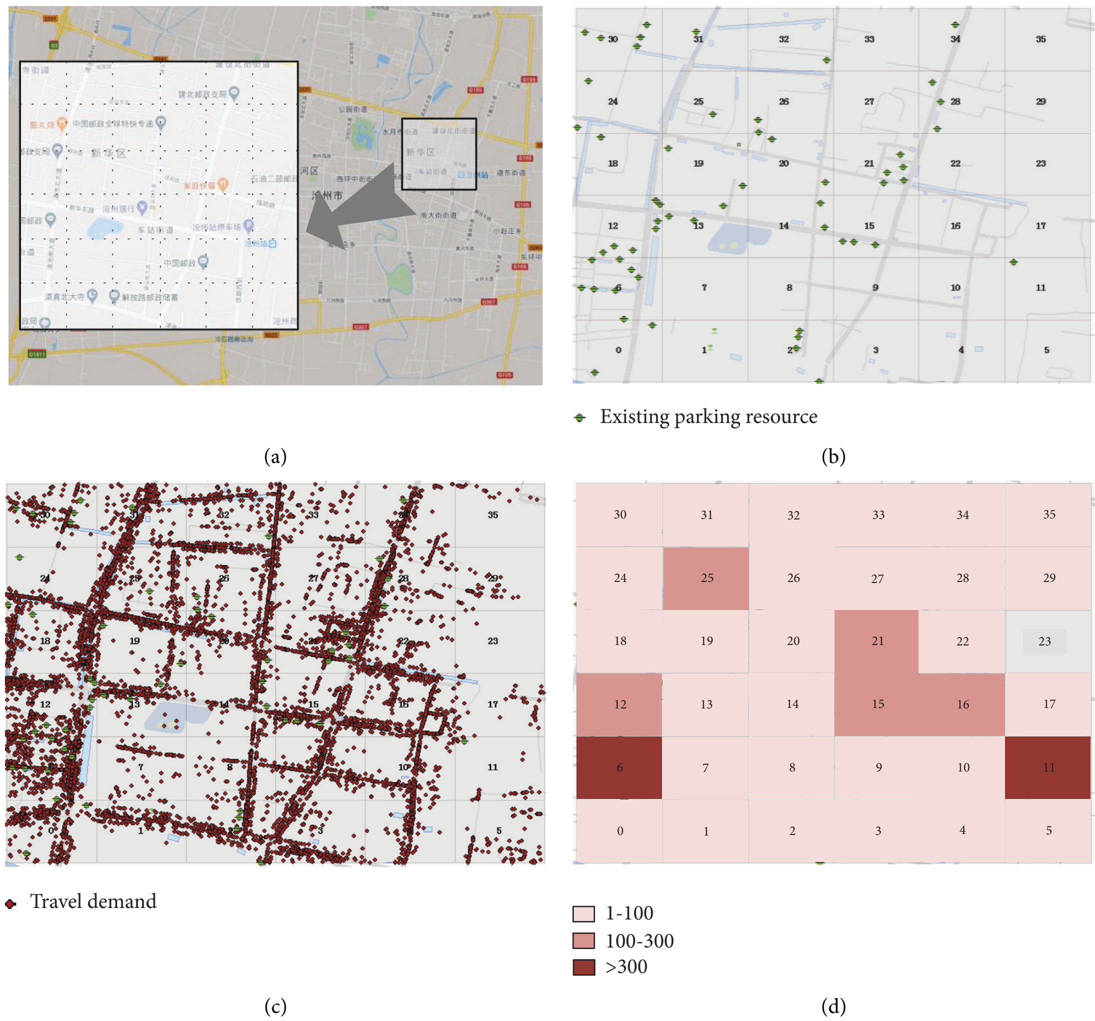


Figure 5: The data preprocessing and parking demand estimation. (a) Study area and grid split. (b) Mapping existing parking resource into grids. (c) Mapping travel demand data into grids. (d) The estimated parking demand.

construction conditions. Constraint (7) indicates that the walking distance of all served drivers should be shorter than the threshold. Constraint (8) indicates that parking facility capacity can only be introduced if and only if new parking facilities are constructed. Constraint (9) implies that for each key demand-supply imbalanced grid $i \in \widehat{G}$, new parking facilities must be constructed if possible, where ε is a sufficiently small positive number. Finally, constraints (10)–(12) represent the decision variable constraints.

