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Review Article

Parking reservation techniques: A review of research topics, considerations, and optimization methods

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HIGHLIGHTS

- The combination of reserved and non-reserved spaces should consider the supply of parking slots.
- Driver preferences and fairness factors are being considered in the allocation model.
- The pricing strategy can be integrated with the allocation model by affecting demand.
- The performance of optimization for parking reservations on the overall transport system is uncertain.

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ABSTRACT

Growing private vehicle use and a limited supply of parking resources have increased competition for parking spaces. Ineffective searching for parking spaces is a significant barrier to smooth traffic flow. Smart technology-generated parking reservations are regarded as an excellent way to increase parking efficiency and lessen traffic. Although there is increased attention on smart parking research and parking reservation optimization, a scoping review is currently lacking. Therefore, the purpose of this paper is to provide a comprehensive review of the research literature related to parking reservations. Out of the original 438 publications identified in this search, 99 were eventually chosen for analysis. The review categorized parking reservations into four research topics: inventory control, allocation decisions, pricing strategies, and performance evaluation. The elements considered in these research themes, modeling techniques, and evaluation criteria are explored in detail. In addition, the challenges and further enhancements of parking reservation optimization are discussed. It is believed that the findings from this study will be beneficial in further research on parking reservations.

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1. Introduction

For travelers and traffic managers in metropolitan areas, the increasing number of vehicles and the limited availability worsen urban parking problems. On the one hand, due to a lack of resources and inaccurate parking information, the time drivers spend searching for spaces accounts for a considerable amount of the cost of travel. It has been reported that in a typical urban center, about 30% of vehicles search for parking, with an average cruise time of 8.1 min per vehicle (Shoup, 2006). This inefficient parking search adds to traffic congestion, air pollution, and accidents while also wasting drivers' time and fuel. For example, in the Chicago metropolitan area such searches result in up to 39 million vehicle miles traveled, 1.9 million gallons of gasoline, and over 29,000 tons of CO_2 emissions annually (Ayala et al., 2012). On the other hand, there are a great deal of unoccupied resources due to the temporal and spatial variations in parking supply and demand. In the Beijing metropolitan area, 44% of private parking spaces are found to be vacant during the daytime (Yan et al., 2021). These problems have prompted more research into effective parking solutions.

The development of information technology and mobile internet technologies has made it possible for drivers to easily access real-time parking availability and price data. Extensive study has therefore been conducted on a number of efficient parking management strategies, including shared parking (Shaaban and Tounsi, 2022; Xie et al., 2022), park and ride (Kurek and Macioszek, 2022; Macioszek and Kurek, 2021), and parking guidance (Xie et al., 2023b). Parking reservation (PR) technology in the field of intelligent transportation systems (ITS) has been developed to provide drivers with guaranteed parking spaces to reduce driver competition. The obvious benefits of PR are reduced cruising time, increased parking utilization and revenue, and even lessened traffic congestion (Kotb et al., 2017). This innovative method is thought to be an efficient solution to alleviate parking problems because it simultaneously benefits drivers, parking lots, and city parking managers. Much research has been conducted on reservation allocation and pricing; however, a scoping review of this area is lacking. Therefore, this paper aims to review the research literature related specifically to parking reservations.

The remainder of this article is structured as follows. The approach and review procedure are described in the following section. This is followed by each research topic and methodology for parking reservation optimization. Next, the challenges and opportunities are discussed. Finally, the paper is summarized.

2. Method

We conducted a thorough review of literature published between January 2000 and December 2022. 438 recent papers

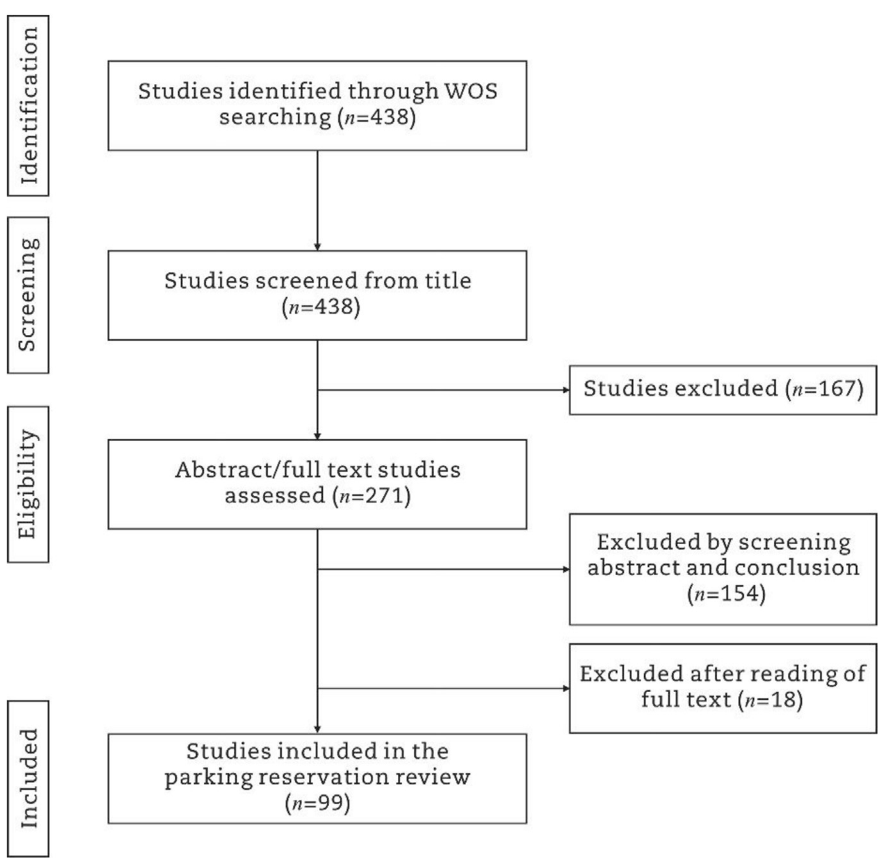

Fig. 1 – Flowchart of the review's screening.

were uncovered by a literature search using the keyword “parking reservation” or “parking allocation” or “parking assignment” that was conducted utilizing the search engine Web of Science (WOS). After removing duplicate records, the identified studies' relevance was examined by first evaluating the title, followed by the abstract and/or full text. Only studies focused on vehicle reservation optimization were chosen. This technique led to the identification of 99 studies in total for further consideration (Fig. 1).

Based on their topics, these studies were broadly divided into four categories: inventory control, allocation decisions, reservation pricing strategies, and performance evaluation (Kotb et al., 2017). If a study covered multiple topics, each topic was evaluated independently. For each group, considerations and optimization techniques were identified. The fundamental aspects of each study (such as data, methodologies, and factors considered) are compiled in table format for each topic. Finally, recommendations for future research directions and needs are discussed and summarized. Fig. 2 presents the framework for the content of this review.

3. Parking reservation optimization

Parking reservation is a new concept in the smart parking field that provides drivers with guaranteed spaces, thereby reducing or even eliminating competition for spaces among

