Hindawi
Journal of Advanced Transportation
Volume 2020, Article ID 6147974, 11 pages
https://doi.org/10.1155/2020/6147974

Research Article

A Distribution Model for Shared Parking in Residential Zones that Considers the Utilization Rate and the Walking Distance

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Received 6 January 2020; Accepted 11 February 2020; Published 23 March 2020

Guest Editor: Dongfang Ma

Efficient parking tends to be challenging in most large cities in China. Drivers often spend substantial amounts of time looking for parking lots while driving at low speeds, thereby resulting in interference with road traffic. This paper focuses on efficiently allocating parking spaces to the demanders. A double-objective model is proposed that considers both the utilizing rate and the walking distance. First, managers want to utilize parking resources fully. Therefore, they tend to prioritize the efficient distribution of parking spaces in response to parking demands. However, demanders typically choose parking spaces according to convenience. The second objective is the acceptable walking distance from the parking space to the destination. The particle swarm optimization (PSO) algorithm is used to solve this model. We collected parking demand and supply data in a central business district (CBD) of Harbin in China and evaluated the feasibility of the model. The results demonstrate that the proposed model increases the occupying rates of parking lots in residential zones while decreasing the walking distance. The shared use of parking spaces maximizes the utility and alleviates the shortage of parking spaces in downtown.

1. Introduction

Parking efficiently is a significant concern in traffic planning in many modern cities due to the fast increase in the number of private cars [1]. Parking planning has attracted attention from traffic engineers and managers because the unreasonable design of parking lots may reduce the capacity of urban roads and increase the risk of accidents. For example, the shortage of auxiliary parking lots and public parking spaces forces drivers to leave their cars at the roadside, which not only causes traffic congestion but also traffic conflicts. Drivers tend to decrease the speed of their cars to find a parking lot, which will also affect the following vehicles' normal operation. However, it is difficult to thoroughly solve these problems by establishing new parking facilities [2], especially in central business districts (CBDs), where there is a shortage of parking spaces due to limited land use.

Similarly, parking problems are severe in many core areas in the urban city where the buildings are dense. The availability of parking spaces is even more inadequate. The time that travelers spend finding a suitable parking space and walking to his or her workplace may constitute a large part of the total travel time [3]. Cruising process can also produce a substantial amount of congestion and exhaust pollution [4, 5]. However, many residential parking spaces near a CBD are available after the owners go out in daytime. These vacant parking spaces can be meanwhile provided for demanders who go shopping or do other things in a CBD. This mode of availability is cycled every day, which provides a parking gap for demanders who come to CBD in the daytime. Hence, this gap parking mode, which is called shared parking, not only helps the parking space owners get extra profits but also substantially alleviates the urgent parking needs downtown.

Systematic parking management mostly focuses on effective countermeasures for resolving the imbalance between supplies and demands. The proposed parking strategy involves not only increasing the parking supply but also efficiently utilizing current parking lots [6]. Effective parking management requires a more comprehensive consideration of the balance between supply and demand [7–9]. This is challenging for most parking managers. They typically take various methods which include shared parking, publicly displaying available parking spaces, and adjusting parking charges [10, 11]. The safety and reliability of parking facilities during use are considered by managers [12, 13]. The management objectives for parking lots basically include realizing the maximum occupying rate, the minimum cruising duration, and the most rational benefits.

Parking choice, which seems a subjective behaviour for a driver, directly affects parking management strategies [14]. Driver choice behaviour has been extensively studied. Drivers' previous experiences are believed to play a substantial role in the selection of a parking lot [15]. In addition, drivers will take the travel distance, parking cost, and travel purpose into account [16, 17]. Accordingly, shared parking is gradually becoming accepted by suppliers and demanders of parking spaces. The shared parking fee is typically lower than the fee in the nonshared parking mode, and the demanders can easily select the nearest parking lots online in advance. Zargayouna et al. proposed an online shared information system for parking demanders. The drivers could choose the parking spaces in advance, and the searching time was decreased [18]. Kaspi et al. presented a parking reservation method online by use of a Markov model. The applications showed that the total excess time was reduced by more than 14% [19, 20]. Shao et al. suggested that drivers reserved the favorite parking lots on platform, which provided profit both for owners and users [21].

Searching a vacant parking space tends to take a long time and leads to exhaust emission and congestion [22]. Fortunately, intelligent systems, by collecting and releasing the data from demanders and suppliers, can facilitate the automatic distribution of parking spaces [23]. Therefore, managers can more easily plan parking lots and drivers can more easily locate available parking spaces. Many macro- and micromodels of parking management and space distribution have been proposed [24–26]. In addition, the imbalance between parking supply and demand by constructing complex intelligent parking systems is a hot topic. For example, the "Smart Parking" and "Parking guidance" systems can intelligently assign a selected parking space to a driver [27, 28]. Afterwards, parking spaces can be assigned among buildings or lots based on a network algorithm [29]. Jin Cao and Monica Menendez evaluated the practicability and economy of intelligent parking systems and found that the application of an intelligent system reduced the searching duration by 17% [30]. With the rapid development of smart devices and wireless sensor networks, a variety of web-based apps and online parking search sites have emerged in recent years. For example, SpotHero, Pango, and Parkme are web and mobile applications that enable drivers to view parking information and reserve and pay for parking from any smart device in New York City.

The following sections of this paper describe the shared parking characteristics, parking spaces allocating model and solution, case study and conclusions. Section 2 analyzes the shared parking characteristics and then presents parameters and variables to be used later. Section 3 proposes a mathematical model for allocating parking spaces and the particle swarm optimization to solve the model. Based on the data collected from CBD in Harbin, China, a numerical simulation is conducted in Section 4. The last section presents the conclusions of this paper and provides perspectives.

