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Where Am I Parking: Incentive Online Parking-Space Sharing Mechanism With Privacy Protection

Dou An, Qingyu Yang, *Member, IEEE*, Donghe Li, Wei Yu, *Member, IEEE*, Wei Zhao, *Fellow, IEEE*, and Chao-Bo Yan, *Senior Member, IEEE*

***Abstract*—Sharing private parking spaces during their idle time periods has shown great potential for addressing urban traffic congestion and illegitimate parking problems in smart cities. In this article, aiming to address the online parking-space sharing issue while ensuring the privacy of customer parking destination locations, we propose a novel destination privacy-preserving online parking sharing (DPOPS) incentive scheme. In particular, the online parking-space sharing problem is formalized as a social welfare maximization problem in a two-sided market, where parking-space providers (PSPs) and customers are regarded as sellers and buyers. Then, novel threshold value-based rules are designed to determine winners, payments, and reimbursement. Finally, winners are matched by solving a mixed-integer nonlinear programming problem, aiming to minimize the distance between customer's destination and allocated parking space. In addition, the location privacy of the customers' destinations is protected by the Laplace mechanism. We prove that DPOPS achieves several economically effective properties and approximate differential privacy. We analyze the upper bound of the efficiency loss of our scheme. Extensive evaluation results demonstrate that our scheme can not only achieve good performance regarding social welfare, PSP satisfaction ratio, privacy preservation, and computation overhead but also leads to shorter travel distances for customers comparing to the baseline scheme.**

***Note to Practitioners*—In this article, we address the online parking-space sharing issue with considering the parking-space providers (PSPs) and customers' individual utility while preserving the location privacy of customers' destinations. Most of the previous works focused on designing a centralized mechanism for allocating parking spaces without considering the protection of the customers' location privacy. In particular, we propose an online parking-space sharing scheme called DPOPS, including a novel threshold value-based winner determination rule and a parking-space allocation rule. The proposed scheme DPOPS allows the PSPs and customers submit their bids and asks according to their own willingness and is able to improve the utilization of private parking spaces during their idle time periods. Moreover, the location privacy of customers' destinations is protected by the Laplace mechanism. The experiments demonstrate that the proposed approach outperforms the exponential-based scheme in terms of PSP satisfaction ratio and the travel distance for parking-space customer. The proposed scheme is helpful in managing the vacant parking space in a competitive market and can be readily implemented in the real-world online parking-space sharing systems.**

***Index Terms*—Differential privacy, efficiency loss, online incentive-based scheme, parking-space sharing, resource management, smart cities.**

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Dou An and Donghe Li are with the School of Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an 710049, China, and also with the MOE Key Laboratory for Intelligent Networks and Network Security, Xi'an Jiaotong University, Xi'an 710049, China (e-mail: douan2017@xjtu.edu.cn; lidonghe@stu.xjtu.edu.cn).

Qingyu Yang and Chao-Bo Yan are with the SKLMSE Laboratory, School of Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an 710049, China, and also with the MOE Key Laboratory for Intelligent Networks and Network Security, Xi'an Jiaotong University, Xi'an 710049, China (e-mail: yangqingyu@mail.xjtu.edu.cn; chaoboyan@mail.xjtu.edu.cn).

Wei Yu is with the Department of Computer and Information Sciences, Towson University, Towson, MD 21252 USA (e-mail: wyu@towson.edu).

Wei Zhao is with the American University of Sharjah, Sharjah, United Arab Emirates (e-mail: wzhao@aus.edu).

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I. Introduction

WITH the advance of sustainable transportation and mobility technologies, sharing resources, such as private parking spaces (i.e., residential spaces and office parking lots) during their idle time periods, has great potential for addressing traffic congestion and illegitimate parking problems in smart cities [1], [2]. The huge gap between vehicle ownership and the number of parking spaces in modern cities, especially in large cities, has become the main cause of congestion and illegal parking. For instance, it has been reported that, by the end of 2017, there were approximately 5.64 million vehicles in Beijing, but the number of parking spaces was only 3.81 million [3]. More seriously, the gap for residential parking spaces in the city is 1.29 million [3]. In addition, as a known parking-challenged city, it is estimated that 30% of cars on the street are hunting for spaces in San Francisco, CA, USA [4].

Thus, enabling owners to share temporarily vacant parking spaces with customers has shown great potential for improving parking-space utilization and attracted growing attention in both industry and academia [5], [6]. Fig. 1 shows the demand for parking in a 24-h period, which varies by usage category (residential, office, and restaurant) [7]. Through sharing parking spaces in peak demand periods, the stress of finding parking spaces can be significantly reduced [7].

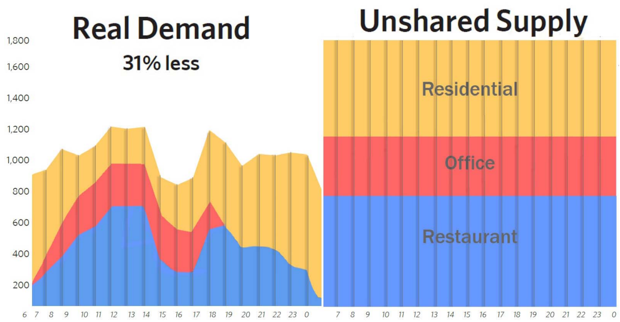

Fig. 1. Parking demands after sharing parking spaces [7].

In light of this, with the support of mobile networking and computing technologies, parking-space sharing platforms and applications are increasingly fulfilled by governments through the vision of smart cities deployment, as well as by startups seeking to introduce new platforms [5], [8]. For instance, SpotHero offers parking sharing services in 12 major cities in the USA [8]. Nonetheless, most existing platforms collect available parking spaces with a fixed price from the owners and then distribute them to customers who seek the parking benefits. The owners of parking spaces and the customers are price takers, and their utility and willingness are generally ignored. In other words, the attraction of the platform will be discounted if the parking space provider (PSP) cannot obtain a satisfactory reward or the customer cannot get an appropriate parking space as desired.

To this end, PSPs and customers must be incentivized [5], [9] to participate in the platform voluntarily. Although a large number of insightful incentive schemes have been investigated in the areas of crowdsensing and radio spectrum allocation [10], most have focused primarily on satisfying the workers and users, who have single-unit demand for tasks or channels, by maximizing the profit or minimizing the payoff. Nonetheless, there are some key differences between the parking space sharing scenario and other existing efforts. On one hand, in the parking space sharing scenario, the customers participate in the platform unpredictably variable multiple time periods that demands for parking services, and the arrival and departure of the participants are random. On the other hand, in addition to the properties of truthfulness, individual rationality, it is necessary to guarantee the satisfaction of parking service for customers, and thus, minimizing the distance between a customer's destination and the identified parking space should be considered.

In this case, designing an incentive scheme such as an auction is a promising way to address the parking space sharing issue. While most existing auction schemes stimulate participants to submit bids and asks truthfully to obtain the maximum utility [11], [12], nonetheless, the customers who demand parking spaces suffer from the potential privacy disclosure by submitting their destinations. In the parking space sharing system, the destination coordination of the customer needs to be submitted in order to find the proper parking space nearby. Once true destinations of customers are submitted, inference attacks [13] could be launched by an adversary, who can be either internal or external, and may be capable of observing the generated auction results so that the true destinations could be inferred from the results. It is imperative to preserve the destination location privacy of the customer who demands a parking space, the disclosure of which could put the privacy information of the customer at the risk of exposure (home address, workplace, and so on).

To protect the destinations of parking-space customers (PSCs) from being inferred by an adversary, in this article, we employ the principle of differential privacy, which is one of the representative state-of-the-art approaches for incentive-based schemes [14], along with cryptography [15] and anonymity [16], in terms of computational complexity and allocation efficiency. Generally speaking, differential privacy ensures that the output of a mechanism cannot be significantly affected by the change of a single input. The goal of this article is to design an incentive-based scheme that pairs PSCs and providers optimally while protecting the destination location privacy for customers.

The contributions of this article can be summarized as follows.

1) *DPOPS Scheme:* In this article, we conduct the first systematic study and propose a new online double auction, denoted the destination privacy-preserving online parking sharing (DPOPS) scheme, which matches the PSPs and customers. In our scheme, the optimal decisions regarding winner determination and payments are made by a threshold valuation-based rule, while the distances between the customers' target destinations and the allocated parking spaces are minimized. The differential privacy-based mechanism ensures the guarantee of protecting the destination location privacy of PSCs.
2) *Properties:* We prove that our DPOPS scheme satisfies incentive compatibility for PSCs, individual rationality, as well as weak budget balance for all participants. We also prove that our DPOPS scheme is able to achieve (ε, δ)-differential privacy protection for the destination location of PSC.
3) *Efficiency Analysis:* We conduct the efficiency loss analysis of DPOPS scheme. Through theoretical analysis, we further prove the upper bound of the efficiency loss of our scheme and present the relationship between efficiency loss and the number of the winning PSPs and customers, which, to the best of our knowledge, is among the first efforts on efficiency analysis regarding a multiunit online double auction scheme.
4) *Extensive Evaluation:* We conduct extensive simulations based on a real-world scenario in the city of Beijing, China, to demonstrate the significant performance of the proposed incentive scheme in comparison to two baseline schemes. The results show that DPOPS outperforms the scheme that utilizes the exponential mechanism with respect to PSC travel distance.

The remainder of this article is organized as follows. We conduct a literature review in Section II. In Section III, we present the preliminaries of this article, including threat and system models and definitions. In Section IV, we present the problem formalization and design objectives. In Section V, we introduce the proposed DPOPS scheme in detail. We theoretically prove the desired properties and conduct efficiency loss analysis in Section VI. In Section VII, we evaluate the effectiveness of our proposed scheme. Finally, we conclude this article in Section VIII.

II. Related Work

In this section, we conduct a review of research literature closely relevant to our study, including parking-space sharing, the design of incentive schemes, and location privacy protection.

A. Parking-Space Sharing

The growth rate of parking spaces is far lower than that of car ownership over the past few decades. Thus, a number of efforts have been made to increase the utilization of parking spaces [5], [17]–[19]. For example, Kong *et al.* [5] designed an urban parking management cloud platform and introduced a parking-space auction market based on one-sided Vickrey–Clarke–Groves (O-VCG) auction. The proposed parking-space auction market was validated to be effective in terms of strategy proofness and allocative efficiency. With the explosion of the sharing economy, intelligent transportation systems have sought to leverage the sharing vacant parking spaces to increase their utilization as a viable way to alleviate parking issues [5], [7], [8], [19]. For instance, Shao *et al.* [19] proposed a parking-space sharing model for embracing shared use of residential parking spaces between residents and public users, which utilizes a winning strategy to maximize the use of private resources and benefit the community as a whole. Indeed, countless startups in China, the United States, and Europe have been focusing on the business of sharing parking spaces [7], [8]. A few research efforts have given any attention to the design of the parking-space sharing systems [20], [21]. For example, Wang *et al.* [20] modeled and addressed the optimal allocation pricing of reservable and unreservable parking resources by maximizing the social surplus of the customers. In [21], a smart parking system was proposed to assign and reserve an optimal parking space based on the driver's cost function by solving an MILP problem.

B. Incentive Schemes

Designing effective incentive schemes to address resource allocation problems has gained in popularity, having been applied in the areas of crowdsensing, cloud computing, and the smart grid, among many others [22]–[25]. For instance, Samimi *et al.* [26] designed a truthful auction scheme to match the tasks and resources in cloud markets. Nonetheless, it has been reported that private and sensitive information of participants may be inferred by both external and internal adversaries during the auction process, according to the generated public outputs [11].

C. Location Privacy Protection

To protect the location privacy of vehicles, a number of research efforts have been conducted [27], [28] using cryptography and anonymization techniques [29], [30]. For example, Huang *et al.* [27] designed a reservation scheme for the automated valet parking system that protects the identity and location privacy of vehicle owners. Nonetheless, high computation and communication overhead prevent cryptography and anonymity techniques from being applied to incentive schemes. Differential privacy-based mechanisms have been widely studied [31], [32]. Most are designed for mobile crowdsensing systems and radio spectrum allocation [33], [34].

In comparison with the existing works, in this article, we have made the following contributions. We developed a unified online incentive mechanism designed for the parking-space sharing market that protects the location privacy of PSC destination. A threshold price rule was investigated and applied for winner and payment determination. Furthermore, a mixed-integer nonlinear programming (MINLP) problem was formalized to match winning PSPs and PSCs by minimizing the travel distance between the allocated parking space and the target PSC destination. Efficiency analysis was conducted to prove that the proposed scheme's efficiency loss is well bounded. Finally, our designed scheme was compared with representative baseline schemes.

