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SPA: Smart Parking Algorithm Based on Driver Behavior and Parking Traffic Predictions

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ABSTRACT Smart parking problems have received much attention in recent years. In literature, many smart parking allocation algorithms that considered the parking grid reservation and recommendation have been proposed. However, the parking policies for maximizing parking rate and benefits still can be improved. This paper proposes a smart parking allocation algorithm (SPA), which aims to maximize the benefits created by a given parking lot while guaranteeing the quality of parking services. The proposed SPA algorithm predicts the driver behavior and estimated parking traffic in the near future based on the historical parking records. These predictions help SPA to better match the parking demands and the resource of available parking grids and, hence, improve the utilization and the created benefit of each parking grid. The proposed SPA applies three policies, namely worst-fit (WF-SPA), best-fit (BF-SPA), and parking behavior forecast (PBF-SPA), to allocate the available grids to the vehicles. Performance evaluations reveal that the proposed SPA outperforms exiting work in terms of accumulated parking rate and service quality and, hence, improves the benefits of a given parking lot.

INDEX TERMS Predictions, parking lot, parking behavior, parking grid scheduling, smart parking.

I. INTRODUCTION

Internet of Things(IoT) is an indispensable part of cities life, and has received much attention in recent years. One important application of IoT technology is the smart parking [1]–[3] where some IoT devices, including sensors [4], cameras [5], [6] as well as electric vehicle charger [7], [8], are used in parking lots.

The smart parking scheduling is important since it determines the benefit of the parking lot owner and the efficiency of vehicles which demand to be parked. Parking can be differentiated into two categories: *on-street* parking and *off-street* parking. The *on-street parking* refers to the parking policy that the vehicle parked on the street [9], [10] while *off-street parking* refers to the policy for parking vehicle in a parking lot. In literature, many studies of paid parking aimed to maximize the utilization of a given parking lot. In [11], a recommendation algorithm has been proposed for suggesting the most appreciate parking grid for the oncoming vehicle. This study improves the parking grid utilization of the parking lot. However, it only solves the problem of parking lot traffic management, without considering the policy for increasing benefit of a parking lot owner.

To consider the maximal benefit issue, numerous studies [11]–[14] have adopted the scheme of parking information sharing. The major scheme of parking information sharing is to deliver the parking information to the driver actively. This information includes the location and the number of vacant parking grids in the parking lot. As a result, it creates more opportunities for vehicle parking and hence increases the benefit of the parking lot owner. However, the parking information sharing mechanism is not efficient because that it usually leads to a situation that multiple vehicles are looking for single parking grid.

Some other studies proposed new strategies to resolve the congestion problem. These strategies are mainly classified into two categories: parking grid reservation and parking grid recommendation. In the first class, studies [14], [15] adopted the policy that users reserve vacant parking grids before their vehicles arriving the parking lot. In the other class, studies [16], [17] developed a better policy which not only allows users to reserve parking grids but also provides users

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with more information, including the driving directions and the best parking lot near the designated destination. However, this method leads to the situation that the parking grids have always been reserved. The drivers that reserve the parking grids are often absent.

Study [18] further improves the strategy of parking grid reservation. Based on the current location of the vehicle, the proposed strategy further estimated the time that the vehicle arrives the parking lot. The scheme will allocate a parking grid to the vehicle when the estimated time is approached. The proposed scheme can prevent the vehicle from absence and improve the utilization of the available parking grids. However, the scheme does not predict the parking time of the vehicle. When the traffic is large, this solution does not be aware of the available time of each parking grid. Therefore, the proposed scheme cannot timely allocate the appropriate parking grid to the vehicle with the reserved parking grid.

The goal of this paper is to maximize the benefits of the parking lot owner. The main idea behind the proposed SPA is to predict the parking time of each vehicle based on the history of parking records. This can better predict the available time of each occupied parking grid, making that SPA can better manage its resource. Another important concept supporting the proposed SPA is the prediction of the parking traffic based on the historical parking traffics. This also helps SPA better predict the parking demands. Since SPA predicts the resource of parking grids and the parking demands in the near future, it can better schedule the grids to match the parking demands such that the maximal benefit can be received.

The contributions of this paper are itemized as follows.

1) *Predicting the length of parking for each vehicle:* The proposed SPA algorithm predicts the parking behavior of each user based on his/her parking history. According to the user's parking behavior, the parking grid with appropriate available parking length is assigned to the appropriate vehicle. Compared with the related studies [13], [14], and [15], the proposed SPA can better manage the resource of parking grids.
2) *Improving parking rate:* The proposed SPA algorithm predicts the number of vehicles which will be parked at the next time point on each weekday, based on the historical parking records. Together with the predictions of the parking length of each parked vehicle, the proposed SPA makes a better schedule between parking demands and the resources of available parking grids. Compared with [15], [16], and [17], the SPA algorithm improves the utilization of each parking grid and hence improves the parking rate.
3) *Achieving better service quality:* The proposed SPA algorithm predicts the number of vehicles which will be parked at the next time point on each weekday and the available time of each occupied parking grid. The utilization of parking grids can be improved. This also indicates that more parking demands can be satisfied. Compared with [17] and [18], the service quality can be improved.
4) *Improvement of utilization and benefits:* Based on the predictions of driver's behavior and the parking traffics, the proposed SPA can pre-lookup the space-time table which depicts the available resources in the near future. In addition, the SPA predicts the benefit of each incoming vehicle based on the driver's behavior and estimates the incoming parking traffics. As a result, the proposed SAP improves the utilization of the parking grids and the benefits obtained from the parking vehicles.

The remainder of this work is organized as follows. Section 2 reviews the existing work related to this study. Section 3 illustrates assumptions, network environment and problem formulation of the proposed approach. Section 4 presents the design and details of the proposed SPA algorithm. The experimental study is proposed in Section 5. Finally, Section 6 offers a conclusion and future work.

II. RELATED WORK

This section presents the existing algorithms of finding parking space. We explain how they work and their advantages, along with their limitations.

A. BLIND SEARCH

Blind search is the most common method to find parking grid. The 'Blind Search' approach is based on a simple strategy applied by drivers when no parking information provided. In this strategy, drivers keep cruising for parking grids within a certain distance to their destination and stop to search until they find an idle parking grid. This method can cause congestion in the parking lot.

B. PARKING INFORMATION SHARING

Parking Information Sharing adopted commonly by the current state-of-the-art smart parking system design [12]. Parking information sharing would utilize a variable message sign (VMS) or through the Internet to tell the driver, the location and the amount of vacant parking space in one parking lot [13]. This would help driver know the information about vacant parking space and he would not have to cruise the entire parking lot to get a vacant space. The disadvantage of this system is that drivers will compete for a limited parking space during busy hours.

C. BUFFERED PARKING INFORMATION SHARING

This mechanism [14] is commonly adopted by the current state of the smart parking system design. Buffered parking information sharing was similar to parking information sharing. The difference was in the buffered aspect. This would mean that the information about the vacant space is buffered (reduced). For example, there were six vacant spaces, but in VMS there were only four vacant spaces displayed. This system has a disadvantage in its inability to fully solve the multiple-car-chasing-single-space problem.

D. RESERVATION WITH MOBILE PARKING APPLICATION

Reservation-based smart parking system [14], [15] was a system that designed to solve multiple-car-chasing-single-space and congestion while still allowing parking lot exploration to find a vacant space. This system utilized information technology and used various applications to allow user to reserve vacant parking space before they physically arrive at their destination. It has been tested in a simulation to solve the problem described before [14]. The disadvantage is that it could not utilize the parking lot effectively. It leads to the reserved parking space to be left empty while waiting for the reserving user to come physically. This system has also caused the fairness problem for users who have directly come to the parking lot and have not made a reservation. This user can see an empty vacant parking space but cannot occupy it because the space has already been reserved.

E. PARKING SLOT RECOMMENDATION

In [16], an intelligent parking guidance and parking grid recommendation algorithm is proposed. The user views information on the system, searches for parking lots around the destination through the mobile client or web searching, and reserves the parking grid between the start and end parking time. After successful booking, the system will also provide users with driving directions. The algorithm provides the user with the best parking lot near the designated destination, provides user positioning and navigation for the city parking grid, improves the parking lot utilization rate, and alleviates the problems of parking difficulties and parking confusion to some extent. The parking grid recommendation algorithm aims to select the nearest empty parking grid from the entrance to the parking lot. However, the article does not consider the parking habits of users.

Study [17] proposed a mobile car parking application that recommends a parking grid to the car driver based on the driver's will. The drawback is that the recommended parking grid algorithm can only be focused on a specific parking lot. Furthermore, the historical behavior and traffic are not considered.