4. Experiment Results and Discussion

In this section, numerical experiments are conducted to demonstrate the feasibility and effectiveness of the proposed parking resource allocation optimization method. An illustrative example of a 1.8 km×1.8 km area in Cangzhou with parking resources survey data and travel demand data is conducted. Moreover, the impact of the maximal walking distance and the effectiveness of the weight coefficient were assessed.

4.1. Data Preparation and Computational Results. The experiments were conducted in Cangzhou, Heibei Province, covering 1.8 km × 1.8 km. As shown in Figure 5(a), the study area was first divided into 36 grids, where each grid measured 300 m × 300 m. Thereafter, to obtain essential parking resource supply information, data on existing parking resources in the study area were collected. Thereafter, the collected parking resource survey data were mapped onto grids, as shown in Figure 5(b). In addition to the supply information, parking demand information is also needed to identify the key imbalanced grids. Further, as shown in Figure 5(c), the travel demand data were mapped onto grids, including 431,593 trips. Considering that parking demand forecasting is a challenging and independent research field that only provides a single parameter in this study, the parking demand forecasting process was simplified and the big data-driven framework proposed by Guan et al. [44] was used for parking demand estimation; that is, the estimated parking demand in each grid was obtained, as shown in Figure 5(d).

According to equations (1) and (2), parking resources and parking demand in grids can be calculated based on the collected information. Table 1 lists the calculated parking resources and parking demand and their differences.

As shown in Figure 6(a), the imbalanced rate information was integrated into the map, where the rate increased with the color change from light to dark. In this study, the threshold of the imbalanced rate was set as 0.4; that is, if the imbalanced rate was larger than 0.4, the grid was identified as a key demand-supply imbalanced grid; otherwise, it was not. Moreover, the threshold can be set flexibly according to different regions and requirements. The results show that there were 11 key imbalanced grids. The other parameters related to the parking resource allocation optimization problem were set as follows: maximal walking distance $d_{\max} = 200$ meters.

The proposed parking resource allocation optimization model was coded and solved using CPLEX, and the computational experiments were run on a 1.8 GHz Core i7 PC with 16 GB of RAM. The proposed model can be solved within 1 min. Figures 6(b) and 6(c) illustrate the optimal solution for parking resource allocation, including new parking facility locations and vehicle-to-parking resource assignments. The results show that 180 parking spaces and 1,130 curbside parking spaces should be constructed. Thus, the introduction of these new parking facilities can significantly improve the demand-supply imbalance, as shown in Figure 6(d). Moreover, among the 2953 parking demanders, 2750 can be assigned to parking facilities within the maximal walking distance to their final trip destinations, accounting for roughly 93%, which is an improvement of more than 20% compared to that before optimization.

Table 1: The parking resource and imbalanced rate in each grid.

ID	Parking demand	Parking spaces	Parking gap	Imbalanced rate
0	109	89	20	0.224
1	95	92	3	0.032
2	53	33	20	0.606
3	55	33	22	0.667
4	114	13	101	7.769
5	141	20	121	6.050
6	122	118	4	0.033
7	99	123	−24	−0.242
8	74	63	11	0.148
9	90	56	34	0.378
10	128	20	108	0.844
11	130	13	117	9.000
12	132	126	6	0.047
13	109	112	−3	−0.027
14	89	67	22	0.247
15	99	59	41	0.414
16	131	39	92	0.702
17	128	13	115	8.846
18	110	122	−12	−0.098
19	93	124	−31	−0.333
20	104	116	−12	−0.115
21	98	84	14	0.143
22	79	40	39	0.494
23	49	15	34	2.267
24	74	67	7	0.104
25	73	77	−4	−0.054
26	90	89	−6	−0.075
27	57	72	−15	−0.263
28	33	40	−7	−0.212
29	16	48	−24	−0.500
30	74	58	−9	−0.155
31	69	98	−29	−0.296
32	67	93	−26	−0.279
33	45	75	−30	−0.400
34	26	85	−9	−0.257
35	18	48	−30	−0.625