III. Modeling of the Parking-Space Sharing System and the Location Privacy Threats

In this section, we present the preliminaries, including system model and threat model, as well as the definitions of PSP, PSC, and the broker.

A. System and Threat Model

In the following, we introduce the parking-space sharing model and threat model.

1) Parking-Space Sharing Model: The private parking spaces are quite common in China and other countries. However, it has been reported that there is a huge gap between vehicle ownership and the number of parking spaces in modern cities, which has become the main cause of congestion and illegal parking. Most of the private parking spaces will be vacant in the daytime, resulting in a large waste of resources. Thus, it is reasonable for the parking-space owners to share the private parking spaces during their idle time periods to seek revenue, which has the great potential to increase the utilization of parking spaces and improve social welfare. Therefore, the parking-space sharing market has great demand and has great application potential.

Comparing with the auction method, the centralized scheduling method is more effective. Most existing platforms, such as the economic model in Uber, collect available parking spaces with a fixed price from the PSPs and then distribute them to PSCs who seek the parking benefits. However, in such fixed price-based platforms, the PSPs and PSCs' individual parking willingness will be ignored. Therefore, in this article, we design an auction market that can fully consider the individual demands of both PSPs and PSCs, which is more suitable

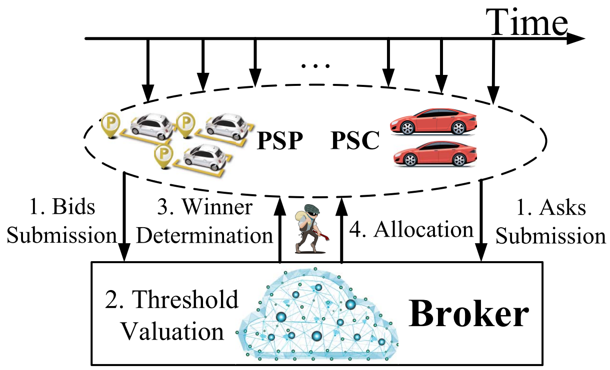

Fig. 2. System model.

for the matching process between PSPs and PSCs. In this article, we have divided the city into several independent areas, grouping similar regions of demand (residential, downtown, and business regions). The car owners, seeking to park in their desired areas bid for the parking spaces according to their own willingness, knowing that, in each area, the allocated parking spaces must be near enough to their destination to satisfy their needs. Otherwise, they would not participate in the service. Thus, participants must submit bidding information according to their own degree of demand for parking spaces.

In this article, we consider a parking-space sharing model that consists of PSPs, PSCs, and the broker (auction platform) and is supported by the Internet of Things (IoT) and mobile networking and computing technologies [35], [36]. The system model is described in Fig. 2. The owner of a parking space, who aims to obtain a certain amount of revenue by sharing his/her parking space during available time periods, is regarded as a provider (PSP). Correspondingly, a vehicle owner, who aims to acquire parking for a target duration, is treated as a PSC. Finally, the broker is denoted as the auctioneer, which runs the auction process based on the bidding and asking information submitted by the PSPs and PSCs, respectively, and is only to assist in making decisions. Furthermore, the broker is responsible for executing the fair and truthful winner determination rule to determine the winning PSP and PSC, as well as the payment rule and the allocation rule (i.e., second-price based winner determination rule) in order to satisfy the following properties of the auction market: individual rationality, incentive compatibility, and weakly budget balance.

During the actual operation of the proposed parking-space sharing market, the PSPs and the PSCs send requests (i.e., bids and asks) to the cloud platform via the applications on their mobile devices. The requests include bidding information, which consists of arrival time, departure time, valuation, and the parking location/target destination. Note that both PSCs and PSPs will determine their desired rental price by themselves according to their willingness. Then, the bidding and asking information are submitted to the cloud platform via the applications on their mobile devices, and the broker will make the decision for the winning PSP and PSC, as well as the payment rule and the allocation rule (i.e., second-price-based winner determination rule). Thus, the actual payment is not equal to the desire rental price of the participants in general, and it is not PSCs' role to decide how much money that they should pay for a parking space. Finally, the PSPs and the PSCs can conveniently view the sale results of private parking spaces and the purchase results of parking-space request, respectively, on the application of mobile devices. To make our solution more practical, we assume that PSPs and PSCs are allowed to enter the platform randomly. In this article, we consider not only parking-space locations but also PSC target destinations.

2) Location Privacy Threat Model: First, in the parking-space sharing auction market, the location information of the PSCs is the most important privacy information. The reason is that once the location information of the PSC is leaked, the privacy of PSCs will be greatly threatened. For example, the location information of destination may include the home address, workplace of the PSCs, and it will also contain the entertainment places, special hospitals, and so on, thereby revealing the PSCs' hobby or health status. Once a malicious adversary obtains such information, he or she will not only conduct targeted advertising for profit but also threaten the personal safety of the PSCs based on their home address and workplace. Thus, the destination location information of the PSCs needs to be protected in the parking-space sharing market.

Thus, we aim to design an online incentive scheme that could share parking spaces efficiently and fairly while preserving the destination privacy of the PSCs. We assume that communication channels and the broker in this article are secured. However, although the broker is assumed to be fully trusted, there is still a risk of PSCs' location information leakage. The real-time location information of the PSC will be submitted to the broker, which is responsible for making the decision of the winning PSP and PSC, as well as the payment rule and the allocation rule. We assume that the adversary is not able to invade into the auction market (broker) to steal the PSCs' location information directly. However, the public matching results also contain the PSCs' location information. The reason is that the PSCs are more likely to seek the parking spaces close to their destination, making that the adversary can infer the location information of the target PSC by collecting its multiple matching results.

In this article, we assume that the adversaries aim to learn the private location information of the car owners by launching inference attacks [13] and focus on designing a privacy-preserving mechanism to defend against such attacks. It is worth noting that other real-world privacy attacks, such as tracking and monitoring, are beyond the scope of this article, as those attacks cannot be protected against by mechanism design. Specifically, we assume that internal semihonest participants and external adversaries are able to obtain specific auction results and infer a user's destination by analyzing auction results. We introduce this kind of inference attack in Section V-E and confirm the feasibility of such an attack. To this end, the purpose of this article is to design a privacy-preserving scheme for protecting the destination location of the PSC during the auction process.

TABLE I
NOTATIONS

Symbols	Descriptions
C, P	A set of PSCs and PSPs
α_i, β_j	Bidding type of PSP i and PSC j
r_i, r_j	Rental price (parking fee) of PSP i (PSC j)
ta_i, ta_j	Parking time period of PSP i and PSC j
(xp_i, yp_i)	The coordinates of PSP i's parking space
(xc_j, yc_j)	The coordinates of PSC j's destination
ε, δ	The privacy parameter
f_i^t, f_j^t	The reimbursements (payment) of PSP i (PSC j)
d_i, d_j	The allocated rental time (parking time) of PSP i (PSC j)
WC, WP	A set of winning PSCs and PSPs
ep^t, ec^t	The threshold price of PSPs and PSCs at time slot t

B. Two-Sided Market Model for Online Parking-Space Sharing

We now model the online parking-space sharing problem as a two-sided market, in which the PSPs act as sellers and the PSCs act as buyers. The market will be triggered when there are buyers and sellers simultaneously. The system operates in a time-slotted fashion. The time slot is set by the broker, and in this article, we consider the time slot is one hour. In addition, the PSPs and the PSCs can arrive and depart from the market dynamically, without advance knowledge of the auction.

Generally speaking, the PSPs announce information about their available parking spaces, including the parking spot locations, the available time period, and the desired compensation. The PSCs will submit their asks for parking available spaces, including target destinations, the parking time period, and the anticipated expenses. In the following, we introduce the notations and assumptions for the PSPs, PSCs, and the broker, respectively.

1) Parking-Space Providers: Denote all the available parking spaces from PSPs as an integer set P. Specifically, regarding the submission process, the PSP will first decide the available time period and then submit their bidding information, which consists of arrival time, departure time, valuation, and the parking location to the cloud platform via the applications on their mobile devices at any time. The bidding type of PSP is expressed as a quadruple tuple α_i, which represents his/her supplies in the market

$$\alpha_i = \langle ts_i, tl_i, r_i, \mathbf{Loc_i} \rangle \quad (1)$$

where ts_i and tl_i represent the time slot when PSP i arrives and leaves the market, respectively. Thus, the total available time period of PSP i can be expressed as $ta_i = tl_i - ts_i$. Denote r_i as PSP i's ideal rental price (per hour). Finally, $\mathbf{Loc_i} = (xp_i, yp_i)$ indicates the location coordinates of parking spaces provided by PSP i.

To make the parking-space sharing market feasible, several assumptions for the PSPs are considered. We assume that the time periods of the parking spaces can be allocated to different PSCs in different time periods. To avoid collision, the ideal rental price should be private information for each PSP. In addition, each PSP could submit a false bidding type $\bar{\alpha}_i$ to seek a higher profit. To ensure a realistic scenario, we assume that the PSP could misreport a later arrival time or an earlier departure time (i.e., $[\bar{ts}_i, \bar{tl}_i] \in [ts_i, tl_i]$), a false rental price $\bar{r}_i$, but cannot cheat regarding the parking-space location. Finally, we assume that the PSP will not launch a false name bidding attack [37] in the market. Note that some "smart" bidders may create multiple identities to manipulate auction results, and such behavior is denoted as false name bidding attack, which are outside the scope of this article.

2) Parking-Space Customers: The PSCs who demand parking service act as buyers, as represented by integer set C. Similar to the PSPs, the PSCs should also submit bidding types to represent their requirements for parking services. The bidding type of PSC $j \in C$ can be expressed as a quadruple tuple β_j

$$\beta_j = \langle ts_j, ta_j, r_j, \mathbf{loc_j}, dm_j \rangle \quad (2)$$

where ts_j and ta_j represent the time slot that PSC j arrives at the market and the total parking time, respectively, r_j represents the ideal parking fee (per hour) of PSC j, $\mathbf{loc_j}$ represents the location coordinates of PSC j's destination, and dm_j represents the maximum acceptable distance from the allocation parking space to the PSC's destination.

There are also some assumptions about the PSCs. First, if a PSC wins the chance to park, they will be assigned to a fixed parking lot during their reported parking time period. This means that the PSC will not be asked to move their vehicles during the reporting parking time periods. The ideal parking fee of each PSC is assumed to be kept as private information in order to avoid collusion among PSCs. Also, a PSC may submit false bidding type $\bar{\beta}_j = \langle \bar{ts}_j, \bar{ta}_j, \bar{r}_j, \mathbf{loc_j}, dm_j \rangle$, where $\bar{ts}_j$ and $\bar{ta}_j$ represent the false arriving time and false parking time in order to satisfy $\bar{ts}_j \geq ts_j$ and $\bar{ta}_j \leq ta_j$ and $\bar{r}_j$ represents the false parking fee. Nonetheless, we assume that PSC j cannot misreport his/her destination coordinates of $\mathbf{loc_j}$. We also assume that the PSC is not allowed to launch the false name bidding attack [37].

3) Broker: The broker is denoted as the auctioneer, which is a trusted third-party platform in this article. The broker runs the auction process based on the bids α_i and asks β_j submitted by the PSPs and PSCs, respectively. We assume that both the PSPs and PSCs are familiar with the bidding rules and can only bide in the form of bids α_i and asks β_j. In particular, the broker determines the winning PSP and PSC, as well as the payment rule and the allocation rule. Recall that, in the real-world scenario, a large number of third-party service providers [38], which integrate cloud resources from different cloud providers and provide customers a unified application programming interface (API) to leverage the resources, can be regarded as brokers. We also assume that the broker in this article is the cloud platform, and the broker is trusted and honest. It means that the broker is secure and will not be hacked by the adversaries to steal the PSPs and PSCs' information, and meanwhile, the broker will make the decision of the auction market fairly and honestly.

IV. Problem Formalization and Design Objective

In this section, we first formalize the online parking-space sharing problem as a social welfare maximization (SWM) problem and then present the design objective of this article.

A. Problem Formalization

In this article, the winning PSP and the winning PSC sets are denoted as WP and WC. For those winning PSP $i \in WP$ and PSC $j \in WC$, the reimbursements and payments at time slot t are denoted as f_i^t and f_j^t, while the allocated rental time periods and parking time periods are denoted as d_i and d_j. For the winning PSCs, the parking time period is denoted as their reported parking time period: $d_j = ta_j$. Considering the fact that both the PSPs and PSCs could misreport their bidding types, we use $\bar{f}_i$ and $\bar{d}_i$ to represent the winning information by reporting the false bidding types.