2. Shared Parking Characteristics and Term Definitions

2.1. Problem Description. Shared parking basically involves the collection, release, and processing of information from supply and demand sides. These operations can be handled by an online shared parking system. Normally, reserving a parking space online is ahead of one's actual occupation. Drivers need to search the suitable parking spaces in advance. The demander side seems to play an active role because it can choose parking lots and cancel reservations at will. Parking locations depend on drivers' preferences because they tend to take the properties of parking lots, walking distances, and parking fees into account in most cases. However, the shared parking system can provide recommendations based on optimization models as well. These models generally consider the walking distance of drivers after parking, time windows of supply and demand, and utilization of parking spaces.

2.2. Conditions for Shared Parking. Shared parking is an effective way of optimizing the utilization of parking spaces, especially in large cities. To realize parking sharing, three conditions should be satisfied: (1) multiple destinations are located around the parking lots; (2) the walking distance after parking is within an acceptable range; (3) parking spaces are open to the public or vehicles are conditionally allowed to park. These conditions may meet people's needs regarding access to multiple destinations after parking and may ensure that drivers choose parking spaces in advance. Shared parking is typically an inherent part of downtown, as the same parking space serves multiple destinations within acceptable walking distance. For example, the parking lots of a residential zone may practically be shared by the people who work in an office building or shop in a supermarket nearby. Many parking spaces in a residential zone will be free during the daytime when there are urgent parking demands at the office building or the supermarket.

Shared parking may realize benefits for every participant. Owners of parking spaces can specify free periods on the platform where the drivers can easily search. A residential property or a parking management company can use some algorithms to manage parking spaces more efficiently. Shared parking can be simply described as follows. There are several destinations near the parking lots. Assume that each destination generates parking demands on a specified day and there is more than one residential zone near each destination. The owners of parking spaces formulate a leasable timetable of parking spaces according to their travel habits, commuting time, and occupying time. Then, the timetable will be available on the parking management platform. A shared parking space may have one or more sharing periods. Every start time and end time for sharing should be specified on the management platform in advance. The platform normally allocates the parking spaces according to the requirements of demanders. If the demanders have no special requirements, the platform will automatically allocate parking spaces in accordance with the leasable timetable.

2.3. Term Definitions. The essential terms used in this paper are described as follows:

D: Commercial zones studied in this paper.

A: The set of destinations near the commercial zones, namely, $A = \{a/a = 1, 2, \ldots, k\}$, where k is the number of all destinations. The number of parking demands which are generated from each destination on a specified day is i. And there is no less than one residential zone near each destination.

H: The set of shared parking spaces in the residential zones, namely, where h_i is the number of parking spaces.

M: The set of parking demands, namely, $M = \{m/m = 1, 2, \ldots m_i\}$, where m_i is the number of all overflowing parking demands.

x_{mh}: A binary variable. $x_{mh} = 1$ represents that parking demands can be successfully distributed to parking spaces; otherwise, $x_{mh} = 0$.

In summary, x_{mh} is determined via

$$x_{mh} = \begin{cases} 1, & \text{distributed successfully}, \\ 0, & \text{else}. \end{cases} \tag{1}$$

y_h: the parking space utilization means the ratio of the shared duration to the whole available duration

t^m_{arr}: the time when the demander arrives to the scheduled parking space

t^m_{lea}: the time when the demander leaves the parking space

t^m_{dur}: the actual occupying duration of a parking space

$$t^m_{dur} = t^m_{lea} - t^m_{arr}. \tag{2}$$

a^s_h: the start time when the parking space is available

b^e_h: the end time when the parking space is available

s_h: the actual available duration of a parking space, which covers from a^s_h to b^e_h for per time gap

$$s_h = b^e_h - a^s_h. \tag{3}$$

d_{mh}: a variable that indicates whether the demanding time follow into the available time gap

f: the walking distance from the parking space to the destination

L_{mh}: the walking distance that drivers can be acceptable

L_{max}: the maximum walking distance after parking

To analyze the influence of walking distance after parking on driver's choice, we conducted a survey in Le Song CBD in Harbin city, China. This survey was inspired by Waerden et al. in 2017 [31]. We proposed eight levels of waking distaces after parking, that were less than 200 m, 200 to 250 m, 250 to 300 m, 300 to 350 m, 350 to 400 m, 400 to 450 m, 450 to 500 m, and more than 500 m. The description of the question is "How far is your acceptable distance after parking?". The survey lasted for 7 days including weekdays and weekends. A total of 685 valid questionnaires were collected and 34 participants could accept more than 350 m. It meant that more than 95% of participants were unwilling to walk more than 350 m after parking. According to this survey, this study proposed that the acceptable maximum walking distance is equal to 350 m.

3. Methodology

3.1. Model Assumptions and Constraints. To realize parking sharing between the commercial zones and the residential zones, we propose a biobjective model. Assumptions and constraints are imposed to ensure the operability and the feasibility of the model.

3.1.1. Model Assumptions. The following assumptions are imposed in the model:

(1) The parking lots in the residential zone are accessible to the demanders and the parking spaces are easy to reach, namely, that there are no locks or other obstacles.
(2) The owners of the parking spaces comply with the platform regulations. They may choose the period for sharing their parking spaces, namely, they may set the sharing time window and the unit time price.
(3) Demanders who want to utilize the shared parking spaces should understand and abide relevant regulations. For example, if they occupy the parking spaces after the shared time ends, they will accept the penalty charging method.
(4) The demanders have no preference for specific parking lots in residential zones.