4.2. Assessing Impact of the Maximal Walking Distance. As previously mentioned, for a trip, users must walk between parking facilities and origins/destinations. Thus, walking distance is an important indicator for evaluating the quality of spatial distribution of parking resources. In this study, it was assumed that if drivers are assigned to parking facilities, the walking distance should be controlled at a threshold. The threshold value can affect the optimal scheme for parking resource allocation. Thus, a sensitivity analysis was conducted to assess the impact of maximal walking distance on the optimization of parking resource allocation. The value of the walking distance threshold was increased from 200 to 400 m at intervals of 50 m. Figure 7 illustrates the optimal solutions under different maximal walking distances and the optimal solution without new parking facilities. The starting point of the arrow in Figure 7 represents the grid where the user's parking location is located, and the ending point is the grid where the user's actual destination is located. It can be seen from the figure that with the increase of the maximal walking distance, some users who were unable to find parking spaces at smaller walking distances can be served, and some grids have also increased the construction of parking spaces to serve users who could not be served before.

Table 2 lists the solution details. The results reveal that the total walking distances, number of new parking facilities, and served drivers increased with the increase of the maximal walking distances. This is because the unserved drivers can be assigned to parking facilities with longer walking distances under the higher threshold. However, the total cost decreases dramatically with the increase of the threshold because as the threshold increases, the number of unserved drivers decreases, which increases the penalty cost. However, when the threshold reaches 350 m, the total cost remains stable because all drivers can be served and penalty cost is eliminated.

4.3. Investigating the Effectiveness of the Weight Coefficient. This section shows the manner in which the optimization results change with various combinations of values of the weighting factors α, β, χ in the objective function. The factors were changed in 0.2 intervals, and there were a total of 21 combinations.

When $\chi = 0$, the penalty cost for unserved users is ignored, and the objective function becomes the minimum total travel and operating costs. Consequently, the optimal

