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TSM-SP: Time-Sharing Matching Shared Parking System Based on Time Window and Dynamic Pricing

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Abstract—With the continuous growth of urban parking demand, the difficulty of finding available parking spaces has become a prominent problem, primarily due to improper parking behavior of human drivers and limited parking resources. The rise of autonomous vehicles (AVs) offers new opportunities to alleviate traffic pressure caused by improper parking behavior, with intelligent navigation and autonomous scheduling expected to enhance the efficiency of transportation systems. Meanwhile, by optimizing private parking resources utilization, shared parking helps address the issue of limited parking resources. However, due to mismatches between requested parking durations and available shared parking time, existing shared parking systems often suffer from low utilization and high parking request rejection rates. To address these challenges, this paper proposes a shared parking space (SPS) allocation system with AVs based on time-sharing matching. This approach enables AV to utilize two different SPSs during parking, thereby maximizing the utilization of shared parking time. By adjusting the price of SPSs, the system guides the rational distribution of AVs, while maintaining the total parking cost of users across two-stage allocation. Simulation results show that TSM-SP increases the average SPS utilization by at least 16%, reduces the rejection rate of parking requests by more than 50%, and lowers the average total parking cost of users by at least 16%, compared with baseline methods.

Index Terms—Smart parking, shared parking, dynamic pricing, time-sharing matching, time window.

I. Introduction

As urbanization continues to accelerate, the increasing demand for efficient transportation systems has led to the integration of consumer electronics [1], cyber-physical systems (CPS) [2], and smart mobility technologies [3], [4]. This integration plays a critical role in improving the user experience during daily commutes. For example, with the utilization of autonomous vehicle (AV) technology, the time to cruise for a parking space (PS) can be reduced and travel routes can be optimized. However, the mismatch between the supply and demand of parking resources has led to urban parking difficulties. Studies show that the parking demand gap in commercial areas generally exceeds 50% during peak hours [5], while the idle rate of parking spaces in residential areas, enterprises, and institutions during off-peak hours reaches 30% to 40% [6]. This spatial-temporal mismatch not only directly causes more than 30% of traffic congestion, as a consequence of additional traffic flow generated by cruising for parking [7].

Traditional supply-side solutions that explore additional PSs are limited by urban land resource constraints, which makes it difficult to cope with the growing parking demand. In response to this challenge, the shared parking model has become an important innovation manner in the field of smart transportation [8]–[10]. With the shared parking model, idle parking spaces in residential areas near working places can be allocated to vehicles. As a result, this shared parking mode alleviates traffic congestion caused by cruising for parking, especially during peak hours, and also generates revenue for owners of shared parking spaces (SPSs).

Most existing studies [11]–[13] on shared parking adopt reservation-based or sequential decision-making frameworks, where parking requests are processed in stages (e.g., reservation followed by allocation). In these approaches, each parking request is typically assigned to a single SPS, and the parking duration is treated as an indivisible unit without temporal decomposition. Specifically, the reservation mechanism collects parking requests of users (including desired destination location and parking duration) and matches them with available SPS available shared parking time. Requests that do not fit the available shared parking time are rejected, referred to as larger-than-reject. Consequently, when most users require longer parking duration than the available shared parking time, this mechanism reduces SPS utilization and fails to effectively alleviate traffic congestion. In contrast, AV technology can mitigate this limitation by enabling flexible scheduling, autonomous relocation, and dynamic matching between parking demand and shared parking resources [14].

Furthermore, the price mechanism has been found to be an important factor in improving the utilization rate of PSs [15]–[17]. Otherwise, even with a well-designed parking allocation strategy, the parking management system may fail to attract a growing number of users. Common price mechanisms can be roughly divided into two categories, fixed pricing and dynamic pricing. Compared with

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fixed pricing, dynamic pricing adjusts the price of PSs in real time according to changes in supply and demand for parking requests. Consequently, the utilization of dynamic pricing can improve the income of PS owners while enhancing the utilization of parking spaces. Motivated by the above, a more intuitive idea is to apply the dynamic pricing mechanism to the shared parking model. However, there has not been much work on dynamic pricing in the context of shared parking [18], [19].

In order to make up for the research gaps mentioned above, this paper proposes a shared parking system, the time-sharing matching shared parking system (TSM-SP), which is based on a time window and combined with dynamic pricing. The main contribution of this paper can be concluded as two parts:

- Unlike traditional shared parking systems, which assign each parking request to a single SPS without decomposing the parking duration [12], [20], the proposed system adopts a time window-based mechanism, which splits the parking duration of an AV request into two segments and allocates them to different SPSs. This not only reduces the rejection rate of parking requests but also improves the utilization rate of SPSs.
- Combined with dynamic pricing, TSM-SP integrates pricing with the two-stage allocation process. Prices are adjusted to reflect the temporal feasibility of SPSs, transfer costs, and users' parking cost invariance across the two-stage allocation, so that AVs are guided to feasible SPS segments without additional cruising. In a word, this pricing scheme improves SPS utilization, and keeps the total parking cost of users unchanged across the two-stage allocation.

The rest of our paper is organized as follows: Section II investigates the literature on shared parking systems and dynamic pricing. Section III presents the overview of TSM-SP and explains its operation steps. In Section IV, we explore decision-making for optimal drop-off/pick-up (D/P) points and PLs. In Section V, we illustrate the dynamic pricing strategy in TSM-SP in detail. Finally, the numerous simulation results are shown in Section VI, and conclusions about this study are summarized in Section VII.

II. Related Work

A. Shared Parking Systems

With the development of information and communication technology, the shared parking model has been proposed [20]–[24]. This model integrates idle PS resources in commercial areas, residential areas, and other places to create an innovative parking approach. For example, a mixed-integer nonlinear programming model and heuristic approaches were proposed in work [20], which aimed to maximize the spatial-temporal utilization of shared parking resources. Considering the uncertainty in the arrival/departure time of drivers, a reservation and allocation model was investigated in work [21] for the shared-parking platform. This model maximized the parking utilization level and kept the service failure rate below a threshold value. Similarly, to improve the platform revenue, parking utilization, and charging utilization of electric vehicles, four matching rules embedded into a rolling-horizon framework were compared in work [22]. To optimize the matching of supply and demand in parking-dense districts, maximize platform revenue, and minimize parking users' travel costs, a rolling shared parking allocation model was established in work [23]. By simulating the operation of shared AVs, the parking land was reduced by 4.5% in Atlanta at a 5% market penetration level in work [24], which proved that the shared AV system had further improved the utilization of parking land.

However, in existing shared parking models, which are typically based on reservation or sequential allocation frameworks, each parking request is assigned to a single SPS, and the parking duration is treated as an indivisible unit without temporal decomposition. As a result, a parking request is rejected when the desired parking duration does not fully match the available shared parking time of an SPS. During peak parking periods, when most individual SPSs cannot independently satisfy the requested durations, a large number of user requests may be denied. Consequently, the utilization efficiency of shared parking resources decreases, and the likelihood of traffic congestion increases.

B. Dynamic Pricing Strategies

Dynamic pricing strategies initially applied to ordinary parking allocation problems [25]–[29], have also proven effective in shared parking scenarios [30]–[32]. Specifically, for effective parking access and space utilization, a dynamic non-cooperative bi-level model to set parking prices in real-time was developed in work [25]. To offer parking reservations with the lowest parking cost for drivers and the highest revenue for parking managers, a new smart car-parking system based on dynamic resource allocation with pricing strategy was proposed in work [27]. Based on an adaptive pricing algorithm and virtual voting, a distributed parking space allocation framework was investigated in work [28], which aimed to enhance the overall revenue of the parking lot owners as well as the comfort of users. In a more advanced parking scenario, autonomous valet parking, a novel intelligent framework based on dynamic pricing and in-advance charging reservations was proposed in work [26]. Considering that competition with uncertain parking demand may lead to inaccurate cost estimation, and that fixed parking prices can intensify parking competition, the work [29] proposed a long-range autonomous valet parking system under uncertain demand and parking pricing. The application of dynamic pricing strategies in the above studies demonstrates their effectiveness and broad applicability, which makes their extension to shared parking allocation problems a natural consideration.