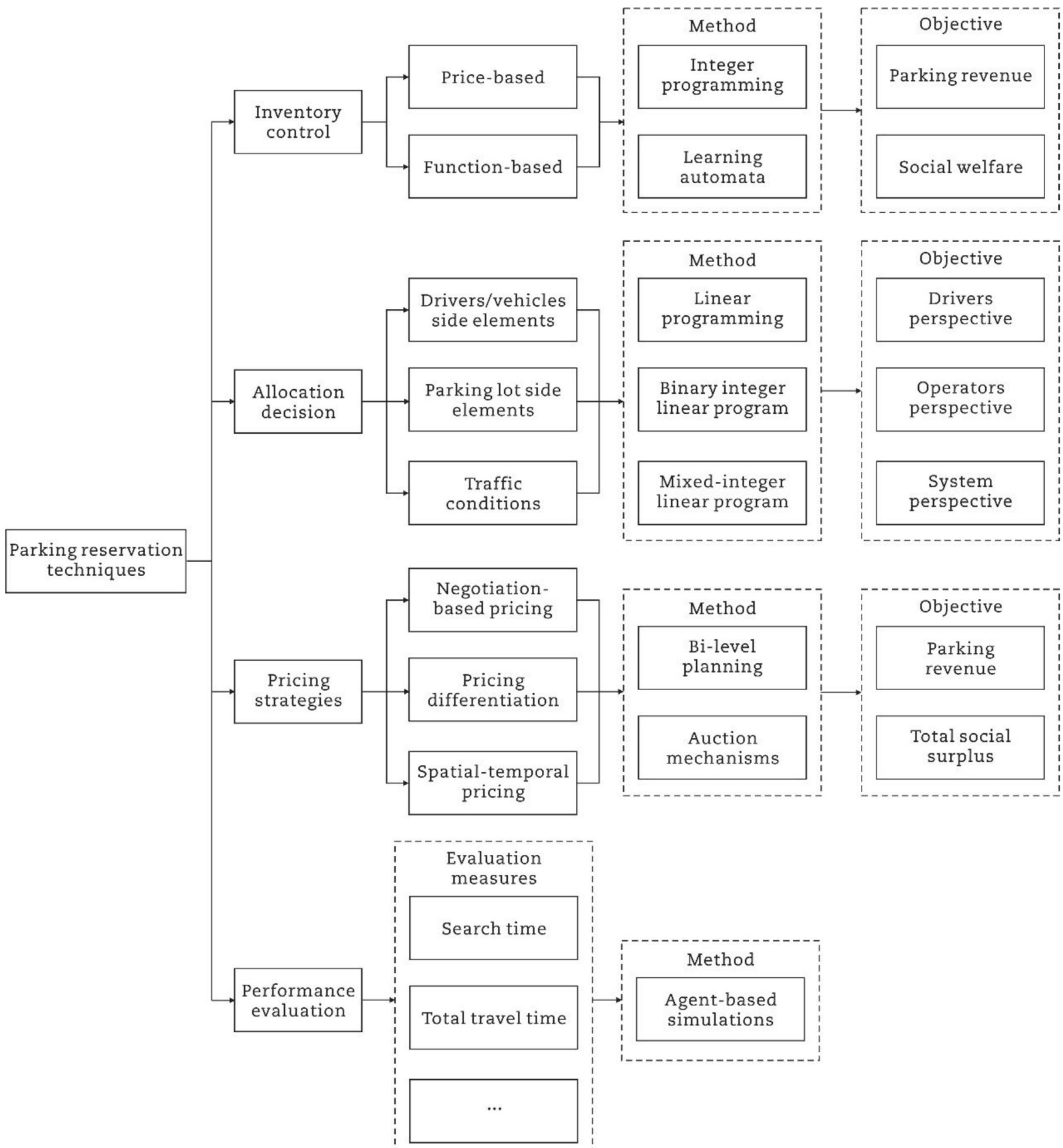

Fig. 2 – Flowchart of the 4 main research topics.

drivers. In addition to reducing traffic and emissions caused by searching for a parking space, a successful parking reservation system also gains the support of drivers by offering benefits such as guaranteed parking availability, reduced queue length, and reduced waiting time. Parking reservations contain a variety of decision-making and optimization-related issues, as well as various considerations and methods. Using the identified literature, we review each research topic (i.e., inventory control, allocation decisions, reservation pricing strategies, and performance evaluation) independently below.

3.1. *Inventory control*

Parking reservation inventory control was first proposed by Teodorovic and Lucic (2006) and was highly inspired by the airline seat inventory problem. A typical reservation inventory system is the "inventory of different types/classes of parking spaces" which indicates the availability of various spaces in the garage. Examples of different categories of spaces include different tariff classes (Roper et al., 2018; Teodorovic and Lucic, 2006) and reserved/unreserved parking spaces (Mei et al., 2020; Waheed et al., 2021; Zhang and Mu, 2018). Reservations can only be made based on that capacity if the inventory of the various spaces is determined.

Inventory control attempts to classify spaces and provide different capacities for each category. Spaces may be divided according to prices or functions from the standpoint of a parking lot. Parking functions include traditional parking, reserved parking, disabled parking, and common parking for both traditional and reserved parking (Waheed et al., 2021; Zhang and Mu, 2018). Demand for parking is based on these categories. To model and optimize parking demand, each category should include the number of demands, parking duration, waiting time, search time, etc. (Teodorovic and Lucic, 2006; Waheed et al., 2021). Related to optimization goals, the majority of this strategy focuses on increasing parking revenue or social welfare (Waheed et al., 2021). Social welfare metrics include total travel time, total waiting time, and vehicle kilometers traveled (VKT). Optimizing parking reservation configuration can directly and effectively improve social benefits or revenue, but these are two conflicting objectives (Mei et al., 2020).

Inventory control is dedicated to setting the supply capacity for different categories of parking spaces, and the commonly used methods are based on integer planning techniques and learning automata (Afshari et al., 2022; Teodorovic and Lucic, 2006; Waheed et al., 2021). Both approaches are implemented based on the assumption that parking demand is known, for example, that vehicles obey a Poisson distribution of arrivals or that the cumulative number of driver arrivals and departures is represented by a stochastic process. Methods based on integer programming tend to have an explicit objective (e.g., maximizing parking revenue) and then incorporate constraints for driver demand and parking availability (Teodorovic and Lucic, 2006). Learning automata are utilized in specific circumstances to create decisions that are evaluated by systematic metrics, such as vehicle waiting time and the probability that a vehicle does not get a reservation. Learning automata outperforms competing approaches based on the idea that it interacts repeatedly with the environment and continuously enhances its decisions (Afshari et al., 2022; Waheed et al., 2021).

Research on inventory control has produced novel findings which indicate that complete parking reservations (CPR) outperform the no-reservations (NR) policy in several service-oriented performance measures. However, due to the scarcity of space, while CPR ensures that some users receive the desired service, certain users will inevitably receive inferior service (Kaspi et al., 2014). Actually, when the parking supply is insufficient, a combination of reserved and unreserved parking spaces can smooth the demand peak and reduce the total travel cost. This is because travelers without reservations are forced to depart earlier to secure a parking space (Yang et al., 2013). There should be some non-reserved parking spaces kept for competition in a specific situation where the parking supply is less than the potential demand but still substantial. Nonetheless, if there is a limited amount of parking available, all parking spaces should be open for reservation to avoid competition (Liu et al., 2016).

Inventory control mainly provides different categories of parking spaces. Parking spaces can be divided into distinct categories according to parking purposes or prices. The current mainstream division is a joint control of reserved and non-reserved spaces. The main objectives of this inventory control strategy are to improve parking revenue or social welfare. A total of 5 studies of inventory control were identified, as summarized in Table 1.

3.2. *Allocation decision*

3.2.1. *Elements considered*

Reservation allocation seeks to match drivers with parking lots/spaces to reduce repeated cruising. Numerous aspects must be considered when deciding how to allocate reservations, contributing to various optimization goals. For example, driver/vehicle-related and parking lots-related elements reflect the demand and supply of reserved spaces, respectively. Because traffic conditions affect driver travel costs, traffic characteristics must also be considered carefully. Below we review these three aspects.

Typically, the driver/vehicle side elements deal with parking requests. Origin, destination, arrival time/start time, departure time/end time, and duration are the most basic elements included in parking requests (Boudali and Ben Ouada, 2017; He et al., 2018; Ning et al., 2022; Nugraha and Tanamas, 2017; Said et al., 2021; Shao et al., 2016; Yan et al., 2021). In addition to these fundamental components, several individual preferences can also be considered to meet individual needs. Driver type (commuters/irregular travelers), reservation type (real-time/share-time reservation), required security level, maximum acceptable driving/walking distance, maximum acceptable waiting time, and price limit are frequently mentioned (Boudali and Ben Ouada, 2017; Chou et al., 2014; Fu et al., 2014; Geng and Cassandras, 2013; Kotb et al., 2016; Koutras et al., 2022; Ning et al., 2022). The driver type is usually related to the purpose of their trips, and the reservation type is associated with the allocation type. Real-time reservation (RTR) is achieved by performing dynamic resource allocation. In the case of RTR,

Table 1 – Key studies of inventory control.

Study	Classification of parking area	Method	Element considered
Teodorovic and Lucic (2006)	Several different parking tariffs	A combination of fuzzy logic and integer programming	Garage capacity; different parking tariffs; parking fees; parking revenues; the numbers of accepted and/or rejected drivers
Roper et al. (2018)	Several different parking tariffs	Integer programming formulation and artificial neural network	Accepted request; total revenue; available capacity; parking tariff classes; dwell time
Zhang and Mu (2018)	Walk-in parking; reservation parking	Computational experiments	Demand and rental price of reservation customers and walk-in customers; the capacity and purchase price of contract supply and temporary supply; the penalty cost of rejecting reservation; the expected revenue
Mei et al. (2020)	Reservation spaces; common spaces	An agent-based simulation and genetic algorithm	Cruising vehicle proportion; queuing vehicle proportion; average cruising time of all vehicles; average waiting time of all vehicles; the average vehicle kilometers of travel (AVKT); average of the total travel time; average total parking fee; total parking space utilization time of the parking lot
Waheed et al. (2021)	Conventional parking; reservation parking; conventional and reservation parking	Learning automata	Waiting time; search time

drivers are continuously assigned the optimal parking spot until they reach their destination. In contrast, share-time reservation (STR) is implemented by performing a static resource allocation based on a time schedule, where the driver can explicitly select their preferred resource and the time window to occupy that resource at any time in the future (Kotb et al., 2016).