For the winning PSP and PSC, we define their utilities as the difference between their ideal remuneration and the actual remuneration, which can be derived by

$$\begin{cases} U_i(\alpha_i) = \sum_t d_i \times (f_i^t - r_i), & i \in WP \\ U_j(\beta_j) = \sum_t d_j \times (r_j - f_j^t), & j \in WC. \end{cases} \tag{3}$$

Obviously, the objectives of PSPs and PSCs are conflicting due to their natural selfishness. To this end, as bids and asks that are submitted from the PSCs and PSPs are processed in the incentive scheme, the broker's objective is to allocate the parking spaces by matching PSPs and PSCs optimally while maximizing the market's social welfare defined as follows.

Definition 1: (Social Welfare Maximization) The broker determines the winning PSP and PSC, as well as the payment rule and the allocation rule to maximize the total utilities of the PSP and PSC, which can be formalized as an SWM problem

$$\begin{aligned} \max:& \sum_t \left\{ \sum_{j \in WC} (r_j - f_j^t) d_j + \sum_{i \in WP} (f_i^t - r_i) d_i \right\} \\ \text{s.t.}& \sum_{j \in WC} d_j = \sum_{i \in WP} d_i \\ & d_i \le tl_i - ts_i \quad \forall i \in WP \\ & d_j = ta_j \quad \forall j \in WC. \end{aligned} \tag{4}$$

Here, the first constraint is the material balance, indicating that all the allocated time periods of the PSP equal to all the allocated parking time periods of the PSC. The second constraint indicates that the allocated time period of a PSP should be no greater than their total available time period. The last constraint indicates that the allocated parking time should be equal to the reported parking time.

Note that the parking-space sharing problem can be formalized as a typical SWM problem. Nonetheless, due to the fact that some "strategic" participants might misreport their bidding types (valuation time, arrival time, and departure time) to promote their utilities, and the auction market operates over a continuous period of time such that the PSPs and PSCs participate in the market at any time. Therefore, it is infeasible for the auctioneer to obtain the optimal auction solution by solving the above-mentioned SWM problem directly. To address the above-mentioned issues, in this article, we aim to design a feasible auction mechanism to enable the share of parking spaces effectively.

B. Design Objectives

In the following, we first introduce the desired properties of our scheme and then present the principle of differential privacy, which will be used to protect the privacy of PSC destination locations.

1) Properties: As a feasible and efficient incentive scheme, the following properties should be satisfied.

1) *Individual Rationality:* All the participants (i.e., PSPs and PSCs) will obtain nonnegative utilities in the parking-space sharing auction market.
2) *Incentive Compatibility:* All the participants will obtain their maximal utilities by reporting truthful bidding types, which ensures the truthfulness of the parking-space sharing auction market.
3) *Weakly Budget Balance:* Payments from the PSCs to the broker should be equal to or larger than that of brokers to the PSPs.

2) Principle of Approximate Differential Privacy: We now introduce the principle of approximate differential privacy [33] that will be further utilized to protect PSC destination privacy in our scheme. Note that differential privacy is capable of ensuring that, after receiving the output, the adversary cannot distinguish between two neighboring inputs with high confidence. The formal definition of approximate differential privacy is given as follows.

Definition 2: (Approximate Differential Privacy) A randomized algorithm F satisfies (ε, δ)-differential privacy if, for any two input D and D', which only have one single data difference, and the output of the algorithm F is within a fixed range R

$$\mathbf{Pr}[F(D) \in R] \le exp(\varepsilon) \times \mathbf{Pr}[F(D') \in R] + \delta. \tag{5}$$

Here, ε is the privacy parameter and is defined by the broker. Note that the smaller ε is, the more difficult it will be for an adversary to distinguish the input data sets D and D', where the data are referred to as the PSC's destination.

To illustrate the definition of differential privacy clearly, we provide an example, which correlates to Fig. 3. Generally speaking, the concept of differential privacy ensures that an adversary cannot infer the exact input of a function from its output (the function in this article is the auction process) with a high degree of confidence. In this figure, the x-coordinate represents the possible values of function $f()$, and the y-coordinate represents the possibility of a specific output. The black line represents the original input set D and the red line represents the neighboring input set D'. Note that a neighboring set indicates that there is only one differing data point between sets D and D'. When function $f()$ satisfies the principle of differential privacy, for any output r, the relationship between the probability (p_1) of getting D as the input data set and the probability (p_2) of getting D' as the input data set is: $(p_1)/(p_2) \le e^{\varepsilon} + \delta$. This indicates that,

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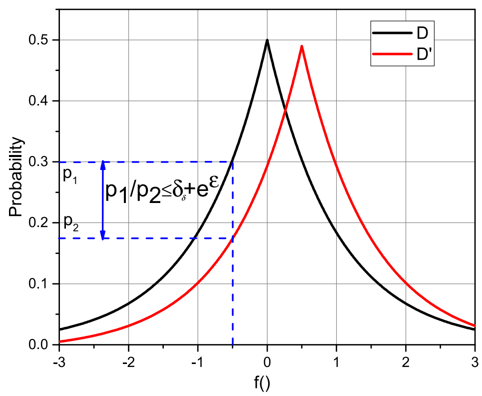

Fig. 3. Differential privacy model.

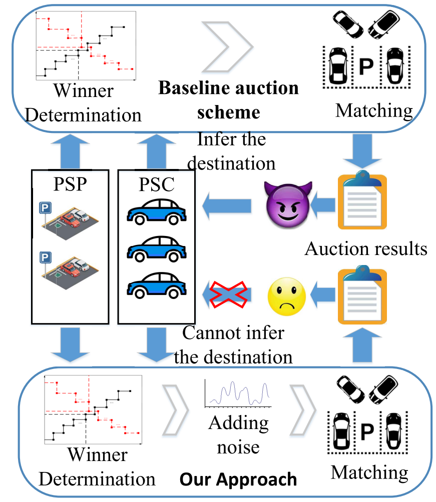

Fig. 4. Procedure.

for any external observer (an adversary), there is only $\varepsilon + \delta$ chance of identifying the exact input set as D or D' from the output. The differential privacy parameters ε and δ are random small positive numbers that determine the size of noise which is added to the location coordinates. The selection of these two parameters will lead to a tradeoff between allocation satisfaction and privacy performance, meaning that a small privacy parameter will result in a better allocation efficiency, whereas the large privacy parameter will result in a better privacy performance, at the expense of allocation efficiency.

V. Solution Methodology: DPOPS

In this section, we first introduce the overall process of the proposed incentive scheme called DPOPS and then present the detailed components, including bid submission, winner determination, payment rule, and allocation. Finally, we use an example to illustrate how DPOPS guarantees the privacy protection of a PSC's destination from being inferred by an adversary.

A. Overview and Design Rational

In this article, aiming at addressing the online parking-space sharing problem, an incentive online auction mechanism is proposed. Several previous research efforts have focused on the double auction mechanism as applied to different scenarios [5], [39]–[41]. Nonetheless, we cannot directly utilize those mechanisms in the scenario of this article for the following reasons. First, the parking-space sharing market in this article is an online market with multiple buyers and multiple sellers, meaning that bidders (PSPs and PSCs) are allowed to enter the market at any time. Thus, the auction mechanism must make the best decision without knowing any future bids. Second, there are several differences between the parking-space sharing market and energy trading markets [39], [41]. Specifically, the matching of parking spaces is more rigorous. In the energy trading market, the winning buyer can be charged by multiple winning sellers as long as material balance is maintained. However, in the parking-space sharing market, a parking space cannot serve multiple customers at the same time, and the winning PSP's available parking time should be no less than the allocated winning PSC's parking time. Above all, it is infeasible to directly use the auction mechanisms that introduced in [39]–[41] in the parking-space sharing market considered in this article.

In this article, we design an incentive online parking-space sharing scheme that includes the following procedures. In the parking-space sharing market, we should make determinations on the winning PSPs and PSCs first and then match them one-to-one based on their supply/demand parking times as well as the travel distance between the PSC's destination and the locations of parking spaces. To this end, we divide the auction mechanism into two interconnected stages without affecting the properties. The first stage is the valid price-based winner determination process that is designed to determine the winners as well as their payments. The second stage is the allocation process that is designed to match the winning buyers and sellers. As shown in Fig. 4, the top of the figure indicates the baseline scheme without privacy preservation, whereas the bottom of the figure indicates the DPOPS scheme, which is composed of three major components: 1) Step 1—bid submission and preprocessing; 2) Step 2—winning bid selection and payment/reimbursement rule determination; and 3) Step 3—allocation.

Specifically, at the beginning of each time slot, the broker collects asks and bids from the PSCs and PSPs and then selects the winning bids and asks according to the threshold value. Then, the broker determines the winning PSC's actual payment and the winning PSP's reimbursement according to their submitted demand and supply and their ideal parking fee and rental price. Finally, the broker matches the winning PSP and winning PSC by solving an MINLP problem, which aims to minimize the travel distance between the PSC's destination and the allocated the parking space of PSP. Also, with respect to differential privacy-based protection, specific noise is added to protect the PSC's destination privacy.

B. Step 1: Bid Submission and Preprocessing

In this section, we first introduce the bid submission and then present the computing method of threshold price that will be used to determine the winners and payments.

1) Bid Submission: In this step, at the beginning of each time slot, each bidder will submit their bidding types defined by (1) and (2). Due to the wide distribution of PSCs and PSPs in the city, in order to improve the efficiency of the scheme, the broker divides the market into multiple noncoincident markets according to the submitted bids and asks, and each market operates independently.

As mentioned in Section III-A2, the auction process may put the PSC's private information (i.e., the coordinates of the destination) at the risk of disclosure. Note that the location information is only used during the allocation process. The adversary is able to infer the location information of the target PSC by collecting its multiple matching results. In order to prevent the inference attacks described in Section III-A2, we aim to make the results of the allocation process undistinguishable. To this end, we propose the differential privacy-based method so that the PSC's destination information can be protected from being inferred. Differential privacy ensures that the adversary cannot determine the PSC's true location with 100% certainty from the PSC's matching results. In the following, we first present the lemma of the Gaussian mechanism [42].

Lemma 1 (Gaussian Mechanism): Consider a function f having l_2-sensitivity Δ. The Gaussian mechanism ensures that the function f achieves (ε, δ)-differential privacy by adding the normally distributed noise $N(0, \sigma)$, in which $\sigma \geq ((2ln(1.25/\delta))^{1/2}\Delta)/(\varepsilon)$.

Lemma 1 indicates that the PSC's destination coordinates can be protected against inference attacks by adding noise. The broker will first add Laplace noise to the location coordinates of the PSC's destination at the beginning of the auction process, for PSC $j \in C$

$$\begin{cases} xc_j{}^* = xc_j + \kappa_1 \\ yc_j{}^* = yc_j + \kappa_2 \end{cases} \tag{6}$$

where κ is the random noise that satisfies $N(0, ((2ln(1.25/\delta))^{1/2}\Delta)/(\varepsilon))$. Also, Δ represents the sensitivity and can be calculated as $\Delta = \max_{i,j \in C}((x_i - x_j)^2 + (y_i - y_j)^2)^{1/2}$.

2) Threshold Price: In the DPOPS scheme, the threshold price is used to determine the winning PSP and PSC, as well as their final payment and reimbursement. We now present the computing method of threshold price.

We consider a scenario in which there are m_p PSPs and m_c PSCs that are available to participants in the parking-space sharing market at time slot t and save them as set AP^t and set AC^t. The available state indicates that the participants are eligible to take part in the auction market. The available state will be formally defined in Section V-C.