3.1.2. Constraints on Various Parking Demand Periods. Because travel purposes differ, parking times differ among drivers for the same parking space. Therefore, each parking demand is restricted by the dwell time of other demands:

$$n_{m_1 m_2} = \begin{cases} 1, & \left(t^{m_1}_{arr}, t^{m_1}_{lea}\right) \cap \left(t^{m_2}_{arr}, t^{m_2}_{lea}\right) \neq \varnothing, \\ 0, & \left(t^{m_1}_{arr}, t^{m_1}_{lea}\right) \cap \left(t^{m_2}_{arr}, t^{m_2}_{lea}\right) = \varnothing, \end{cases} \quad m_1, m_2 \in M. \tag{4}$$

3.1.3. Constraints on the Shared Timetable and Parking Demand Periods. Similar to the parking demand, the sharing period of a parking space is related to the owner's travel habits and commuting time. The demanding duration should be content with the available time gap of a parking space. So the demand decision matrix $D = [d_{\mathrm{mh}}]$, where $m = 1, 2, \ldots, M$ and $h = 1, 2, \ldots, H$:

$$d_{\mathrm{mh}} = \begin{cases} 0, & \left(t_{\mathrm{arr}}^{m}, t_{\mathrm{lea}}^{m}\right) \in \left(a_h^s, b_h^e\right), \\ 1, & \text{else}. \end{cases} \tag{5}$$

3.2. Mathematical Model of Parking Space Allocation. The shorter the walking distance after parking is, the more likely a demander will choose the corresponding parking space. The walking distance tends to be the dominant factor for demanders. However, for parking platforms, the shared space utilization rate is the main consideration because a higher utilization rate is associated with higher profits. Therefore, the most important objective of allocating parking spaces is to maximize the utilizing rate, as expressed in equation (6). The premise is that the walking distance does not exceed the maximum acceptable distance, as expressed in equation (7). Integrating the objective function and the specified constraints, the model can be expressed as follows.

$$\max\ y = \frac{\sum_{h_i=1}^{H} \sum_{m_i=1}^{M} t_{\mathrm{dur}}^{m} x_{\mathrm{mh}}}{S(H)}, \tag{6}$$

$$\begin{aligned} f &= \min_{L_{\mathrm{mh}} \le L_{\max}} x_{\mathrm{mh}} L_{\mathrm{mh}}, \\ \text{subject to,} \quad & x_{m_i} + n_{m_i m_j} \cdot x_{m_j} \le 1, m_i, \quad m_j \in m; m_i \ne m_j, \\ & d_{\mathrm{mh}} \cdot x_{\mathrm{mh}} = 0, \quad m \in M; h \in H, \\ & \sum_h x_{\mathrm{mh}} \le 1, \end{aligned} \tag{7}$$

where $S(H) = \sum_{h_i} s_h$, $s_h = \sum_{h_i} (a_h^s - b_h^e)$.

3.3. Particle Swarm Optimization Algorithm. Currently, Genetic Algorithm [32, 33], Markov Chains [34], and Neural Network Algorithm [35, 36] are widely used to solve multiobjective optimization problems. Although these algorithms can obtain a set of feasible solutions which satisfies the objective function, problems such as slow convergence and complex coding began to become apparent when the number of problem reach a larger size. PSO can overcome such problems of traditional global searching algorithms. PSO is inspired by the foraging behaviour of birds in nature and then gradually developed based on global searching algorithms. Compared with other heuristic algorithms, PSO algorithm is suitable for solving large-scale multiobjective problems. It converges fast to optimal solution and encodes simply because it only uses a few parameters for tuning [37–39]. Based on the mentioned characteristics, the PSO algorithm is applied to solve the double-objective model that considers the utilizing rate and the walking distance.

PSO algorithm generally includes some particles which can be expressed by two vectors, namely, a position and a velocity. The first vector means a potential action to address a problem and the second means the changing direction and magnitude variable. For example, in a dimension d space involving I particles, the position set of the i_{th} particle can be described as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, $i = 1, 2, \ldots, I$. Meanwhile, its speed can be described by $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. The particle's position can be fixed by two factors, namely, the inertia factor ω and the learning factors c_1 and c_2. The individual optimal position p_{id} and the global optimal position p_{gd} are able to adjust their positions. The update of a particle position set $\{x_k\}$ and the velocity set $\{v_k\}$ is a random process with substantial random features. The following equations express the updating performance of the position and velocity of the i_{th} particle. They mean an iterating process from step k to $k+1$.

$$v_{\mathrm{id}}^{k+1} = \omega v_{\mathrm{id}}^{k} + c_1 r_1 \left(p_{\mathrm{id}}^{k} - x_{\mathrm{id}}^{k}\right) + c_2 r_2 \left(p_{\mathrm{gd}}^{k} - x_{\mathrm{id}}^{k}\right), \tag{8}$$

$$x_{\mathrm{id}}^{k+1} = x_{\mathrm{id}}^{k} + v_{\mathrm{id}}^{k+1}. \tag{9}$$

In the formula (8), r_1 and r_2 represent the independent random values which distribute uniformly from 0 to 1. c_1 and c_2 are learning factors, which are typically integers that are equal to 2.

