Parking Reservation Auction for Parked Vehicle Assistance in Vehicular Fog Computing

Yi Zhang, *Student Member, IEEE,* Chih-Yu Wang, *Member, IEEE,* and Hung-Yu Wei, *Senior Member, IEEE*

***Abstract*—Vehicular fog computing (VFC) is a promising approach to provide ultra-low-latency service to vehicles and end users by extending the fog computing to conventional vehicular networks. Parked vehicle assistance (PVA), as a critical technique in VFC, can be integrated with smart parking in order to exploit its full potentials. In this paper, we propose a smart VFC system by combining both PVA and smart parking. A VFC-aware parking reservation auction is proposed to guide the on-the-move vehicles to the available parking places with less effort and meanwhile exploit the fog capability of parked vehicles to assist the delay-sensitive computing services by monetary rewards to compensate for their service cost. The proposed allocation rule maximizes the aggregate utility of the smart vehicles and the proposed payment rule guarantees incentive compatibility, individual rationality, and budget balance. We further provide an observation stage with dynamic offload pricing update to improve the offload efficiency and the profit of fog system. The simulation results confirmed the win-win performance enhancement to the fog node controller (FNC), the smart vehicles and the parking places from the proposed design.**

***Index Terms*—Vehicular fog computing (VFC), parked vehicle assistance (PVA), multi-round auction**

I. Introduction

With the rapid growth of connected devices in Internet of Things (IoT)-based network systems and new applications and services for 5G, such as virtual reality (VR), augmented reality (AR) and real-time online gaming, fog computing plays an important role to provide low latency service by migrating the urgent computation workload from cloud data centers to computing service at network edges of the 5G network [1, 2]. Nevertheless, the deployment of computing services and resources at network edges is a serious challenge to the service provider in fog computing [3, 4].

Vehicular fog computing (VFC) is a promising approach to provide such a low latency service by extending the fog computing to conventional vehicular networks [5]. To cope with the explosive application demands, roadside units (RSUs), which are generally deployed in different areas of a city, can be upgraded by equipped with fog computing servers to provide both communication and computation services to those mobile terminals. However, the fog computing service is limited due to the density of RSUs. Moreover, RSUs confront heavy load with the increasing number of service requests. The idea of parked vehicle assistance (PVA) has been investigated to be useful to deliver content in vehicular ad hoc networks (VANETs) where the number of RSUs is insufficient [6–10]. Note that the parked vehicles can act as static network infrastructures to improve connectivity by sharing and exchanging contents with moving vehicles.

On the other hand, due to the increased population and limited spatial resource of the city, limited parking places cause severe parking issues. The previous study shows that a large portion of traffic intensity in a major city is due to the congestion caused by the vehicles searching for parking slots [11]. Besides, unnecessary time and energy of vehicles are wasted during their searching for parking. To guide the vehicles to the available parking slots with less effort, time and fuel consumption, smart parking system (SPS) has been widely investigated [12–15]. Nevertheless, most proposed designs are limited to solely satisfy the parking demands. The potential benefits of smart parking in other domains, such as VFC, is not explored yet.

We find that by integrating PVA and smart parking, we potentially provide a more robust VFC system with lower cost and higher satisfactory to all participants. The VFC-aware smart parking improves the traffic and parking efficiency by leading on-the-move vehicles to the available parking places. Meanwhile, the fog service provider can achieve cost saving by turning off redundant fog computing servers, namely fog nodes (FNs), when the vehicles with fog capability could be attracted to park at proper parking spaces to assist the delay-sensitive computing services. The system is aware of the fact that each vehicle aims to maximize their own utility by considering driving cost, walking cost and parking payment, etc. To compensate for their service cost, the fog service provider motivates the parked vehicles by paying a certain amount of monetary rewards. Moreover, the fog service provider in the long term can save a part of deployment expense and maintenance cost with the aid of parked vehicles.

In this paper, we propose a practical VFC system by combining both PVA and smart parking. The proposed system provides a VFC-aware parking reservation auction to guide the on-the-move vehicles to the available parking places with less effort. We first analyze the bidding strategies of the smart vehicles and the feasible region of the offload price in a single-round scenario and further propose a multi-round

Yi Zhang is with the Graduate Institute of Communication Engineering, National Taiwan University, Taipei 10617, Taiwan (email: yzhang.cn@outlook.com)

Chih-Yu Wang is with the Research Center for Information Technology Innovation, Academia Sinica, Taipei 115, Taiwan (email: cywang@citi.sinica.edu.tw)

Hung-Yu Wei is with the Graduate Institute of Communication Engineering, Graduate Institute of Electrical Engineering, and Department of Electrical Engineering, National Taiwan University, Taipei 10617, Taiwan (email: hywei@cc.ee.ntu.edu.tw)

Corresponding author: Hung-Yu Wei.

auction to improve the offload price through the iterative update process. The proposed auction guarantees incentive compatibility, individual rationality, and budget balance. The simulation results show that the proposed design can improve the system performance compared with conventional and greedy approaches, especially under huge parking demand. The results also show that the proposed system with multi-round auction can achieve win-win performance enhancement to the FNC, the smart vehicles, and the parking places.