After collecting the available bidders in AP^t and AC^t, we use rp_i and tap_i to represent PSP i's ideal rental price and available parking time and use rc_j and tac_j to represent PSC j's ideal parking fee and demand parking time, respectively. Next, the broker will record the PSPs' prices in ascending order and record the PSCs' prices in descending order. Then, we have

$$AP^t = \text{Asc}(AP^t(rp_i)), \quad AC^t = \text{Des}(AC^t(rc_j)) \tag{7}$$

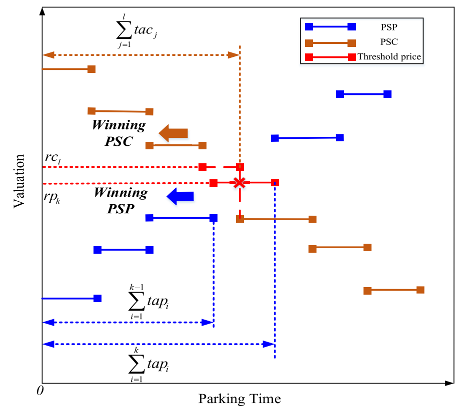

Fig. 5. Threshold price: case A-1.

where Asc() and Des() are defined as operators that record the vector in increasing and decreasing orders of elements, respectively. To compute the threshold price, denoting the demand/supply parking time as the horizontal axis and the valuation as the vertical axis, two lines are drawn to represent PSPs and PSCs. In this figure, the PSCs are represented by a set of falling lines (yellow lines) and the PSPs are represented by a set of rising lines (blue lines). According to the relationship between the highest valuation of PSPs and the lowest valuation of PSCs, to compute the threshold price, we consider the following two cases.

1) *Case A:* The minimum price of the PSC rc_{m_c} is not larger than the maximum price of PSPs.
2) *Case B:* The minimum price of the PSC rc_{m_c} is larger than the maximum price of PSPs.

Case A: The minimum price of the PSC rc_{m_c} is not greater than the maximum price of PSPs (i.e., $rp_{m_p} \geq rc_{m_c}$). As shown in Fig. 5, the broker finds a PSP k and a PSC l that satisfy the following constraints:

$$\begin{cases} rp_k \in [rc_{l+1}, rc_l] \\ \sum_{j=1}^{l} \text{tac}_j \in \left[\sum_{o=1}^{k-1} \text{tap}_o, \sum_{o=1}^{k} \text{tap}_o\right] \end{cases} \tag{8}$$

where rp_k and rc_l represent the rental price of PSP k and PSC l. Also, tap_k and tac_l represent the parking times of PSP k and PSC l, respectively.

Moreover, as shown in Fig. 6, the broker finds a PSP k and a PSC l that satisfy the following constraints:

$$\begin{cases} rc_l \in [rp_k, rp_{k+1}] \\ \sum_{o=1}^{k} \text{tap}_o \in \left[\sum_{j=1}^{l-1} \text{tac}_j, \sum_{j=1}^{l} \text{tac}_j\right] \end{cases} \tag{9}$$

where rc_l and rp_k represent the parking fee of PSC l and rental price of PSP k, respectively. Also, tac_l and tap_k represent the parking times of PSC l and PSP k, respectively. According to (8) and (9), the threshold value can be determined to help the broker in winner selection according to submitted bids and asks. Note that the threshold price ensures that the rental prices of all winning PSPs are smaller than the parking

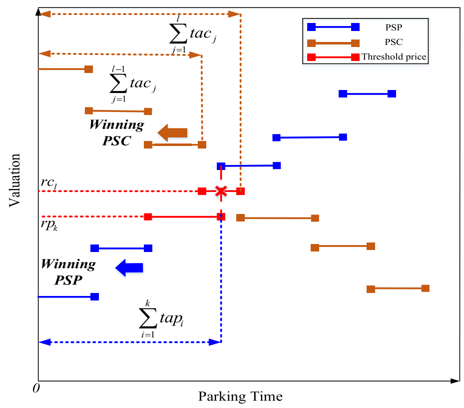

Fig. 6. Threshold price: case A-2.

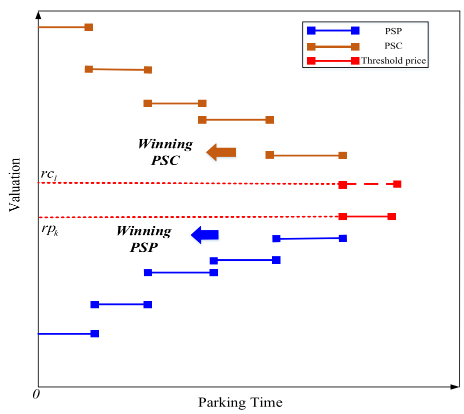

Fig. 7. Threshold price: case B.

fees of all winning PSCs, and the total parking time of all winning parking lots approaches to the total parking time of the winning PSCs.

Case B: The minimum price of PSC rc_{m_c} is larger than the maximum price of PSPs (i.e., $rp_{m_p} \leq rc_{m_c}$), as shown in Fig. 7. PSP k and PSC l can be determined as the m_pth PSP, who has the largest price, and the m_cth PSC, who has the smallest price, i.e., $k = m_p, l = m_c$. After obtaining PSP k and PSC l, the threshold price at this time slot can be determined as

$$\begin{cases} ep_i^t = rp_k & \forall i \in AP^t \\ ec_j^t = rc_l & \forall j \in AC^t. \end{cases} \tag{10}$$

According to the collected bids and asks from PSCs and PSPs, the broker first sorts the PSPs' rental fees in ascending order and sort the PSCs' parking fees in descending order. Then, the broker computes the threshold value according to the aforementioned Cases A and B. Above all, there are the following benefits of our proposed threshold price determination algorithm. First, it guarantees that all the winning PSPs' valuations are not smaller than the winning PSCs' valuations so that the utilities of the winners are never negative. Second, the algorithm ensures that the total winning PSPs' supply parking time is similar to the total PSCs' demand parking time.

C. Step 2: Winner and Payment Determination

In this step, the broker will first determine the PSCs and PSPs that are in an available state. An available PSP is defined as the PSP i that satisfies $t \in [ts_i, tl_i]$, $r_i < \min_{\gamma \in [ts_i, t]} ep_i^{\gamma}$, whereas an available PSC is defined as the PSC j that satisfies $t \in [ts_j, ts_j + ta_j]$, $r_j > \max_{\gamma \in [ts_i, t]} ec_j^{\gamma}$. Then, the broker will calculate the PSC's threshold price ec_i^t and PSP's threshold price ep_i^t. Also, the PSP i that satisfies $r_i < ep_i^t$ and the PSC j that satisfies $r_j > ec_j^t$ are regarded as winners at this time slot.

After that, the actual payment of the PSC is determined by the PSC's threshold price at time slot t as follows:

$$f_j^t = ec_j^t \quad j \in WC^t. \tag{11}$$

Regarding the PSP, recall that in other McAfee-based multi-unit incentive schemes [39], the broker usually chooses a minimum threshold price of the PSP during his/her bidding time periods, in order to ensure the properties of incentive compatibility and individual rationality of the scheme. Nonetheless, in our approach, the broker first calculates the maximum threshold price for each PSP at their available time slot: $\max_{\tau \in [ts_i, t]}\{ep_i^{\tau}\}$. We set the actual reimbursement of the PSP as the minimum value among the PSCs' threshold prices at time slot t: ec_i^t and the maximum threshold price for each PSP at their available time slot $\max_{\tau \in [ts_i, t]}\{ep_i^{\tau}\}$

$$f_i^t = \min\{ec_j^t, \max_{\tau \in [ts_i, t]}\{ep_i^{\tau}\}\} \quad i \in WP^t, \ j \in WC^t. \tag{12}$$

By doing this, we can ensure that the efficiency loss of the DPOPS scheme can be bounded at each time slot and the properties of individual rationality and weak budget balance can also be satisfied. The detailed proofs are given in Section VI.

The above-mentioned payment rule is one way to bound the efficiency loss of the proposed incentive scheme by improving the utility of PSPs. Similarly, we can also bound the efficiency loss of our scheme by improving the utility of PSCs, and the payment rule can be defined accordingly

$$\begin{cases} f_j^t = \max\{ep_i^t, \min_{\tau \in [ts_j, t]}\{ec_j^{\tau}\}\}, & j \in WC^t, \ i \in WP^t \\ f_i^t = ep_i^t, & i \in WP^t. \end{cases} \tag{13}$$

D. Step 3—Allocation

We now introduce Step 3 for the allocation rule of DPOPS. After determining the winners and the payment rule, the broker is responsible for matching the winning PSCs and PSPs, making sure that the parking spaces that are allocated to the winning PSCs are as close to their destinations as possible. Thus, the key for the allocation process is matching the winning PSC and PSP while minimizing the distance from the winning PSCs to the corresponding parking spaces.

To match the winning PSP and PSC in an efficient manner, we propose an optimization model for the broker. Specifically, we formalize the parking-space allocation problem as an MINLP problem to match the winning PSP and PSC, aiming at minimizing the distance of each pair of PSC and PSP. The optimization problem can be expressed as

$$\min \sum_{i\in WP^t, j\in WC^t} a_{i,j} \times \frac{\sqrt{(xc_i{*} - xp_j)^2 - (yc_i{*} - yp_j)^2}}{\max_{m\in WC^t, n\in WP^t} \sqrt{(xc_m{*} - xp_n)^2 - (yc_m{*} - yp_n)^2}} \tag{14}$$

$$\text{s.t.} \sum_{j\in WC^t} a_{i,j} \leq 1 \quad \forall i \in WP^t \tag{15}$$

$$\sum_{i\in WP^t} a_{i,j} \leq 1 \quad \forall j \in WC^t \tag{16}$$

$$\text{tac}_j \times a_{i,j} \leq \text{tap}_i \times a_{i,j} \quad \forall i \in WP^t,\; j \in WC^t \tag{17}$$

$$\sum_{j\in WC^t} a_{i,j} = \sum_{i\in WP^t} a_{i,j} \tag{18}$$

$$a_{i,j} = \{0, 1\} \quad \forall i \in WP^t,\; j \in WC^t \tag{19}$$

and

$$\sqrt{(xc_i - xp_j)^2 - (yc_i - yp_j)^2} \leq dm_j \tag{20}$$

where $a_{i,j}$ is an integer value that can only be 0 or 1, $a_{i,j} = 1$ indicates that the ith winning PSP matches the jth winning PSC, whereas $a_{i,j} = 0$ indicates that the ith winning PSP does not match the jth winning PSC. Also, $(xc_i{*}, yc_i{*})$ and (xp_j, yp_j) represent the location coordinates of winning PSP i and winning PSC j, respectively. WC^t and WP^t represent the winning PSC set and winning PSP set, respectively. Finally, tap_i and tac_j represent the parking time and available parking time period, respectively.

The objective in (14) is to minimize the distance between the location of the PSC's destination and PSP's parking space. Equation (14) indicates the sum of the distance of location of each PSC's destination and each PSP's parking space. Note that the distance needs to be normalized in order to obtain a better solution to the optimization problem. The first constraint [see (15)] indicates that one PSP can only be allocated to one PSC. Likewise, the second constraint [see (16)] indicates that one PSC can only be assigned to one PSP. The third constraint [see (17)] indicates that the parking time of PSC is not larger than the available parking time period of PSP. Next, constraint [see (18)] indicates that the winning PSP or the winning PSC will be fully allocated so that allocation efficiency can be maximized. The last constraint [see (20)] indicates that the PSCs will not be assigned to a parking space that is too far from their destination.

After the allocation process, several winning PSCs or PSPs may not be allocated to a related PSP or PSC and they will be removed from the winning set. For the rest of the winners, the broker will determine the allocated parking time period d_i for them. For the winning PSC $j \in WC$, the allocated parking times are determined as their reported parking time period: $d_j = ta_j$. For the winning PSP $i \in WP$, the allocated parking time periods are determined by the reported parking time of the related PSC: $d_i = ta_j$, where ta_j represents the parking time of the related PSC j. After that, the broker updates the bidding types of the related winning PSC and PSP and then carries out the auction process at the next time slot.

TABLE II
BIDS AND ASKS FROM PSPS AND PSCS

	Number#	Bidding time	Valuation	Demand/supply
PSP	1	0,3	6	3
	2	0,1	9	1
	3	0,3	12	3
PSC	1	0,2	15	2
	2	0,3	11	1

E. Illustrative Examples

We first present an illustrative example to demonstrate how our auction market works. Considering that there are three PSPs and two PSCs participating in the auction market, and their bidding types are expressed in Table II. In this case, all of the PSPs and PSCs are available at time slot 1. Then, according to the threshold price rule, we know that the threshold price of PSPs is determined as the valuation of PSP 2, whereas the threshold price of PSCs is determined as the valuation of PSC 2, with the value of 11. Then, we know that PSP 1, with valuation of 6, and PSC 1, with valuation of 11, are determined as the winners, and the payment of PSP 1 is 9, whereas the payment of PSC 1 is 11.

We now present two illustrative examples to demonstrate how adversaries could obtain a PSC's destination location by launching inference attacks and how the DPOPS works to protect PSC destination privacy. Recall that in Section III-A2, we assume that potential adversaries can be either semihonest and internal or can be external and are capable of obtaining the auction results. In the following, as inspired by [40], we first investigate an inference attack against the PSC's destination privacy.