The term ω, applied in global and local search, means the inertia factor. If it is large, the PSO algorithm is biased towards global search. If it is small, the algorithm is biased towards local search. The value of ω mostly adopts the linearly decreasing weighting strategy in the classical PSO iterative process, as expressed in equation (10), which is randomly distributed in the range of [0.1, 0.9].

$$\omega_k = \omega_{\mathrm{end}} + \left(\omega_{\mathrm{ini}} - \omega_{\mathrm{end}}\right) \frac{K - k}{K}. \tag{10}$$

In the formula (9), ω_{end} and ω_{ini} are defined as constants and their values are 0.4 and 0.9. The terms k and K are defined as the present and maximum iterative times, respectively. Figure 1 presents a flowchart of PSO algorithm. The process of obtaining optimal solutions is shown as follows:

(1) Creation and initialization of the parameters: the parameters involve the particles number, learning factors, weighting factors, maximum iterative times, current positions, and velocities

(2) Calculation and determination of the particles values: these values involve the fitness value, individual, and group optimized value

(3) Calculation and update of the inertia factor via equation (10)

(4) Iteration and replacement of the particles positions and velocities by use of formulas (8) and (9)

(5) Update and determination of the optimal values for individual and group particles

(6) Calculating stop or returning: the research will suspend and the calculating values will be exported when the times of maximum iteration is achieved, or go back to (3)

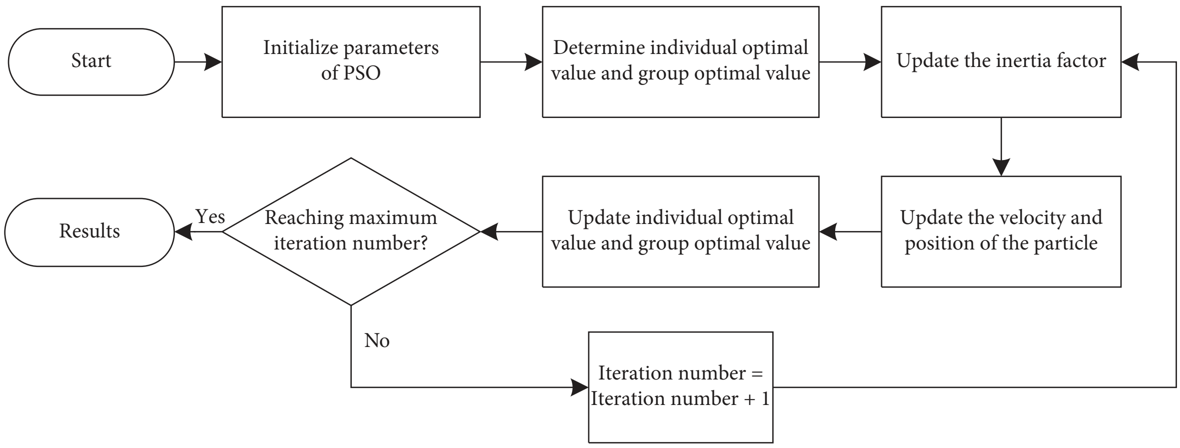

Figure 1: Flowchart of the PSO algorithm.

4. Case Study

4.1. Data Setup

4.1.1. Study Area. In order to observe the application of the developed model, the essential parking data was collected in Le Song CBD in Harbin City, China. It is one of the most prosperous commercial centers in the city. There are two commercial zones: Le Song Plaza and Song Lei Commercial Building. Two residential zones, namely, Peace Community and Triumph Square, are also located near the CBD. The commercial activities of Le Song Plaza and Song Lei Commercial Building are intensive during the daytime, which results in high parking demands. At the same time, the parking spaces in Peace Community and Triumph Square that are near the commercial zones are not fully utilized. The geographical locations of the four study zones in this paper are illustrated in Figure 2.

4.1.2. Data Preparation. To solve a dynamic online problem such as parking space distribution, a large amount of spatiotemporal data, including the walking distance after parking, the parking requests in commercial zones, and the idle parking spaces in residential zones, is necessary for identifying the optimal solution.

Table 1 lists the walking distances after parking between commercial and residential zones. These distances are actual distances between the entrances or exits of the buildings and the parking spaces. The distance between Le Song Plaza and Triumph Square is 213 m, the distance between Song Lei Commercial Building and Peace Community is 268 m, and the distance between Song Lei Commercial Building and Triumph Square is 296 m. However, the pairwise distance between Le Song Plaza and Peace Community is 472 m. The walking distance data set between these two commercial zones will not be used in this paper because the distance exceeds 350 m due to their geographical locations and intersection.

Le Song Plaza and Song Lei Commercial Building have no real-time parking requests because there is no shared parking guidance or distribution system. Therefore, the parking request data are represented by data regarding the vehicles in the commercial building parking spaces. The survey period was determined by the residents' commuting time in this area, from 9:00 AM to 5:00 PM. Table 2 shows the number of demands, the destination of each demand, and t_{dur}.

A total of 347 parking requests in these two commercial buildings during the 8-hour period is recorded in Table 2. Tables 3 and 4 show the shared parking lots and their rental time windows in Peace Community and Triumph Square, respectively. Note that the parking lots include both underground and ground parking lots. The Peace Community can provide a total of 150 parking lots for requests submitted by demanders while the Triumph Square provides approximately 100 parking lots. Suppose that no special events or holidays affect demanders' parking preference.

4.1.3. Parameter Settings. The multiobjective model of shared parking distribution can be solved by PSO algorithm. In the parameter optimization, the population size is taken as 50, the maximum iterative times is taken as 100, learning factors is taken set as 2, respectively ($c_1 = c_2 = 2$), the inertia factor is taken as 0.9 ($w_{\mathrm{ini}} = 0.9$), and the ending inertial factor is set as 0.4 ($w_{\mathrm{end}} = 0.4$). The optimization process is implemented according to Figure 2. A total of 50 independent runs of all algorithms is performed. After running the algorithms, we can obtain the demands from two commercial buildings to Peace community and Triumph Square.

4.2. *The Characteristic of Parking.*

The utilizing rate of parking spaces reflects the performance of a parking lot. The more vacant parking spaces the parking lots have, the more the spaces can be provided for sharing. Figure 3 illustrates the utilization rate of Triumph Square and Peace community during daytime (between 9:00 and 17:00). We can observe that the parking lots have an obvious temporal characteristic in residential zones. Particularly, in Peace Community, two low peak periods (9:00–11:00 and 15:00–17:00 pm) are shown during daytime.