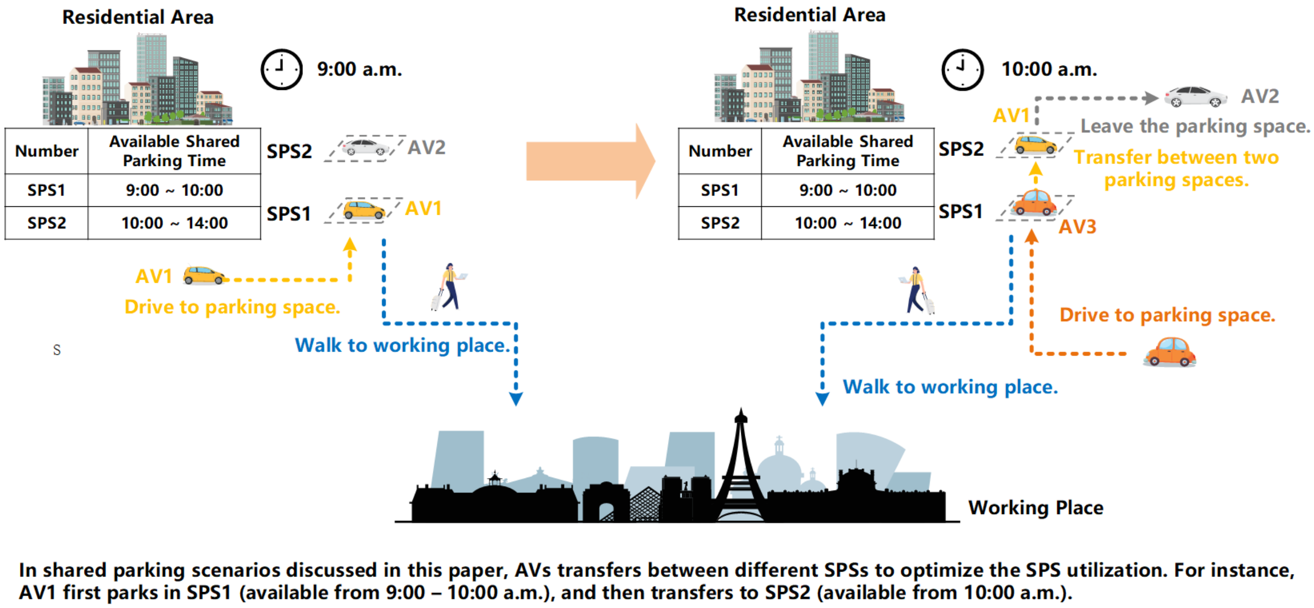

Fig. 1. The shared parking scenario of TSM-SP.

Although dynamic pricing has been studied in shared parking, most existing models apply pricing only after fixed one-shot allocation, neglecting the transfer costs when AVs move between SPSs. In this work, pricing is tightly coupled with the two-stage time window-based allocation by jointly considering parking requests, SPS temporal-spatial availability, and inter-SPS transfer costs, thereby guiding feasible segmented allocations. This integration of pricing with time window-based allocation constitutes the main pricing innovation of our system.

III. Overview of Time-Sharing Parking System Based on Sliding Window and Dynamic Pricing

A. Overview

In line with the objective of traditional shared parking systems, we consider the following scenario: users drive from their start points to their workplaces. As PSs at the workplace are fully occupied, users are required to continue driving to nearby residential areas where SPSs are available. After parking their AVs there, they walk back to their workplaces. The entire process is illustrated as the left part of the arrow in Fig. 1.

Traditional shared parking mechanisms always allocate vehicles to SPSs based on the shared parking time, which typically meets or exceeds the parking duration requested by users (referred to as a match in the following text). Consequently, the parking schedule is illustrated in Fig. 2. There is no doubt that the traditional shared parking mechanisms are practical and intuitive. However, during peak hours, a large number of parking requests may be rejected due to the limited shared parking time for each SPS, which in turn could intensify traffic congestion. In order to solve this problem, we adopt the strategy of time-sharing matching in TSM-SP based on a time window, shown as the right part of the arrow in Fig. 1. Specifically, time-sharing matching is to decouple the desired parking duration of a parking request, which cannot fully match the available shared parking time of a single SPS (as AV1 and AV2 shown in Fig. 3), into two periods that can be assigned to two different SPSs (as AV1 shown in Fig. 4). This design is consistent with prior studies, which adopt two-stage allocation structures in shared parking systems to balance effectiveness and computational feasibility [33]. Allowing more allocation rounds would dramatically increase problem complexity and operational overhead. In addition, empirical evidence from transfer-penalty studies [34] indicates that users experience a substantial decrease in satisfaction with each additional transfer, and the marginal disutility of the second or third transfer can exceed that of the first. Therefore, restricting each AV to at most one transfer (two SPS allocations) helps maintain user acceptance and aligns with realistic behavioral patterns. The size of the time window is set as the red part in Fig. 3.

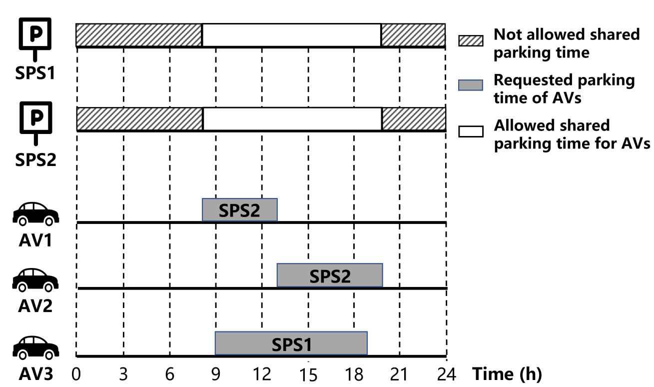

Fig. 2. The parking schedule with traditional shared parking mechanisms. Here, AV1 and AV2 are allocated to SPS2, while AV3 is allocated to SPS1.

Considering the convenience enabled by the time-sharing process in our proposed shared parking system

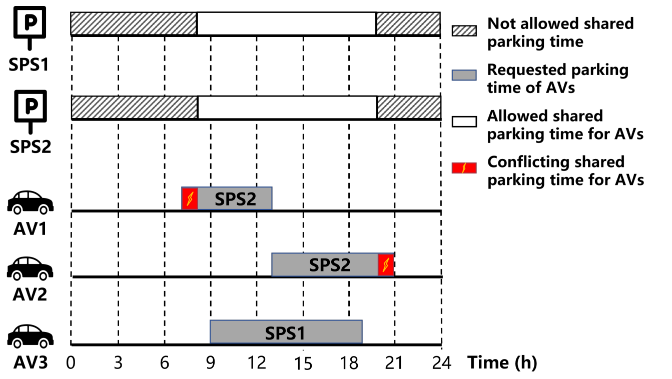

Fig. 3. Conflict between parking duration of requests and shared parking time of SPSs. In this picture, the parking duration of AV1 and AV2 are conflict with the shared parking time of SPS2.

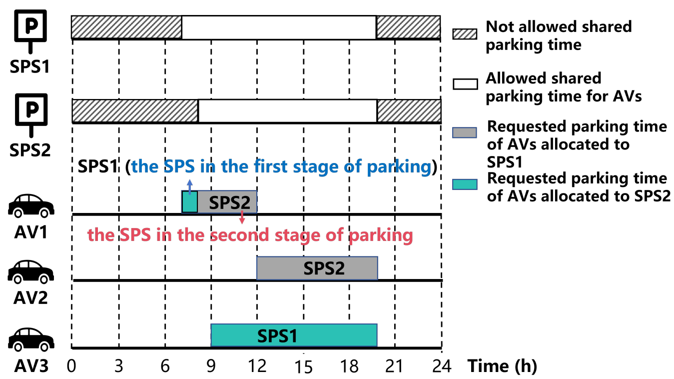

Fig. 4. The parking schedule with TSM-SP time-sharing matching mechanism.

(TSM-SP), we incorporate AVs as a primary research entity. In this context, users (i.e., owners of AVs) only need to guide AVs to the first SPS (allocated in the first stage of time-sharing allocation) before proceeding to their workplaces. The second stage of the parking process is then completed autonomously by the AV. The main entities utilized in TSM-SP are listed as follows.

- User: Users are owners of AVs and initiators of parking requests. The information in parking requests includes the desired arrival time (that is, the parking starting time of AVs), expected departure time (the time AVs end parking), and destination of users. It should be noted that parking requests of users are considered equivalent to those of AVs. These two concepts will be used interchangeably in different semantic contexts throughout the rest of this paper.
- AV: AVs are executors of the parking action, and their initial locations are the same as those of users who own them. Specifically, AVs first deliver users to the SPS in the first stage of parking, stay there for the first parking period, and then drive to another SPS in the second stage of parking autonomously.
- SPS: SPSs are defined as private PSs that owners share with third-party platforms during their idle periods (such as when residents drive their vehicles to work or for leisure and do not use their private PSs. These periods are commonly referred to as shared parking time). Owners of private PSs usually specify two time points: the starting shared parking time and the ending shared parking time[1]. Within the available shared parking time of SPSs, the third-party platform publishes the SPS information and leases it to other users who need to park.
- Global Controller (GC): The GC can be regarded as a proxy for third-party parking management platforms, and it is mainly responsible for interacting with AVs and SPSs. By collecting relevant information (such as the expected departure time, the desired arrival time, the starting shared parking time, and the ending shared parking time), GC is able to determine the parking price by utilizing dynamic pricing, and then allocate AVs to proper SPSs based on the time-sharing allocation algorithm.