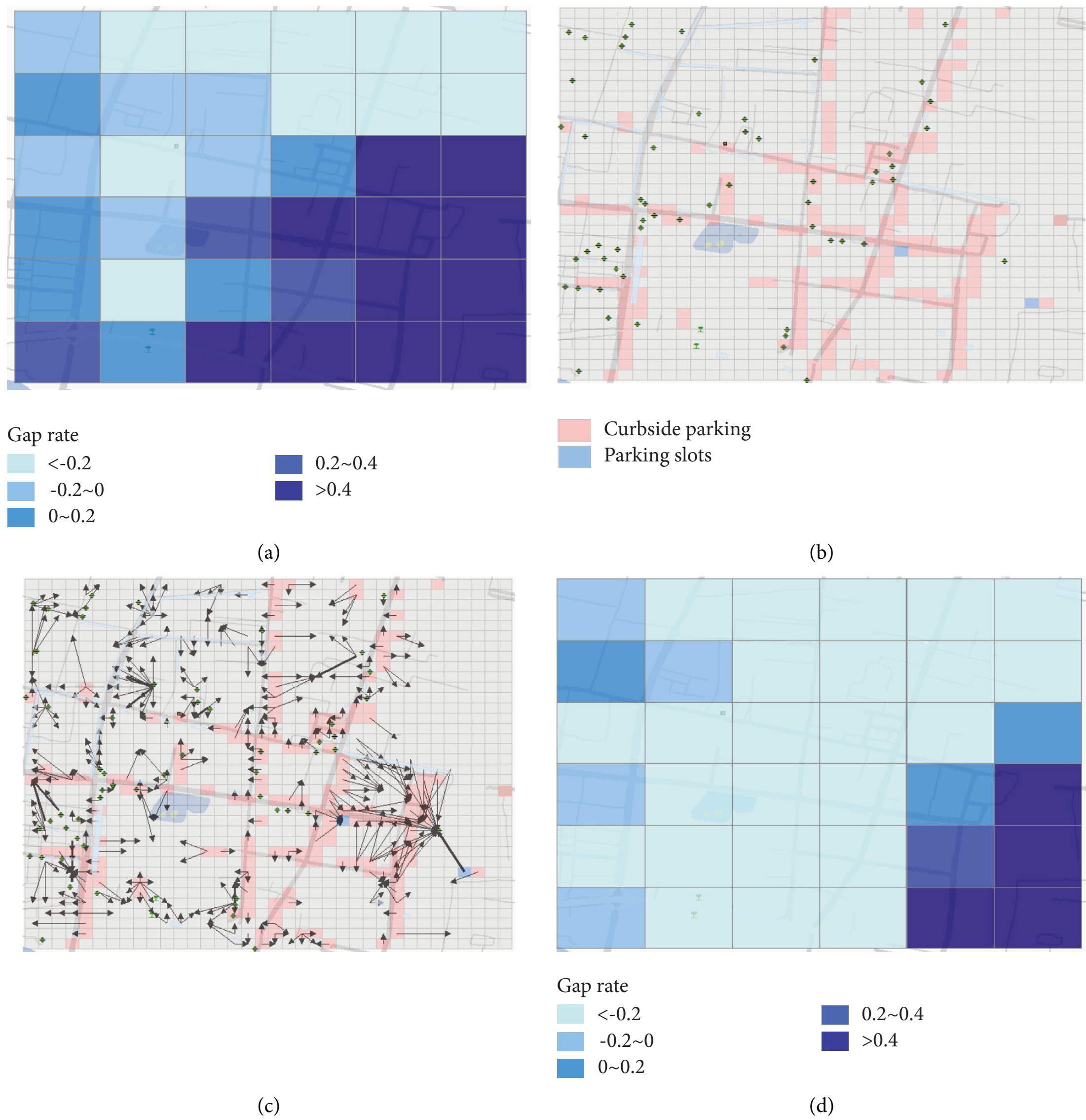


Figure 6: The optimization results of the parking resource allocation. (a) Existing imbalanced rate. (b) Optimal new facility location. (c) Vehicle-to-resource assignment. (d) Imbalanced rate after optimization.

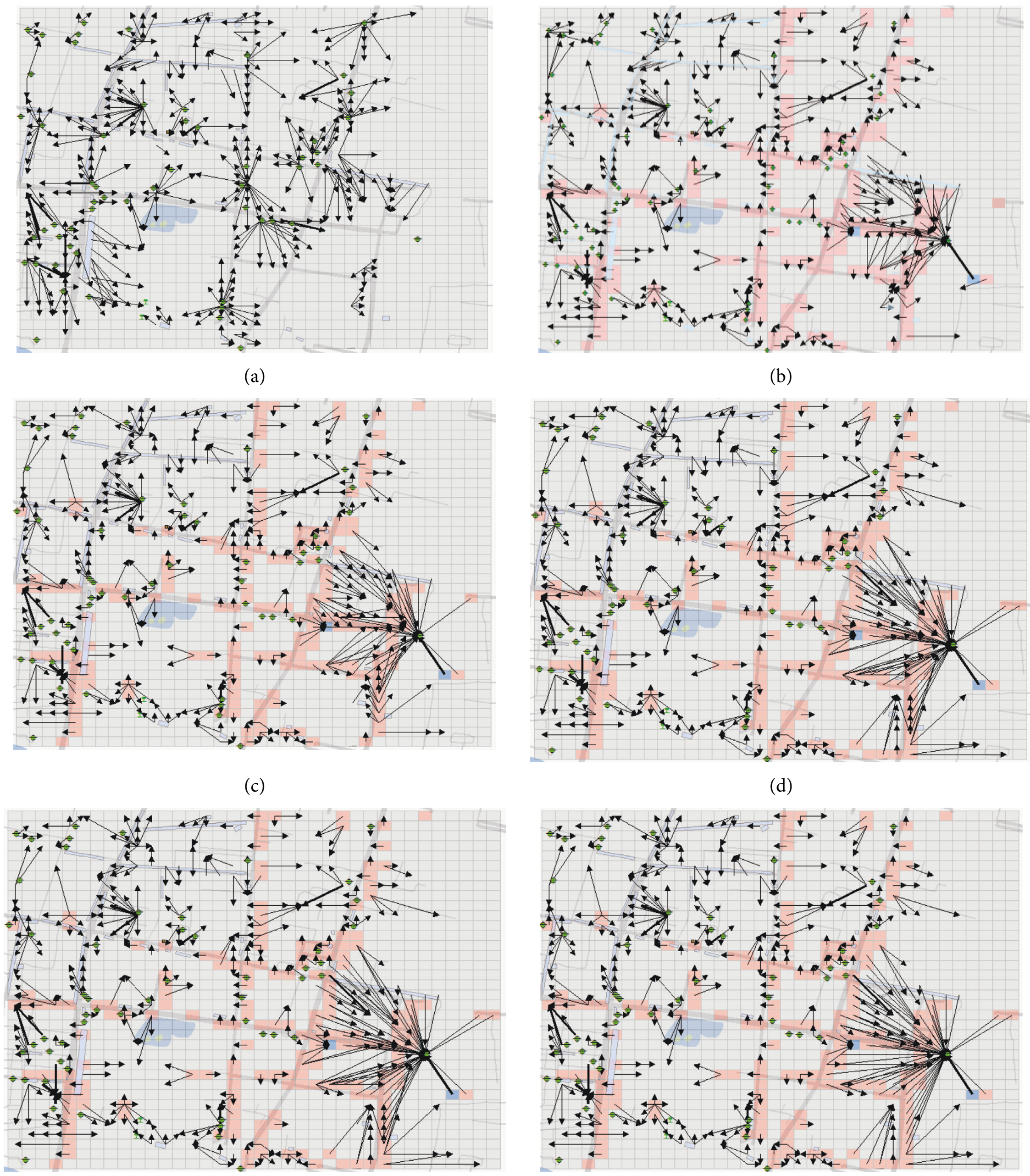
solution is completely inconsistent with the actual situation, which may lead to illegal parking without searching for an available space. Thus, six cases of $\chi = 0$ were excluded from the combinations. Finally, there were a total of 15 meaningful cases. All instances were solved using CPLEX, and the results are summarized in Table 3.