Inference Attack: First, we assume that the adversaries, as internal participants in the system (e.g., "strategic" PSPs), collude with each other, and share their information about the target PSC's matching results. We also assume that external adversaries can have access to the generated output of the DPOPS scheme. In general, the adversaries are able to obtain the target PSC's matching results in multiple time periods.

Then, we assume that the adversaries collect n times matching results of the target PSC. We denote the allocated parking spaces of these n times results as a set $AP = [D_1, D_2, D_3, \ldots, D_m]$, and the related location coordinates are denoted as $(X_1, Y_1), (X_2, Y_2), \ldots, (X_m, Y_m)$. Finally, we use n_i to represent the number of times that parking space D_i is assigned to the target PSC, where n_i satisfies $\sum n_i = n$.

After that, the PSC's inferred destination location coordinates (x_c, y_c) can be calculated as

$$(x_c, y_c) = \left(\sum \frac{n_i}{n} X_i, \sum \frac{n_i}{n} Y_i\right). \tag{21}$$

Without Protection: We now introduce an example to demonstrate the efficiency of the proposed inference attack scheme without any privacy protection. As shown in Fig. 8, we consider a realistic area in the city of Xi'an, China. The selected region can be divided into 5 × 5 grids. We assume that there exists one target PSC, whose real destination is

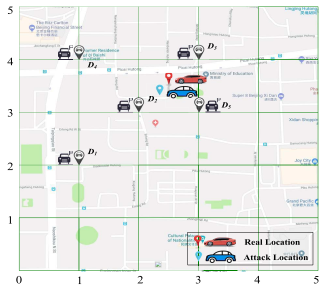

Fig. 8. With inference attack.

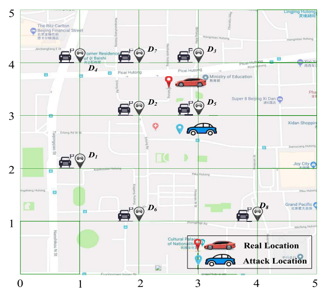

Fig. 9. With protection.

(2.5, 3.5), has participated in the market for 50 time slots, while the adversary has collected all 50 matching results successfully. The potential allocated parking spaces are denoted as $AP = [D_1, D_2, D_3, D_4, D_5]$, $n_1 = 7, n_2 = 18, n_3 = 17, n_4 = 3, n_5 = 5$, which are located at (1,2), (2,3), (3,4), (1,4), and (3,3) on the map. Then, according to (21), the inferred destination location coordinates can be calculated as $x_c = 2.24$ and $y_c = 3.26$, which is very close to the real location (2.5, 3.5).

With Protection: We now evaluate the efficiency of the inference attack under the DPOPS scheme in this article. As shown in Fig. 9, we consider the same target PSC, who has also participated in the market for 50 time cycles and might be allocated to eight potential parking spaces: $AP = [D_1, D_2, \ldots, D_8]$, $n_1 = 5, n_2 = 7, n_3 = 7, n_4 = 6, n_5 = 5, n_6 = 7, n_7 = 3, n_8 = 14$, which are located at (1,2), (2,3), (3,4), (1,4), (3,3), (2,1), (2,4), and (4,1). In this case, the inferred destination location coordinates can be calculated as $x_c = 2.74$ and $y_c = 2.62$. Obviously, compared with the scenario without privacy protection, the destination of the PSC in this case cannot be inferred accurately by the adversary.

VI. Theoretical Analysis

In this section, we first prove that DPOPS achieves the desired properties and then conduct theoretical analysis to quantify the efficiency loss of DPOPS.

A. Properties

In the following, we prove that DPOPS satisfies the properties of individual rationality, incentive compatibility for PSCs, budget balance, and (ε, σ)-differential privacy.

Theorem 1: DPOPS achieves individual rationality for each participant.

Proof: For participants who win the auction $i \in WP^t$, $j \in WC^t$,, according to the payment rule in Section V-C, their actual payments are determined by the threshold price

$$f_i^t = \min\{ec_j^t, \max_{\tau\in[ts_i,t]} \{ep_i^\tau\}\}, \quad i \in WP^t, \; j \in WC^t \quad (22)$$

$$f_j^t = ec_j^t, \quad j \in WC^t. \quad (23)$$

Moreover, according to the winner determination rule described in Section V-B2, the PSC whose ideal price r_j is greater than his/her threshold price ec^t at time slot t is regarded as the winning PSC, whereas the PSP whose ideal price r_i is smaller than the PSP's threshold price ep^t at time slot t is regarded as the winning PSP. Thus, for all the winners $i \in WP^t$, $j \in WC^t$, we have

$$f_i^t = \min\{ec_j^t, \max_{\tau\in[ts_i,t]} \{ep_i^\tau\}\} > ec^t \quad \forall i \in WP^t \quad (24)$$

$$f_j^t = ec_j^t < ep^t \quad \forall j \in WC^t. \quad (25)$$

After that, according to the allocation rule described in Section V-D, the allocated parking time period d_i, d_j of the winner $i \in WP^t, j \in WC^t$ is positive numbers (i.e., $d_i > 0, d_j > 0, \forall i \in WP, j \in WC$). Thus, we can conclude that all of the winners will obtain nonnegative utilities as

$$U_i(\alpha_i) = \sum_t (f_i^t - r_i) \times d_i > 0, \quad i \in WP \quad (26)$$

$$U_j(\beta_j) = \sum_t (r_j - f_j^t) \times d_j > 0, \quad j \in WC. \quad (27)$$

Considering the participants who are not able to win in the auction process, their utilities remain 0. Thus, the utility for each participant is nonnegative and can be expressed as

$$U_i(\alpha_i) = \sum_t (f_i^t - r_i) \times d_i \geq 0, \quad i \in P \quad (28)$$

$$U_j(\beta_j) = \sum_t (r_j - f_j^t) \times d_j \geq 0, \quad j \in C. \quad (29)$$

In conclusion, DPOPS achieves individual rationality for each participant. □

Theorem 2: DPOPS achieves incentive compatibility for the PSCs.

Proof: Recall that in Section III-B, we assume that PSCs could lie about their bidding types to claim greater rewards. Considering the realistic factors, a PSC can only misreport a later arrival time and an earlier departure time: $[\bar{ts}_j, \bar{ts}_j + \bar{ta}_j] \in [ts_j, ts_j + ta_j]$ and a false rental price $\bar{r}_j$. Thus, we consider the PSC's utility in the following two scenarios: 1) misreporting the ideal price $\bar{r}_j$ and 2) misreporting the parking time period $[\bar{ts}_j, \bar{ts}_j + \bar{ta}_j]$.

Misreporting the Ideal Price: First, we consider the scenario in which a PSC $j \in C$ wins the auction with ideal price r_j, and his/her actual payment is f_j. In this case, the ideal price of PSC j is greater than the threshold price $r_j > eb^t$. When the PSC misreports an ideal price that is still greater than the threshold price $\bar{r}_j > ec^t$, he/she will still win the auction with payment f_j and the utility remains unchanged as a result. When the PSC misreports an ideal price that is smaller than the threshold price $\bar{r}_j < ec^t$, he/she loses the opportunity to obtain the parking service, and the utility will decrease as a result. In conclusion, the PSCs who win the auction cannot improve their utility by misreporting the ideal price

$$U_j(\bar{\beta}_j) = \sum_t (r_j - \bar{f}_j^t) \times \bar{d}_j \geq 0, \quad j \in WC^t. \tag{30}$$

Second, we consider a PSC $j \in P$ who cannot win the auction with the ideal price $r_j < ec^t$, where ec^t represents the threshold price at time slot t. When the PSC misreports an ideal price that is still smaller than the threshold price, the utility will remain 0. When the PSC misreports an ideal price that is greater than the threshold price, he/she will win the auction with payment $\bar{f}_j = ec^t$. Thus, the actual payment of PSC j is greater than the truthful ideal price: $\bar{f}_j = ec^t > r_j$. In this case, the utility will decrease as a negative value

$$U_j(\bar{\beta}_j) = \sum_t (r_j - \bar{f}_j^t)\bar{d}_j < U_i(\beta_j) = \sum_t (r_j - f_j^t)d_j = 0.$$

In conclusion, the PSCs cannot improve their utilities by misreporting ideal prices.

Misreporting the Parking Time Period: In this case, we consider a PSC $j \in C$ who cannot win the auction with the reported parking time period $[ts_j, ts_j + ta_j]$. We assume that the PSC j misreports a false parking time period as $[t\bar{s}_j, t\bar{s}_j + t\bar{a}_j] \in [ts_j, ts_j + ta_j]$. Nonetheless, in this case, he/she will still lose the opportunity to win in the auction, and the utility remains 0 as a result. Considering a PSC $j \in C$ who wins in the market with the truthful parking time period, if he/she misreports a short parking time period $[t\bar{s}_j, t\bar{s}_j + t\bar{a}_j] \in [ts_j, ts_j + ta_j]$, he/she could lose the opportunity to win in the auction process, and the utility will not increase as a result. Thus, the PSCs cannot improve their utilities by misreporting the parking time periods.

Thus, we conclude that our proposed scheme achieves incentive compatibility for PSCs. Similarly, if the payment rule is determined by (13), the DPOPS scheme can be proved to achieve incentive compatibility for PSPs. □

Theorem 3: DPOPS achieves weak budget balance.

Proof: According to the fourth constraint [see (18)] in the allocation process in Section V-D, we know that the allocation will ensure the material balance under DPOPS. Thus, we have $\sum_{i \in WP} d_i = \sum_{j \in WC} d_j$.

Regarding to the payment and compensation rules of the winning PSCs and PSPs, respectively, which are shown in (11) and (12), we know that the payments of all the winning PSCs are not smaller than the compensations of winning PSPs

$$f_j^t \geq f_i^t \quad \forall j \in WC, \; i \in WP, \; t \in T. \tag{31}$$

Then, we have

$$\sum_{j \in WC, t \in T} d_j \times f_j^t - \sum_{i \in WP, t \in T} d_i \times f_i^t \geq 0. \tag{32}$$

Thus, we can conclude that the proposed scheme achieves a weak budget balance. □

Theorem 4: DPOPS achieves (ε, δ)-differential privacy.

Proof: Recall from Section V-D that a Gaussian noise $N(0, ((2ln(1.25/\delta))^{1/2}\Delta)/(\varepsilon))$ is added to the objective function. As mentioned in [42], for $c^2 > 2ln(1.25/\delta)$, the Gaussian mechanism with parameter $\sigma \geq c\Delta/\varepsilon$ introduces (ε, δ)-differential privacy. Thus, we conclude that our scheme will achieve (ε, δ)-differential privacy by adding the noise $N(0, \delta)$, where $\delta \geq ((2ln(1.25/\delta))^{1/2}\Delta)/(\varepsilon)$

$$Pr[f(D)+x1] \leq e^{\varepsilon} Pr[f(D')+x2]+\delta, \quad x1, x2 \sim N(0, \sigma).$$

The detailed proof can be found in [42].

To summarize, we conclude that the proposed scheme achieves (ε, δ)-differential privacy. □

B. Efficiency Loss

We now analyze the upper bound of the efficiency loss [40] of our DPOPS scheme and present the relationship between the efficiency loss and the number of winning PSPs and PSCs. To the best of our knowledge, we are the first to analyze the efficiency loss of an online multiunit double auction scheme.

1) Definition of Efficiency Loss: We first define the efficiency loss of our DPOPS scheme. Considering one auction round at time slot t, there are a total of m_p available PSPs and m_c available PSCs. Denote tc_j and rc_j, $j = 1, \ldots, m_c$ as the demand parking time slots and their ideal parking fees of the m_c PSCs, respectively. Similarly, tp_i and $rp_i, i = 1, \ldots, m_p$ are used to represent the supply parking time slots and their ideal rental prices of the m_p PSPs, respectively. Then, we assume that the threshold price is determined by the bth PSC and sth PSP. Thus, there are $b - 1$ PSCs and $s - 1$ PSPs who successfully win the auction. Denote their allocated time periods as dc_j and dp_i, and denote the corresponding payment and reimbursement as pc_j and pp_i. Recall from Section V-B2 that we know the reimbursements of the winning PSPs are not smaller than the threshold price: $pp_i \geq rp_s, i = 1, 2, \ldots, s-1$.