B. Operation process of TSM-SP

To provide a more comprehensive explanation of the TSM-SP system described in this study, we present a detailed step-by-step illustration on how the system handles user parking requests. The complete processing workflow is depicted in Fig. 5.

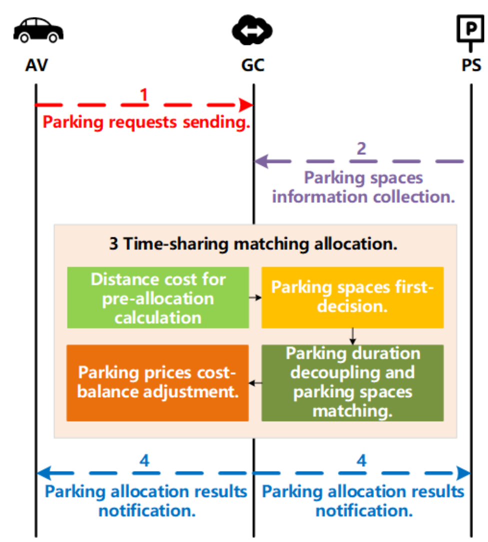

Fig. 5. Schematic flow chart of TSM-SP.

Step 1 (Parking requests sending): Users initiate parking requests and send parking requests to GC through agents installed on AVs. The parking request contains information such as the desired arrival time, the expected departure time, and the workplace (WP, equivalent to destination) of users.

Step 2 (PS information collection): On the day before parking allocation, owners of SPSs submit the shared parking time of their private PSs, including the starting shared parking time and ending shared parking time, to the GC.

[1]The shared parking time is equal to its ending shared parking time minus starting shared parking time

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Step 3 (Time-sharing matching allocation): This step can be further divided into four sub-steps, SPSs pre-allocation, parking prices first-decision, parking duration decoupling & SPSs matching, and parking prices cost-balance adjustment separately.

- Firstly, GC calculates the distance cost for pre-allocating an AV to the SPS. Specifically, the distance cost includes the distance from the start point to the SPS, and the distance from the SPS to the workplace.
- Secondly, after deriving the pre-allocation distance cost for assigning an AV to an SPS, GC will calculate the predicted parking price based on the SPS occupancy rate. For example, if PS0 is shared from 8:00 to 12:00 and the 8:00–10:00 slot has already been allocated to AV0 at 5 RMB/h, assigning AV1 to the remaining 10:00–12:00 slot increases the occupancy rate of PS0. Therefore, the predicted parking price for AV1 is set higher, e.g., 7.5 RMB/h. Then, 7.5 RMB per hour represents the predicted parking price for allocating AV1 to PS0.
- Thirdly, after completing SPS pre-allocation and pricing, GC reviews the allocation results. If the parking duration exceeds the shared parking time of the allocated SPS, GC decomposes it into an normal segment (the parking duration segment within the shared parking time of the allocated SPS) and the excess segment (the parking duration segment earlier or later than the shared parking time of the allocated SPS). The excess segment is then matched with another available SPS. If a feasible match is found, the second-stage SPS for that AV is confirmed. Otherwise, the parking request is rejected.
- Finally, GC will re-decide the parking price for AVs allocated to SPSs in the second stage of parking. In order to achieve the balance between the profitability of SPS owners and the parking cost of users, with the transfer cost of AVs between two SPSs to be considered, a cost-balance dynamic pricing algorithm is designed in TSM-SP. Additionally, to ensure user satisfaction, TSM-SP only allocates AVs to two different SPSs at most.

Step 4 (Parking allocation results notification): GC informs AVs whether their parking requests have been allocated successfully. If the allocation is successful, the AV will be notified with the allocated SPS and corresponding parking period. GC will also notify SPSs which parking requests have been allocated to it so that SPSs can check the actual arrival of AVs.

IV. Design of Time-Sharing Matching Algorithm Based on Sliding Window

In this section, the time-sharing matching algorithm will be discussed in detail, as Part A shown in Fig. 6. With time-sharing matching, the parking duration of AVs is decoupled into a normal segment and an excess segment for matching with dedicated SPSs. Consequently, an AV may be allocated to two separate SPSs to satisfy its parking duration, thereby reducing the rejection rate of parking requests. Specifically, the time-sharing matching algorithm can be divided into four steps, as illustrated by Step 3 of Fig. 5.

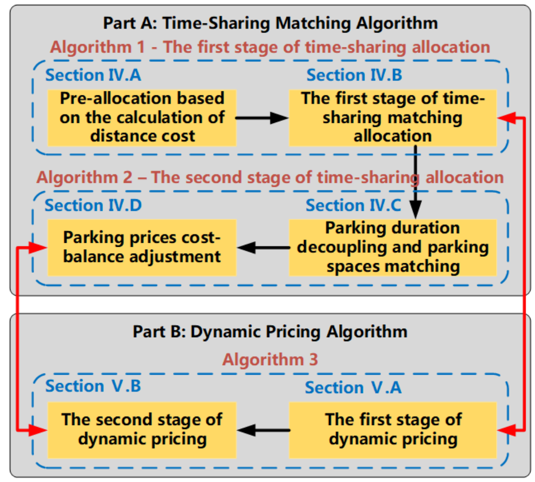

Fig. 6. Algorithm flows in Section IV and V.

A. Pre-allocation based on the calculation of distance cost

The first step of time-sharing matching algorithm is the distance cost for pre-allocation calculation (starting from line 1 to line 8 in Algorithm 1). In contrast to traditional shared parking allocation methods, which typically assess feasibility by matching the desired parking duration with the available shared parking time, TSM-SP first derives the minimum starting shared parking time and maximum ending shared parking time of all SPSs (line 1 in Algorithm 1). To calculate the minimum starting shared parking time, we compare the starting shared parking time of all SPSs, and take the minimum value to be the minimum starting shared parking time. Similarly, we compare the ending shared parking time of all SPSs, and take the maximum value to be the maximum ending parking time. These bounds are subsequently used to determine whether a parking request can be pre-allocated to SPSs. If a parking request's desired arrival time is earlier than the minimum starting shared parking time, or its expected departure time is later than the maximum ending parking time, it will be rejected during pre-allocation (starting from line 4 to line 5 in Algorithm 1). Otherwise, the parking request will be allocated to the SPS (starting from line 6 to line 16 in Algorithm 1) according to the total parking cost of pre-allocation. In addition, we assume that there will be no overlap in parking duration between AVs allocated to the same SPS.

To reduce the parking cost of users, parking price, driving distance, and walking distance are all considered during the pre-allocation process. Specifically, the driving distance refers to that AVs travel from their start points to SPSs pre-allocated, while the walking distance denotes the distance users must walk from SPSs to their workplaces. Here, the driving distance and walking distance constitute the overall distance cost in scenarios where SPSs are pre-allocated. For computational convenience, both driving

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Algorithm 1 Pre-allocation for SPSs.

1: get the desired arrival time t_a, the expected departure time t_d, the minimum starting shared parking time t_{min}, and the maximum ending shared parking time t_{max}
2: set $c_{min}^{pre} \leftarrow +\infty, PS_{fst} \leftarrow null$
3: **for** each AV requests for parking **do**
4:   **if** $t_a < t_{min}$ or $t_d > t_{max}$ **then**
5:     reject the AV parking request
6:   **else**
7:     **for** each SPS PS_{cur} **do**
8:       calculate the distance monetary cost c_d^{pre} according to Eq. (1)
9:       calculate the predicted parking price p_r by assuming the AV to the current SPS
10:       calculate the parking price cost c_m^{pre} according to Eq. (2)
11:       calculate the total parking cost c_{sum}^{pre} for the pre-allocation with the current SPS as Eq. (3)
12:       **if** $c_{min}^{pre} > c_{sum}^{pre}$ **then**
13:         $PS_{fst} \leftarrow PS_{cur}$
14:       **end if**
15:     **end for**
16:   **end if**
17: **end for**
18: **return** PS_{fst}

and walking distances are converted into time by dividing distance by the corresponding speed. To further quantify these costs in economic terms, we adopt the Value of Time (VoT) [35] concept, which translates the converted time into a corresponding monetary value c_d^{pre}, as shown in Eq. (1).

$$c_d^{pre} = (\frac{d_r}{v_a} + \frac{d_w}{v_u}) * VoT \tag{1}$$

where c_d^{pre} is the distance cost for pre-allocation, d_r is the driving distance, v_a is the driving speed of AVs, d_w is the walking distance, and v_u is the walking speed of users. The computational complexity of this pre-allocation process is $O(NM)$, where N is the number of AV requests and M is the number of SPSs, since each request evaluates all candidate SPSs.