A. Related Work

To provide low-latency service to vehicles and end users, VFC has been widely studied [16–18]. A VFC-based architecture [16] is proposed to enhance the quality of user experience in latency-sensitive applications by using software-defined networking (SDN) technology to the conventional vehicular networks. In order to decrease task offloading complexity in VFC-enable VANETs, where the network topology dynamically changes caused by the mobility of vehicles, an efficient predictive framework [17] is provided to adaptively upload the tasks to the fog computing servers through direct uploading or predictive relay transmissions. The limited battery capacity of in-vehicle user equipments (UEs) in VFC framework is considered in [18], where an energy-efficient resource allocation algorithm [18] is developed to solve the joint workload offloading and power control problem by applying queuing theory to derive the stochastic traffic models at UEs and FNs.

The potential of PVA is investigated in the literature. The results in [6] show that even a small proportion of PVA vehicles can greatly promote the network connectivity. Theoretic analysis, realistic survey, and simulation of PVA are investigated in [7]. The fairness in exploiting the energy resources of parked vehicles is considered in [8] to extend the RSU service coverage, which is constrained to not excessively drain parked vehicle batteries. D2D-based content delivery is proposed in [9], where parked vehicles around the street form vehicular social communities with the moving vehicles passing along the road through D2D communications. A Stackelberg game has been developed to obtain the equilibrium of the competition and cooperation among RSUs, moving vehicles and parked vehicles during the content delivery [10].

In research field as well as from economic interests, a lot of smart parking solutions have been proposed to efficiently guide the drivers to satisfying parking slots [12–15]. A full survey [15] of the SPS state-of-the-art over the period of 2000–2016 has been provided and thoughtfully classified, including parking information collection, system deployment, and service dissemination. By considering driver's cost function, an optimal parking reservation allocation using mixed-integer linear programming (MILP) is proposed to assign and reserve parking spaces to drivers with specific requirements [12]. An effective cloud-based smart parking architecture is provided based on IoT technology, which automatically monitors and manage parking space [14]. The system prototype is successfully implemented by a Zigbee wireless sensor network (WSN) and a data center serving as a cloud. In the literature with game-theoretic approaches, a dynamic resource allocation, reservation, and pricing smart parking system is proposed to minimize the overall system cost [19]. However, the uncoordinated selfish behavior of drivers is not addressed and will potentially degrade the system efficiency. A demand-based parking pricing mechanism is proposed by predicting the occupancy rate of individual parking areas using machine learning approach [20], where an amount of historical parking data are required. With the development of electric vehicle (EV) accompanied by the rapid growth of the EV charging infrastructure, a noncooperative game-theoretic approach using Rosen-Nash normalized equilibrium [21] is provided to deal with the parking-lot EV charging scheduling problem. For commercial use, SFpark [22] and LA ExpressPark [23] are two intelligent parking program by utilizing smart parking meters. The demand-responsive parking pricing is piloted by both SFpark and LA ExpressPark to realize the goal of increasing the availability of public parking spaces and decreasing traffic congestion and pollution.

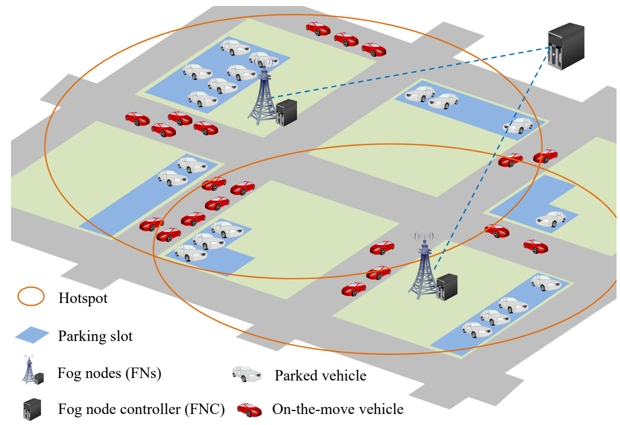


Fig. 1. Local network scenario

To best of our knowledge, the idea of combining both PVA and smart parking is not explored in the literature yet.

B. Contributions and Organization

Our main contributions are as follows.

- We propose a parked vehicle assisted VFC system, which integrates both PVA and smart parking. On the one hand, the proposed system offers an opportunity to lead moving vehicles to the available parking places with less effort. On the other hand, the proposed system exploits the fog capability of parked vehicles to assist the delay-sensitive computing services and meanwhile achieve the energy saving of the FNC by turning off redundant FNs. To best of our knowledge, we are the first team to propose this idea and provide a comprehensive design to address the efficiency and selfishness issues in this approach.
- A multi-round multi-item parking reservation auction is proposed to attract the on-the-move vehicles carried with CPU resources by monetary rewards for service offloading. Since the optimal choice of the offload price is challenging to get a close form given the auction structure, we provide multi-round offload pricing update to transfer the CPU resources of the parked vehicles to improve the system

performance. The proposed auction is incentive compatible, individual rational and budget balance.