F. RESERVATION AND DYNAMIC ALLOCATION

In [18], a dynamic allocation method is proposed to reserve parking grid. The location of a user can be obtained using mobile technology with GPS when the user reserves a parking grid through the application of smartphone. According to the current location of that user, the proposed application calculates the estimated time arrived with this user. The user will be allocated a suitable parking grid before he arrives in the parking lot. The proposed mothed would reduce the need of the driver for finding the free parking lot. However, it may cause the problem that some user reserves parking grids when there are many idle parking grids, but there is no parking grid when the user arrives at the parking lot. Moreover, this method does not take into account the historical traffic and behavior of the driver.

This paper proposes a parking schedule algorithm which considers the driver behavior and the estimated parking traffic in the near future based on the historical parking records. According to the predictions, the resource of parking grids can be better scheduled based on the parking demands of drivers.

III. NETWORK ENVIRONMENT AND PROBLEM FORMULATION

The section initially introduces the network environment and assumptions of this work. Then, the problem formulation is proposed.

A. NETWORK ENVIRONMENT

Let $V = \{v_1, v_2, \ldots, v_n\}$ denote the n vehicles where driver u_i owns vehicle v_i. Assume that the considered parking lot $R=\{R_1, R_2, \ldots, R_w\}$ consists of w parking grids. Each parking grid is assumed to offer parking service to at most one vehicle at any given time. In the entrance of smart parking lot, there is a monitoring system which can recognize the license plates. When a user arrives the parking lot, the monitoring system will recognize the license plate number. This number will be sent to the backend system as an input of our algorithm to make a decision that either allocates one appropriate parking grid or refuses the parking service.

Each parking grid has an electronic bulletin board, a sensor, and a control panel. The bulletin board is used to show the ID of the car which is allowed the car to park in that grid. The sensor will detect whether or not the parking grid has been occupied. The control panel is installed on the ground, aiming to refuse the car to be parked. If the proposed algorithm refuses the arrived car, all bulletin boards of the available parking grids will display 'has been reserved' and the corresponding control panels will refuse the car to be parked in the available grids. Therefore, the driver can only follow the guidance to exit the parking lot. If the algorithm allows the arrived car to have the parking service, the best parking grid can be assigned to the car, and an indicator light above the parking grid will flash to guide the user to find the allocated parking grid. After the car reaches the allocated parking space, the control panel will be pushed down so that the driver can park the car in the parking grid. Since the parking grids can be booked by VIP users, the available time period of the empty parking grids should be well scheduled and be allocated to the best arriving car to guarantee that the VIP users always have available parking grids to park their cars when they arrive the parking lot. As a result, the best car whose predicted parking time length will be assigned to the appropriate parking grid according to the proposed algorithm, even though the grids have been booked by VIP.

Though the VIPs have specified the parking time period, however, to tolerate the difference between predicted and real parking lengths and guarantee that the VIPs always have available parking grids, the algorithm will reserve a small number of available parking grids. The utilization of idle parking period will impact the benefit, especially when there are few available parking grids. This is the main reason that parking policies and benefits are highly correlated.

B. PROBLEM FORMULATION

This paper aims to develop a park guiding mechanism, which arranges and guides an incoming vehicle to an idle parking grid such that the total benefit obtained by the owner of the parking lot can be maximized during a specific period T.

Let T be partitioned into q equal time units $T = \{t_1, t_2, \ldots, t_q\}$. Let $t_{current}$ denote the current time unit. The past, current, and future time periods in T can be expressed by $T^{past} = [t_1, t_{current-1}]$, $T^{current} = [t_{current}, t_{current}]$, and $T^{future} = [t_{current+1}, t_q]$, respectively. Let $h = (t_{start}, t_{end}, vehicle, loc)$ denote the contents of a parking record, where t_{start} and t_{end} denote the time points of entering and exiting parking lot, respectively while the *vehicle* and *loc* denote the vehicle ID and the parking grid ID, respectively. Let $H_i = \{h | h.vehicle = v_i\}$ denote the set of historical parking records of user in T^{past}. Let $H = \{h_1, h_2, \ldots, h_m\}$ denote the set of all parking records of parking lot R. Let $h.length$ denote the parking length (measured by hours) of the parking record h. It is obvious that

$$h.length = \lceil h.t_{end} - h.t_{start} \rceil \tag{1}$$

Let Ω_j denotes the set of parking records whose parking lengths are j-hour, where $1 \leq j \leq \eta$. That is, $\Omega_j = \{h|\ h.length = j\}$. Let $\sigma_{j,k}$ be a Boolean variable representing whether or not record $h_k \in H$ belongs to Ω_j. It is obvious that:

$$\sigma_{j,k} = \begin{cases} 1, & h_k \in \Omega_j \\ 0, & h_k \notin \Omega_j \end{cases}. \tag{2}$$

Let φ denote the basic benefit which can be treated as the parking fee per hour. Herein, we assume that the parking length of a vehicle will be simply treated as one hour when it is less than one hour.

Let B_{past} and B_{future} denote the parking fees received in T^{past} and T^{future}, respectively. Equ. (3) depicts the calculation of B_{past}.

$$B_{past} = \sum_{h_k \in H, h_k.t_{\text{end}} \neq null} \sigma_{j,k} * j * \varphi \tag{3}$$

As shown in Equ. (3), the benefit obtained at the current time can only count those vehicles that have leaved their parking grids before the current time. That is, their parking records should satisfy the condition that field $h.t_{end}$ is not null.

The following discusses how to calculate the benefit obtained in the future. This benefit can be classified into two categories. The first category is that some vehicles have occupied the parking grids before $t_{current}$ but have not yet leaved in time $t_{current}$. Their benefits will be received in the future when they leave the parking grids. Let $B_{current}$ denote the benefits that will be obtained for those vehicles that have already occupied the parking grids before $t_{current}$. Herein, we notice that we did not know the parking lengths of these vehicles because they still not leave the parking grids. The $B_{current}$ only counts the benefits from t_{start} to $t_{current}$ for any record $h \in H$. Let notations $\lambda^{i,j}_{occupy}$ be Boolean variable representing that the state of the parking grid R_i is occupied at time t_j. That is,

$$\lambda^{i,j}_{occupy} = \begin{cases} 1 & if\ R_i\ is\ occupied\ at\ t_j \\ 0 & otherwise \end{cases} \tag{4}$$

Equ. (5) shows the evaluation of $B_{current}$.

$$B_{current} = \sum_{h \in H, h.loc = R_i, h.t_{end} = null} \sum_{t_j = h.t_{start}}^{t_j = t_{current}} \lambda^{i,j}_{occupy} \times \varphi \tag{5}$$

Let notation $\lambda^{i,j}_{park\_future}$ be a Boolean variable representing the prediction whether or not the parking grid R_i is parked in the T^{future}. Let p_{fp} denote the probability of false positive and φ_{fp} denote the loss of benefit when false positive occurs in the future. Similarly, let p_{fn} denote the probability of false negative and φ_{fn} denote the loss of benefit when false negative occurs in the future. Let B_{future} denote the benefit of the parking lot. Equ. (6) calculates the value of B_{future}.

$$B_{future} = \sum_{h \in H, h.loc = R_i} \sum_{t_j = t_{current+1}}^{t_j = t_q} \times \left[\begin{array}{l} \left(1 - p_{fp}\right)\left(1 - p_{fn}\right) \lambda^{i,j}_{park\_future} \times \varphi - \\ \left(p_{fp} \times \varphi_{fp}\right) - \left(p_{fn} \times \varphi_{fn}\right) \end{array} \right] \tag{6}$$

For all $h \in H$, the goal of this paper is to maximize the benefits obtained by the owner of a given parking lot. Exp. (7) reflects the goal of this paper.

Objective:

$$\boldsymbol{Max}(B_{past} + B_{current} + B_{future}) \tag{7}$$

Several constraints should be satisfied while the obtained benefit is maximized. The first constraint is the parking grid constraint. Assume that each parking grid has one of three states, including occupied, reserved and available states. Similar to the notation $\lambda^{i,j}_{occupy}$, let notation $\lambda^{i,j}_{available}$ be a Boolean variable representing that whether or not the state of the parking grid R_i is available at time point t_j. That is:

$$\lambda^{i,j}_{available} = \begin{cases} 1 & if\ R_i\ is\ available\ at\ t_j \\ 0 & otherwise \end{cases} \tag{8}$$

Since each parking grid can stay in exactly one of the two states, the following parking grid constraint should be satisfied.