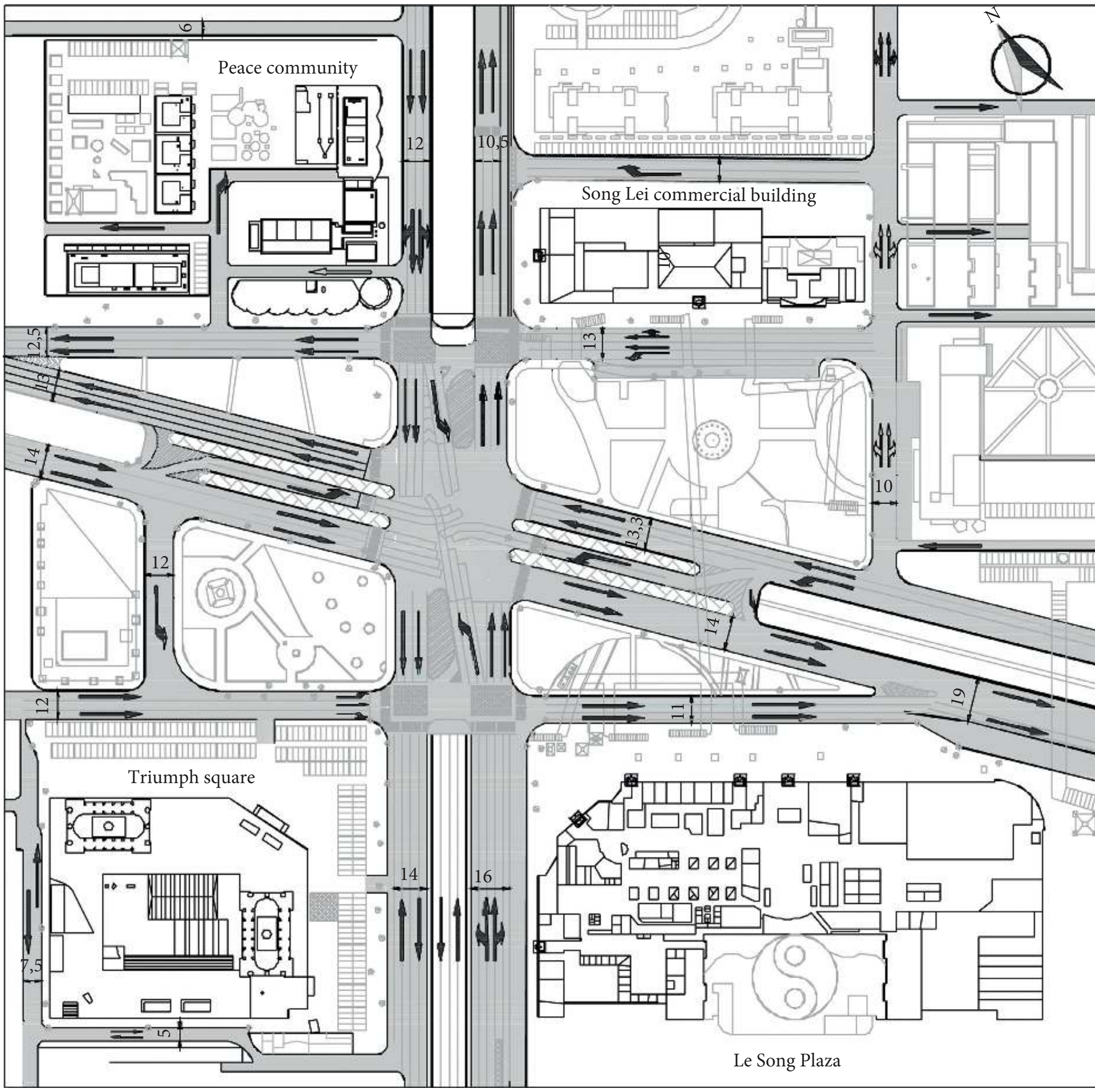

Figure 2: Study area.

Table 1: Walking distance after parking.

Commercial zones	Residential zones	
	Peace community (m)	Triumph square (m)
Le Song Plaza	472	213
Song Lei commercial building	268	296

The number of vehicles arriving at the commercial buildings reflects the potential parking demands. As shown in Figures 4 and 5, the number of arriving vehicles to Le Song Plaza and Song Lei commercial building varies as time goes by. The maximum demanding peak appears at 11:00 and 15:00. However, the nearby residential zones may provide the parking lots just then, as shown in Figure 3. As a result, the sharing of parking lots between residential and commercial zones tends to be a feasible approach to alleviate parking demands in commercial zones.

4.3. Analysis of the Results. The model considers two objectives, maximum utilization of spaces and minimum walking distance after parking. The two objectives represent the optimal utilization of public parking lots and the optimal

Table 2: Parking demands.

No.	Time	t_{dur}	Destination (1, 2)
1	9:00	9:00-10:30	1
2		9:00–11:00	2
3		9:00–11:00	1
4		9:00–15:00	2
⋮	⋮	⋮	⋮
346	16:00	16:00–16:3 0	2
347		16:00-17:00	1

1 represents Le Song Plaza and 2 represents Song Lei Commercial Building.

Table 3: Vacant parking spaces in Peace Community.

No.	Rental time window
1	9:00–12:00
2	9:00–11:00
3	9:00–14:00
...	...
149	16:00–17:00
150	16:00–17:00

Table 4: Vacant parking spaces in Triumph Square.