B. The first stage of time-sharing matching allocation

The parking price for pre-allocation is calculated by real-time occupancy of PSs (detailed in the next section). As a result, the parking price cost (starting from line 9 to line 10 in Algorithm 1) can be derived by the requested parking duration t_p (the expected departure time minus the desired arrival time) multiply the pre-parking price, as shown in Eq. (2). Following that, the total parking cost for pre-allocation can be derived as Eq. (3).

$$c_m^{pre} = t_p * p^{pre} \tag{2}$$
$$c_{sum}^{pre} = c_d^{pre} + c_m^{pre} \tag{3}$$

where c_m^{pre} is the parking price cost for pre-allocation, t_p is the requested parking duration, p^{pre} is the pre-parking price, and c_{sum}^{pre} is the total parking cost of pre-allocation.

Pre-allocation follows the principle of First Come First Served (FCFS). More precisely, the pre-allocation of SPSs is performed according to the sequence in which parking requests are submitted. During the pre-allocation process, the total parking cost associated with allocating an AV to each SPS is first calculated based on Eqs. (1) - (3). The PS with the minimum total parking cost is then selected as the pre-allocated SPS for the AV (starting from line 12 to line 18 in Algorithm 1).

C. Parking duration decoupling and parking spaces matching

During pre-allocation, parking requests that start before the starting shared parking time or finish after the ending shared parking time are excluded. However, an AV may still be allocated to a SPS, with its parking time partially exceeding the available shared parking time window, which starts from the starting shared parking time and finishes with the ending parking time. In this subsection, we will discuss how to divide the parking requests in the SPS that have an excess segment, and then match the other available PSs (starting from line 1 to line 19 in Algorithm 2). The computational complexity of this stage is $O(NlogN + NM)$, including sorting and greedy matching. In addition, the number of successfully allocated AVs is upper-bounded by the total capacity of all SPSs. By allowing each AV to be assigned to at most two SPSs, the proposed method enlarges the feasible solution space and reduces the rejection rate.

1) Parking duration division: First, we need to sort pre-allocated parking requests in the SPS according to their desired arrival time (in ascending order, as line 3 in Algorithm 2). Then, those sorted parking requests are checked one by one to identify any violations of available shared parking time window (from line 4 to line 17 in Algorithm 2). Once an AV is found to have a parking duration that extends beyond the available shared parking time window, the duration of excess segment is calculated (line 6 in Algorithm 2). According to Section IV. A, there are two possible scenarios for the excess segment: it occurs either before the starting shared parking time or after the ending shared parking time, as shown in Eqs. (4) - (5).

$$t_e^1 = t_b - t_a \tag{4}$$
$$t_e^2 = t_d - t_e \tag{5}$$

where t_e^1 is the excess segment when the desired arrival time is earlier than the starting shared parking time, t_b is the starting shared parking time, t_a is the desired arrival time, t_e^2 is the excess segment when the expected departure time later than the ending shared parking time, t_d is the expected departure time, and t_e is the ending shared parking time.

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Algorithm 2 Parking duration decoupling and parking requests matching

```
1:  set W_t ← 0, PS_sec ← null
2:  for each SPS do
3:      sort parking requests allocated to the SPS during
        pre-allocation according to the desired arrival time
        in ascending order
4:      for each parking request allocated to the current
        SPS do
5:          if the parking request has an excess segment
            parking duration then
6:              calculate the duration of excess segment t_e
                according to Eq. (4) - Eq. (5)
7:              update the time window as W_t ← t_e
8:              for for each SPS PS_e excluded the current SPS
                according to priority in descending order do
9:                  if the corresponding time window of the SPS
                    is occupied by AV then
10:                     continue
11:                 else
12:                     confirm the secondary allocated SPS as
                        PS_sec ← PS_e
13:                     break
14:                 end if
15:             end for
16:         end if
17:     end for
18: end for
19: return PS_sec
```

2) Parking spaces matching: With the utilization of a heuristic algorithm based on a time window and greedy strategy, the calculated excess segment is matched with other available SPSs (from line 8 to line 15 in Algorithm 2). Specifically, the distance between each alternative SPS and the current SPS is calculated to determine its priority, with greater distances corresponding to a lower priority. Then SPSs are matched in descending order of priority. During the matching process, the duration of calculated excess segment is used as the size of a time window, which is then compared with each alternative SPS in sequence (from line 9 to line 14 in Algorithm 2). If a match is successful, that is, a SPS is found that can accommodate the excess segment, then the SPS is designated to the AV in the second stage of parking associated with the parking request. It should be noted that the secondary allocation PS herein is not deemed as the second PS where the AV arrives. If the desired arrival time is earlier than the starting shared parking time of the SPS in the first stage of parking, then the SPS in the second stage of parking is the first SPS where the AV arrives. If the expected departure time is later than the ending shared parking time of the SPS in the first stage of parking, then the SPS in the second stage of parking is the second PS where the AV arrives. Finally, if the match fails, the parking request will be rejected.

D. Parking prices cost-balance adjustment

Given that transferring AVs between SPSs introduces additional costs following successful secondary allocation, a dynamic pricing algorithm is proposed to balance the revenue of SPS owners and the parking cost of users. The algorithm is detailed in the next section.

V. Design of Dynamic Pricing Based on Real-Time Utilization

The dynamic pricing strategy proposed in this paper is structured into two distinct phases (as shown in Fig. 7), namely Step B (parking prices first-decision) and Step D (parking prices cost-balance adjustment), which are elaborated in Section IV and can be referred to the Part B in Fig. 6. The first stage of dynamic pricing strategy is designed to determine the parking price for the pre-allocation of PSs, based on their real-time occupancy (starting from line 1 to line 2 in Algorithm 3). In the second stage, for the purpose of balancing the transfer cost between two SPSs with the revenue obtained by SPS owners, the dynamic pricing strategy seeks to recalculate a parking price according to the distance between two SPSs (starting from line 4 to line 13 in Algorithm 3).

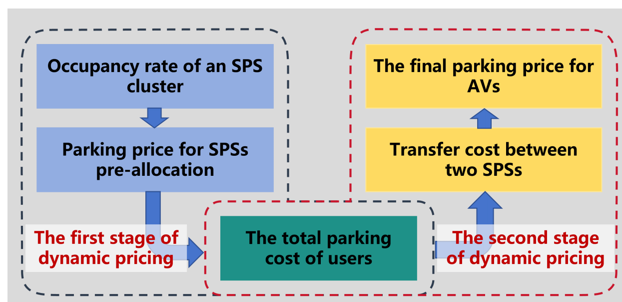

Fig. 7. Diagram of dynamic pricing.

Algorithm 3 Dynamic pricing based on real-time SPS utilization

```
1:  set p_pre ← 0, p_fin ← 0
2:  calculate the occupancy rate of a SPS assuming the
    AV is allocated to it according to Eq. (6)
3:  get the parking price for the SPS pre-allocation p_pre
    according to Eq. (7)
4:  for each SPS do
5:      for each AV allocated the SPS do
6:          if the AV needs reallocation then
7:              calculate the transfer cost between two SPSs
                according to Eq. (8)
8:              update the final parking price p_fin as Eq. (9)
9:          else
10:             set p_fin ← p_pre
11:         end if
12:     end for
13: end for
14: return p_fin
```

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A. The first stage of dynamic pricing

Given that SPSs in residential areas are typically private-owned, for convenience, we adopt a cluster-based computation approach, wherein all SPSs within a block are treated as a single unit (SPS cluster). Then, the occupancy rate of the SPS cluster o_r can be calculated as Eq. (6).

$$o_r = \frac{o+1}{\Omega} \tag{6}$$

where o is the number of occupied SPSs, $o+1$ calculates the occupied number of SPSs after allocating the current AV to the SPS cluster, and Ω is the total number of SPSs in the SPS cluster.

Considering that with the higher occupancy rate of SPS clusters, it is reasonable to have higher parking prices. Consequently, a segmented pricing strategy is designed as shown in Eq. (7). In the literature, parking pricing is widely recognized to be closely related to supply–demand conditions and occupancy levels [16], [25], [32], [36]. When the SPS cluster occupancy rate is less than 50%, it indicates that the SPS is relatively sufficient, and user competition is limited. As the occupancy increases, parking resources become constrained and competition intensifies, requiring dynamic price adjustment. Therefore, the 50% threshold is adopted as a representative midpoint to distinguish different supply–demand conditions. This design is also consistent with congestion pricing principles and performance-based parking pricing strategies, where prices are adjusted according to occupancy levels to reflect resource scarcity and regulate demand.

$$p_{pre} = \begin{cases} p_b, & \text{if } o_r < 0.5 \\ p_b * \frac{\lfloor (o_r+0.5)*10 \rfloor}{10}, & \text{if } o_r \geq 0.5 \end{cases} \tag{7}$$

where p_{pre} is the parking price for SPSs pre-allocation, p_b is the parking base price, referring to the minimum payment made by users to the SPS owners for utilizing a SPS, and o_r is the occupancy rate of a SPS cluster calculated according to Eq. (6).