1) PARKING GRID CONSTRAINT

$$\lambda^{i,j}_{occupy} + \lambda^{i,j}_{available} = 1 \tag{9}$$

In addition to the parking grid constraint, another constraint should be satisfied when finding the optimal solution of our goal given in Exp. (7). This constraint is that any vehicle can only occupy at most one grid at any given time. Let notation $\delta^{i,j,k}$ be a Boolean variable representing that whether or not the vehicle v_i occupies parking grid R_j at time point t_k. That is,

$$\delta^{i,j,k} = \begin{cases} 1 & \textit{if } v_i \text{ occupies } R_j \text{ at } t_k \\ 0 & \textit{otherwise} \end{cases} \tag{10}$$

Equ. (11) reflects the unique vehicle constraint.

2) UNIQUE VEHICLE CONSTRAINT

Consider any $h \in H$.Let $h.loc = R_j$ and $h.vehicle = v_i$. For vehicle $v_i \in V$ and time slot $t_k \in [h.t_{start}, h.t_{end}]$, we have

$$\sum_{j=1}^{w} \delta^{i,j,k} = 1 \tag{11}$$

Similarly, each parking grid can be occupied by at most one vehicle at any given time. This constraint should be satisfied for all parking record $h \in H$. Equ. (12) reflects this constraint.

3) UNIQUE PARKING GRID CONSTRAINT

Consider any $h \in H$.Let $h.loc = R_j$. For parking grid $R_j \in R$ and $t_k \in [h.t_{start}, h.t_{end}]$, we have

$$\sum_{i=1}^{n} \delta^{i,j,k} = 1 \tag{12}$$

IV. THE PROPOSED PARKING SCHEDULING ALGORITHM

The proposed algorithm mainly consists of three phases. The first phase is called the *Data Preprocessing Phase*, which aims to remove the invalid data from the collected parking records. Then, the second phase, called *Parking Behavior Analysis Phase*, further analyzes the parking behavior for each user. The third phase, called *Vehicle Selection and Allocation Phase*, aims to select proper vehicles from the incoming vehicles and allocate them to the available parking grids. The following presents the detail of each phase.

Table 1 gives an example which will be used throughout this paper.

TABLE 1. The parking history of the vehicle v_i.

License plate	#Rec.	$h.t_{start}$	$h.t_{end}$	$h.length$
v_1	h_1	11/11/2017 10:53:24	11/11/2017 12:28:29	2
	h_2	11/5/2017 10:54:53	11/5/2017 12:08:20	2
	h_3	11/25/2017 10:59:18	11/25/2017 13:07:18	3
	h_4	11/4/2017 10:53:48	11/4/2017 12:35:07	2
	h_5	11/19/2017 10:53:30	11/19/2017 12:04:15	2
	h_6	11/26/2017 10:53:49	11/26/2017 12:43:35	2
v_2	h_1	11/21/2017 10:27:18	11/21/2017 15:47:05	6
	h_2	11/25/2017 10:22:16	11/25/2017 10:31:36	1
	h_3	11/28/2017 10:18:48	11/28/2017 15:27:50	6
...	...			...
v_i	h_1	11/25/2017 18:46:35	11/25/2017 19:33:47	1
	h_2	11/14/2017 13:42:18	11/14/2017 15:36:36	2

A. DATA PREPROCESSING PHASE

This phase aims to check the validity of collected parking information and recover or remove the invalid data. Recall that each parking record can be represented as a 4-tuple form as $h = (t_{start}, t_{end}, vehicle, loc)$. This phase will firstly check if the values of t_{start} and t_{end} fields fall in the valid range of day time. Then the parking length

$$h.length = \lceil h.t_{end} - h.t_{start} \rceil$$

will be verified. The values of *vehicle* and *loc* will also be checked. The records with invalid values of t_{start}, t_{end}, *vehicle*, *loc* or parking length will be removed. After finishing this phase, all input data are guaranteed to be valid.

As shown in table 1, the first parking record of vehicle v_1 shows that the start time and the end time are 11/11/2017 12:28:29 and 11/11/2017 10:53:24, respectively. According to Equ. (1), the parking time length *h.length* of the vehicle v_1 is 2. Similarly, the parking time lengths of h_2, h_3, h_4, h_5, and h_6 are 2, 3, 2, 2, and 2, respectively.

B. PARKING BEHAVIOR ANALYSIS PHASE

This phase aims to examine the historical parking records and analyzes the parking records of each user. Recall that notation $\sigma_{j,k}$ is a Boolean variable representing that any parking history h_k belongs to Ω_j. Let $f_{i,j}$ denote the number of records of user that parks his vehicle with length j-hour. Equ. (13) gives the calculation of $f_{i,j}$ value.

$$f_{i,j} = \sum_{h_k \in H_i} \sigma_{j,k} \tag{13}$$

Let $p_{i,j}$ denote the probability of user parking for j-hour. Equ. (14) exhibits the calculation of $p_{i,j}$.

$$p_{i,j} = \frac{f_{i,j}}{\sum_{j=1}^{\eta} f_{i,j}} \tag{14}$$

Let $L_i^{predict}$ denote the expected length of parking time of user. Equ. (15) depicts the calculation of $L_i^{predict}$.

$$L_i^{predict} = \left\lceil \sum_{j=1}^{j=\eta} j * p_{i,j} \right\rceil \tag{15}$$

Consider the example given in Table 1. The parking history of the vehicle v_1 consists of two types of parking time length: 2 hours and 3 hours. Vehicle v_1 parked 1 times for 3 hours and 5 times for 2 hours. That is, $p_{1,2} = \frac{5}{6} = 0.83$ and $p_{1,3} = \frac{1}{6} = 0.17$. According to Equ.(15), we have $L_1^{predict} = 3$. This also indicates that the expected parking time length of v_1 is 3-hour.

In the case that the greedy algorithm is applied, the vehicle with the largest expected parking length will be selected when the incoming number of vehicles is larger than the number of available parking grids. The variance of the expected value of parking length of each vehicle will be further considered in case that the expected parking lengths of several incoming vehicles are identical. Let the notation σ denote the standard deviation of each user's parking time length. The standard deviation is defined as:

$$\sigma_{i,j} = \sqrt{\sum_{j=1}^{\eta} p_{i,j} * \left(j - L_i^{predict}\right)^2} \tag{16}$$

C. VEHICLE SELECTION AND ALLOCATION PHASE

This phase aims to select proper vehicles when the number of incoming vehicles larger than the number of available parking grids. Let $V^j = \left\{v_1^j, v_2^j, \ldots v_{x_j}^j\right\}$ be the set of x_j vehicles that request for parking at time t_j. Let $R^{j,available} = \{R_1^j, R_2^j, \ldots R_{y_j}^j\}$ denote the set of y_j available parking grids at time t_j. Let $R_k^j.avl\_length$ denote the length of available time duration of parking grid R_k at time t_j.

The $L_i^{predict}$ will be treated as the length of parking time of vehicle $v_i \in V^j$. In case that v_i is selected to be parked at grid R_k at time t_j, the following condition should be satisfied.

$$L_i^{predict} \leq R_k^j.avl\_length$$

According to the value of $L_i^{predict}$ of each vehicle v_i, the elements in set V^j can be sorted in a non-increasing order, which is denoted by notation $\hat{V}^j = \{\hat{v}_1^j, \hat{v}_2^j, \ldots \hat{v}_{y_j}^j\}$.

Continue the example given in Table 1, the predicted parking time length of the vehicle v_1 is $L_1^{predict} = 3$ hours. According to Equ. (15), the predict parking lengths of vehicles v_2, v_3, and v_4 are 5 hours, 2 hours, and 2 hours, respectively. Since the predicted lengths of parking time of vehicles v_3 and v_4 are identical, according to Equ. (16), the standard deviation of the parking time length of the vehicle v_4 is smaller than v_3. Finally, the set of ordered vehicle is $V^j = \{v_2, v_1, v_4, v_3\}$.

The following proposes three policies, including *Worst-Fit*, *Best-Fit*, and *Forecast Income*, for allocating the parking grids to the selected vehicles.