No.	Rl Te window
1	9:00–12:00
2	9:00–11:00
3	9:00–11:30
...	...
108	15:00–16:00
109	15:00–17:00

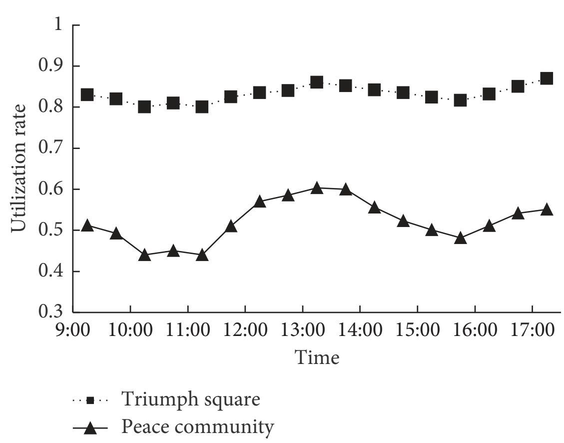

Figure 3: The changes of utilization rate between residential zones.

walking distance for the drivers. In addition, to efficiently guide drivers' parking, the optimal solution prioritizes the walking distance. Figures 5–7 show the assigned demands from two commercial buildings to the Peace Community and Triumph Square in the parking sharing plan.

Based on the characteristics of parking spaces supply and demand, the excessive demands of Le Song Plaza are distributed to Triumph Square and the demands of Song Lei Commercial Building are allocated to Peace Community and Triumph Square. It is possible to implement a shared parking distribution plan in CBD. In addition, the demands that are allocated by the three sharing plans during the study period are approximately equal; however, the peak hours of demand allocation to parking spaces differ. The peak hours of the sharing plans from Le Song Plaza to Triumph Square and from Song Lei Commercial Building to Triumph Square are 13:00–14:00, while the sharing plan from Song Lei Commercial Building to Peace District exhibits the lowest demand during this time. This is because the staff of Triumph Square go home at noon and leave many parking spaces open, whereas the opposite occurs in Peace Community.

The parking demands of Le Song Plaza cannot be allocated to Peace Community, which may be the cause of this phenomenon. The main time intervals when the demands of Song Lei Commercial Building are allocated to Peace Community are 10:30–12:00 and 14:00–16:00 since the residents in the community drive more during this time, thereby leaving many lots vacant.

Figure 7 shows the results of the sharing plan between Song Lei Commercial Building and Triumph Square. Cars drive from Song Lei Commercial Building to Triumph Square Parking all the time after 11:00, except 14:00-15:00. A possible explanation is that the staff of Song Lei Commercial Building return to their workplace from 13:00-14:00 and they prefer to walk across the street compared to driving through the street.

For travelers, they tend to pay more attention to travel time. Walking distance after parking commonly becomes an important factors considering by drivers. Figures 8–10 show the total walking distance among three distribution plans. For the distribution plan of Le Song Plaza and Triumph Square, the distance increases dramatically from about 1.5 km to 6.6 km at 13:30, and then steadily decreases to around 0.1 km at 15:00. From 15:00 to 17:00, the distance reaches a maximum value at 16:30. And for the distribution plan of Song Lei commercial building and Triumph Square, the changes of distance are similar as in Figure 8. This phenomenon indicates that the number of parking lots provided by Triumph Square is much more during 13:00 to 14:00 than other time. Therefore, the operator can transfer a large amount of parking requests in these two commercial zones to Triumph Space in order to ease the congestion of commercial zones. Compared to other distributions, the walking distance between Song Lei commercial building and Peace Community shows lowest during 13:00 and 14:00.

As discussed previously, distances that exceed 350 m were eliminated from the study data. The average walking distances are summarized in Figure 11. It denotes the ratio of the total walking distance to the requests. The average walking distance was approximately 250 m, and most of these distances were shorter than 300 m, which illustrates that the empirical application is successful. In other words, in the case of ensuring the walking distance, the shared parking distribution plan can effectively improve the utilization rate of parking lots in residential zones and alleviate congestion in commercial zones. In addition, most of the

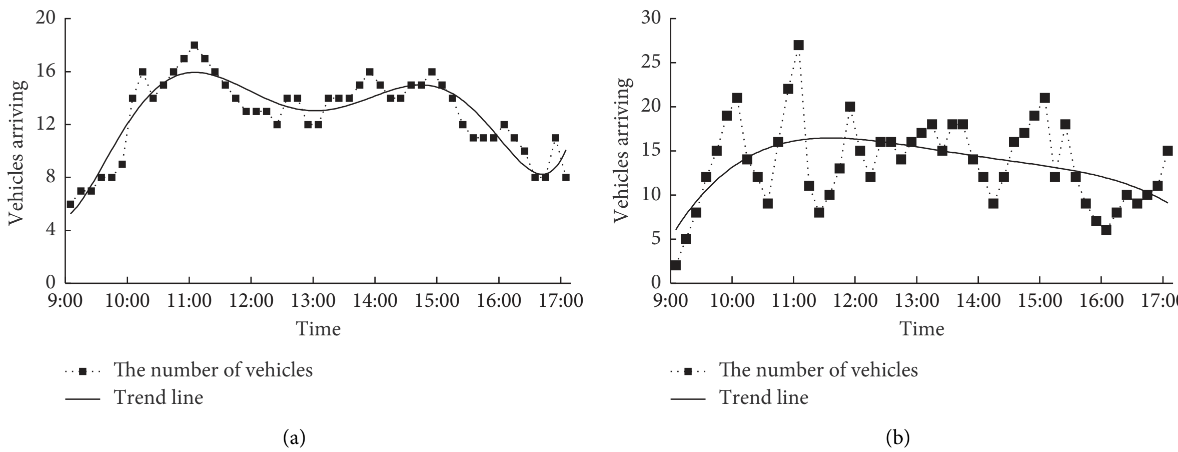

Figure 4: The changes of vehicle arriving between commercial zones. (a) Le Song Plaza. (b) Song Lei commercial building.