Elements on the parking lot side are typically correlated with location, capacity, cost, and other attributes. The location-related factors include its proximity to nearby hotspot destinations, etc., which has an impact on drivers' walking and driving distances. Crucial determinants in the modeling process are parking capacity, real-time availability, and parking cost (He et al., 2018; Levin, 2019; Mondal et al., 2021; Said et al., 2021; Yan et al., 2021). Other research has focused more precisely on parking spot attributes such as security level, size, status, position, and type of parking spot (normal or disabled) (Boudali and Ben Ouada, 2017; Kotb et al., 2016).

Heterogeneous traffic conditions (e.g., partial congestion) near parking entrances and exits affect the parking experience. The traffic flow in the vicinity can result in delays in adjacent parking lots, which impacts the allocation choice (Xie et al., 2022). Road travel speeds are determined by node traffic conditions, which can be embedded in reservation algorithms, such as that by Taherkhani et al. (2016).

The relationship between driver demand, supply of parking lots, and traffic condition is complex and interrelated. Understanding how these three aspects interact with each other can help in creating an optimal allocation model. In general, the driver's origin, destination, arrival time, and parking duration demand are determined before the trip. For driver parking demand, elements related to parking location and cost, as well as road traffic conditions, influence their choice of parking lots around their destination. More specifically, drivers' parking choice is often represented by the logit model in Eq. (1). The parking selection utility function $U(i)$ is usually calculated by the parking cost, including the driver's driving time $t(i)$, the walking distance from the parking lot to the destination w_{id}, and parking fees (multiplied by the parking price per unit $f(i)$ and parking duration t_{park}), as presented in Eq. (2) (Mei et al., 2020). The location of the parking lot and the price of parking affect the walking distance and the parking fees, which further affect the utility of parking choice. Similarly, traffic conditions, such as road delays and congestion, have a significant impact on the driving time of drivers traveling to the parking lot. An important goal in allocation decisions, from the perspective of all drivers, is to match drivers to parking lots in a way that minimizes travel costs for all travelers. Concerning parking lots, those with higher demand are likely to set higher prices, more detailed methods can be found in Kotb et al. (2016) and Lu et al. (2021). Additionally, real-time availability information can be impacted by traffic conditions. For instance, if a parking lot is difficult to access, it may take longer for drivers to arrive and exit, which can reduce the effective capacity. For traffic conditions, there is no doubt that roads and parking lots around destinations with high demand have more severe congestion. In summary, parking demand of drivers, supply of parking lots, and traffic conditions always interact with each other.

Careful consideration of all of these factors is necessary when creating an effective parking allocation model. Allocation models can be constructed from different perspectives with various objectives, such as minimizing travel costs for drivers, maximizing parking benefits, and reducing traffic congestion.

$$P(i) = \frac{\exp(-\eta U(i))}{\sum_{p \in P_c} \exp(-\eta U(i))} \tag{1}$$

where $U(i)$ represents the parking selection utility of drivers to the parking lot i and η is the utility sensitivity coefficient.

$$U(i) = a_1 t(i) + a_2 w_{id} + a_3 f(i) t_{park} + a_4 \zeta \tag{2}$$

where ζ is the random item, and a_1, a_2, a_3, and a_4 are the important coefficients.

3.2.2. *Allocation approach*

Fig. 3 is an illustration of a parking reservation allocation. It is assumed that an existing parking platform integrates the supply of parking lots in the area and can make allocation decisions for drivers' reservation behavior. Before starting or during traveling, a driver submits a parking request (i.e., parking demand) to the parking platform. The request comprises a start time and an end time for parking. Based on the occupancy and reservation status of each parking lot (i.e., parking supply), the parking platform responds to whether the parking request is successfully assigned. If there is a parking lot that meets the required time window, then the parking platform will deliver an acceptance of the reservation and inform the driver of the assigned parking lot. The parking platform considers the intensity of traffic on the roads while allocating spaces. While there is an available time slot to match user demand, PL3 is congested with traffic due to queues of vehicles at its entrances and exits, thus the user is eventually assigned to PL2. The reservation request will be rejected if there are no slots available to accommodate the demand.

Most reservation allocation modeling is based on several approaches, where the choice of the modeling approaches depends on the nature of the decision variables and the constraints determined by the complexity of the problem. In parking allocation, integer linear programming (ILP) is applied when the decision variables represent discrete decisions (Mejri et al., 2016). Binary integer linear programming (BILP) is utilized when the decision variables can only take a value of 0 or 1 to indicate whether to allocate a parking space to a particular driver or not (Chou et al., 2018; Mouskos et al., 2000; Shao et al., 2016; Ning et al., 2020). This simple linear programming allows for static allocations for a given target and deterministic demand. However, this allocation ignores future moment demands. Therefore, a real-time, periodic dynamic allocation method is then proposed. This parking allocation problem is always formulated as a mixed-integer linear programming (MILP) at each decision point defined in a time-driven sequence. The solution of each MILP is an optimal allocation based on current state information and is updated at the next decision point. That means that the model can continuously update the parking space assigned to drivers until they arrive (Geng and Cassandras, 2012, 2013; He et al., 2018; Kotb et al., 2016; Yan et al., 2021). When the constraints involve nonlinearity, MINLP is then developed (Zhao et al., 2021a). Further, considering the actual arrival/departure time is difficult to be consistent with that registered on the platform, the parking unpunctuality is

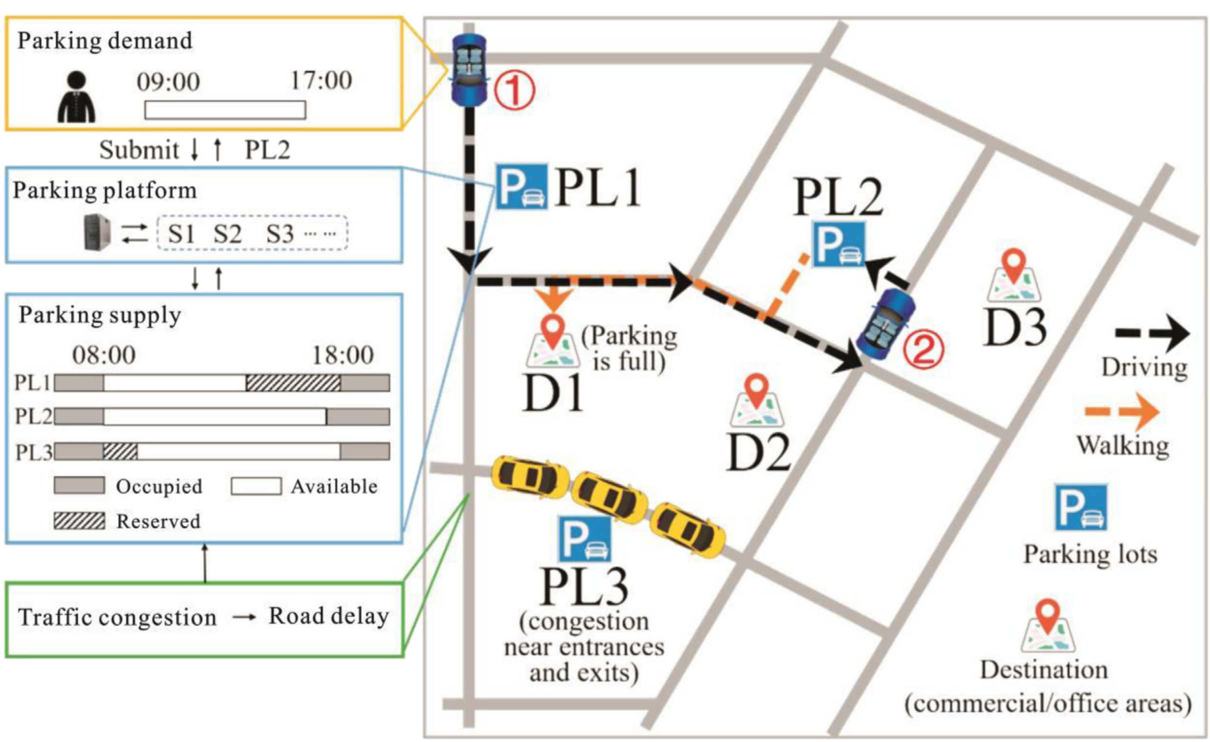

Fig. 3 – Illustration of parking allocation (Xie et al., 2022).