Worst-Fit:

The *Worst-Fit* policy aims to find the grid with the largest idle period and allocates the grid to the selected vehicle. Let $R^{longest}$ denote the grid with maximal available time period in the $R^{j,available}$. That is

$$R^{longest} = arg \max_{1 \leq i \leq y_j} R_i^j.avl\_length \tag{17}$$

Let $v^{largest}$ denote the vehicle with the largest prediction parking length in $\hat{V}^j$. That is

$$v^{largest} = arg \max_{1 \leq i \leq x_j} L_i^{predict} \tag{18}$$

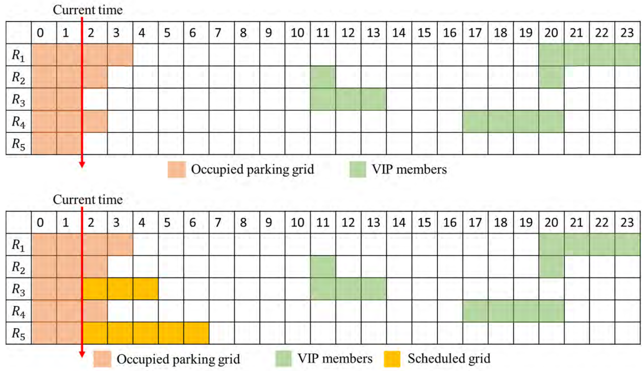

FIGURE 1. An example of ***Worst-Fit***.

By applying the ***Worst-Fit*** policy, the vehicle $v^{largest}$ will be selected from the sorted set $\hat{V}^j$ according to Equ. (18), where $v^{largest}$ demands for the largest parking length. Then the $v^{largest}$ will be guided to the parking grid $R^{longest}$ which is determined according to Equ. (17). Then we will remove $R^{longest}$ from $R^{j,available}$ and remove $v^{largest}$ from $\hat{V}^j$. The abovementioned vehicle selection and parking grid allocation operations will be repeatedly executed until all available parking grids are allocated.

As shown in Fig. 1, there are five parking grids. In this example, it is assumed that some parking grids have been already allocated by VIP members. Assume that there is a set V^2 of vehicles arriving at 2 o'clock. Continue the previous example. Vehicles v_2 and v_1 are selected to be allocated since their estimated parking lengths are 5 and 3 hours, respectively. There are two idle parking grids R_3 and R_5 at 2 o'clock. The vehicle v_2 which has the largest parking length will be guided to the idle parking grid R_5 which has the longest available time length. Obviously, the vehicle v_1 will be guided to the remaining parking grid R_3. The formal Worst-Fit algorithm is presented in below.

1) BEST-FIT

Different from *Worst-Fit*, the *Best-Fit* policy guides the vehicle to the idle grid with the most appropriate available length. Let $v^{largest}$ denote the vehicle with largest predicted parking length in $\hat{V}^j$. Let R^{best} denote the most appropriate grid to $v^{largest}$. Equ. (19) determines the grid to play the role of R^{best}.

$$R^{best} = arg \min_{1 \leq i \leq y_j} \left(R_i^j \cdot avl\_length - L_{v^{largest}}^{predict}\right) \tag{19}$$

Based on Equ. (19), the most appropriate parking grid R^{best} will be allocated to the vehicle $v^{largest}$. After that, we should remove R^{best} from $R^{j,available}$ and remove $v^{largest}$ from $\hat{V}^j$. The abovementioned operations should be repeatedly executed until all the parking grids are allocated.

According to Table 1, assume that there is a set V^2 of vehicles arriving at 2 o'clock. Continue the previous example, v_2 and v_1 are the two vehicles that are predicted to have the longest parking lengths 5 and 3 hours, respectively. There are two idle grids R_3 and R_5 at 2 o'clock. By applying Equs.

Procedure 1 Worst-Fit

Inputs:

1. The set of incoming x_j vehicles $V^j = \left\{v_1^j, v_2^j, \ldots v_{x_j}^j\right\}$ that request for parking at time t_j.
2. The set of w parking grids $R = \{R_1, R_2, \ldots, R_w\}$.
3. The set of y_j available parking grids at time t_j $R^{j,available} = \{R_1^j, R_2^j, \ldots R_{y_j}^j\}$.
4. The set of VIP vehicles $V^{VIP} = \left\{v_1^{VIP}, v_2^{VIP}, \ldots v_{|V^{VIP}|}^{VIP}\right\}$.
5. IDs of VIP members and their parking requests.

Outputs:

1. Schedule grids in set $R^{j,available}$ for vehicles in set V^j

/* Fill in VIP members */
For each VIP vehicle $v_i^j \in V^j$ {
  Calculate grid $R^{longest}$ according to Equ. (17);
  Assign v_i^j to grid $R^{longest}$;
  V^j. remove (v_i^j);
  $R^{j,available}$. remove $(R^{longest})$;
  Update $(R^{*,available})$; }
/* select vehicle */
$x = x_j - |V^{VIP}|$;
$y = |R^{j,available}|$;
Calculate $L_i^{predict}$ according to Equ. (15), $1 \leq i \leq x$;
Let $\hat{V}^j = \{\hat{v}_1^j, \hat{v}_2^j, \ldots \hat{v}_{y_j}^j\}$ be sorted vehicles in non-increasing order according to $L_i^{predict}$;
For $(i = 1; i \leq x; i++)${
  $R^{longest} = arg \max_{1 \leq i \leq y} R_i^j.avl\_length$;
  If $(L_i^{predict} \leq R^{longest}.avl\_length)${
    Assign $\hat{v}_i^j$ *to* $R^{longest}$;
    $R^{j,available}$ *.remove* $(R^{longest})$;}}

Procedure 2 Best -Fit

Inputs:

1. The set of incoming x_j vehicles $V^j = \left\{v_1^j, v_2^j, \ldots v_{x_j}^j\right\}$ that request for parking at time t_j.
2. The set of w parking grids $R = \{R_1, R_2, \ldots, R_w\}$.
3. The set of y_j available parking grids at time t_j $R^{j,available} = \left\{R_1^j, R_2^j, \ldots R_{y_j}^j\right\}$.
4. The set of VIP vehicles $V^{VIP} = \left\{v_1^{VIP}, v_2^{VIP}, \ldots v_{|V^{VIP}|}^{VIP}\right\}$.
5. IDs of VIP members and their parking requests.

Outputs:

1. Schedule grids in set $R^{j,available}$ for vehicles in set V^j.

/* Fill in VIP members *
For each VIP vehicle $v_i^j \in V^j$ {
  Calculate grid $R^{longest}$ according to Equ. (17);
  Assign v_i^j to grid R^{best};
  V^j. remove (v_i^j);
  $R^{j,available}$. remove (R^{best});
  Update $(R^{*,available})$; }
/* select vehicle */
$x = x_j - |V^{VIP}|$;
$y = |R^{j,available}|$;
Calculate $L_i^{predict}$ according to Equ. (15), $1 \leq i \leq x$;
Let $\hat{V}^j = \{\hat{v}_1^j, \hat{v}_2^j, \ldots \hat{v}_{y_j}^j\}$ be sorted vehicles in non-increasing order according to $L_i^{predict}$;
For $(i = 1; i \leq x; i++)${
  Calculate R^{best} according to Equ. (19);
  If $(L_i^{predict} \leq R^{best})${
    Assign $\hat{v}_i^j$ *to* R^{best};
    $R^{j,available}$ *.remove* (R^{best});}}

(18) and (19), we have $v^{largest} = v_2$ and $R^{best} = R_5$. As a result, the Best-fit policy allocates grid R_5 to vehicle v_1. Then the remaining grid R_3 will be allocated to vehicle v_2. The following formally presents the algorithm Best-Fit.

2) PARKING BEHAVIOR FORECAST SCHEME

The *Parking Behavior Forecast*(PBF) *Scheme* will predict parking behavior based on parking history. We consider that the parking behaviors of the same day, say Monday, in the past few weeks will be similar. For instance, suppose the current time is 8:00 o'clock on Monday. We aim to predict parking behaviors which can be explored from the parking records whose starting times are around 8:00 o'clock in the past few Mondays. Let $today^{-k}$ denote the previous k dates of *today*. Let *DAY*(date) be the function that transfers the date to the day in a week. For example, assume today is '2018/04/19' which is 'Thursday'. We have $today^{-7}$ = '2018/04/12' and $DAY(today^{-7})$ ='Thursday'. Let *last_day* represent the day of $DAY(today^{-7})$. Assume one day can be partitioned into ζ time periods with equal length. Let $V_j^{last\_day}$ denote the set of vehicles whose parking staring time belong to the j-th time period of *last_day*. Let $P_j^{last\_day}$ denote the number of elements in $V_j^{last\_day}$. For example, if the ζ is equal to 24, every time slot is one hour. Assume $P_2^{last\_Tue} = 5$. It indicates that there are five vehicles parked starting from the second time period on last Tuesday. Let $P_j^{last\_day}[i]$ denote the number of vehicles in $V_j^{last\_day}$ which satisfy the condition that their parking lengths are identical to i-hour. Let $\Phi_j^{last\_day}$ denote the set of all $P_j^{last\_day}[i]$, for all $1 \leq i \leq \eta$. That is,

$$\Phi_j^{last\_day} = \left\{\left\{P_j^{last\_day}[i]\right\} \mid 1 \leq i \leq \eta, j \neq null\right\} \quad (20)$$

Assume that today is Monday. Table 2 depicts the parking behavior of the last Sunday. For instance, $P_2^{last\_Sun}[3] = 0$ indicates that there is no vehicle satisfying the condition that the parking starting time is in the second time period on last

TABLE 2. Parking statistics data (PSD).