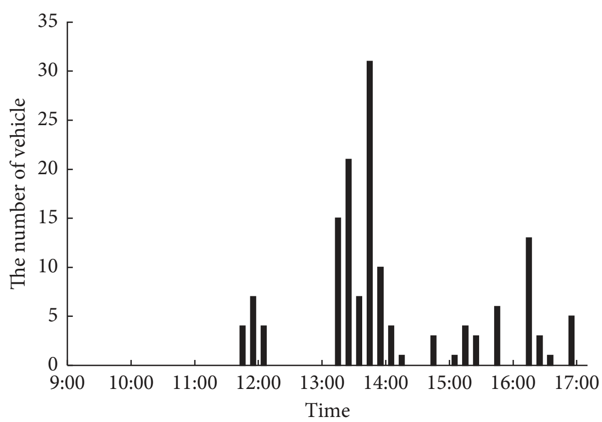

Figure 5: Distribution plan between Le Song Plaza Commercial Building and Triumph Square.

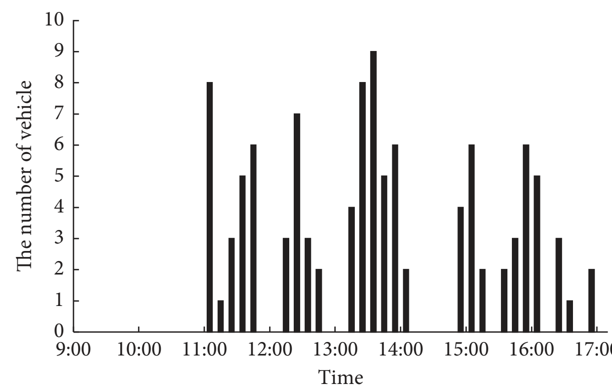

Figure 7: Distribution plan between Song Lei Commercial Building and Triumph Square.

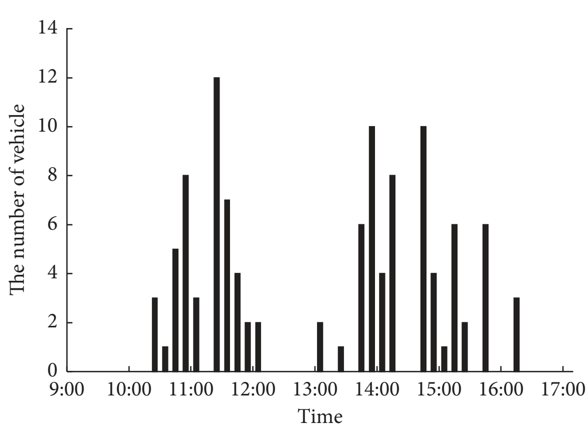

Figure 6: Distribution plan between Song Lei Peace Community.

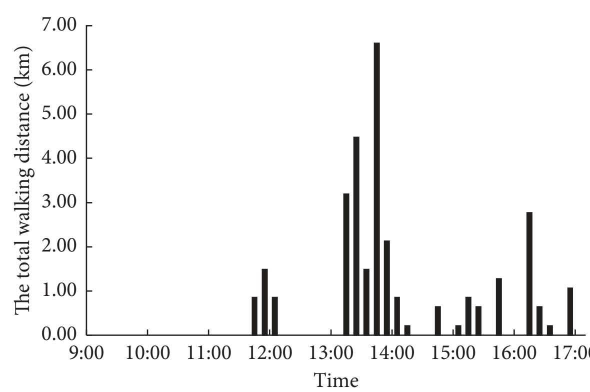

Figure 8: Total walking distance after parking from Le Song Plaza to Triumph Square.

walks will be less than 3.5 min in duration at the typical speed of an adult (1.2 m/s). Note that time spent waiting for the traffic lights at intersection is not included. As a result, the walking time may be only 1/5 or less of the driver's time for finding spaces.

Figure 12 shows the utilizing rate of parking lots in Triumph Square when using the distributing algorithm. The utilization rate of parking lots tends to be 10% higher when we apply the distributing algorithm, especially during 14:00 to 16:00. Figure 13 shows the utilizing rate of parking lots in Peace Community when using the distributing algorithm.

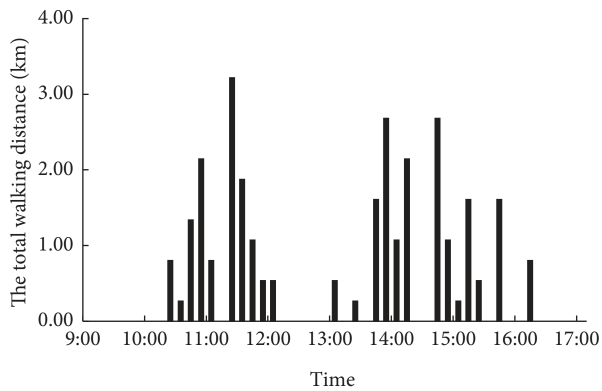

Figure 9: Total walking distance after parking from Song Lei Commercial Building to Peace Community.

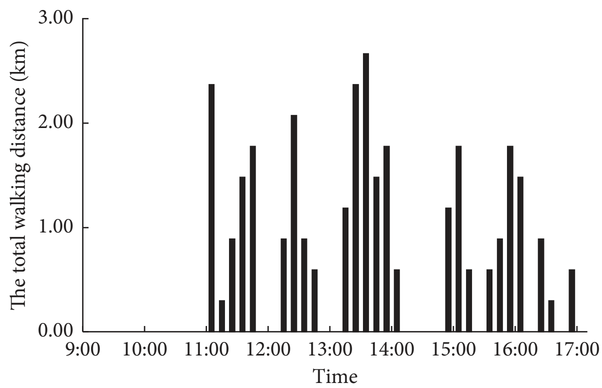

Figure 10: Total walking distance after parking from Song Lei Commercial Building to Triumph Square.