4.3.1. Extreme Cases with $\chi = 1$, $\alpha = 0$, and $\beta = 0$. As shown in Table 3, $\chi = 1$ corresponds to the situation where the travel cost and operating cost are ignored, and the total cost is the highest in all cases. This is because both the total walking distance and number of new parking facilities increase.

When $\beta = 0$, travel cost is ignored. Drivers choose a farther parking facility within the given walking distance threshold, and thus fewer new parking facilities are needed to satisfy the same parking demand. In all cases with $\beta = 0$, the number of new parking facilities was minimal, that is, 630. However, the total walking distance was the highest, approximately 70,000 m, which represents the case of sacrificing driver convenience.

$\alpha = 0$ indicates that the operating cost is neglected. In other words, parking facilities can be constructed as required. In these cases, it is convenient for drivers to park because they do not need to walk long distances to reach parking facilities. Table 3 shows that all cases with $\alpha = 0$ had a minimal total walking distance and the highest number of new parking facilities.

4.3.2. Cases with α, β, $\chi \neq 0$ or 1. When α, β, and χ attained values between 0 and 1, a weighted balance among the walking distances, new facility construction, and unserved drivers was obtained. As shown in Table 3, with the increase of the weight coefficient α on operating cost, the total number of new parking facilities decreased from 1310 to



(a) (b) (c) (d) (e) (f)

Figure 7: The optimal solutions under different maximal walking distance thresholds. (a) Assignment with existing parking resources. (b) $d = 200$ m. (c) $d = 250$ m. (d) $d = 300$ m. (e) $d = 350$ m. (f) $d = 400$ m.

Table 2: The optimal results under different maximal walking distances.

Walking distance threshold	200 without new facilities	200	250	300	350	400
Total cost	—	13712	6473	900	236	235
Walking distance	—	36457	41018	46422	46104	46066
New spaces	—	1310	1390	1456	1471	1475
Served parkers	2120	2750	2859	2943	2953	2953
Total demand	2953	2953	2953	2953	2953	2953
Percentage	71.8	93.1	96.8	99.6	100	100

Table 3: The optimal results of different weighting factor combinations.