B. The second stage of dynamic pricing

Upon the first parking price being derived, the SPS pre-allocation and reallocation can be completed according to Step A to Step C in Section IV. In order to balance the parking cost of users, especially the transfer cost between two SPSs for AVs that need reallocation, with the revenue of SPS owners (that is, the parking price cost of users), the second stage of dynamic pricing is investigated as follows. Firstly, the transfer cost between two SPSs c_t is calculated as Eq. (8), where travel time is obtained via dividing distance by speed and then converted into monetary cost using VoT. Then, the final parking price for AVs that need reallocation p_{fin} can be derived as Eq. (9).

$$c_t = (\frac{d_p}{v_a} + \frac{d_{w'}}{v_u}) * VoT \tag{8}$$

$$p_{fin} = \frac{(c_m^{pre} - c_t)}{t_d - t_a} \tag{9}$$

where c_t is the transfer cost between two SPSs, d_p is the distance between two SPSs, $d_{w'}$ is the walking distance from the workplace to the secondary allocated SPS, p_{fin} is the final parking price, and c_m^{pre} is the parking price cost obtained by Eq. (2).

With this second stage of dynamic pricing, the revenue gained by SPS owners has decreased slightly, as the second SPS selected is selected based on its distance from the first one, in order from nearest to farthest. However, the total parking cost of users does not increase, and the utilization rate of all SPSs is increased. This is because the excess segment of requested parking duration has been reallocated to a new SPS. As a consequence, the revenue gained by SPS owners and the parking cost of users are well-balanced.

VI. Simulation Results

To demonstrate the effectiveness of TSM-SP, we conduct simulations as follows built under the opportunistic network environment (ONE) [37]. The simulation scenario refers to the downtown area of Helsinki city with 4500 × 3400 m^2, as shown in Fig. 8. Under these settings, simulation-based evaluation provides a controlled environment to analyze the proposed mechanism under dynamic and uncertain conditions, which is difficult to achieve using real-world datasets. The road network map in ONE is derived from publicly available OpenStreetMap (OSM) data. The ONE simulator is implemented and executed in a Java environment, from which the mobility and allocation logs are exported after each run. The resulting datasets are then processed and visualized using Microsoft Excel. Consistent with the previous description, we adopt SPS clusters as the basic unit of allocation in the simulation. To reduce inconsistencies among individual SPSs within a cluster, we assume that all SPSs in the same cluster have identical available shared parking time. The specific selection of an individual SPS within a SPS cluster, once an AV arrives, is beyond the scope of this study and will not be discussed further.

As depicted in Fig. 8, a Point of Interest (POI) is located at the center of the city, representing a business district that serves as a common destination for users. There are residential areas around the POI. We cluster the private SPSs within these residential areas into six SPS clusters, denoted as PL in the figure. The available shared parking time of SPSs in different PLs varies. For example, the available shared parking time for SPSs in PL1 and PL2 is [8:00 ∼ 9:00] (that is, the starting shared parking time is 8:00, and the ending shared parking time is 9:00), and the available shared parking time for SPSs in PL3, PL4, PL5, and PL6 is [9:00 ∼ 12:30]. As one of the primary agents in the parking allocation process, AVs are

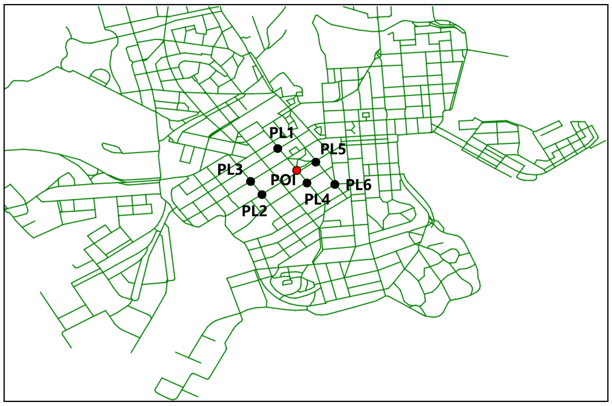

Fig. 8. Layout of simulation scenario.

TABLE I
Details of Simulation Parameters

Description	value
Number of SPSs in a SPS cluster	40
Value of Time (VoT)	12
Speed of AVs	17 m/s
Speed of users	1.25 m/s
Parking base price	5 ¥/h
Simulation time	2 h

initially distributed at random locations throughout the city. The initial location of an AV is considered equivalent to the starting point of a user. The AV parking duration is divided into two groups, one-third of AVs are assigned a parking time from 8:30 to 9:30, while the remaining AVs are assigned a parking time from 9:30 to 12:30. Additional details of the simulation parameters are provided in Table I.

Since the main functional modules of the proposed TSM-SP in this paper can be divided into two parts, namely SPS allocation and dynamic pricing, the selection of baseline algorithms also takes both aspects into consideration. The specific comparison algorithms are listed as follows.

- TSM-SP: The shared parking system proposed in this paper, utilizes time-sharing matching based on time window as an allocation algorithm, and dynamic pricing to decide parking price.
- TSM-ZP: This is a variant of TSM-SP, which utilizes the same allocation algorithm as TSM-SP, but utilizes a zone-based pricing algorithm [36] to decide parking price. Specifically, the zone-based pricing algorithm divides PLs into three areas: red, blue, and green according to the distance from POI. For example, the PL within 400 meters of POI is divided into the red zone, the PL within 400-800 meters of POI is divided into the blue zone, and the PL within 800 meters of POI belongs to the green zone.
- DRP-SP: This is a shared parking optimization framework based on a rolling-horizon parking allocation model [38], which is used to compare the validity of SPS allocation module with TSM-SP. The rolling-horizon parking allocation model compares the requested parking duration of AVs with the time window of SPSs. However, it does not consider the decoupling of parking duration. In order to ensure the validity of comparison experiment, the pricing algorithm used in this simulation is the same as that of TSM-SP.
- FCFS: This shared parking system utilizes a First Come First Served (FCFS) allocation algorithm, without dividing the request parking duration of AVs, and dynamic pricing which is the same as TSM-SP. As a result, it is used to compare the advanced nature of SPS allocation algorithms.
- SAB-SP: This system employs a heuristic algorithm based on simulated annealing for SPS allocation, assigning SPSs in ascending order of the parking request submitted by users. To ensure the validity of parking allocation algorithms, SAB-SP adopts the same dynamic pricing strategy as that used in TSM-SP.

The evaluation metrics used in the simulation are summarized as follows, including metrics related to the effectiveness of both the SPS allocation algorithm and the dynamic pricing algorithm.

- Number of parked AVs: This indicator calculates the number of successful parking AVs in each PL, and is a comparative indicator of SPS allocation algorithm.
- Occupancy rate: The occupancy rate is calculated as the number of parked AVs divided by the total number of SPSs in each PL, which belongs to the comparative indicator of SPS allocation algorithm.
- Total revenue of PLs: The total revenue for each PL is calculated by summing the parking price cost paid by all AVs parked within it. This metric serves to validate the effectiveness of both the dynamic pricing algorithm and the SPS allocation strategy.
- Rejection rate of parking requests: The rejection rate is defined as the ratio between failed and total parking requests, serving as a key evaluation metric for the SPS allocation algorithm.
- Average total parking cost of users: The average total parking cost of users is calculated as the mean of total parking costs, including distance cost and parking price cost, incurred by all users who successfully parked. This metric serves as a comparative indicator for both the SPS allocation algorithm, and the dynamic pricing algorithm.

In order to ensure the validity and authenticity of simulation results, we set up four groups of AVs for experiments, with the number of AVs being 200, 240, 280, and 320, respectively. In addition, we will show experimental results from perspectives of AV number, PL deployment, and POI number to verify the advanced nature of our proposed algorithm. What needs to be explained in advance is that, since TSM-ZP is a variant of TSM-SP, simulation results of these two systems are consistent in the indicators of the number of parked AVs,

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the occupancy rate, and the rejection rate of parking requests.

A. Impact of AV number

In this part, the number of AVs is increased from 200 to 320. The effectiveness of proposed algorithm is evaluated under two conditions: when the number of AVs is less than the total number of SPSs, and when it exceeds the total number of SPSs. Specific experimental results are depicted in Fig. 9.

As shown in Fig. 9, compared with other shared parking systems, the application of TSM-SP has the largest number of parked AVs in the case of all AV configurations with different quantities. Thanks to the time-sharing allocation algorithm, TSM-SP makes use of both PL1 and PL2 to park AVs, which increases the utilization rate of SPSs. With the increase in the number of AVs, the number of parked AVs under TSM-SP increases and then stabilizes due to capacity limits, while other methods quickly reach saturation and remain unchanged. Moreover, TSM-SP achieves a more balanced utilization across PL1–PL6, whereas other methods mainly rely on PL3–PL6. In terms of the rejection rate of parking requests, TSM-SP achieves the lowest rate among all methods, and even attains a zero-rejection outcome when the total SPS capacity is sufficient to accommodate all AVs. As the number of AVs increases, the rejection rate of TSM-SP gradually rises but remains significantly lower than that of the other methods, which increase sharply due to limited capacity. However, with the increasing number of AVs, the rejection rate of parking requests is also gradually increasing, because the number of SPSs is limited, and the number of AVs that cannot be allocated at one time according to the parking duration is increasing.