We assume that demand time slot tc_j (supply time slots tp_i) of the PSC (PSP) is independent samples from distribution TC (TP). Furthermore, we assume that the ideal parking fees of the m_c PSCs are drawn independently of a distribution R_c with continuous density f and support on the compact interval $[\underline{c}, \overline{c}]$, and the ideal rental prices of the m_p PSPs are drawn independently of a distribution R_p with continuous density g and support on the compact interval $[\underline{p}, \overline{p}]$. Also, note that the density functions f and g are nonzero minimum values, $\chi = \min\{f(x) : \underline{c} \leq x \leq \overline{c}\} > 0$, $\omega = \min\{g(x) : \underline{p} \leq x \leq \overline{p}\} > 0$.

Meanwhile, we designate TA as the minimum number of demand and supply parking time periods of the total s PSPs and b PSCs, and we have

$$\mathrm{TA} = \min\left\{\sum_{j=1}^{b} tc_j, \sum_{i=1}^{s} tp_i\right\}. \tag{33}$$

Thus, at time slot t, the efficiency loss can be defined as the loss of the winning PSPs and PSCs utilities that can be divided into the following three parts.

1) *Broker's Loss* Loss_a*:* It is defined as the trading profits that are taken by the broker.
2) *Threshold Loss* Loss_b*:* It refers to the potential trading value of the PSCs/PSPs whose submitted parking fees/rental prices are chosen as the threshold price.

3) *Sacrificed Loss* Loss_c*:* It refers to the sacrificed demand/supply parking times of the winning PSCs/PSPs.

Specifically, the broker's loss is determined by the difference between the actual payments of PSCs and the reimbursements of PSPs

$$\begin{aligned}\text{Loss}_a &= \sum_{j=1}^{b-1} pc_j \times dc_j - \sum_{i=1}^{s-1} pp_i \times dp_i \le \text{Loss}_a^* \\ &= (rc_b - rp_s) \times \min\left(\sum_{j=1}^{b-1} tc_j, \sum_{i=1}^{s-1} tp_i\right). \qquad (34)\end{aligned}$$

The threshold loss can be expressed as the difference between the bth PSC's potential payment and the sth PSP's potential reimbursement

$$\begin{aligned}\text{Loss}_b &= pc_b \times dc_b - pp_s \times dp_s \le \text{Loss}_b^* \\ &= (rc_b - rp_s) \times \left(\min\left(\sum_{j=1}^{b} tc_j, \sum_{i=1}^{s} tp_i\right)\right. \\ &\qquad \left. - \min\left(\sum_{j=1}^{b-1} tc_j, \sum_{1}^{s-1} tp_i\right)\right). \qquad (35)\end{aligned}$$

Note that even though the exact value of the sacrificed loss cannot be figured out accurately, its potential range can be expressed. First, considering the scenario in which the parking time period of the winning PSCs is greater than the parking time period of the winning PSPs (i.e., $\sum_{j=1}^{b-1} tc_j \ge \sum_{i=1}^{s-1} tp_i$), where the sacrificed loss satisfies

$$\begin{aligned}\text{Loss}_c &= \text{Loss}_c^* \le (rc_1 - rc_b) \times \left(\sum_{j=1}^{b-1} tc_j - \sum_{i=1}^{s-1} tp_i\right) \\ &\le (rc_1 - rc_b) \times tp_s. \qquad (36)\end{aligned}$$

On the other hand, consider the scenario where the parking time period of the winning PSPs is greater than the parking time period of the winning PSCs (i.e., $\sum_{j=1}^{b-1} tc_j \le \sum_{i=1}^{s-1} tp_i$), and the sacrificed loss satisfies

$$\begin{aligned}\text{Loss}_c &> \text{Loss}_c^* \\ \text{Loss}_c^* &\le (rp_s - rp_1) \times \left(\sum_{i=1}^{s-1} tp_i - \sum_{j=1}^{b-1} tc_j\right) \\ &\le (rp_s - rp_1) \times tc_b. \qquad (37)\end{aligned}$$

Then, we define the total loss as

$$\text{Loss}(b, s) = \text{Loss}_a + \text{Loss}_b + \text{Loss}_c. \qquad (38)$$

Recall that the total social welfare of the auction market can be expressed as

$$\begin{aligned}\text{Social}(b, s) &= \sum_{j=1}^{b}(rc_j - pc_j) \times tc_j + \sum_{i=1}^{s}(pp_i - rp_i) \times tp_i \\ &\quad + \sum_{j=1}^{b-1} pc_j \times dc_j - \sum_{i=1}^{s-1} pp_i \times dp_i. \qquad (39)\end{aligned}$$

Thus, we introduce the ratio of total loss to total social welfare, which is referred to as the efficiency loss [40]

$$\text{Ine}(b, s) = \frac{E[\text{Loss}(b, s)]}{E[\text{Social}(b, s)]}. \qquad (40)$$

Since the ideal parking fees, rental prices, and parking times of PSPs and PSCs are random variables, we take expectations of $\text{Loss}(b, s)$ and $\text{Social}(b, s)$ and denote their ratio as a measure of how much efficiency is lost in comparison with the total market value during the online double auction process.

2) Analysis of Efficiency Loss: We now prove that the efficiency loss of the DPOPS scheme is well bounded. Before doing that, we first introduce two lemmas.

Lemma 2: For the PSC $j = 1, 2, \ldots, m_c - 1$, we have

$$\frac{1}{\varphi(m_c + 1)} \le E[rc_j - rc_{j+1}] \le \frac{1}{\chi(m_c + 1)} \qquad (41)$$

where m_c represents the number of PSCs, and for the PSP $i = 1, 2, \ldots, m_p - 1$, we have

$$\frac{1}{\tau(m_p + 1)} \le E[rp_{i+1} - rp_i] \le \frac{1}{\omega(m_p + 1)} \qquad (42)$$

where m_p represents the number of PSPs, and χ and ω are constants defined in the following equations:

$$\varphi = \max\{f(x) : \underline{c} \le x \le \overline{c}\} \ge \chi > 0 \qquad (43)$$

$$\tau = \max\{g(x) : \underline{p} \le x \le \overline{p}\} \ge \omega > 0. \qquad (44)$$

Lemma 2 indicates the expectation that the difference in any two adjacent PSP's (PSC's) parking fees (rental prices) rp_i, rp_{i+1} (rc_j, rc_{j+1}) are bounded. The detailed proof of Lemma 2 can be found in [40]. In the following, we present a lemma to quantify the efficiency loss of our DPOPS scheme.

Lemma 3: We assume that expectation of the PSC's parking time is larger than 0: $0 < E[TC]$, and the expectation of the PSP's parking time is limited: $E[TP] < \infty$. Then, the efficiency loss of our DPOPS scheme during each time slot can be bounded as follows:

$$\text{Ine}(b, s) \le \Delta \max\left(\frac{1}{b-1}, \frac{1}{s-1}\right) \qquad (45)$$

where Δ is a constant.

The proof of lemma 3 can be found in the Appendix.

Theorem 5: The efficiency loss of DPOPS scheme satisfies $Ine \le \max(Ine^t)$.

Proof: According to Lemma 3, we have proved that the efficiency loss of DPOPS during one time slot will be bounded by

$$\text{Ine}^t(b^t, s^t) \le \Delta^t \max\left(\frac{1}{b^t - 1}, \frac{1}{s^t - 1}\right). \qquad (46)$$

As $(a + b)/(c + d) \le \max((a)/(c), (b)/(d))$, we have

$$\begin{aligned}\text{Ine} &= \frac{\sum_1^T E[\text{Loss}^t(b^t, s^t)]}{\sum_1^T E[\text{Social}^t(b^t, s^t)]} \\ &\le \max\left(\frac{E[\text{Loss}^1(b^1, s^1)]}{E[\text{Social}^1(b^1, s^1)]}, \ldots, \frac{E[\text{Loss}^T(b^T, s^T)]}{E[\text{Social}^T(b^T, s^T)]}\right) \\ &= \max(Ine^t). \qquad (47)\end{aligned}$$

In conclusion, the efficiency loss of the DPOPS scheme is bounded. □

It is worth mentioning that, in the parking-space sharing market investigated in this article, the number of PSCs and PSPs that participate in the market is relatively large during each time slot, and the number of PSPs and PSCs who win the auction will also be relatively large as well. Thus, the upper bound of efficiency loss of the DPOPS scheme is a relatively small value that much less than 1.

VII. Performance Evaluation

To validate the effectiveness of our DPOPS scheme, we have conducted an extensive performance evaluation. In the following, we first present the methodology and then show the evaluation results.

A. Methodology

In our evaluation, we consider a real-world scenario that involves a 5×5 km^2 region in the city of Beijing, China, in which there are a number of vehicles and parking spaces [41]. The PSPs and the PSCs are allowed to take part in the incentive scheme during the total 24 available time slots per day. Moreover, we assume that the valuations of the PSCs for parking spaces are uniformly distributed from 0 to 5 RMB per hour, and the parking times of the PSCs and the available times are uniformly distributed from 1 to 24. The random fashion of the customers' arrivals and departures are quantified by the Poisson process $P(X = k) = (\lambda^k)/(k!)e^{-\lambda}$, where we set $\lambda = 20$. We set the privacy parameter ε in the differential privacy as 0.01.

To evaluate the effectiveness of DPOPS scheme, we compare the performance of our approach with two baseline schemes. The first is based on the exponential-based mechanism [32], and the second is based on the offline distribution mechanism [39]. The exponential mechanism, as a state-of-the-art differential privacy mechanism, aims to randomly select the output that provides the maximum utility while protecting the privacy of the participants. In this scenario, the exponential mechanism first randomly assigns one PSC to the PSP according to the utility that the PSCs matches with the PSP. Regarding the offline distribution mechanism, it is an optimization problem that aims to match as many PSPs and PSCs as possible and minimize the travel distance without considering bidding types. Thus, this is also called a centralized scheduling method, and it will achieve the maximum satisfaction ratio and minimum travel distance for PSCs. It is similar to the allocation mechanism shown in Section V-D, the difference being that the centralized scheduling method aims to match all the participants rather than winning participants. The offline distribution problem can be expressed as follows, utilizing the same notations as (14) in Section V-D:

$$\min \sum_{i\in P^t, j\in C^t} a_{i,j} \times \frac{\sqrt{(xc_i - xp_j)^2 - (yc_i - yp_j)^2}}{\max_{m\in C^t, n\in P^t} \sqrt{(xc_m - xp_n)^2 - (yc_m - yp_n)^2}} \tag{48}$$

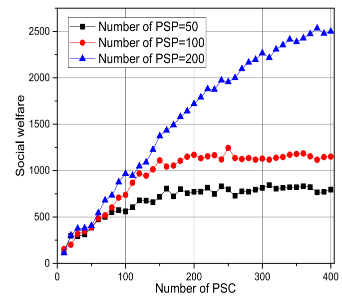

Fig. 10. Social welfare versus different numbers of PSP.

$$\text{s.t.} \sum_{j\in C^t} a_{i,j} \le 1 \quad \forall i \in P^t \tag{49}$$

$$\sum_{i\in P^t} a_{i,j} \le 1 \quad \forall j \in C^t \tag{50}$$

$$\text{tac}_j \times a_{i,j} \le \text{tap}_i \times a_{i,j} \quad \forall i \in P^t,\ j \in C^t \tag{51}$$

$$\sum_{j\in C^t} a_{i,j} = \sum_{i\in P^t} a_{i,j} = \min\{P^t, C^t\} \tag{52}$$

and

$$a_{i,j} = \{0, 1\} \quad \forall i \in P^t,\ j \in C^t. \tag{53}$$

Note that the settings of the two schemes are the same as those of DPOPS scheme. We evaluate these schemes with respect to parking-space sharing, destination privacy protection, and computation overhead.

B. Evaluation of Parking-Space Sharing

To evaluate the effectiveness in parking-space sharing, the following three metrics are considered: 1) social welfare indicating the total utility of PSPs and PSCs; 2) PSP satisfaction ratio is defined as the ratio between the parking spaces allocated to PSCs and the total supply at each time slot; and 3) PSC's satisfaction ratio defined as the ratio between the proportion of successful transacted parking spaces to the total parking-space demands from PSCs.

1) Social Welfare: We first evaluate the variations in social welfare versus the number of PSPs and PSCs. As shown in Fig. 10, social welfare increases with the growth in the number of PSCs. Nonetheless, we can also observe that under certain values of PSPs, the social welfare nearly converges to a constant value when the number of PSCs is greater than a certain value. The reason for this is that, when the number of parking spaces is fixed, increasing PSCs results in a more competitive auction market, and the social welfare remains unchanged as a result. In addition, social welfare increases with the growth in the number of PSPs when the number of PSCs remains constant.