Weighting factors			Objective values			
α	β	χ	Total cost	Total walking distance	New parking spaces	Served parkers
0	0	1	40600	69966.61	1872	2750
0	0.2	0.8	32573.24	35083.23	1930	2750
0	0.4	0.6	24546.48	35119.6	1930	2750
0	0.6	0.4	16519.72	35119.6	1930	2750
0	0.8	0.2	8492.96	35119.6	1930	2750
0.2	0	0.8	32485.31	71607.92	630	2750
0.4	0	0.6	24370.61	70945.74	630	2750
0.6	0	0.4	16255.92	69456.91	630	2750
0.8	0	0.2	8141.23	70945.74	630	2750
0.2	0.2	0.6	24467.22	36457.75	1310	2750
0.2	0.4	0.4	16442.67	36477.81	1311	2750
0.2	0.6	0.2	8418.61	36485.07	1327	2750
0.4	0.2	0.4	16355.37	38417.41	1257	2750
0.4	0.4	0.2	8334.44	36457.75	1310	2750
0.6	0.2	0.2	8241.72	38258.29	1254	2750

1254. Further, when $\alpha = \beta$, travel and operating costs are equally important. Therefore, regardless of $\alpha = \beta = 0.2$ or 0.4, the total walking distance and the number of new parking facilities are the same in the optimal solutions. In contrast, when $\alpha = 0.6$, $\beta = 0.2$, and $\chi = 0.2$, the operating cost is more important than the walking distance, and an increase of 73 new parking facilities and reduction of 1773.22 meters walking distance can be observed compared with the case of $\alpha = 0.2$, $\beta = 0.6$, and $\chi = 0.2$. Thus, in practical applications, an appropriate weight coefficient combination should be chosen based on the major concerns of real-life problems.

In practical applications, the corresponding coefficients are often set according to different scenarios. From the operator's point of view, the construction cost is often the most important one, and the convenience of users is often sacrificed when a certain utilization rate can be ensured. Therefore, the weighting coefficient in the construction of profitable parking facilities is $\alpha \geq \beta \geq \chi$. However, from the users' perspective, what they consider is often more convenient parking, so if it is a government-led parking facility construction of public welfare nature, the coefficient is generally $\beta \geq \chi \geq \alpha$.

5. Conclusion

In summary, based on a two-level grid model, this study explored a framework for the parking resource allocation optimization problem. First, the collected travel data and existing parking resource data were mapped onto upper-level grids. Thereafter, the gap between parking demand and existing supply in each upper-level grid was calculated, and the key demand-supply imbalanced grids were identified. Furthermore, ILP was proposed for solving the parking facility location and vehicle-to-resource assignment problems in lower-level grids. Finally, a real-world case study was conducted to demonstrate the feasibility and effectiveness of the proposed method. Compared to the imbalanced rate before and after optimization, the method proposed in this study can significantly relieve difficult-to-park and inconvenient-to-park problems.

However, the proposed method has certain limitations in practical applications. Generally, directly selecting an available piece of land for parking facility construction in urban areas is challenging, particularly in metropolitan areas. Therefore, the limitation of this model is that it is more suitable for developing regions where land resources are more abundant and systematic parking planning has not been carried out. In future studies, further studies on integrating parking resource management policies, including pricing and sharing measures, will be conducted to improve the research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was supported by the Fundamental Research Funds for the Central Universities (2020YJS077) National Natural Science Foundation of China under grant nos. 71901021, 71621001, and the Fundamental Research Funds for the Central Universities (2019JBZ003).

References

[1] K. Shi, B. Di, K. Zhang, C. Feng, and L. Svirchev, "Detrended cross-correlation analysis of urban traffic congestion and NO 2 concentrations in Chengdu," *Transportation Research Part D: Transport and Environment*, vol. 61, pp. 165–173, 2018.

[2] P. Zhao and H. Hu, "Geographical patterns of traffic congestion in growing megacities: big data analytics from Beijing," *Cities*, vol. 92, pp. 164–174, 2019.

[3] D. Shoup, "Pricing curb parking," *Transportation Research Part A: Policy and Practice*, vol. 154, pp. 399–412, 2021.