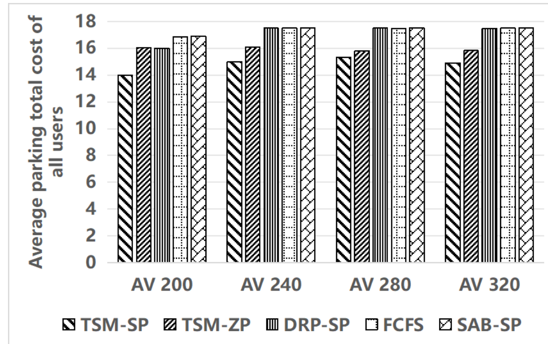
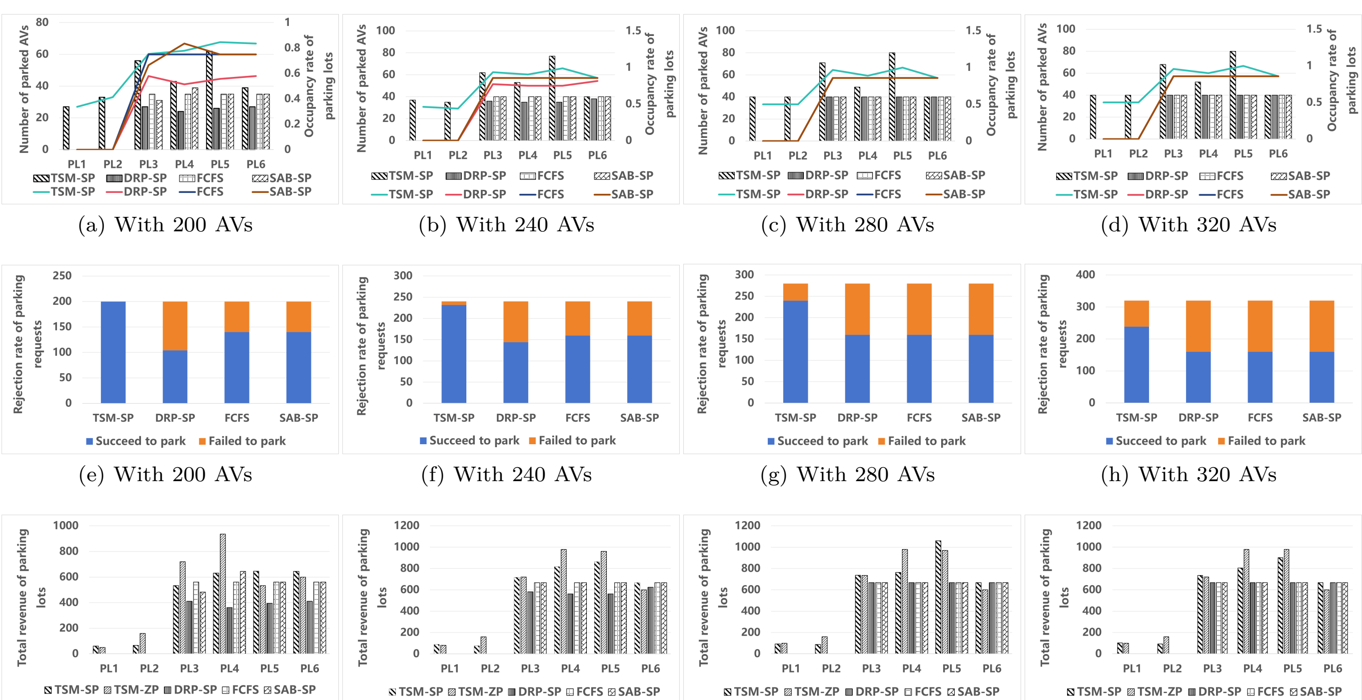


Fig. 10. Average total parking cost of users as the number of AVs increases.

For total revenue gained by SPS owners, TSM-ZP has the most, and TSM-SP ranks second under all AV configurations with different quantities. With the increase in the number of AVs, the revenue of SPS owners shows a trend of rising first and then declining. This is because the capacity of PL is limited, and the number of AVs with long parking durations is also increasing. As a result, the number of AVs allocated to SPSs decreases, which leads to a decrease in the revenue of SPS owners. However, the more benefits SPS owners receive, the greater the parking cost for users. The average parking total cost of all users is shown in Fig. 10 with the increasing number of AVs. Consistently, the average total parking cost for users under the utilization with TSM-ZP is higher than that for



(a) With 200 AVs (b) With 240 AVs (c) With 280 AVs (d) With 320 AVs

(e) With 200 AVs (f) With 240 AVs (g) With 280 AVs (h) With 320 AVs

(i) With 200 AVs (j) With 240 AVs (k) With 280 AVs (l) With 320 AVs

Fig. 9. Influence of AV number. (a)-(d): Number of parked AVs and occupancy rate in different PLs. (e)-(h): Rejection rate of parking requests with different number of AVs. (i)-(l): Total revenue of different PLs with increasing number of AVs.

TSM-SP, which demonstrates the effectiveness of dynamic pricing strategy proposed in this paper, particularly in balancing revenue gained by SPS owners with parking cost of users. Compared with the other three shared parking systems, TSM-SP achieved the highest parking revenue and maintained the lowest average parking total cost of all users. This is due to the application of the time-sharing allocation algorithm in TSM-SP, which splits the parking duration that cannot meet the AV request at one time in the other three shared parking systems, DRP-SP, FCFS, and SAB-SP, into two segments and matches with two SPSs respectively.

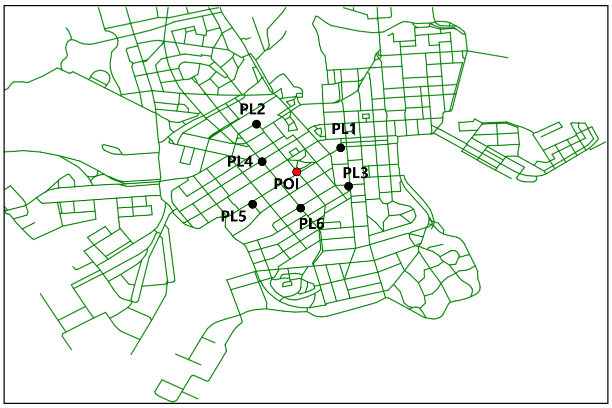


Fig. 11. Simulation settings with changed PL deployment.

To demonstrate the superiority of TSM-SP more intuitively, we list the parking service satisfaction rates (defined as the number of successfully allocated parking requests divided by the total number of parking requests) of the four shared parking systems under different AV number settings in Table II. It should be noted that the capacity of each PL has been changed to 100, which means there are a total of 600 SPSs in this simulation scenario. As shown in Table II, the satisfaction rate of TSM-SP reaches 1 when the numbers of AVs are 300, 400, and 500. However, the satisfaction rate of TSM-SP decreases when the AV number is 600. This is because the number of AVs that require time-sharing allocation increases, and they cannot be allocated to the SPS for the second stage of parking due to fiercer competition. For the other three shared parking systems, as 30% of the AV's desired parking duration is set to not match the shared parking time of a single SPS, the satisfaction rate only reaches 0.7 when the AV numbers are 300, 400, and 500. Similarly, when the AV number reaches 600, the completion for SPS allocation is intensified and the satisfaction rate is decreased.

B. Impact of PL deployment

Aiming to study the impact of PL deployment on different shared parking systems, we changed the PL deployment as shown in Fig. 11, and the changed simulation results are shown in Fig. 12. Compared with Fig. 9, although the deployment of PL has changed, TSM-SP proposed in this paper still performs well in the number of parked AVs and the rejection rate of parking requests.

TABLE II
The parking service satisfaction rate of all shared parking systems with different AV numbers

Satisfaction Rate	AV 300	AV 400	AV 500	AV 600
TSM-SP	1	1	1	0.967
DRP-SP	0.7	0.7	0.7	0.667
FCFS	0.7	0.7	0.7	0.667
SAB-SP	0.7	0.7	0.7	0.667

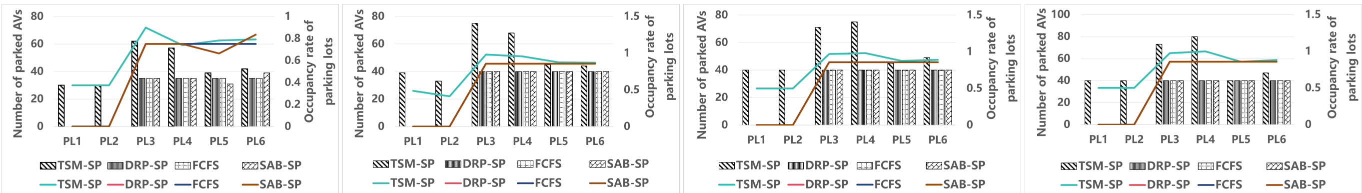
With the increase in the number of AVs, the number of parked AVs under TSM-SP increases and then stabilizes, while other methods quickly reach saturation. Meanwhile, TSM-SP maintains more balanced utilization across PLs. Similarly, the number of parking AVs initially increases followed by a slight decrease, due to the limited number of SPSs. It is also for the same reason that as the number of AVs increases, the rejection rate of parking requests also increases. Although the rejection rate of TSM-SP increases gradually, it remains significantly lower than that of the other methods. Regarding the number of parking AVs and the request rejection rate, it can be reasonably concluded that the deployment of PLs, in general, does not significantly affect the performance of shared parking systems used for comparison in this paper. Because factors considered by shared parking systems are mainly the available SPSs and the parking duration of AVs. If the distance from start points of users to SPSs and the available shared parking time provided is appropriate, the parked AVs always can be allocated.