incorporated as a stochastic factor in the allocation model (Jiang and Fan, 2020). These problems are solved by applying solvers CPLEX (Alfonsetti et al., 2015; He et al., 2018; Kotb et al., 2016; Levin, 2019; Ning et al., 2020; Xie et al., 2022; Yan et al., 2021), Gurobi (Wang et al., 2022), reformulations (Geng and Cassandras, 2012, 2013), or heuristics (Abidi et al., 2015; Doulamis et al., 2013; Duan et al., 2020; Jiang et al., 2021; Mejri et al., 2016; Ning et al., 2022; Xie et al., 2021; Xu and Sun, 2022; Zhang et al., 2020). Recent developments in deep reinforcement learning (DRL) have provided new insights into the solution of challenging sequential decision-making issues. DRL provides a feasible approach to optimize parking allocation as the intelligent agents interact with the environment. The DRL model initially assesses the state of the parking lot and the vehicle parking demand. Based on this state, the model makes a decision or takes an action (i.e., assigns a vehicle to a particular parking space). Following this action, the model receives a reward or penalty from the environment based on how efficient the parking allocation was. An efficient allocation could be one that minimizes the total distance vehicles traveled, maximizes utilization of space, or satisfies other defined criteria. The objective of training the model is to discover an optimal policy—a set of actions that maximizes the overall reward over time (Xie et al., 2023a; Zhang et al., 2022c).

The majority of the parking request data in such a model are presumptive. Simple demand information is empirically assumed by the authors, providing information on the destination, parking duration, acceptable walking distance, and acceptable parking price (Jiang et al., 2021). A more popular approach is to assume that parking requests follow a Poisson distribution (Chou et al., 2018; Geng and Cassandras, 2013; Mejri et al., 2016; Shao et al., 2016), or a normal distribution (Wang et al., 2022). Parking duration is assumed to follow a negative exponential distribution (Geng and Cassandras, 2013; Shao et al., 2016; Xie et al., 2022), a uniform distribution (Mejri et al., 2016), or Gamma distribution (Duan et al., 2020). A few studies have used actual demand data gathered by parking applications, traffic vehicle arrivals or inferred parking requests based on datasets of taxi trajectories (Duan et al., 2020; Wang et al., 2022; Yan et al., 2021; Zhao et al., 2021a). Parking supply data is based on both geographic information of parking lots in actual environments (Geng and Cassandras, 2013; Kotb et al., 2016; Mejri et al., 2016; Xie et al., 2022) and simulations (Chou et al., 2018; He et al., 2018; Mouskos et al., 2000; Rehena et al., 2018). Surveys or inferring the availability of shared parking lots (such as residential private parking lots) that can be utilized as suppliers might provide more precise information on supply periods, especially if the supply involves shared parking lots (Duan et al., 2020; Zhao et al., 2020, 2021a).

The objectives of reservation allocation are based on the following views: drivers, parking lots, travel system, or a mix of these perspectives. The goal for drivers is to reduce the overall cost of drivers' travel (Yan et al., 2021). Travel costs include search costs due to finding availability, driving costs to arrive at the parking lot, walking costs to the destination from the parking lot, and parking costs (He et al., 2018; Mouskos et al., 2000; Xu and Sun, 2022). In addition, demander satisfaction is also regarded as an allocation objective, which was considered as a function of the walking distance and the parking price (Jiang et al., 2021). The objectives from the viewpoint of parking lots are increasing parking utilization or revenue (Chou et al., 2018; Jiang and Fan, 2020; Wang et al., 2022; Zhao et al., 2021a). It is easy to understand that revenue comes from the parking fees paid by the assigned users. Moreover, operating expenses and the penalties paid to drivers due to request rejections can also be subtracted to obtain profits (Chou et al., 2014; Ning et al., 2020, 2022; Jiang and Fan, 2020; Shao et al., 2016). From the standpoint of the transportation system, the primary objectives are to increase social welfare, service more clients, or alleviate traffic congestion (Geng and Cassandras, 2013; Levin, 2019; Panayiotou et al., 2021). Specifically, the cost of driving/cruising for the same amount of time might be different due to the non-identical value-of-travel-time across drivers. The optimal allocation should give available parking slots to drivers who value the slots most to achieve maximum of social welfare (Zou et al., 2015). Numerous studies also focus on the combination of the above-mentioned objectives (Duan et al., 2020; Fu et al., 2014; Jiang et al., 2021; Kim et al., 2020; Kotb et al., 2016; Koutras et al., 2022; Xie et al., 2022; Zhang et al., 2020).

In general, "one person per spot" and time-varying parking availability capacity restrictions form the basis of the reservation allocation constraints (Mouskos et al., 2000; Nugraha and Tanamas, 2017; Xie et al., 2022). Additionally, several fairness constraints are taken into account for better parking resource allocation, including adjusting the priority of assigning spaces to drivers based on their proximity to their destinations (Geng and Cassandras, 2012, 2013; Kotb et al., 2016; Ning et al., 2020), modeling the aggregate social benefit to represent fairness (Alfonsetti et al., 2015), or evaluating them based on multiple criteria like historical user behavior and the urgency (Sadreddini et al., 2021). To reserve the optimal parking space, drivers' preferences are also considered. This can be accomplished by directly examining the driver's preference when selecting a parking lot (Fu et al., 2014; Mahdi et al., 2018) or by setting weights to express their interest in minimizing walking distance and parking fees (Geng and Cassandras, 2013). From another perspective, the preferences of the parking lot willing to offer the service can also be considered. Obviously, parking lots prefer to serve vehicles that bring in higher incentives or revenue. Therefore, the parking duration of vehicles can be ranked to construct a list of preferences for parking lots (Kim et al., 2020). Road traffic conditions, vehicle speed and parking forecast availability are also considered to prevent localized congestion and pollution peaks (Mladenovic et al., 2021; Schlote et al., 2014). It is important to note that the aforementioned allocation mechanism significantly relies on the fixed parking demand and supply and ignores some participation uncertainty. This is one of the research topics that have attracted attention recently. For example, in practice, drivers may arrive or depart earlier or later than the arrival or departure time windows they have submitted. Given this lack of punctuality, chance-constraint (Wang et al., 2022) and parking unpunctuality time window (PUDW) (Jiang and Fan, 2020) are proposed to avoid conflicts among parkers and reduce the service failure rate.

Table 2 – Key studies of allocation decision.

Study	Method	Element considered	Objective	Evaluation metrics
Mouskos et al. (2000)	Binary integer linear program	Capacity, available spaces, cost (fixed monetary value and a fixed walking time)	Minimize the total system-wide parking cost	–
Mejri et al. (2016)	A simulated annealing-based meta-heuristic	Arrival rate, parking duration, costs (estimated walking distance, estimated driving distance, estimated parking congestion impact)	Minimize total cost	Request satisfaction ratio, average walking distance, the overall parking lots occupancy ratio, average response time
Kotb et al. (2016)	Mixed-integer linear programming (MILP)	Parkers (maximum total price, maximum total walking distance, type of parking), spot (normal or disabled), type of reservation, fairness, traffic (normal and dense traffic)	Minimizing the total monetary cost for the drivers and maximizing the utilization of parking resources	Total utilization, revenue, searching time, total cost, wandering
Shao et al. (2016)	Binary integer linear programming	Available time windows, parking requests, selling price, buying price	Maximizing operating revenue while minimizing the loss due to rejection	Net revenue (profit) and acceptance (or rejection) rates, parking utilization rate
Chou et al. (2018)	Expected revenue gap algorithm (binary integer linear programming)	Parking demand, customer class (by categorizing their parking length time), parking supply	Maximum expected revenue	Utilization of parking spaces, acceptance rate of parking requests
Levin (2019)	Linear programming formulation	Parking availability, walking time, and the effects of the parking assignment and route choice on traffic flow	Minimize total system travel time (waiting time, driving time, walking time)	Travel time, walking time
Ning et al. (2020)	A binary integer linear programming model	Preference (proximity and parking cost)	Maximizing the platform's profits	Profits, acceptance rate
Panayiotou et al. (2021)	Integer linear program (ILP) -based α-fair utility allocation algorithm	Arrival time/departure time, minimum/maximum charging requirement	Maximizing the constant elasticity welfare function	Fairness, efficiency
Yan et al. (2021)	Mixed integer programming model	Driver and owner types, latest arrival time, duration, location, available time of parking space, driving time, walking time, travel cost, taxi fee	Total travel cost saving of drivers	Fulfillment rate of demands, utilization rate of shared parking spaces
Xu and Sun (2022)	Ant colony-genetic algorithm	Parking cost (search cost and travel cost)	Minimize the total parking cost	Parking lot utilization rate, service demand quantity
Xie et al. (2022)	Integer linear program	Parking demand; parking lots supply	Maximum parking revenue and minimize total costs	Platform revenue, parking slot utilization, and the acceptance rate of parking requests, average walking distance
Ning et al. (2022)	A metaheuristic algorithm (advanced and adaptive tabu search (AATS))	Parking demand, parking preferences, shared parking rental price, penalty of waiting	Maximize the integrated profit of the system	Total integrated profit, total allocated demands, total space utilization, and total computing time