[4] G. Cookson and B. Pishue, *The Impact of Parking Pain in the US, UK and Germany*, INRIX Research, Kirkland, WA, 2017.
[5] D. Ayala, O. Wolfson, B. Xu, B. Dasgupta, and J. Lin, "Parking slot assignment games," in *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pp. 299–308, Chicago Illinois, November, 2011.
[6] V. Čuljković, "Influence of parking price on reducing energy consumption and co2 emissions," *Sustainable Cities and Society*, vol. 41, pp. 706–710, 2018.
[7] Z. Qian and R. Rajagopal, "Optimal dynamic parking pricing for morning commute considering expected cruising time," *Transportation Research Part C: Emerging Technologies*, vol. 48, pp. 468–490, 2014a.
[8] Z. Qian and R. Rajagopal, "Optimal occupancy-driven parking pricing under demand uncertainties and traveler heterogeneity: a stochastic control approach," *Transportation Research Part B: Methodological*, vol. 67, pp. 144–165, 2014b.
[9] F. He, Y. Yin, Z. Chen, and J. Zhou, "Pricing of parking games with atomic players," *Transportation Research Part B: Methodological*, vol. 73, pp. 1–12, 2015.
[10] M. Nourinejad and M. J. Roorda, "Impact of hourly parking pricing on travel demand," *Transportation Research Part A: Policy and Practice*, vol. 98, pp. 28–45, 2017.
[11] D. C. E. Ferreira and J. D. A. E. Silva, "Simulation of a Parking Reservations System to Mitigate Cruising for Parking," in *Proceedings of the Transportation Research Board (Meeting)*, January, 2013.
[12] C. Shao, H. Yang, Y. Zhang, and J. Ke, "A simple reservation and allocation model of shared parking lots," *Transportation Research Part C: Emerging Technologies*, vol. 71, pp. 303–312, 2016.
[13] H. Xiao, M. Xu, and Z. Gao, "Shared parking problem: a novel truthful double auction mechanism approach," *Transportation Research Part B: Methodological*, vol. 109, pp. 40–69, 2018a.
[14] H. Xiao and M. Xu, "How to restrain participants opt out in shared parking market? A fair recurrent double auction approach," *Transportation Research Part C: Emerging Technologies*, vol. 93, pp. 36–61, 2018b.
[15] C. M. Li, Y. Tao, and S. Q. Liu, "A shared parking space optimization model to alleviate China's parking problem considering travelers' tiered credit risk," *Transportation Letters*, vol. 13, pp. 45–52, 2019.
[16] I. Yaqoob, I. A. T. Hashem, A. Gani et al., "Big data: from beginning to future," *International Journal of Information Management*, vol. 36, no. 6, pp. 1231–1247, 2016.
[17] Y. Zhao, H. Zhang, L. An, and Q. Liu, "Improving the approaches of traffic demand forecasting in the big data era," *Cities*, vol. 82, pp. 19–26, 2018.
[18] N. Cárdenas-Benítez, R. Aquino-Santos, P. Magaña-Espinoza, J. Aguilar-Velazco, A. Edwards-Block, and A. Medina Cass, "Traffic congestion detection system through connected vehicles and big data," *Sensors*, vol. 16, no. 5, pp. 599–611, 2016.
[19] Y. Yang, Z. Z. Yuan, and R. Meng, "Exploring traffic crash occurrence mechanism towards cross-area freeways via an improved data mining approach," *Journal of Transportation Engineering Part A Systems*, 2022a.
[20] Y. Yang, K. Wang, Z. Yuan, and D. Liu, "Predicting freeway traffic crash severity using XGBoost-bayesian network model with consideration of features interaction," *Journal of Advanced Transportation*, vol. 2022, Article ID 4257865, 16 pages, 2022b.
[21] H. Tezcan, "Using parking pricing as a travel demand management tool at a university campus: an example for Istanbul Technical University," *Transportation Letters*, vol. 4, no. 3, pp. 181–192, 2012.
[22] S. Fei, "Parking versus public transport subsidies: case study of Nanjing, China," *Transportation Letters*, vol. 8, no. 2, pp. 1–8, 2016.
[23] N. Zheng and N. Geroliminis, "Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing," *Transportation Research Part B: Methodological*, vol. 83, pp. 36–58, 2016.
[24] X. Zhang, H. Yang, and H.-J. Huang, "Improving travel efficiency by parking permits distribution and trading," *Transportation Research Part B: Methodological*, vol. 45, no. 7, pp. 1018–1034, 2011.
[25] W. Liu, H. Yang, and Y. Yin, "Expirable parking reservations for managing morning commute with parking space constraints," *Transportation Research Part C: Emerging Technologies*, vol. 44, pp. 185–201, 2014a.
[26] W. Liu, H. Yang, Y. Yin, and F. Zhang, "A novel permit scheme for managing parking competition and bottleneck congestion," *Transportation Research Part C: Emerging Technologies*, vol. 44, pp. 265–281, 2014b.
[27] Z. Chen, Z. Xu, M. Zangui, and Y. Yin, "Analysis of advanced management of curbside parking," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2567, no. 1, pp. 57–66, 2016.
[28] C. Lei and Y. Ouyang, "Dynamic pricing and reservation for intelligent urban parking management," *Transportation Research Part C: Emerging Technologies*, vol. 77, pp. 226–244, 2017.
[29] Z. Mei, C. Feng, W. Ding, L. Zhang, and D. Wang, "Better lucky than rich? Comparative analysis of parking reservation and parking charge," *Transport Policy*, vol. 75, pp. 47–56, 2019.
[30] D. C. Shoup, *The High Cost of Free-Parking*, APA Planners Press, Chicago, 2005.
[31] T. Litman, *Parking Pricing Implementation Guidelines*, Victoria Transport Policy Institute, Canada, 2011.
[32] H. Yang, W. Liu, X. Wang, and X. Zhang, "On the morning commute problem with bottleneck congestion and parking space constraints," *Transportation Research Part B: Methodological*, vol. 58, pp. 106–118, 2013.
[33] M. A. Kazemi, M. Sedighizadeh, M. J. Mirzaei, and O. Homaee, "Optimal siting and sizing of distribution system operator owned EV parking lots," *Applied Energy*, vol. 179, pp. 1176–1184, 2016.
[34] M. Nourinejad, S. Bahrami, and M. J. Roorda, "Designing parking facilities for autonomous vehicles," *Transportation Research Part B: Methodological*, vol. 109, pp. 110–127, 2018.
[35] Y. Du, S. Yu, Q. Meng, and S. Jiang, "Allocation of street parking facilities in a capacitated network with equilibrium constraints on drivers' traveling and cruising for parking," *Transportation Research Part C: Emerging Technologies*, vol. 101, pp. 181–207, 2019.
[36] P. C. Vythoulkas, "Alternative approaches to short term traffic forecasting for use in driver information systems," *Transportation and traffic theory*, vol. 12, pp. 485–506, 1993.
[37] A. L. Ding, "Prediction of traffic flow time series based on statistical learning theory," *Computer and Communications*, vol. 20, no. 2, pp. 27–30, 2002.
[38] C. R. Bhat, J. Guo, S. Srinivasan, and A. Sivakumar, *Guidebook on Activity-Based Travel Demand Modeling for Planners*, Univ. Texas at Austin, Austin, TX, USA, 2003.