Fig. 12 (i) - (l) shows the total revenue gained by SPS owners, which is presented in PL units. Similar to Fig. 9, TSM-ZP achieved the highest total revenue among all shared parking systems, thanks to the zone-based pricing algorithm. TSM-SP comes closely behind. With the increase in the number of AVs, the revenue of TSM-SP first increases and then slightly fluctuates, while the other methods remain relatively stable. The other three shared parking systems, DRP-SP, FCFS, and SAB-SP, achieved the same total revenue as all of them implemented the same dynamic pricing proposed in this paper. The average total parking cost of users under the change PL deployment is shown in Fig. 13. Likewise, despite the change in the PL deployment, TSM-SP still achieves a minimum average total parking cost of users, owing to the implementation of time-sharing matching and dynamic pricing algorithms.

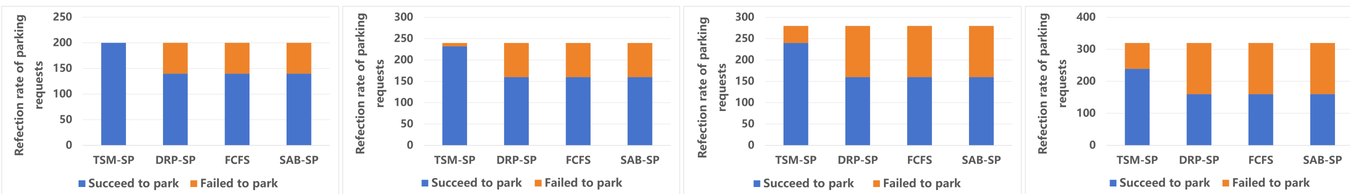
C. Impact of POI numbers

In order to avoid the randomness of simulation results, we increase the number of POIs to three (as shown in Fig. 14), and carry out the simulation experiment with the same parameters configuration as Fig. 8. The detailed simulation results are shown in Fig. 15.

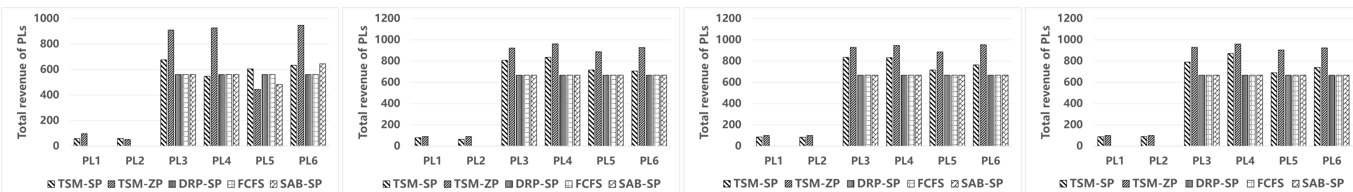
Specifically, as the number of AVs increases, the number of parking AVs and the occupancy rate of SPSs are gradually increasing, too. However, both metrics tend to stabilize when the number of AVs exceeds 280 due



(a) With 200 AVs (b) With 240 AVs (c) With 280 AVs (d) With 320 AVs



(e) With 200 AVs (f) With 240 AVs (g) With 280 AVs (h) With 320 AVs



(i) With 200 AVs (j) With 240 AVs (k) With 280 AVs (l) With 320 AVs

Fig. 12. Impact of PL deployment. (a)-(d): Number of parked AVs and occupancy rate in different PLs. (e)-(h): Rejection rate of parking requests with different number of AVs. (i)-(l): Total revenue of different PLs with increasing number of AVs.

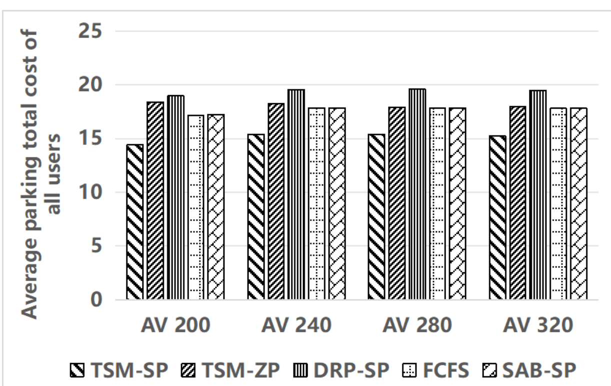


Fig. 13. Average total parking cost of users with changed PL deployment.

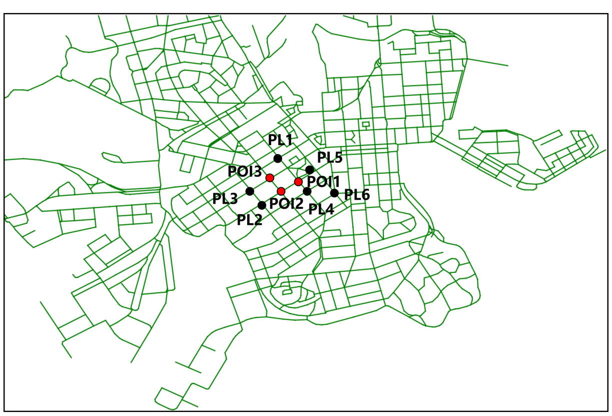
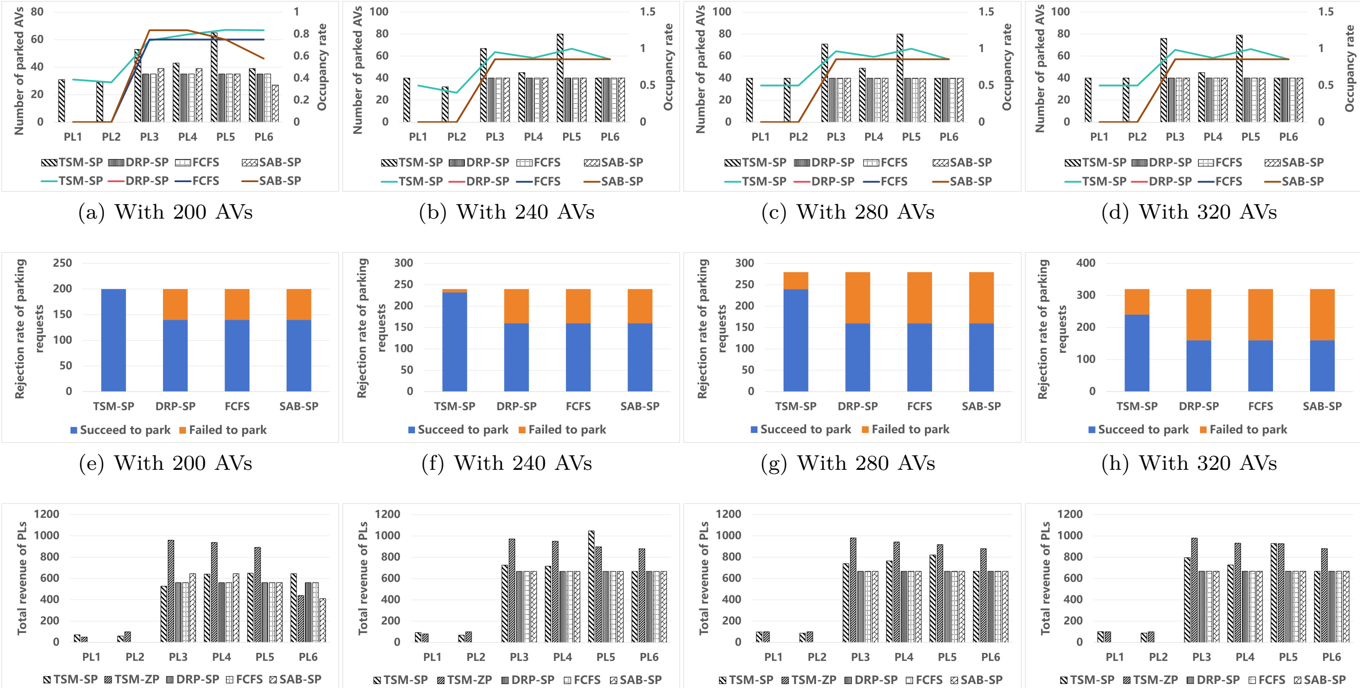


Fig. 14. Simulation scenario with three POIs.

to capacity constraints, while other methods reach their limits earlier and remain unchanged. The number of parked AVs and the average occupancy rate of shared PLs (equal to the average occupancy rate of six PLs) are the same when the number of AVs is 280 and 320. This is because the total number of SPSs is limited, and can only accommodate a maximum of 240 AVs. The observed trend in the parking request rejection rate, as the number of AVs increases, further validates the correctness of this interpretation. In addition, although the rejection rate of TSM-SP increases gradually, it remains significantly lower than that of the other methods under all configurations. Due to the limited parking duration requested by AVs and the shared parking time provided by SPSs, DRP-SP, FCFS, and SAB-SP can only accommodate a maximum of 160 AVs, regardless of the increase in the number of AVs.