Times	1 h	2 h	3 h	4 h	5 h	6 h
$P_2^{last\_Mon}$	0	0	0	2	0	0
$P_3^{last\_Mon}$	0	0	0	0	0	0
…	…	…	…	…	…	…
$P_6^{last\_Mon}$	0	1	0	1	0	0
…	…	…	…	…	…	…
$P_2^{last\_Sun}$	2	1	0	2	0	0
…	…	…	…	…	…	…

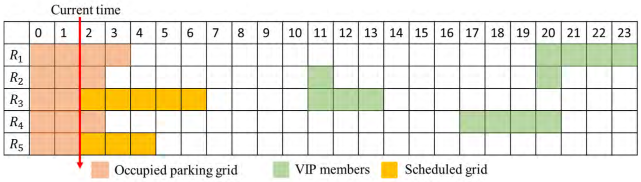

FIGURE 2. The example of ***Best-Fit.***

Sunday and its parking length is 3-hour. Since we have

$$P_2^{last\_Sun}[1] = 2, P_2^{last\_Sun}[2] = 1, P_2^{last\_Sun}[3] = 0,$$

$P_2^{last\_Sun}[4] = 2$, $P_2^{last\_Sun}[5] = 0$ and $P_2^{last\_Sun}[6] = 0$. This also implies that

$$\Phi_2^{last\_Sun} = \{P_2^{last\_Sun}[1], P_2^{last\_Sun}[2], P_2^{last\_Sun}[4]\}$$

The set $\Phi_j^{last\_day}$ can be obtained from the parking history. Let $\hat{\Phi}_j^{last\_day}$ denote the sorted list of $\Phi_j^{last\_day}$ based on the value of i. That is,

$$\hat{\Phi}_j^{last\_day} = (P_j^{last\_day}[6], P_j^{last\_day}[5], \ldots P_j^{last\_day}[1]).$$

Take Table 2 as an example. We have

$$\hat{\Phi}_2^{last\_Sun} = (P_2^{last_{Sun}}[4], P_2^{last_{Sun}}[2], P_2^{last\_Sun}[1]).$$

The following will formally present the proposed *PBF Scheme* using the above-defined notations. At the conceptual level, the algorithm *PBF* mainly consists of two steps. The first step is called *virtual scheduling* which schedules the vehicles based on the history behavior $\Phi_j^{last\_day}$, where j denotes the current time period. That is, before the vehicle arriving the parking lot, we assume that the parking behavior of the next moment can be predicted by applying $\hat{\Phi}_j^{last\_day}$. The virtual scheduling step will apply the Worst-Fit policy to allocate the parking grids to the vehicles. When the vehicle actually arrives parking lot, the second step, called *actual scheduling*, will be initiated. In the *actual scheduling* step, we will predict the parking length of the driver and then allocate the parking grid to the vehicle in the way similar to the allocation made in *virtual schedule* step. Herein, we notice that the first step can further consider a window, say τ, which allows the virtual scheduling pre-lookup more future time slots. That is, the virtual scheduling will refer the parking traffics of $\Phi_j^{last\_day}, \Phi_{j+1}^{last\_day}, \ldots, \Phi_{j+\tau-1}^{last\_day}$.

The following presents the detail of the proposed algorithm *PBF* scheme. In the *virtual scheduling* step, the *PBF* firstly predicts the traffic and the drivers' behavior and then applies the *Worst-Fit* policy to allocate the grid with the largest available time to the vehicles which are predicted to demand for the largest parking length. The following gives an example to illustrate the *virtual scheduling* step. Assume that the current status of the parking lot is shown in Fig. 3. According to Table 2, the largest parking time length in the set of $\hat{\Phi}_2^{Monday}$ is 4-hour. In the sixth time period of last Monday, there are one parking record with 4-hour and another parking record with 2-hour in set $\hat{\Phi}_6^{Monday}$. According to historical parking records, the *virtual scheduling*step predicts that there are two vehicles with 4 parking length expected to arrive in the second time period. Therefore, the *virtual scheduling* step preschedules grids R_3 and R_5, as marked with red shadow ink in Fig. 4, to the two vehicles. In addition, the *virtual scheduling* step predicts two vehicles with 2 and 4 parking lengths to be arrival in the sixth time period. It preschedules grids R_3 and R_5 for the two vehicles. As shown in Fig. 4, the grids marked with blue shadow ink depict this preschedule.

However, the abovementioned preschedule is based on prediction of the parking traffic. The actual situation might be different with the predictions. The following illustrate how *PBF* handles the actual situation. Suppose that the actual parking demands of all arrival vehicles v_2, v_1, v_3, and v_4 are 5, 3, 2, and 2, respectively in the second time period. The *actual scheduling* step will select the vehicles whose parking length is closest to but does not exceed the prediction. Since v_2 has a length of parking 5 that is longer than the prescheduling parking length 4, the *PBF* will not consider v_2. Alternatively, the *PBF* selects v_1 and v_3 to fill grids R_5 and R_3, respectively. As shown in Fig. 5, the grids marked with yellow ink represent this schedule. Continue this example. Assume that there are actually two vehicles, say v_5 and v_6, which are predicted to have the parking demands of 2 hours and 4 hours in the sixth time periods, respectively. The PBF can schedule grids R_3 and R_5 for vehicles v_5 and v_6, respectively. As shown in Fig. 5, the grids marked with blue ink depict this schedule. In summary, there are totally three idle hours of grids R_3 and R_5 during time periods [0, 9].

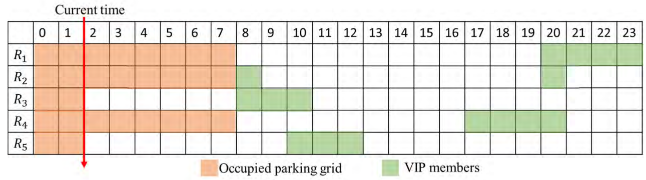

FIGURE 3. The current status of the parking lot.

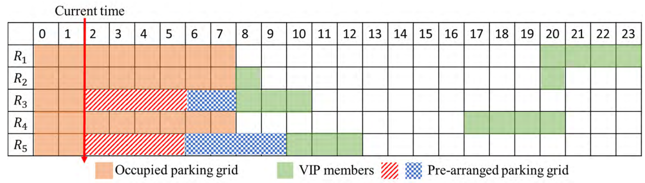

FIGURE 4. The pre-arranged parking grid.

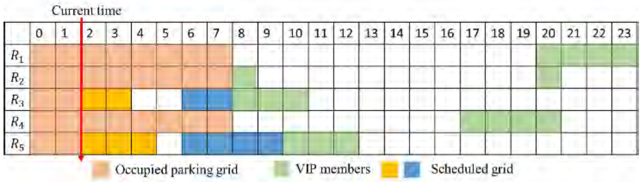

FIGURE 5. The example of *parking behavior forecast*(PBF).

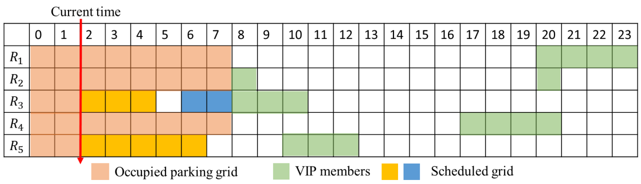

FIGURE 6. The vehicles v_2 and v_1 are filled into the parking grids R_3 and R_5, respectively.

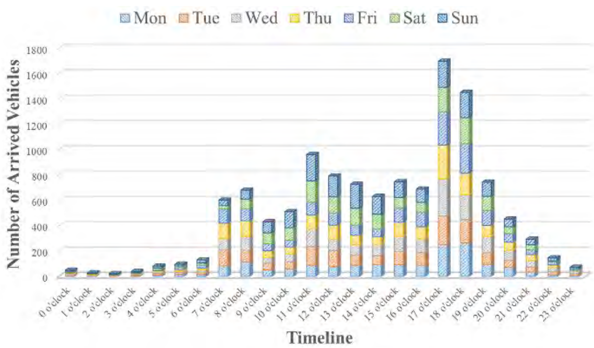

FIGURE 7. The average parking traffic from 0 o'clock to 23 o'clock of each day in a week.