These reservation allocation models are frequently compared against the first-book-first-serve (FBFS) model (Chou et al., 2018; Doulamis et al., 2013; Ning et al., 2020; Sadreddini et al., 2021; Shao et al., 2016; Xie et al., 2022), or a greedy algorithm (Alfonsetti et al., 2015; Mejri et al., 2016; Mladenovic et al., 2021) to determine how effective they are. The evaluation metrics are similar regardless of which objective is specified. Driver-based metrics include walking distance, request acceptance rate/the request satisfaction ratio, total travel time, searching time, total cost, and extra driving distance (He et al., 2018; Kotb et al., 2016; Koutras et al., 2022; Mejri et al., 2016; Mondal et al., 2021; Ning et al., 2022; Rehena et al., 2018; Xiao et al., 2021; Xie et al., 2022). Evaluation metrics from a parking lot perspective involve resource utilization rate, parking facility occupancy rate, turnover rate, and total revenue (Geng and Cassandras, 2013; He et al., 2018; Koutras et al., 2022; Kotb et al., 2016; Mejri et al., 2016; Ning et al., 2022; Nugraha and Tanamas, 2017; Rehena et al., 2018; Wang et al., 2022; Xiao et al., 2021; Xie et al., 2022; Xu and Sun, 2022; Zhao et al., 2020). Evaluation metrics from a system perspective include social welfare, service failure rate, the gap between reality and models, total computing time, and response time (Geng and Cassandras, 2013; He et al., 2018; Ning et al., 2022; Mejri et al., 2016; Wang et al., 2022). Environment-related metrics include fuel consumption saving, emissions reduction of CO, HC, and NO_x (Han et al., 2017).

The allocation decision is dedicated to achieving an optimal match between drivers and parking lots/spaces. Driver-related parking request and preference elements, characteristics such as location and price of the parking lot, and road traffic conditions are typically taken into account. The majority of reservation allocation methods are based on linear programming models and their expansions, with driver travel cost, parking utilization or revenue, and social welfare as optimization objectives. In recent years, consideration of drivers' subjective preferences, fairness, and uncertainty of reservation allocation have become more realistic to the actual scenarios. Table 2 summarizes the elements and methods applied in the allocation decision.

3.3. *Pricing strategies*

Pricing strategies are often combined with reservations to guide the parking market. Pricing schemes for parking reservations can affect parking demand and enhance utilization in locations with high demand. Pricing policies affect not only the utilization but also the traffic flow in the surrounding area (Kotb et al., 2016; Mei et al., 2020). Pricing-based reservation can be classified as negotiation-based pricing (Hashimoto et al., 2013; Zhang et al., 2019), pricing differentiation (Rao, 2011; Yan et al., 2011), and spatial-temporal pricing (Kotb et al., 2016; Lu et al., 2021).

3.3.1. *Negotiation-based pricing*

Bi-level planning is a popular technique for modeling negotiation-based pricing. This approach strives to ensure that transactions are facilitated at a balanced market price by considering the dynamic interactions between vehicles and parking lots. The bi-level structure of the formulation is depicted in Fig. 4. The upper-level parking owners (leaders) decide the parking price for each period to maximize their revenue. The lower-level users (followers) simultaneously determine their parking location to minimize their disutility. The disutility of travel is usually a function of the proximity of the parking space to the destination, parking fees, congestion, and travel costs (Fotouhi and Miller-Hooks, 2021; Tian et al., 2018; Wang and Wang, 2019). The disutility affects not only the decision of customers but also the total demand (Lei and Ouyang, 2017). Drivers may decide not to

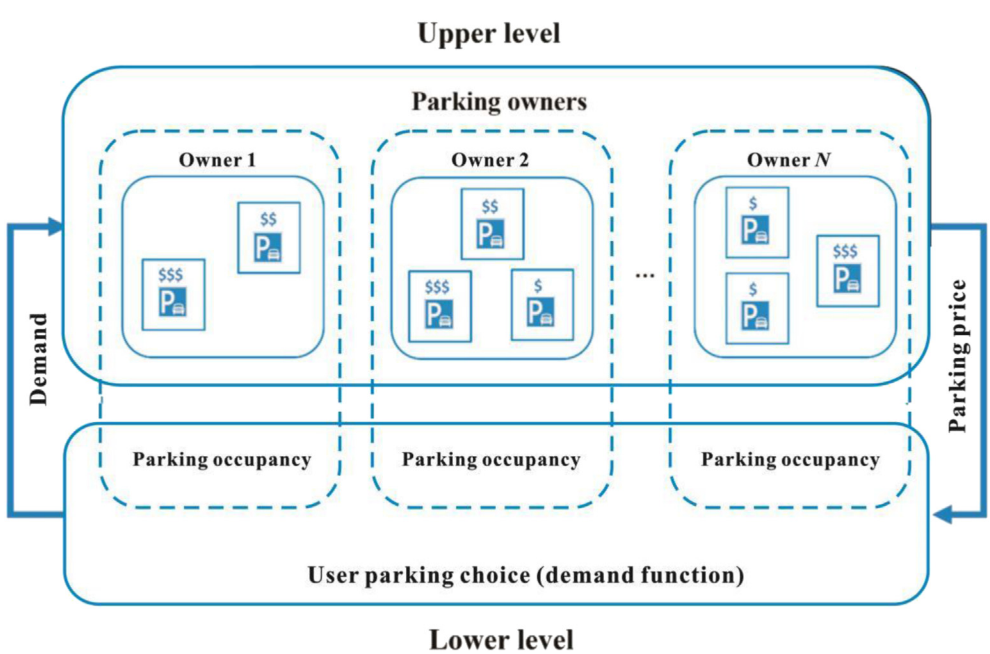

Fig. 4 – Bi-level structure of the parking-pricing problem (Fotouhi and Miller-Hooks, 2021).

travel if the price is excessively high and the disutility is too severe. Parking prices are often set with an upper and lower bound. The local authority can decide the upper price limit, while the lower limit is the minimum fee the parking owner is willing to accept (Fotouhi and Miller-Hooks, 2021). In addition to the revenue objective, the total social surplus (the sum of producer and consumer surpluses) is the most common optimization objective (Tian et al., 2018; Wang and Wang, 2019). Current advances in dynamic pricing based on bi-level programming are focused on the participants, the manner in setting prices, the demands of drivers, and the solution strategy. In terms of participants, previous techniques assumed the existence of a single agent setting prices or a single owner. In practice, however, there are typically multiple parking facilities in an area, with several owners competing with each other to maximize their benefits. As a result, the modeling problem gradually extends from a single-owner problem to a multi-owner scenario. This expansion not only increases uncertainty in demand and supply, but also makes modeling and solving more complex (Fotouhi and Miller-Hooks, 2021). The typical pricing scheme varies over time as a result of interactions with parking demand. Additionally, drivers make their reservations at different points in advance of their desired parking slots (i.e., for two drivers who want a parking reservation at the same time, one may submit a request 1 h in advance while another may request only 30 min in advance). Therefore, valuable information about demand and supply for future planning periods is also effectively taken into account in dynamic decision-making (Lei and Ouyang, 2017). When it comes to drivers' demand, users are classified into different demand types, with each type determined by the origin and destination, parking start time, parking duration, etc. The amount of each type follows the inverse demand function of the negative utility of parking (Lei and Ouyang, 2017). In particular, considering that random delays in customers' departure would lead to a service failure, a parking reservation system equipped with flexibility was established. This flexibility is achieved by relocating customers or asking customers to wait for an amount of time (Wang and Wang, 2019). As for the solution method, due to the high nonconvexity and the curse of dimensionality of these problems, solving them is usually a nontrivial task. Researchers typically address them by reformulating, such as a diagonalization method with an embedded gradient ascent approach in Fotouhi and Miller-Hooks (2021), continuum approximation in Wang and Wang (2019), or a non-myopic approximate dynamic programming (ADP) approach in Lei and Ouyang (2017).