Moreover, Fig. 11 shows the cumulative distribution function (cdf) of social welfare under DPOPS and the scheme based on the exponential mechanism. We can see that the social welfare under DPOPS is slightly better than that of the scheme based on the exponential mechanism, but the gap is relatively small. This is because social welfare is determined by the winner and payment determination, and the differential

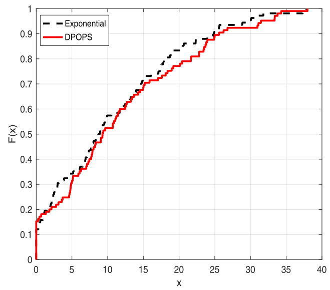

Fig. 11. Social welfare versus different schemes.

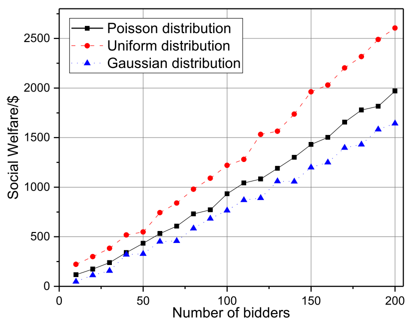

Fig. 12. Social welfare under different arrival and departure distributions of participants.

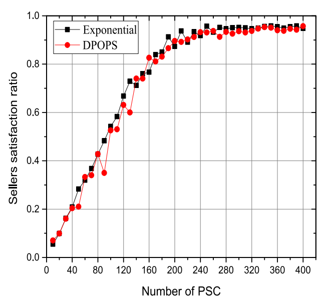

Fig. 13. Allocation efficiency versus different schemes.

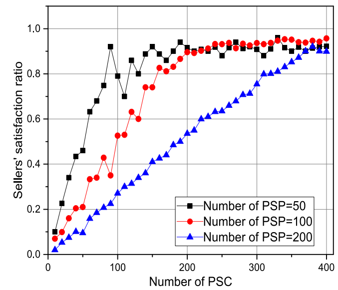

Fig. 14. Allocation efficiency versus number of PSCs.

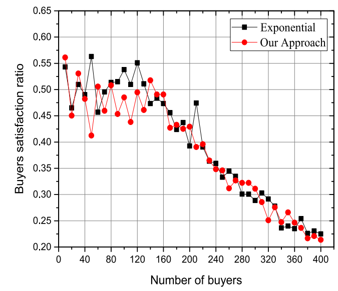

Fig. 15. PSC satisfaction ratio versus different schemes.

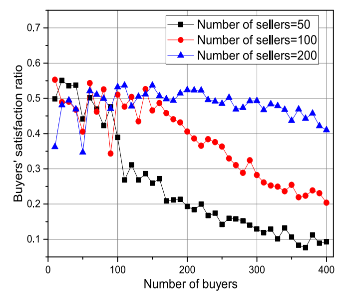

Fig. 16. PSC satisfaction ratio versus number of PSCs.

privacy mechanism during the allocation process will not affect social welfare.

In Fig. 12, we show the social welfare of DPOPS scheme when the arrival and departure of the PSCs and PSPs follow different distributions (i.e., Poisson distribution, uniform distribution, and Gaussian) and as the number of bidders varies. We observe that when the number of bidders increases, the number of winning PSPs and PSCs increases, leading to higher social welfare. In addition, the social welfare of uniform distribution is the highest, with the Poisson distribution in the middle, and the Gaussian distribution always the lowest.

2) PSP Satisfaction Ratio: We depict the evaluation of PSP satisfaction ratio in Figs. 13 and 14. Fig. 13 shows the successful allocation ratio of parking spaces when the number of PSCs varies from 10 to 400 for both DPOPS scheme and the scheme based on the exponential mechanism. As shown in the figure, with the increase in the number of PSCs, the allocation efficiency approaches 1. In addition, the two schemes achieve nearly the same performance. In addition, the PSP satisfaction ratio achieves convergence when the number of PSCs is greater than a certain value. This is because the number of winning providers remains relatively steady when the number of parking spaces is fixed.

Regarding our DPOPS, Fig. 13 shows that the allocation efficiency of parking spaces increases as the number of PSCs increases. For instance, when the numbers of PSPs and PSCs equal 200 and 400, respectively, the PSP satisfaction ratio of our scheme reaches 0.9. We can also observe that under the same number of customers, increasing PSPs the reduces the allocation ratio.

3) PSC Satisfaction Ratio: The PSC satisfaction ratios of our DPOPS scheme and the exponential mechanism-based scheme, as measured by the percentage of winning PSCs, are shown in Fig. 15. Obviously, we can observe that the PSC satisfaction ratio drops when the number of PSCs increases. This occurs because when the number of PSPs is fixed, more PSCs results in the market becoming more competitive. Once the parking spaces are almost entirely allocated, the PSC satisfaction ratio drops as a consequence. In addition, the results of the two schemes compared are similar. Fig. 16 shows that the

TABLE III
FINAL PAYMENTS IN DIFFERENT AREAS

Area	Number of PSCs	Winning rate of PSCs	Payment
Area 1	100	55%	4.59
Area 2	200	45%	5.18
Area 3	300	32%	6.36

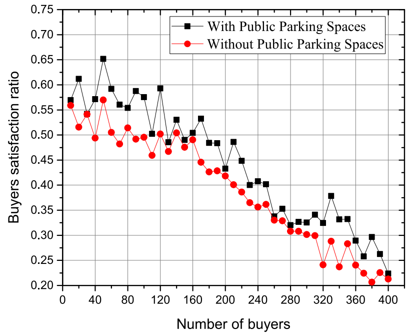

Fig. 17. Performance on parking-space sharing market.

PSC satisfaction ratio increases with the growth of the number of PSPs.

4) Payments in Different Areas: In Table III, we conduct simulations to demonstrate the payments in different areas of the city. We choose three areas in the city with different PSCs in the simulation. Specifically, Area 1 with 100 PSCs represents the residential area, Area 2 with 200 PSCs represents the downtown area, and Area 3 with 300 PSCs represents the central business area. The number of PSPs in all areas is 1000. In Table III, we can see that the payment will increase with the increase of PSCs. The reason for this is that in Area 3, the competition between PSCs increases, leading to an increase in the final payment, which is consistent with general market rules.

5) Scenario With Public Parking Spaces: Next, considering the scenario in which PSCs are able to park their vehicles at public parking spaces, we carry out an additional simulation to evaluate performance. In this scenario, there are 200 PSPs and 20 public parking spaces simultaneously available. The PSC satisfaction ratio is shown in Fig. 17. We can see from the figure that, with the availability of public parking spaces, the satisfaction of PSCs increases significantly. The reason for this is that some of the PSCs can be satisfied by the public parking spaces, thus reducing the competitive pressure in the auction market.

C. Evaluation of Destination Privacy Protection

To measure the performance of privacy protection, we introduce the commonly used metric known as privacy leakage.

Definition 3 (Privacy Leakage): For a mechanism M, denote D and D' as two bid/ask profiles which only differ in one bidder's valuation, with $M(D)$ and $M(D')$ as the generated output of input D and D'. Privacy leakage is then defined as $PL = \sum_{o \in \mathrm{O}} \Pr[M(\vec{\beta}) = o] \ln((\Pr[M(\vec{\beta}) = o])/(\Pr[M(\vec{\beta}') = o]))$.

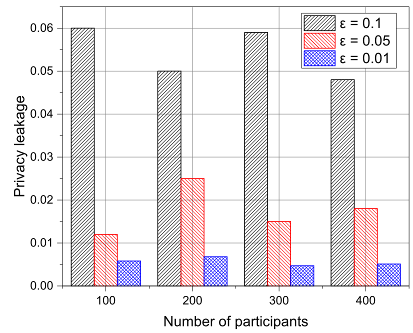

Fig. 18. Privacy leakage.

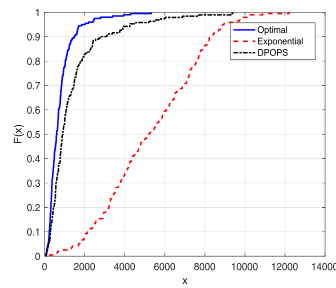

Fig. 19. PSC travel distance under different schemes.

Fig. 18 shows the privacy leakage values of our DPOPS scheme when the privacy parameters equal 0.01, 0.05, and 0.1, respectively. From the figure, we can see that the value of privacy leakage is relatively small because the DPOPS scheme achieves differential privacy. The privacy leakage is smaller than 0.06 when the number of participants is 100 and the privacy parameter is 0.1. In addition, we observe that the privacy leakage follows the same trends as the privacy parameter. In general, as the privacy leakage values are within an acceptable range according to our evaluation, we can conclude that the adversary cannot distinguish the PSC's destination with high probability.

In addition, note that adding noise to PSC location coordinates for the purpose of destination privacy protection could result in the PSCs not being able to park in the nearest parking spaces. Thus, in order to quantify the dissatisfaction caused by noise added by the privacy protection mechanism, we evaluate the PSCs' total travel distances from their destinations to the allocated parking spaces. Fig. 19 shows the PSC total travel distance under the three schemes. Obviously, the DPOPS scheme outperforms the scheme based on the exponential mechanism in terms of travel distance. Nonetheless, the offline optimal mechanism achieves the best performance, meaning that the customers are assigned to the nearest parking spaces. This is because the scheme based on the offline optimal mechanism is not taking any destination privacy protection measures. In addition, in Fig. 20, we can see that in using our DPOPS scheme, the travel distances of PSCs remain almost the same despite different privacy parameters (i.e., 0.01, 0.05, and 0.1).

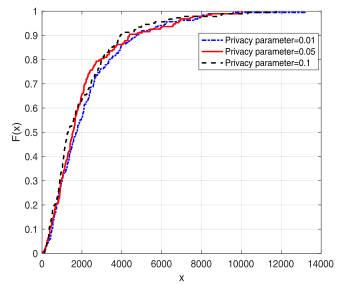

Fig. 20. PSC travel distance under different values of ε.

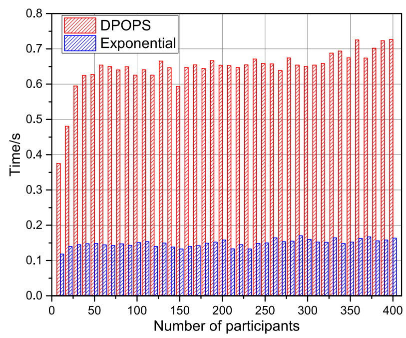

Fig. 21. Computation overhead.

D. Evaluation of Runtime

Fig. 21 compares the complexities of our DPOPS scheme and the scheme based on the exponential mechanism as the number of participants varies from 10 to 400 in the market. We observed that the running time of our DPOPS scheme is less than 0.8 s even with a large input size and remains steady as the number of participants increases. In addition, it is no surprise that our scheme takes longer than the exponential mechanism-based scheme, because our scheme matches winning PSPs and PSCs by solving an MINLP problem, while the exponential mechanism-based scheme executes the allocation process by calculating the score function of the winners, which is a simpler problem. Overall, the time consumption of our DPOPS scheme is acceptable.

VIII. Conclusion and Future Works

In this article, we have proposed a novel incentive scheme called DPOPS for providing privacy protection in the online parking-space sharing system. We have proved that DPOPS achieves weak budget balance, individual rationality, customer-incentive compatibility, and differential privacy. We have also presented the upper bound of the efficiency loss of our scheme. Through extensive evaluation, we have validated that our DPOPS can achieve good performance with respect to social welfare, PSP satisfaction ratio, as well as privacy protection. Meanwhile, by applying the DPOPS scheme, customer travel distances between allocated parking spaces and target destinations are shorter compared with the representative exponential mechanism-based scheme. Moreover, designing incentive auction mechanisms with an upper bound of efficiency loss that achieve incentive compatibility for both PSP and PSC is a promising way to improve the utilization of idle parking space while guaranteeing utilities for PSPs and PSCs, which will be considered as an ongoing work.

Appendix

The proof of lemma 3 is expressed as follows.