On the contrary, if the *PBF* is not applied, fewer benefits can be obtained. The following adopts *Worst-Fit* policy and compares the results with that of *PBF*. In the second time period, the *Worst-Fit* policy will select the vehicles with longest parking length. Therefore, vehicles v_2 and v_1 which are predicted to have parking lengths 5-hour and 3-hour, are selected, respectively. The grids R_5 and R_3 are allocated for v_2 and v_1, respectively. As shown in Fig. 6, the grids marked with yellow ink depict this schedule. In the sixth time period, two vehicles v_5 and v_6 which are predicted to have the parking demands of 2 hours and 4 hours arrive at the parking lot, respectively. The *Worst-Fit* policy can only arrange grids R_3 to vehicle v_5 and the demand of vehicle v_6 cannot be satisfied, since its predicted parking length exceeds the available length of grid R_5. As shown in Fig. 6, the grids marked with blue ink depict this schedule. In summary, there are totally four idle hours of grids R_3 and R_5 during time periods $[0, 9]$. Compared with the result of PBF, the Worst-Fit policy results in one more idle hour.

V. PERFORMANCE EVALUATION

This section presents the performance evaluation of the proposed SPA method in terms of accumulated parking rates and the number of rejected vehicles. The proposed algorithm does not consider the rejected service as the input data. In case

Procedure 3 Parking Behavior Forecast Scheme

Inputs:

1. The set of incoming x_j vehicles $V^j = \left\{v_1^j, v_2^j, \ldots v_{x_j}^j\right\}$ that request for parking at time t_j.
2. The set of w parking grids $R = \{R_1, R_2, \ldots, R_w\}$.
3. The set of y_j available parking grids at time t_j $R^{j,available} = \{R_1^j, R_2^j, \ldots R_{y_j}^j\}$.
4. The set of VIP vehicles $V^{VIP} = \left\{v_1^{VIP}, v_2^{VIP}, \ldots v_{|V^{VIP}|}^{VIP}\right\}$.
5. IDs of VIP members and their parking requests.

Outputs:

1. Schedule grids in set $R^{j,available}$ for vehicles in set V^j.

```
/* Fill in VIP members */
For each VIP vehicle v_i^j ∈ V^j {
    Calculate grid R^longest according to Equ. (17);
    Assign v_i^j to grid R^best;
    V^j. remove (v_i^j);
    R^{j,available}. remove (R^longest);
    Update(R^{*,available}); }
/* select vehicle */
x = x_j − |V^VIP|;
y = |R^{j,available}|;
Calculate Φ_j^{last_day} according to Equ. (18),
1 ≤ i ≤ x;
Let V̂^j = {v̂_1^j, v̂_2^j, ... v̂_{y_j}^j} be vehicles sorted in
non-increasing order according to Φ_j^{last_day};
For (i = 1; i ≤ x; i++){
    R^longest = argR_i^j.avl_length;
    If (L_i^predict ≤ R^longest.avl_length and
    L_i^predict ≤ Φ_j^{last_day}){
        Assign v̂_i^j to R^longest;
        R^{j,available}.remove(R^longest); } }
```

that the number of available parking slots is few, a parking service might be rejected. However, this record will not be considered as the input in our simulation database and algorithm. The experiments only count the number of rejected service for measuring the performance of the compared algorithms. In the experiments, the proposed WF-SPA, BF-SPA, and PBF-SPA are compared with existing work [18] which proposed an Event-Driven algorithm, or ED in short, to cope with the problem of parking allocation and reservation. The ED algorithm mainly adopted the dynamic allocation method. The ED algorithm is described below. First, the user can reserve a parking grid using internet application. Then the ED algorithm calculates the arriving time of the requested user and further makes a prediction whether or not there exist any vehicle which will finish parking before the arriving time. If it is the case, the algorithm will allocate the available parking to the requested user. The proposed SPA adopts three policies,

TABLE 3. Simulation setting.

Parameter	Value
Simulator	MATLAB
The number of parking grids	100-900
Daily traffic	1600-2000
The number of parking lots	16
The number of VIPs	258

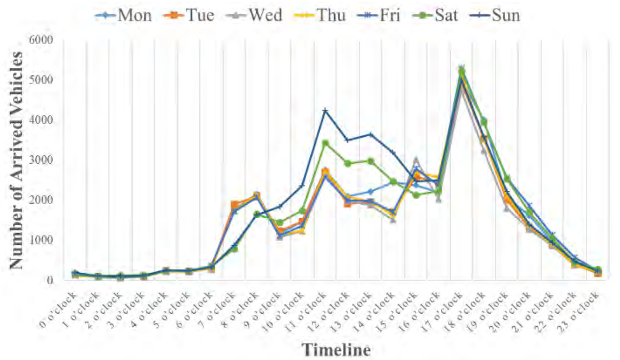

FIGURE 8. The average traffic from monday to sunday in each month.

which are Best-Fit based SPA, Worst-Fit SPA, and Parking Behavior Forecast based SPA, which are noted by WF-SPA, BF-SPA, and PBF-SPA, respectively.

A. SIMULATION ENVIRONMENT

In the experimental study, the MATLAB is used as the simulation tool. The following illustrates the parameters considered in the simulation environment. The simulation adopts data collected from 16 real parking lots in Haiyan County, Jiaxing City, Zhejiang Province, China from December 2017 to May 2018. The daily traffic is ranging between 1600 and 2000. However, to measure the performance, the number of parking grids is changed, ranging from 100 to 900 in each parking lot. The number of VIPs is 258. The following gives the setting of parameters in the experiments.

Fig. 7 depicts the average parking traffics of each hour of each day in one week. The parking traffic raises from 7 o'clock and drops from 20 o'clock every day. When the parking traffic is low, the parking grids can always meet the parking demands of all vehicles in any parking lot, resulting in the similar performance of all compared algorithms. Therefore, the simulation will only consider the data collected from 7 o'clock to 20 o'clock every day.

Fig. 8 further summaries the collected data of every month and depicts the average parking traffic of each hour from Monday to Sunday within a month. The maximum parking traffic appears around 17 o'clock every day, with a total of roughly 5000 vehicles per month. It is observed that the traffic curves from Monday to Friday are similar, while the curves of Saturday and Sunday are similar. In the following, the performances of the compared algorithms are investigated in two parts: the weekend parking traffic and the weekday parking traffic.

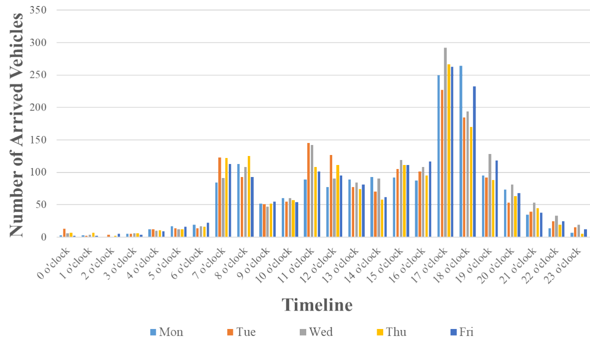

FIGURE 9. Daily traffic from monday to friday.

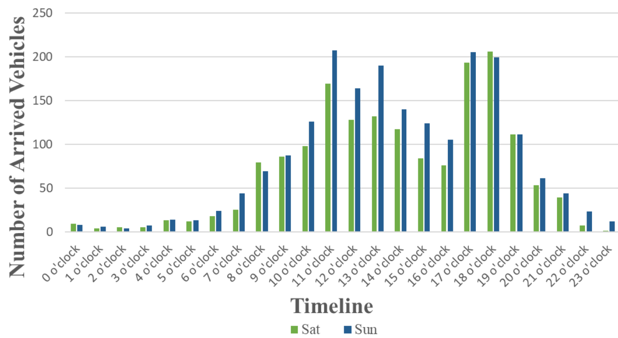

FIGURE 10. Daily traffic from saturday to sunday.

As shown in Fig. 9, there are three traffic peaks, which are 7 to 8 o'clock, 11 to 12 o'clock, and 17 to 18 o'clock. Fig. 10 depicts that the weekends have two traffic peaks: 11 to 13 o'clock and 17 to 18 o'clock. Note that the parking traffic of each time points does not exceed 300.