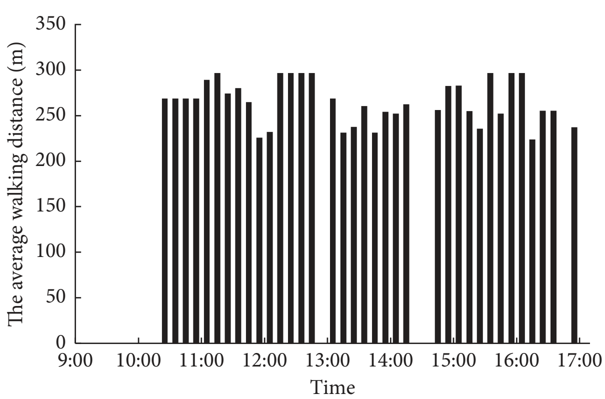

Figure 11: Average walking distance after parking.

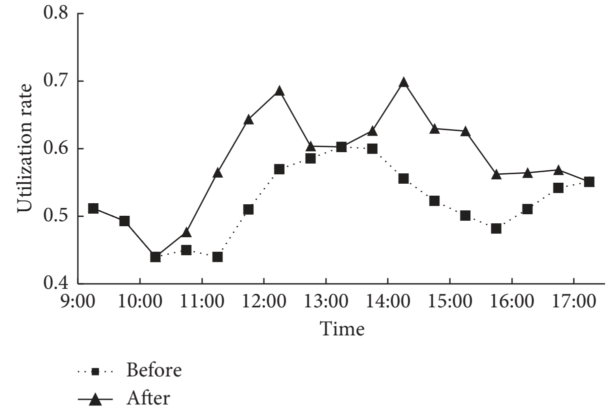

Figure 12: Utilizing rate of parking lots in Triumph Square.

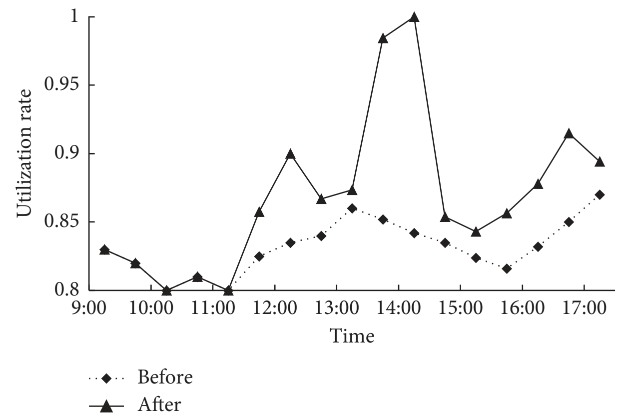

Figure 13: Utilizing rate of parking lots in Peace Community.

Similarly, the utilization rate of parking lots increases about 10%.

It can be seen from the Figures 12 and 13, the utilization rates of parking lots in both residential zones and commercial zones have temporal characteristics. Using the sharing plan and distributing algorithm, the vacant parking lots are taken full use. Meanwhile, the parking demands in commercial zones are alleviated accordingly.

5. Conclusions

This paper analyzes shared parking allocation problems between parking demands in commercial buildings and parking supplies in residential zones. The concept of shared parking is proposed, which is according to the preconditions of shared parking implementation. Then, the feasibility of shared parking between parking requests from commercial buildings and private paid or public free parking lots in residential zones is initially evaluated by analyzing the characteristics of shared parking, which include win-win, convenience, economy, and real-time performance. Next, a bitarget parking spaces allocating model involving the minimum walking distance and the maximum utilization is proposed. The model comprehensively considers the drivers' walking distance and the utilization of parking spaces. It not only receives reception requests for buildings in commercial zones, but also assigns them to corresponding vacant parking lots in accordance with the model hypothesis and parking space-time constraints. PSO algorithm is applied to solve the parking allocation model. Finally, a numerical simulation is conducted to determine whether the allocation model can feasibly realize shared parking in residential zones by collected data. The results demonstrate that the paid or free use of the vacant parking lots in the residential zones can effectively attract parking requests from the surrounding commercial buildings. The proposed model can increase the utilization of parking spaces in residential zones and decrease the walking distance after parking.

The shared parking scheme in residential areas has demonstrated potential value because it can reduce traffic congestion, exhaust gas pollution, and time wasting due to parking difficulties at nearly zero cost. Although not thoroughly studied in this paper, the commercial value (economic profits) of the shared schemes, against the background of fast-paced lifestyles and Internet technology, cannot be ignored. In the future, the shared parking strategy will be combined with the customer-to-customer (C2C) model to realize a win-win outcome for drivers, parking lot owners, and the platform. Profits can be maximized on the basis of the original multiobjective allocation model, namely, the driver spends the minimal amount on parking fees, the parking space owner earns the maximal amount of income, and the shared platform obtains the maximal profit. The shared parking scheme did not consider drivers' choice behaviours. Thus, the validity of this multiobjective model can be improved by incorporating the drivers' subjective selection.

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 no conflict of interest.

Authors' Contributions

Wenhui Zhang designed the structure of paper and studied the literature. Junjun Tang wrote and revised the paper. Fan Gao established the model and conducted numerical simulation. Shurui Sun and Qiuying Yu collected parking data and analyzed parking demand and supplement. Bohang Liu proposed the methodology and solving algorithm.

Acknowledgments

The research was funded by the Fundamental Research Funds for the Central Universities (2572018BG01), Open Subject of Traffic Safety and Control Lab in Hebei Province (JTKY 2019003), National Natural Science Foundation of China (71701215), Foundation of Central South University (502045002), Postdoctoral Science Foundation of China (2018M630914 and 2019T120716), and National Key Research and Development Projects (2017YFC0803901).

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