Another frequently used method in the parking reservation and sharing research field is auctions. An auction is essentially a bidding mechanism that is used to determine the price at which they will be sold under certain auction rules. Auctions typically involve three stakeholders, the bidder, the auctioneer, and the parking platform. Each bidder submits a sealed bid to the parking platform during the auction. The bids consist of one or more consecutive time slots and a bid price. The bid price represents the driver's perception of the value of the parking. Given a parking demand and limited parking resources, the auctioneer (seller) tries to find an efficient allocation scheme that maximizes parking revenue/user utility/social welfare (Hashimoto et al., 2013; Shao et al., 2020; Zhang et al., 2019). Researchers have made many advances in auction methods. The one-sided auction is one type of auction used in reservation and sharing. This auction method allows only bidders to submit parking demand, bid price, and parking preference information to the platform. To optimize bidder welfare, the platform creates an allocation and payment structure based on integrated parking supply information (such as public and shared parking) (Kong et al., 2018). Another kind of sequential auction mechanism that expects to increase profits is also designed to solve the parking pricing problem. That is, the allocation is done in order of expected revenue per unit of time (Hashimoto et al., 2012, 2013). Considering that the interests of both demanders and suppliers should be concerned, a more realistic double auction mechanism has been proposed to provide a more flexible matching scheme and increase the transaction size for the parking market. Different from one-sided auction, double auction allows suppliers to raise their bids as the demanders (Xiao et al., 2018). In such a scenario, participants (both suppliers and demanders) can provide information to the parking platform regarding the availability and demand for parking spaces. To constrain potential participants to opt out, Xiao et al. (2018) combined the priority attributes of participants in a double auction to establish a more equitable circular auction mechanism. Despite the different auction methods, auction-based pricing approaches involve two important decisions: space allocation and payment rules. The space allocation decision is similar to the elements considered in Section 2.2, with the objectives of maximizing user utility, platform revenue, social welfare, etc. (Shao et al., 2020; Zhang et al., 2018, 2019). For payment rules, the Vickrey-Clerke-Groves (VCG) auction mechanism is frequently used for revenue allocation (Chen et al., 2015; Zhang et al., 2018, 2019). This allocation method satisfies individual rationality, budget balance, and incentive compatibility, encourages all drivers to provide truthful bids, and will attract several agents to join the platform.

3.3.2. *Pricing differentiation*

Pricing differentiation is an additional method for reservations. Pricing differentiation's main goal is to establish different rates for various space classes. Parking spaces are divided into various service categories. There are different perspectives to classify parking categories, such as economic and commercial or basic and premium based on class (Roper et al., 2018; Yan et al., 2011), or leisure and corporate based on usage (Rao, 2011). The former classification is comparable to the analogy of airline seats. Economical places charge less and offer lower-quality services, while commercial spaces cost more and offer greater service. The quality of service can be measured by several indicators, including the distance from the parking space to the entrance/exit, the size of the parking space, and the convenience of parking (Yan et al., 2011). The latter classification into leisure and corporate class is based on the user demographic and is appropriate for parking lots with various travel purposes, such as shopping malls. The leisure category is reserved for the general public, while the corporate category is reserved for internal employees (Rao, 2011).

3.3.3. Spatial-temporal pricing

Spatial-temporal pricing is usually based on parking resource utilization, location-based, or associated with travel cost savings. Pricing schemes based on resource utilization are expected to use parking availability to update price to decrease drivers' cruising time and traffic congestion in congested locations (Wang and He, 2011). A straightforward implementation is to artificially set a price factor based on the percentage of occupied spaces, that is, to multiply the original parking price by a certain percentage for different occupancy rates (Kotb et al., 2016). The price increases or even surpasses the original price as the utilization rate rises. A more scientific update of prices is based on the evolution of the number of resources allocated by the reservation system (Tucker et al., 2019; Tucker and Alizadeh, 2020). Location-based pricing depends on the distance between the parking lot and the CBD. A reasonable parking fee should satisfy the condition that the closer to the CBD, the more expensive the parking fee is (Lu et al., 2021). Another type of theory suggests that parking reservations ought to be valued according to the time saved on travel since they lower the time spent looking for spaces compared to regular parking. A technique for reservation price that accounts for the value of the time saved has been proposed in addition to charging a parking fee (Tsai and Chu, 2012). Further, by paying additional late-for-reservation fees, those arriving later than the reservation expiration time can retain their reservation (Wu et al., 2021). It's crucial to note that most of these three pricing strategies do not exist as standalone modeling. Instead, they are frequently incorporated into parking allocation models (Kotb et al., 2016; Tucker et al., 2019; Tucker and Alizadeh, 2020) or are combined with other travel modes to reduce the total travel cost from a traffic flow equilibrium perspective (Liu et al., 2014a, 2014b, 2016; Lu et al., 2021; Wu et al., 2021).

To summarize, the pricing strategy for parking reservations can be divided into negotiation, pricing differentiation, and spatial-temporal pricing. Negotiation-based pricing is mainly modeled through bi-level planning and auction mechanism. Price differentiation establishes prices based on several categories of parking spaces, which can be further investigated in combination with inventory control. Spatial-temporal pricing can be developed according to real-time availability, distance from the parking lot to CBD, and the value of search time saved by making a reservation. Table 3 summarizes the elements considered and pricing methods in parking reservations.

3.4. Performance evaluation

The purpose of the performance evaluation is to thoroughly explore the effects of parking reservations. Intuitively, it can be expected that a properly implemented reservation system should reduce the time searching for a suitable space, thus reducing pollution and waste of resources. However, the impact of parking reservations on the overall travel system is uncertain, which is one of the goals of the performance evaluation. The majority of evaluation measures are system-based, such as search time, walking distance, total travel time, the number of accepted reservations, the volume of traffic, and possible emissions reductions (Chen et al., 2016; Ferreira and Silva, 2017; Kurauchi and Iida, 2008; Ni and Sun, 2017; Tasseron and Martens, 2017a, b; Zhao et al., 2021b).

Performance evaluation commonly evaluates the impact of parking behavior from the perspective of the whole travel system, and the most prevalent strategy is based on simulation, particularly agent-based modeling. Agent-based simulations, like PARKAGENT (Benenson et al., 2008), can organically combine the microscopic behavior of individuals in complex systems with the macroscopic nature of the system. During the parking process, the simulation reflects the movements and choices made by the traffic-congested vehicles on the road. The simulation usually consists of vehicle agents, parking lot agents, and network agents. There is a list of attributes for each agent. Vehicle attributes include origin, destination, vehicle category, location on the road network, parking selection conditions, etc. The vehicle category is often divided into regular and intelligent agents, which is also a representation of reservation and non-reservation behavior. In other words, only intelligent vehicles can make reservations, while regular vehicles can only find parking spaces by searching. The characteristics of parking lots include capacity, location, price, status, etc. Road network attributes include link length, link lanes, link density, speed, intersections, and link-intersection connections (Tasseron and Martens, 2017b). Current advances in PARKAGENT simulation are mainly related to various research areas and agents, as well as the movement or decision-making behavior of the agents. In terms of study areas, PARKAGENT allows for different area-wide simulations, such as including only on-street parking (Tasseron and Martens, 2017b), considering both on-street and off-street parking (Tasseron and Martens, 2017a), or even involving a city core area (Ni and Sun, 2017). From the aspect of vehicle agents, several vehicle types or parkers with multiple travel purposes are being examined increasingly frequently. For example, the division of vehicles into regular and smart vehicles allows for performance evaluation under the coexistence of reservation and non-reservation behaviors. In more detail, Tasseron and Martens (2017a) classify driver agents such as residents, workers, and visitors in terms of travel activity characteristics. As for the agents' movement, current researchers are incorporating functions related to parking selections to create a more realistic simulation. Selecting probability or utility functions is a typical strategy for choosing parking alternatives (Ni and Sun, 2017; Tasseron and Martens, 2017a). The drivers often choose the perceived lower-cost parking lot. Dijkstra's shortest path algorithm is frequently embedded when vehicles choose their travel routes (Tasseron and Martens, 2017b). The updating of road states then involves, for example, traffic flow models (Ni and Sun, 2017). In general, the progress and improvements in performance evaluation through PARKAGENT simulation are mainly in the different vehicle agents and vehicle movement behaviors. Different vehicle agents have various attributes and movement behaviors, which can lead to changes in system

Table 3 – Key studies of pricing strategies.