B. PERFORMANCE STUDY

A good parking allocation algorithm will have a high utilization of parking grids such that the number of available parking grids is small while increasing the income benefits of the owner of the parking lot. The following defines *parking rate* $P_{w,T}$ which is measured by the total number of occupations of the parking grids to the total number of parking grids. Equ. (21) gives the calculation of parking rate.

$$P_{w,T} = \frac{\sum_{j=T_{start}}^{T_{end}} \sum_{i=1}^{i=w} \lambda_{occupy}^{i,j}}{w * (T_{end} - T_{start})} \tag{21}$$

A large value of $P_{w,T}$ indicates that the parking allocation algorithm creates big benefits. Fig. 11 compares performances of the TP-C, WF-SPA, BF-SPA, and PBF-SPA algorithms in terms of parking rate of weekday. The number of parking grids varies ranging from 100 to 900. The common trend of the compared four algorithms is that the parking rate is decreased with the number of parking grids. The accumulated parking rates are increased with time. In comparison, the proposed *PBF-SPA* approach is better than the other three algorithms in all cases. This occurs because that *PBF-SPA* can additionally predict the number of vehicles which will be parked at the next time point on each weekday, based on the history parking records. Therefore, the parking grids can

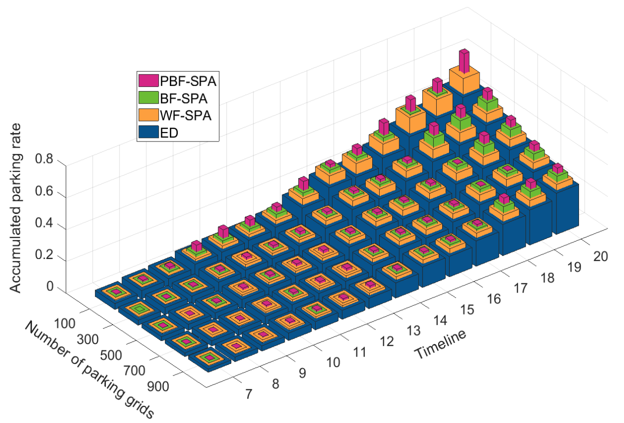

FIGURE 11. Parking rate for a different number of parking grids on weekdays.

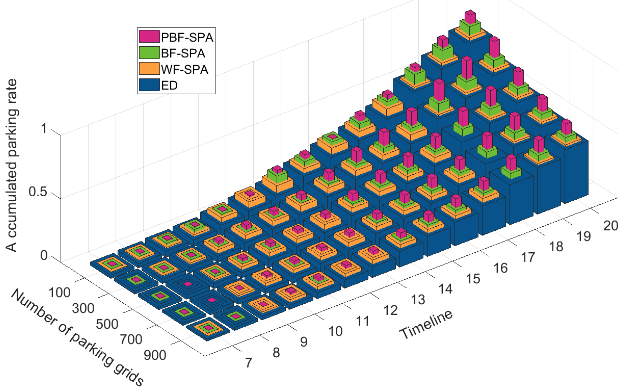

FIGURE 12. Parking rate for a different number of parking grids on weekends.

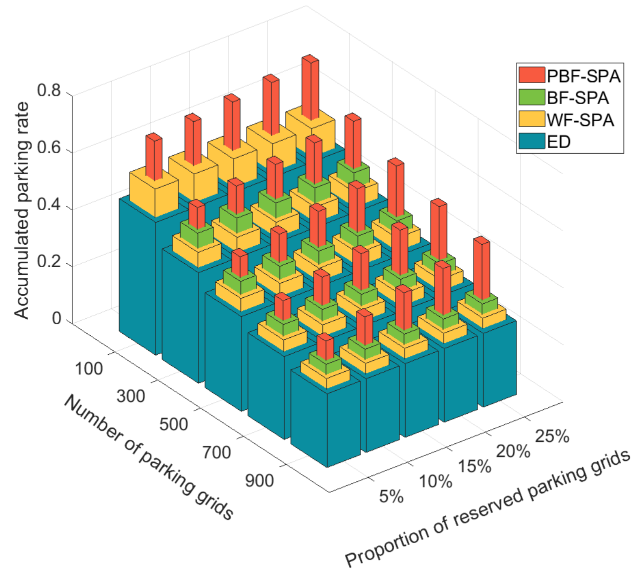

FIGURE 13. Parking rate for different proportion of reserved parking grids on weekdays.

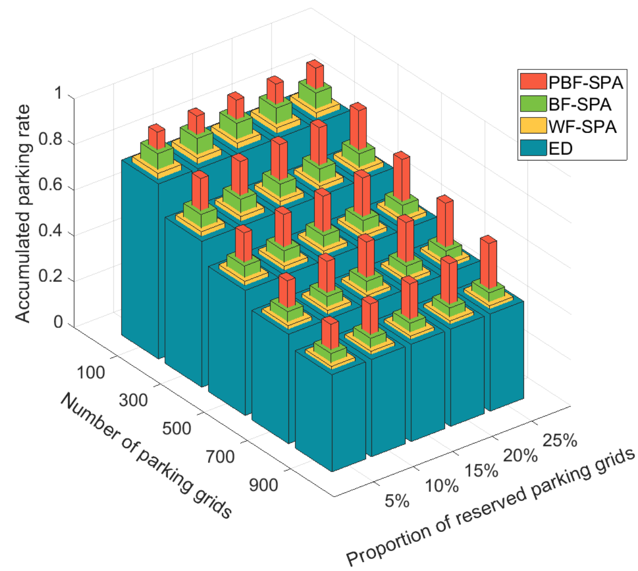

FIGURE 14. Parking rate for different proportion of reserved parking grids on weekends.

be managed to improve the parking rates. The proposed WF-SPA and BF-SPA have better performances than ED. This occurs because that the paring grid allocated to the requested user by applying ED cannot be utilized the requested user arrives. When the average parking time is generally short, the performance of BF-SPA is better than that of the WF-SPA. This occurs because that the BF-SPA algorithm results in a lot of fragmentation spaces. In case that the vehicle parking time is short, the fragmentation spaces of the available parking grids can be mostly filled. As a result, the BF-SPA outperforms the WF-SPA from 17 to 20 o'clock in the weekend, as shown in Fig.12. Conversely, when the average parking time is generally long, the WF-SPA is better than BF-SPA. This result can be found at 20 o'clock of a weekend when the number of parking grids in the parking lot is 100, as shown in Fig.12. In general, the performance of BF-SPA is better than that of WF-SPA.

Figs. 13 and 14 depict the accumulated parking rates of weekdays and weekends, respectively. The number of parking grids is varied ranging from 100 to 900 while the proportion of reserved parking grids is varied ranging from 5% to 25%. A common trend in Figs. 13 and 14 is that the accumulated parking rate is decreased with the number of parking grids. This occurs because that the larger number of parking grids leads to more available parking grids which reduce the accumulated parking ratio. The reserved parking grids normally reserved by some VIPs who have paid for guaranteeing their parking to be successful. The accumulated parking rate of the proposed PBF-SPA is increased with the proportion of reserved parking grids. The major reason is that the owner of the VIP grids generally like to park their vehicles since they have paid for the parking grids. The proposed WF-SPA and BF-SPA are also better than the ED algorithm. This occurs because that the prediction of the parking length is not accurate since ED did not refer the parking behavior of each user. In addition, the available parking grids have low

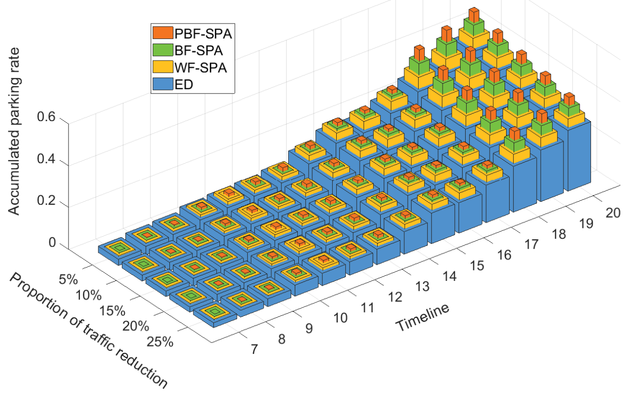

FIGURE 15. Parking rate for different proportion of traffic reduction on weekdays.