Regarding the total revenue gained by SPS owners, as shown in Fig. 15 (i) - (l), TSM-ZP achieved the highest total revenue because of the zone-based algorithm. The total revenue achieved by TSM-SP ranks second, and much higher than the other three shared parking systems. With the increase in the number of AVs, the revenue of TSM-SP shows an increasing trend and then stabilizes due to saturation, while the other methods remain relatively constant. This proves the effectiveness of time-sharing allocation algorithm proposed in this paper, which allocates more AVs to SPSs, improves the utilization rate of SPSs, increases the profitability of SPS owners eventually, and does not be influenced by the number of POIs. The average total parking cost of users is shown in Fig. 16. It can be seen that TSM-SP achieved the lowest average total parking cost of users among all shared



(a) With 200 AVs (b) With 240 AVs (c) With 280 AVs (d) With 320 AVs

(e) With 200 AVs (f) With 240 AVs (g) With 280 AVs (h) With 320 AVs

(i) With 200 AVs (j) With 240 AVs (k) With 280 AVs (l) With 320 AVs

Fig. 15. Impact of POI quantity. (a)-(d): Number of parked AVs and occupancy rate in different PLs. (e)-(h): Rejection rate of parking requests with different number of AVs. (i)-(l): Total revenue of different PLs with increasing number of AVs.

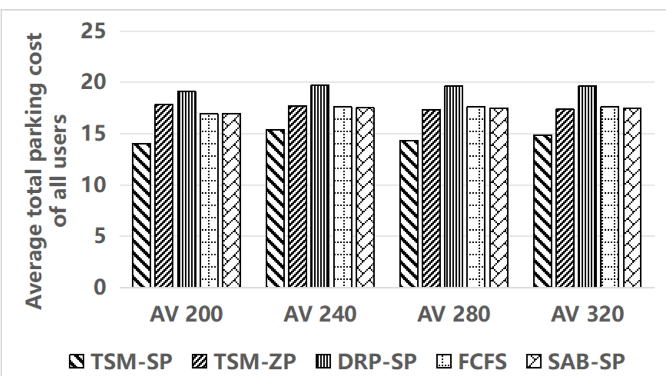


Fig. 16. Average total parking cost of users with three POIs.

parking systems, while TSM-ZP achieved the highest. This is because the zone-based pricing algorithm in TSM-ZP focuses on increasing the parking price, in order to direct the congested traffic flow to SPSs with low utilization in the outer ring. However, it does not balance the parking price well with the parking cost of users. The average total parking cost of users achieved by the remaining three shared parking systems is not much different, due to the limitations of AV request parking duration and shared parking time available for SPSs, which proves the effectiveness of the time-sharing allocation algorithm in reducing parking costs of users.

D. VoT Sensitivity Analysis

To evaluate the robustness of TSM-SP with respect to VoT parameter, we conducted additional experiments using four VoT values: 10, 12, 14, and 16, as shown in Table III. The simulation results indicate that variations in VoT affect only the average total parking cost of users, while all other key metrics remain stable across different VoT settings. Therefore, only the user cost metric is reported for clarity. It can be clearly observed from Table III that higher VoT values lead to higher average total parking costs for users. However, TSM-SP still achieves the lowest average total parking cost of users among all baselines. These findings confirms that TSM-SP is insensitive to VoT in terms of system-level allocation performance.

TABLE III
Average total parking cost of users under different VoT settings

Value of VoT	TSM-SP	DRP-SP	FCFS	SAB-SP
10	14.8361	17.3517	17.3516	17.3793
12	14.9758	17.4843	17.4841	17.5194
14	15.0795	17.6171	17.6185	17.6572
16	15.2194	17.7499	17.7483	17.7914

E. Impact of Uncertainty

To evaluate robustness of the proposed TSM-SP system, we introduce AV request delay and cancellation with 240 AVs under the same settings as Section VI-A, where the delay probability is 0.2, the cancellation probability is 0.1, and the maximum delay is 1800 s. We consider three scenarios: delay only, cancellation only, and both combined. It is worth noting that TSM-SP utilizes all six PLs, whereas baselines only utilize four PLs. The simulation results show that all methods experience performance degradation under uncertainty, with higher rejection rates and lower occupancy. Nevertheless, TSM-SP consistently achieves lower rejection rates and lower average total parking costs than baselines, demonstrating strong robustness under stochastic conditions.

TABLE IV
Key metrics with delay and cancellation uncertainties

Delay Only	OR	RR	TR	AC
TSM-SP	0.6641	0.1333	439.9663	14.1237
DRP-SP	0.7018	0.4542	517.125	16.8655
FCFS	0.8571	0.3333	667.5	17.7525
SAB-SP	0.8571	0.3333	667.5	17.7912
Cancellation Only	OR	RR	TR	AC
TSM-SP	0.7464	0.0583	525.9084	15.3415
DRP-SP	0.8571	0.3583	667.5	18.3956
FCFS	0.8143	0.3667	624	17.4884
SAB-SP	0.7768	0.3958	592.5	17.4315
Delay & Cancellation	OR	RR	TR	AC
TSM-SP	0.6293	0.1917	398.6383	13.8006
DRP-SP	0.7714	0.4875	582	19.9929
FCFS	0.7500	0.4167	561	17.0804
SAB-SP	0.7714	0.4	583.5	17.2713

OR: Occupancy Rate; RR: Rejection Rate; TR: Total Revenue; AC: Average Total Parking Cost.

VII. Future Directions

It should be noted that TSM-SP restricts each AV to a maximum allocation of two SPSs. On the one hand, due to the limited parking resources available in the city, further subdivision may cause a waste of resources. On the other hand, frequent transfers between SPSs may cause user dissatisfaction, thereby reducing the acceptability and practicality of the system. However, the research of this paper is limited to the transfer of AVs between SPSs. If the vehicle and PS types are expanded, the time-sharing matching problem between electric vehicles or electric autonomous vehicles in different PSs can be discussed. PS types can be on-street PSs, off-street PSs, public PSs or private PSs.

It should be acknowledged that these assumptions limit the generality of the current TSM-SP model. Nevertheless, within scenarios where AVs exhibit predictable mobility patterns and SPS clusters share similar availability structures, the applicability of our system remains unaffected. Future extensions that relax these assumptions, with realistic mobility traces incorporated, will further enhance the practicality and scalability of the proposed framework.

Additionally, in future work, we plan to explore the integration of machine learning or reinforcement learning (ML/RL) methods into the TSM-SP framework. ML/RL models may provide advantages in demand prediction and adaptive pricing, and could complement the optimization-based mechanism developed in this study. Additionally, future work will seek to relax the perfect-compliance assumption adopted in this work, such as incorporating communication delays, probabilistic user compliance, booking cancellations, and user-experience constraints into the whole framework. This represents an important extension for improving the robustness of TSM-SP in real-world environments.

VIII. Conclusion

To address the high rejection rate of parking requests and the resulting insufficient SPS utilization in urban shared parking systems, this paper proposed a time-sharing allocation-based SPS scheduling algorithm and names the system TSM-SP. Considering the mismatch between AV parking duration and the available shared parking time of SPSs, the proposed algorithm allocates part of the AV parking duration to two different SPSs, thereby improving overall SPS utilization efficiency. On this basis, a dynamic pricing mechanism is further introduced to adjust parking prices and guide demand distribution across different SPSs. While ensuring the interests of SPS owners, the pricing strategy effectively controls users' parking costs and balances the benefits of both parties. Overall, TSM-SP improves average SPS utilization by at least 16%, reduces parking request rejection rates by over 50%, and decreases the average total parking cost of users by at least 16%, demonstrating the effectiveness of integrating time-sharing allocation with dynamic pricing.

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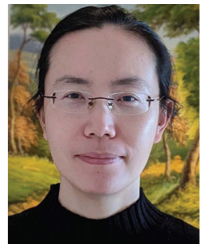

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