[39] P. Wang, Z. R. Huang, and H. Gong, “Transportation engineering in the big data era,” *Journal of University of Electronic Science and Technology of China*, vol. 42, no. 6, pp. 806–816, 2013.

[40] X.-j. Zhao and J.-y. Zhao, “Research on model of resource management for traffic grid,” *Procedia Engineering*, vol. 15, pp. 1476–1480, 2011.

[41] S. O’Sullivan and J. Morrall, “Walking distances to and from light-rail transit stations,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1538, no. 1, pp. 19–26, 1996.

[42] K. Chen, J. J. Wang, and F. Han, “CICTP 2012 : multimodal transportation systems : convenient, safe, cost-effective, and efficient,” in *Proceedings of the Twelfth COTA International Conference of Transportation Professionals*, Beijing, China, August, 2012.

[43] D. A. Hensher and J. King, “Parking demand and responsiveness to supply, pricing and location in the Sydney central business district,” *Transportation Research Part A: Policy and Practice*, vol. 35, no. 3, pp. 177–196, 2001.

[44] Y. Guan, Y. Wang, X. Yan, H. Guo, and Y. Zhou, “A big-data-driven framework for parking demand estimation in urban central districts,” *Journal of Advanced Transportation*, vol. 2020, Article ID 8898848, 13 pages, 2020.