Proof: First, we rewrite Social (b, s) as

$$\begin{aligned}
&\text{Social}(b, s)\\
&= \sum_{j=1}^{b}(rc_j - pc_j) \times tc_j\\
&\quad + \sum_{i=1}^{s}(pp_i - rp_i) \times tp_i + \sum_{j=1}^{b-1} pc_j \times dc_j\\
&\quad - \sum_{i=1}^{s-1} pp_i \times dp_i\\
&= \sum_{j=1}^{b}(rc_j - rc_b) \times tc_j\\
&\quad + rp_s^* \times \left(\sum_{i=1}^{s} tp_i - TA\right) + rc_b \times TA - \sum_{i=1}^{s} tp_i
\end{aligned} \tag{54}$$

where rp_s^* indicates the actual payment of each PSP and rp_s^* is not smaller than the threshold price rp_s: $rp_p^* \geq rp_s$. Moreover, according to (34), there exists $\sum_{i=1}^{s} tp_i \geq TA$. Thus, we have

$$\begin{aligned}
&\text{Social}(b, s)\\
&\geq \sum_{j=1}^{b}(rc_j - rc_b) \times tc_j\\
&\quad + rp_s \times (\sum_{i=1}^{s} tp_i - TA) + rc_b \times TA - \sum_{i=1}^{s} tp_i\\
&= \sum_{j=1}^{b}(rc_j - rc_b)tc_j + \sum_{i=1}^{s}(rp_s - rp_i)tp_i + TA(rc_b - rp_s)\\
&= (rc_1 - rc_2) \times tc_1 + (rc_2 - rc_3) \times (tc_1 + tc_2)\\
&\quad + \cdots + (rc_{b-1} - rc_b) \times \sum_{j=1}^{b-1} tc_j\\
&\quad + \cdots + (rp_2 - rp_1) \times tp_1 + (rp_3 - rp_2) \times (tp_1 + tp_2)\\
&\quad + \cdots + (rp_s - rp_{s-1}) \times \sum_{i=1}^{s-1} tp_i + (rc_b - rp_s) \times TA.
\end{aligned} \tag{55}$$

According to Lemma 2

$$\begin{aligned}
&E[\text{Social}(b, s)]\\
&\geq \frac{1}{\varphi(m_c + 1)} E\left[tc_1 + (tc_1 + tc_2) + \cdots + \sum_{j=1}^{b-1} tc_j\right]\\
&\quad + \frac{1}{\tau(m_p + 1)} E\left[tp_1 + (tp_1 + tp_2) + \cdots + \left(\sum_{i=1}^{s-1} tp_i\right)\right]\\
&= \frac{b(b-1)E[TC]}{2\varphi(m_c + 1)} + \frac{s(s-1)E[TP]}{2\tau(m_p + 1)}.
\end{aligned} \tag{56}$$

For the sake of convenience, c and d are used to represent (55) and (56): $c = (b(b-1)E[TC])/(2\varphi(m_c+1))$, and $d = (s(s-1)E[TP])/(2\tau(m_p+1))$. Regarding the efficiency loss function [see (38)], we first consider the case in which the total s PSPs supply parking time period is larger than the demand parking time period of the total b PSCs, $TA = \sum_{j=1}^{b} tc_j$. Then, the expectation of the efficiency loss function can be written as

$$E[\mathrm{Loss}(b,s)] \le E[rc_b - rc_{b+1}]E\left[\sum_{j=1}^{b} tc_j\right] + E[C]. \quad (57)$$

Then, we consider the following two cases.

Case A ($\sum_{j=1}^{b-1} tc_j \ge \sum_{i=1}^{s-1} tp_i$): In this case, the total demand parking time of the wining PSCs is larger than the total supply parking time of the winning PSPs. The expectation of the loss function $E[Loss(b,s)]$ can be further bounded as

$$\begin{aligned} E[\mathrm{Loss}(b,s)] \le\ & E[rc_b - rc_{b+1}]E\left[\sum_{j=1}^{b} tc_j\right] \\ & + E[(rc_1 - rc_b)tp_s] \\ \le\ & \frac{bE[TC]}{\chi(m_c+1)} + \frac{bE[TP]}{\chi(m_p+1)}. \end{aligned}$$

Then,

$$\begin{aligned} Ine(b,s) &\le \left(\frac{bE[TC]}{\chi(m_c+1)} + \frac{bE[TP]}{\chi(m_c+1)}\right)/(c+d) \\ &\le \left(\frac{bE[TC]}{\chi(m_c+1)} + \frac{bE[TP]}{\chi(m_c+1)}\right)/c \\ &= \frac{1}{b-1}\left(\frac{2\varphi}{\chi} + \frac{2\varphi E[TP]}{\chi E[TC]}\right). \end{aligned} \quad (58)$$

Since $E[TC]$ and $E[TP]$ are constants, we know that $Ine(b,s)$ is bounded by $1/(b-1)$ multiplied by a constant.

Case B ($\sum_{j=1}^{b-1} tc_j \le \sum_{i=1}^{s-1} tp_i$): In this case, the total demand parking time of winning PSCs is smaller than the total supply parking time of the winning PSPs, and we have

$$\begin{aligned} &\mathrm{Loss}(b,c)^* \\ &= \mathrm{Loss}_a^* + \mathrm{Loss}_b^* + \mathrm{Loss}_c^* \\ &= (rc_b - rp_s) \times \min\left(\sum_{j=1}^{b-1} tc_j, \sum_{i=1}^{s-1} tp_i\right) \\ &\quad +(rc_b - rp_s) \times \left(\min\left(\sum_{j=1}^{b} tc_j, \sum_{i=1}^{s} tp_i\right)\right. \\ &\quad \left. - \min\left(\sum_{j=1}^{b-1} tc_j, \sum_{i=1}^{s-1} tp_i\right)\right) + \mathrm{Loss}_c^* \\ &\le (rc_b - rp_s) \times TA + (rp_s - rp_1) \times tc_b \\ &= rc_b \times TA + rp_s \times (tc_b - TA) + rp_1 \times tc_b. \end{aligned} \quad (59)$$

According to (34)–(37), we know that the only difference between the Loss and Loss* is that the PSPs' actual payment in Loss is rp_s^* and in Loss* is rp_s. According to the payment rule [see (12)], we know that the actual payment is not smaller than the threshold price: $rp_s^* \ge rp_s$. In this case, we have $TA = \sum_{j=1}^{b} tc_j$ so that $tc_b - TA < 0$. Thus, if we use rp_s^* to replace rp_s, the total value will be smaller. Thus, Loss can be bounded by

$$\begin{aligned} \mathrm{Loss}(b,s) &\le rc_b \times TA + rp_s^* \times (tc_b - TA) + rp_1 \times tc_b \\ &\le rc_b \times TA + rp_s \times (tc_b - TA) + rp_1 \times tc_b \\ &= (rc_b - rp_s) \times TA + (rp_s - rp_1) \times tc_b. \end{aligned} \quad (60)$$

Then, $E[\mathrm{Loss}(b,c)]$ can be bounded by

$$\begin{aligned} E[\mathrm{Loss}(b,s)] \le\ & E[rc_b - rc_{b+1}]E\left[\sum_{j=1}^{b} tc_j\right] \\ & + E[(rp_s - rp_1)tc_k] \\ \le\ & \frac{bE[TC]}{\chi(m_c+1)} + \frac{sE[TC]}{\omega(m_p+1)}. \end{aligned} \quad (61)$$

Note that we have

$$\frac{\frac{bE[TC]}{\chi(m_c+1)} + \frac{sE[TC]}{\omega(m_p+1)}}{\frac{b(b-1)E[TC]}{2\varphi(m_c+1)} + \frac{s(s-1)E[TP]}{2\tau(m_p+1)}} \le \max\left(\frac{\frac{bE[TC]}{\chi(m_c+1)}}{\frac{b(b-1)E[TC]}{2\varphi(m_c+1)}}, \frac{\frac{sE[TC]}{\omega(m_p+1)}}{\frac{s(s-1)E[TP]}{2\tau(m_p+1)}}\right).$$

Then, we have

$$\mathrm{Ine}(b,s) \le \max\left(\frac{1}{b-1}\frac{2\varphi}{\chi}, \frac{1}{s-1}\frac{2\tau E[TC]}{\omega E[TP]}\right). \quad (62)$$

Combining inequalities (58) and (62), we can bound $Ine(b,s)$ as

$$Ine(b,s) \le \Delta \max\left(\frac{1}{b-1}, \frac{1}{s-1}\right) \quad (63)$$

where Δ is a constant. The proof for the case where $TA = \sum_{i=1}^{s} tp_i$ is similar. □

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Dou An received the Ph.D. degree in control science and engineering from Xi'an Jiaotong University, Xi'an, China, in 2017.

He is currently an Associate Professor with the Department of Automation Science and Technology, School of Electrical and Information Engineering, Xi'an Jiaotong University. His current research interests include cyber-physical systems, Internet of Things (IoT) security and privacy, and incentive mechanism design for smart grid and IoT.

Qingyu Yang (Member, IEEE) received the B.S. and M.S. degrees in mechatronics engineering and the Ph.D. degree in control science and engineering from Xi'an Jiaotong University, Xi'an, China, in 1996, 1999, and 2003, respectively.

He is currently a Professor with the School of Electronics and Information Engineering, Xi'an Jiaotong University, where he is also with the State Key Laboratory for Manufacturing System Engineering and the MOE Key Laboratory for Intelligent Networks and Network Security. His current research interests include cyber-physical systems, power grid security and privacy, control and diagnosis of mechatronic systems, and intelligent control of industrial process.

Donghe Li received the B.S. degree in automation from Xi'an Jiaotong University, Xi'an, China, in 2015, where he is currently pursuing the Ph.D. degree with the Department of Automation Science and Technology, School of Electrical and Information Engineering.

His current research interests include cyber-physical systems, demand response, and privacy preservation in smart grid.

Wei Yu (Member, IEEE) received the B.S. degree in electrical engineering from the Nanjing University of Technology, Nanjing, China, in 1992, the M.S. degree in electrical engineering from Tongji University, Shanghai, China, in 1995, and the Ph.D. degree in computer engineering from Texas A&M University, College Station, TX, USA, in 2008.

He is currently a Full Professor with the Department of Computer and Information Sciences, Towson University, Towson, MD, USA. His current research interests include cybersecurity and privacy, cyber-physical systems, Internet of Things, and distributed computing.

Dr. Yu was a recipient of the 2014 NSF CAREER Award, the 2015 University System of Maryland (USM) Regents' Faculty Award for Excellence in Scholarship, Research, or Creative Activity, and the 2016 USM Wilson H. Elkins Professorship. His research has also received the best paper awards from the IEEE ICC 2008, ICC 2013, IEEE IPCCC 2016, and WASA 2017.

Wei Zhao (Fellow, IEEE) received the Ph.D. degree in computer and information sciences from the University of Massachusetts at Amherst, Amherst, MA, USA, in 1986.

Since 1986, he has been a Faculty Member with the Amherst College, The University of Adelaide, Adelaide, SA, USA, and Texas A&M University, College Station, TX, USA. From 2005 to 2006, he was the Director of the Division of Computer and Network Systems, National Science Foundation, Alexandria, VA, USA, when he was on leave from Texas A&M University. He was the Senior Associate Vice President for research and a Professor of computer science with Texas A&M University. He was the Dean of the School of Science, Rensselaer Polytechnic Institute, Troy, NY, USA, from 2007 to 2008. He was the Founding Director of the Texas A&M Center for Information Security and Assurance, which has been recognized as the Center of Academic Excellence in Information Assurance Education by the National Security Agency. He was the Rector of the University of Macau, Macau. He is currently a Chief Research Officer with the American University of Sharjah, Sharjah, United Arab Emirates.

Dr. Zhao has made significant contributions in distributed computing, real-time systems, computer networks, and cyberspace security as an Elected IEEE Fellow.

Chao-Bo Yan (Senior Member, IEEE) received the B.S. degree from Xi'an Jiaotong University, Xi'an, China, in 2004, and the M.S. and Ph.D. degrees in control theory and engineering from Tsinghua University, Beijing, China, in 2007 and 2012, respectively.

He was a Visiting Scholar with the University of Michigan, Ann Arbor, MI, USA, from 2009 to 2010, and a Post-Doctoral Research Fellow from 2012 to 2014. He is currently an Associate Professor with the Faculty of Electronic and Information Engineering, School of Automation Science and Engineering, Xi'an Jiaotong University. His research interests include modeling, analysis, and optimization of production systems, and cyber-physical systems (CPS) theory and its applications to manufacturing, logistics, and inventory systems.

Dr. Yan is an Associate Editor of the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING and the IEEE ROBOTICS AND AUTOMATION LETTERS and an Editor on the Conference Editorial Board (CEB) of the IEEE Conference on Automation Science and Engineering.