Study	Pricing category	Method	Element considered	Objective
Tsai and Chu (2012)	Spatial-temporal pricing	Binomial pricing	Volatility of vacant spaces, cost of searching for parking, revenue, emissions, parking capacity	–
Kotb et al. (2016)	Spatial-temporal pricing	Mixed-integer linear programming (MILP)	Parkers (maximum total price, maximum total walking distance, including type of parking spot (normal or disabled), type of reservation (real time or share time reservation), fairness; resources (dynamic pricing, capacity), traffic (normal and dense traffic)	Minimizing the total monetary cost for the drivers and maximizing the utilization of parking resources
Liu et al. (2016)	Spatial-temporal pricing	Bi-modal commuting equilibrium	Parking capacity, the price of parking reservation, travel demand	Minimize travel cost
Lei and Ouyang (2017)	Negotiation-based pricing	A multi-period non-cooperative bi-level model	Parking capacity, available parking space, dynamic parking price, different types of users, parking disutility (parking payment, two-way travel cost, two-way walking cost)	Maximizing the total benefit in the upper level, minimizing parking disutilities in the lower level
Roper et al. (2018)	Pricing differentiation	An integer programing formulation and artificial neural network	Accepted request, total revenue, available capacity, parking tariff classes, dwell time	Maximize parking revenue
Wang and Wang (2019)	Negotiation-based pricing	A bilevel Stackelberg game-theoretical model	Relocation distance, waiting time, parking pricing, total number of successful assignments	Maximum social welfare
Shao et al. (2020)	Negotiation-based pricing	An effective multi-stage Vickrey-Clarke-Groves (MS-VCG) auction	(Ex post) demand disturbances (overtime occupation and insufficient utilization)	Maximum social welfare
Fotouhi and Miller-Hooks (2021)	Negotiation-based pricing	A multi-period, stochastic equilibrium problem with equilibrium constraints	Origins, parking occupancy, total travel cost (prices, crowdedness delay, driving cost, walking cost)	Maximize revenues at the upper level, minimize individual disutilities at the lower level
Lu et al. (2021)	Spatial-temporal pricing	Nash equilibrium	Homogenous commuters (common preferred arrival/departure time), unit costs of arriving early and late in the morning and evening, travel time, walking time, queuing at the bottleneck	Reduce the total social cost (TSC)
Wu et al. (2021)	Spatial-temporal pricing	Bi-modal equilibrium	Total social cost, total user cost, travel costs (the travel time cost, the schedule delay cost, the crowding cost, and the transit fare), parking fee, queue length, arrival rate, departure rate, expiration time	Minimize total social cost

performance. Further development of the performance evaluation related to parking reservations can consider more types of vehicles and changing parking behaviors.

Performance evaluation quantifies the effects and impacts generated by parking reservations. Reservation systems have the potential to drastically reduce traffic congestion and travel time (Kurauchi and Iida, 2008; Ni and Sun, 2017), including findings that indicated a statistically significant reduction of up to 3% of total travel time compared to without reservations (Ferreira and Silva, 2017). Drivers of a reservation system benefit from reduced search time and walking distance under virtually all simulated circumstances. However, this benefit of search time comes at a cost to regular drivers (Tasseron and Martens, 2017b). Societal benefits of parking reservations are limited because of the rare impact on total search time and the possible negative health effects of reduced walking distance (Tasseron and Martens, 2017a).

The performance evaluation focuses on how to evaluate the effects and impacts of using PR from a system perspective, such as the total travel time, road traffic volume, and traffic emissions. Although there is a significant reduction in search time and walking distance for drivers who make reservations, the negative impact of parking reservations on regular drivers and the overall travel system is ignored, which deserves to be examined in more depth. Table 4 summarizes the evaluation measures and key findings in performance evaluation.

4. Discussion of challenges and opportunities

The four aspects of inventory control, allocation decision, pricing strategy, and performance evaluation provide different perspectives for parking reservation optimization. From the standpoint of the parking lot, inventory control optimizes supply to meet various user categories. Allocation decisions aim to achieve the optimal match between drivers and parking lots/spaces, where considerations such as driver parking costs, revenues, or social welfare are all taken into account. What these two previous themes have in common is that they are both based on fixed demand and supply. That is, how to use existing resources efficiently and how to serve drivers precisely without changing the existing demand and supply. Pricing strategies, on the other hand, affect user parking costs and thus parking demand through changing parking prices. Therefore, pricing strategy changes parking demand and is a demand management tool. Yet, there is certainly a similarity between these three themes, which often share similar objectives from the perspective of driver parking costs, revenue, or social welfare. In terms of study area and subjects, the former three themes mainly focus on local parking optimization, often in the form of case studies to explore the effectiveness of different optimization strategies. Performance evaluation, however, adopts a broader overview, evaluating the effects about parking reservations on the entire parking system or even the transportation system. In conclusion, it can be said that the four themes of inventory control, allocation decisions, price strategies, and

Table 4 – Key studies of performance evaluation.

Study	Data	Method	Evaluation measure
Kurauchi and Iida (2008)	Stated preference data	Road traffic simulation model with parking choice behavior	Parking fee; walking time; average waiting time; driving time; the time to destination (travelling time; wandering time, waiting time, walking time); ratio of people accessing to PR system; ratio (number) of reserved spaces comparing with total capacities
Ferreira and Silva (2017)	Parking events and traffic volumes	Discrete-event simulation algorithm	Total travel time; average cruising time; number of parking events and number of successful reservations
Tasseron and Martens (2017a)	Detailed data on parking demand from FEATHERS, an activity-based transport model	An agent-based simulation model (PARKAGENT)	Search time; walking distance, total parking time
Tasseron and Martens (2017b)	–	An agent-based analysis (PARKAGENT)	Search time; walking distance; overall time; search time at system level; walking time at system level; overall time at system level; average speed, occupancy rate; ratio of cars that failed to park
Ni and Sun (2017)	–	Agent-based simulation	Total travel time; total walking distance
Zhao et al. (2021b)	Electronic parking toll collections from ETCP company and questionnaire surveys	Integer linear programming model	The number of served public vehicles; potential reduction of traffic emission

performance evaluation are not mutually exclusive. In-depth research is being done on how they can be integrated.

4.1. *Inventory control*

Inventory control was initially proposed to increase parking revenue, taking inspiration from reservation systems in airlines and hotels. Various types of drivers have specific parking fees that they are willing to pay. Therefore, market segmentation of drivers and the establishment of different parking fees can improve parking revenue. In the worst-case scenarios of this market segmentation model, only the wealthy may be able to drive. If vehicle usage declines over time, social inequality will undoubtedly rise. Therefore, it might be possible to change the optimization goal or add constraints related to the number of protected spaces for different types of drivers (Teodorovic and Lucic, 2006).

Some more realistic issues have been considered in recent years with parking monitoring techniques and the practice of online parking reservations. In actuality, it is unlikely that all private vehicles will reserve a parking space in advance. Therefore, how to combine the joint supply of reserved and non-reserved spaces to accommodate driver demand has been investigated. The purposes of these studies include maximizing social benefits and parking efficiency in addition to increasing parking revenue (Mei et al., 2020). A further consideration is that reservation drivers may not be able to reach their destinations owing to schedule changes for different reasons, resulting in wasted reserved parking spaces that cannot be reallocated to other users. Therefore, in addition to spaces only with reservation and conventional spaces with non-reservation, common spaces that can be used with and without reservation are introduced (Waheed et al., 2021).

Following this idea of market segmentation, further development of parking inventory control in the future can be considered in terms of a more fine-grained division of parking lots and driver categories. The inventory management model can be configured from the perspective of a parking lot following various parking demand characteristics, such as dividing commuter and leisure portions for parking lots at shopping malls and self-use and shared-time periods for residential parking lots. How to optimize the supply of different areas or time slots according to the changing demand over time is worthy of further study. One more interesting point is the type of vehicle considered for reservation. The type of vehicle can be a gas-powered or electric vehicle, two-wheeler or four-wheeler. This information is very helpful in reserving an appropriate slot and effectively use the parking space.

4.2. *Allocation decision*

The main focus of parking allocation is how to match drivers with parking spaces effectively. Generally, from a modeling viewpoint, allocation decisions evolve from static to dynamic allocations, gradually taking into account elements such as uncertainty in real-world scenarios. Static allocation is based on fixed parking requests and resource supply but, is hardly adaptable to unexpected travel in future times. Periodic dynamic approaches have been frequently established in recent years to adjust allocation schemes on time (Xie et al., 2022, 2023b). However, current research rarely considers the uncertainty in driver arrival and departure patterns, which may lead to service failures and reduce the effectiveness of these systems (Wang et al., 2022). This arrival and departure uncertainty can be represented by creating flexible time windows or setting random factors (Jiang and Fan, 2020). An incentive for drivers to willingly and truthfully disclose such private information to the system is another interesting topic.