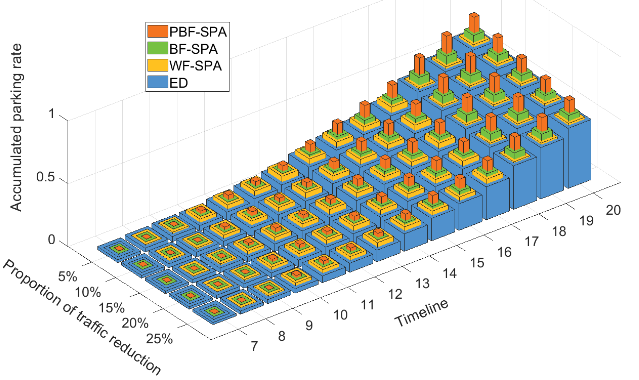

FIGURE 16. Parking rate for different proportion of traffic reduction on weekends.

utilization because they have been allocated to the users who have made reservation but still not arrive the parking lot.

Figs. 15 and 16 investigate the accumulated parking rates of the parking lot with 300 grids on weekdays and weekends, respectively. The parking traffic is varied by scaling the real parking traffic, ranging from 75% to 95%. That is, the traffic is reduced ranging from 5% to 25%. The compared four algorithms have a similar trend that the accumulated parking rates of the four parking mechanisms increase with time but decrease with the proportion of traffic reduction. This occurs because that the low parking traffic reduces the demands for parking and leads to the reduction of parking rate. The proposed PBF-SPA outperforms the other three algorithms in all cases. This occurs because that PBF-SPA predicts the parking length of each vehicle and the parking traffic. The BF-SPA outperforms the WF-SPA on both weekdays and weekends. This occurs because that BF-SPA predicts the parking length of each arrived vehicle and always allocates the grid with appreciate available time length to that vehicle. Aa a result, the grid which is available for a long time can be reserved for the vehicle which requires to be parked for a long time. However, the WF-SPA always allocates the incoming vehicle to the grid with maximal available time length and partitions

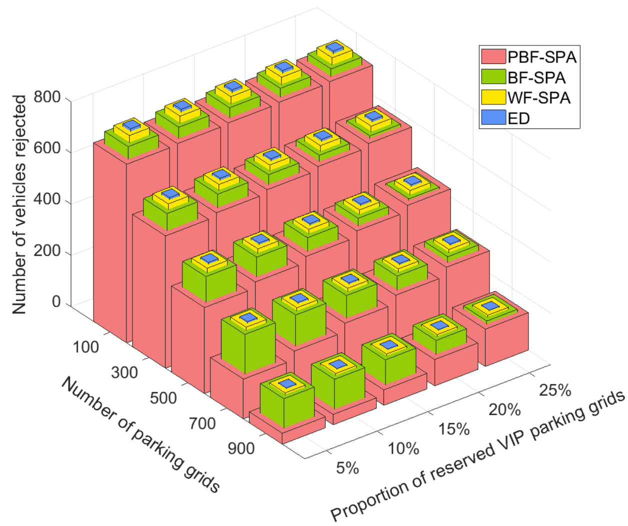

FIGURE 17. Quality of service on weekdays.

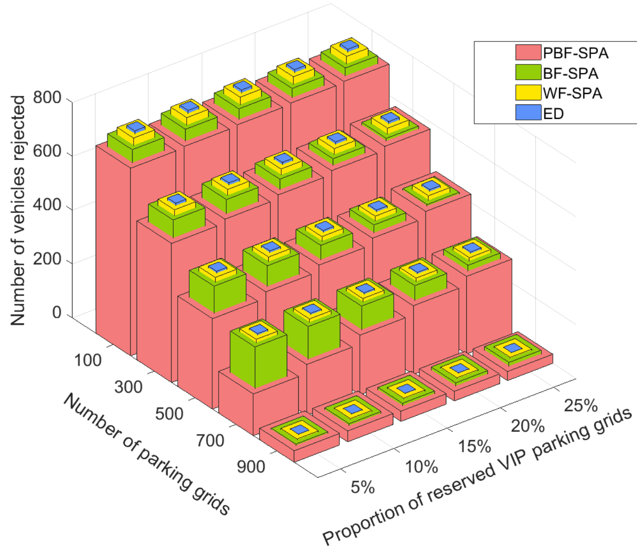

FIGURE 18. Quality of service on weekends.

the available time into several small time segments. When a vehicle requires to be parked for a long time, the WF-SPA cannot meet this requirement.

The quality of service (QoS) is one of the important indexes for the driver to evaluate the parking lot. The number of rejected vehicles represents the QoS of that parking lot. A big number of rejected vehicles also indicate the low benefits obtained by applying the scheduling algorithm. Figs. 17 and 18 measure the performance of the compared four algorithms in terms of the number of rejected vehicles on weekdays and weekends, respectively. Two parameters, including the number of parking grids and the percentage of reserved parking grids, can impact the number of rejected vehicles.

As shown in Figs. 17 and 18, the number of parking grids is varied ranging from 100 to 900 while the proportion of the reserved parking grids is varied ranging from 5% to 25%. One common trend of the compared algorithms is that the

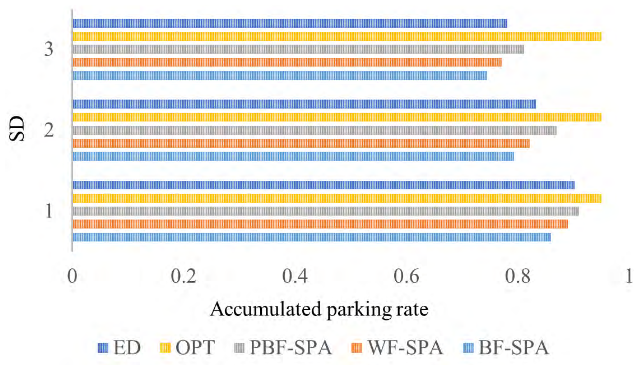

FIGURE 19. Parking rate for different SD.

number of rejected vehicles is decreased with the number of parking grids. This trend can be found in both weekdays and weekends. The reason is obvious that the number of available grids increases with the number of parking grids. The proposed WF-SPA, BF-SPA, and PBF-SPA outperforms the ED in all cases. This occurs because that the proposed algorithms consider the reserved parking grids and predict and schedule the parking vehicles based on the history parking records.

In particular, as shown in Fig. 18, the performances of PBF-SPA algorithm are similar on weekends when the number of parking grids is 900. This occurs because that the average traffic on the weekend is lower than 900. Therefore, the ratios of rejected vehicles of the compared algorithms are very low.

The deviation of prediction of parking time length will lead to low utilization or low quality of service, which will affect the parking rates of parking lots. The following defines deviation, denoted by *SD*, of prediction of parking time length, which is measured by applying Equ. (22).

$$SD = \sqrt{\frac{\sum_{i=1}^{n}\left(h.length - L_i^{predict}\right)^2}{n}} \tag{22}$$

A large value of *SD* indicates that the expected difference in earnings may be larger and the risk is higher. Fig. 19 compares performances of the ED, optimal algorithm (OPT), WF-SPA, BF-SPA, and PBF-SPA algorithms in terms of parking rate. The optimal algorithm (OPT) is assumed that it can magically know not only the parking length of each parked vehicle, but also the time that each user has parking demand. As shown in Fig. 19, the OPT outperforms other four algorithms. The common trend of ED, PBF-SPA, WF-SPA, and BF-SPA is that the parking rate is decreased with SD. In comparison, the proposed *PBF-SPA* approach is better than ED, WF-SPA, and BF-SPA in all cases. This occurs because that *PBF-SPA* can predict the number of vehicles which will be parked at the next time point, based on the history of parking records. Therefore, the parking grids can be well managed to improve the parking rates. The existing ED has better performances than WF-SPA and BF-SPA. This occurs because that ED has prediction for the parking length and supports reservation and dynamic allocation.

VI. CONCLUSION

This paper proposed a smart parking allocation algorithm, called *SPA*, aiming at maximizing the benefits (utilization) of the parking lot. The proposed *SPA* analyzes the user's parking behavior and estimates the parking length of each vehicle. Then *SPA* adopts three policies, including the Worst-Fit, Best-Fit, and Parking Behavior Forecast policies, which are noted by WF-SPA, BF-SPA, and PBF-SPA, respectively. The WF-SPA applies the *Worst-Fit* policy, finds the grids with the largest idle period and schedules them to the selected vehicles. The BF-SPA applies the *Best-Fit* policy and guides the vehicles to the parking grids with most appropriate available lengths. The PBF-SPA, by applying the Parking Behavior Forecast policy, further predicts the parking traffic based on parking history in the near future. According to the predictions of driver behavior and parking traffics, the proposed PBF-SPA can better satisfy the parking demands by scheduling the resource of available parking grids, and hence improve the utilization and benefit of each parking grid. Simulation results verify the performance improvement of the proposed SPA in terms of accumulated parking rate and service quality. Future work will consider different charges on different time periods and develop parking policies to maximize both qualities of service and benefits.

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