Regarding parking demand, currently, most data used to make allocation decisions are based on hypotheses, which may cause bias in the allocation effect. Even though intelligent detection may be used to get parking occupancy data, real demand data is challenging to obtain because it is impossible to detect the unsatisfied fraction of demand. In the future, it may be possible to use parking lot data to learn the stochastic distribution of driver arrival and departure time (Wang et al., 2022) or incorporate current information (such as traffic and parking occupancy) to produce a more reasonable demand (Kotb et al., 2016; Xu and Sun, 2022).

In terms of the elements considered in the allocation process, the allocation decision gradually considers more personalized and equitable elements in addition to satisfying the driver's demand period. The user arrival and departure times are, without a doubt, the most significant and essential criteria to be achieved in the allocation decision. Researchers are thinking of more elaborate allocation strategies that reflect both parking interests and user preferences. The division into user categories and the inclusion of constraints on walking distance, acceptable cost, and other factors for different categories deserve further study (Wang et al., 2022). These user categories and preferences enable the allocation model to give various priorities, leading to a more equitable distribution. Future research, for instance, might prioritize those with disabilities above others and give different rankings to hospitals, schools, and tourist destinations (Rehena et al., 2018).

4.3. *Pricing strategies*

Current pricing strategies related to reservations are evolving from being dominated by parking lots to a dynamic interaction between users and parking lots. From a parking lot perspective, the temporal and spatial value of the parking lot/parking spot is the main factor used to determine prices. Setting higher prices for popular locations and busy periods of the day makes sense. It is significant to remember that national or regional policies should serve as the foundation for the determination of upper and lower price limitations. Unquestionably, this method of setting prices can increase revenue for parking providers. However, in the context of increasingly severe parking problems, pricing strategies are being applied more frequently as a way to manage parking demand in addition to increasing parking revenues. Recent advancements in dynamic pricing for parking reservations enable price change in real-time to match demand. This is often achieved by establishing an inverse function between price and demand (Tian et al., 2018). In the future, user heterogeneity can be taken into consideration since it is clear that different traveler types have different price sensitivity (Wang and Wang, 2019). On the other hand, a deeper examination of how competition among parking lots is viewed to reach regional equilibrium is necessary given that the reality of price setting depends on more than just the interaction between users and parking lots.

In recent years, shared parking has frequently been priced in conjunction with parking reservations as an additional form of parking supply. Researchers have used auction techniques to develop rules for the distribution of spaces and payment for transactions because there is no consistent standard defining the value of shared parking spaces. In an environment with multiple suppliers and multiple demanders, the auction model evolves from a one-side auction to a double auction, where both supply and demand sides can submit bids to the platform. One issue of importance involved in the auction model is ensuring fairness for drivers. The rich are likely to have a higher probability of obtaining a parking space due to high bids (Kotb et al., 2016). As a result, additional priority factors should be taken into account to establish fair allocations, in addition to ranking allocations based on bid prices. In addition, the impact of the withdrawal of participants in shared markets and the new price equilibrium in this uncertain scenario can be considered. If one of the participants (supplier/demander) decreases, the remaining participants of the same type can increase/decrease their bids without losing the chance to win, thus causing an increase/decrease in the price of parking spaces and harming other participants. A reduction in both suppliers and demanders would lead to a waste of resources. Perhaps measures should be taken to encourage participants not to leave the shared market or to explore pricing under uncertain demand (Xiao et al., 2018).

4.4. *Performance evaluation*

Drivers and society may benefit from parking reservation systems. Reduced parking search times and walking distances to destinations may be advantageous to drivers. As a result of shortened parking search periods, traffic jams and pollution may be lessened, traffic safety may be enhanced, and urban environmental quality could be improved. Yet, when considering the transportation system as a whole, parking reservations could lead to extra expenses as well as a shift in driver travel patterns. On the one hand, reservation systems could result in a considerable increase in the cost of (expedient) parking enforcement, which adds to the costs associated with parking sensors and associated reservation technology. The underlying assumption in current reservation modeling is, of course, that vehicles will follow the reservation system following the status of the indicator lights on the parking spaces (reserved or non-reserved). There is no guarantee that all drivers will comply with such a system. Therefore, reservation systems are likely to impose additional costs in terms of parking enforcement or compensation payments for unexpectedly reserved spaces being occupied (Tasseron and Martens, 2017b). On the other hand, implementing parking reservation systems enhances the driving experience, which could make driving for travel more appealing and possibly cause a shift in travel patterns. It is worthwhile to investigate further how many travelers would convert from other modes of transportation to personal vehicle travels in this situation (Kurauchi and Iida, 2008). This increases the negative impact of personal vehicle travel.

4.5. *Others*

The study of parking reservations can be further extended through comparison and association with other parking strategies and integration with other transportation modes. For example, compared with the strategy of dynamic parking fees, findings indicate that reservation methods can produce greater benefits when parking fees are low (Mei et al., 2019). The combination of reservation and guidance strategies helps drivers find reserved spaces with optimal paths (Aydin et al., 2017; Levin and Boyles, 2020). In conjunction with other travel modes, reservation strategies can be developed to decrease the total travel costs, such as transportation network equilibrium under bi-modal scenarios of transit and private vehicle travel (Liu et al., 2016; Xu and Guan, 2017; Yang et al., 2013). Another more advanced scenario involves autonomous vehicles (AVs). This scenario enables vehicles to implement autonomous valet parking (AVP), causing diverse customer demands on parking (or drop-off/pick-up) for various travel planning. Thus, one pressing concern is deciding where to park and where to drop/pick up and find the best parking place at the destination (Khalid et al., 2019; Zhang et al., 2022b). More specifically, electric-powered AVs need to consider charging and parking situations simultaneously (Liu et al., 2022; Zhang et al., 2022a).

5. Conclusions

Parking reservations can improve transportation services throughout the city and in specific areas. In particular, the development of advanced technologies in recent years has facilitated the implementation of parking reservations. Therefore, the purpose of this paper is to review the latest reservation optimization and practices. We expect this well-structured review to help researchers and practitioners in the field of transportation to build smart, sustainable parking reservation systems. A limitation of this study is that it can only summarize the popular new research and cannot address all aspects of parking reservations due to the limited knowledge of the authors. In general, the conclusions made within this study are as follows.

First, inventory control largely considers the division of parking spaces into different categories to improve parking revenue or social welfare through capacity reservation control. Considering the reality of the reservation system, the current mainstream supply strategy is to realize the joint supply of reserved and non-reserved parking spaces. The future expansion of inventory control may begin with a more precise division of parking spaces or vehicle categories, for example, dividing commuter and leisure areas for mall-type parking lots, and classifying vehicles as fuel-consuming and electric vehicles.

Second, reservation allocation needs to consider elements such as parking requests, parking lot characteristics, and traffic conditions. The modeling of allocation decisions has evolved from static to dynamic allocations and is taking arrival/departure uncertainty into account. Parking demand is often generated based on assumed mathematical distributions, and the utilization of multiple sources of traffic data to derive more realistic parking demand can be further explored. Also, allocation decisions are gradually incorporating more personalization and equity elements from simply satisfying parking time demands. Further parameters for driver preferences might be defined, and user categories could be given priority in the allocation.

Third, pricing strategies can be divided into negotiated pricing, pricing differentiation, and spatial-temporal pricing. Negotiation-based pricing achieves an equilibrium price through interaction or negotiation between user demand and price, which relies on bi-level programming or auctions. Pricing differentiation divides parking spaces into distinct categories to set differentiated prices, which can be further combined with inventory control to establish a reasonable fare structure. Spatial-temporal pricing is often integrated into allocation or other models based on parking resource utilization, location, or travel cost savings. However, there was a lack of user heterogeneity, as different user types have varied pricing sensitivities. Future research may also consider the pricing competition across parking lots in the area, in addition to the interaction between user demand and price.

Finally, performance evaluation is mainly based on simulation modeling, which assesses total travel time, traffic volume, and social welfare from a system perspective. Although parking reservations can reduce travel time and traffic volume to some extent, some potential costs may be overlooked. Driver non-compliance could results in losses. Moreover, the implementation of reservation systems may increase the attractiveness of using personal vehicles for travel. Future research should take into account the effect of reservation systems on users' shifts in the mode of transportation.

This article makes contributions in the following aspects; this study systematically reviews and classifies the research topics of parking reservations in existing publications into four areas: inventory control, allocation decisions, pricing strategies, and performance evaluation. The study examines the considerations and optimization objectives in the four themes and identifies aspects that might be further considered for enhancement. In addition, this study summarizes the mainstream methods applied and their evolutionary process to help readers understand the development and future optimization direction.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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