- We evaluate the performance of the proposed VFC system through simulations in realistic settings by considering the street map and parking space deployment in the real world. The simulation results show that an optimal offload price exists and the proposed multi-round auction can improve both the profit of the FNC and the utility of parked vehicles.

The rest of paper is organized as follows. In Section II, we introduce the proposed parked vehicle assisted VFC system. A single-round multi-item parking reservation auction is presented in Section III. Furthermore, we provide a multi-round multi-item parking reservation auction with offload pricing update to increase the profit of the FNC in Section IV. Section V shows our simulation results and, finally, Section VI concludes this work.

II. Problem Formulation

The proposed parked vehicle assisted VFC system is shown in Fig. 1. In the system, we assume a set of $\mathcal{H} = \{h_1, h_2, \cdots, h_K\}$ to represent K hotspots. Each hotspot consists of multiple end-user devices carrying with delay-sensitive computation requests for external computing service. To guarantee the service requirements, sufficient FNs have been deploy near each hotspot to serve those end users. A FNC is responsible to manage those FNs. Besides, there are N *on-the-move* vehicles (moving on the road with certain trip destinations), denoted by a set $\mathcal{B} = \{b_1, b_2, \cdots, b_N\}$. Some of them, called *fog-capable vehicles*, equipped with limited computing resources and have the potential to offload the computation workload from the FNs near the hotspots when they are also parked nearby. There are M parking places owned by private parking operators, denoted by $\mathcal{S} = \{s_1, s_2, \cdots, s_M\}$, which provide parking service to those vehicles searching for parking slots. The real-time parking availability can be collected by parking sensors. The key notations of this paper are listed in TABLE I. We consider a time-slotted system and formulate as follows:

1) Parking places: We introduce $x_{i,j}(t)$ to indicate the arrival event for parking:

$$x_{i,j}(t) = \begin{cases} 1 & \text{if } b_i \text{ parks at } s_j \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The departure event is denoted by $y_{i,j}(t)$ as

$$y_{i,j}(t) = \begin{cases} 1 & \text{if } b_i \text{ parked at } s_j \text{ leaves at time } t, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The reservation state is denoted by $l_{i,j}(t)$ as

$$l_{i,j}(t) = \begin{cases} 1 & \text{if } s_j \text{ has reserved a parking lot} \\ & \quad \text{for } b_i \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

For parking place $s_j \in \mathcal{S}$, the geo-location is known as $\mathcal{X}_j^{\mathrm{s}} \in \mathbb{R}^2$ (GPS coordinates). We denote C_j as the overall parking capacity of s_j. Then, the parking slot inventory [1] at

[1]The parking slot inventory can be regarded as fixed within the proposed auctions by the following two solutions: *i)* reserve a part of available parking spaces for the proposed auctions; *ii)* use the advance reservation period to control the auction frequency so that the processing time of the auction becomes negligible (more flexible).

TABLE I
LIST OF KEY NOTATION

Notation	Definition
$\mathcal{H}$	Hotspots, $\mathcal{H} = \{h_1, h_2, \cdots, h_K\}$
$\mathcal{B}$	On-the-move vehicles, $\mathcal{B} = \{b_1, b_2, \cdots, b_N\}$
$\mathcal{S}$	Parking places, $\mathcal{S} = \{s_1, s_2, \cdots, s_M\}$
$x_{i,j}(t)$, $y_{i,j}(t)$	Indicators of {arrival event, departure event}
$l_{i,j}(t)$	Indicators of reservation state
$\mathcal{X}_j^{\mathrm{s}}$	Geo-location of s_j
C_j	Overall parking capacity of s_j
$C_j(t)$	Parking slot inventory of s_j at time t
$w_{i,j}$	Indicator of b_i if allocated to s_j
$\mathcal{X}_i^{\mathrm{cur}}$, $\mathcal{X}_i^{\mathrm{dest}}$	{Current position, traveling destination} of b_i
r_i^{d}	Average driving speed of b_i
r^{w}	General walking speed of human
$\Phi^{\mathrm{r}}(\cdot)$	Distance function by city roads
$\Phi^{\mathrm{l}}(\cdot)$	Air line distance function
$\tau_{i,j}^{\mathrm{d}}$, $\tau_{i,j}^{\mathrm{w}}$	Remaining {driving time, walking time} of b_i if parks at s_j
$\tau_{i,j}$	Total traveling time, $\tau_{i,j} = \tau_{i,j}^{\mathrm{d}} + \tau_{i,j}^{\mathrm{w}}$
$c_{i,j}^{\mathrm{d}}$	Driving energy cost, $c_{i,j}^{\mathrm{d}} = \theta \tau_{i,j}^{\mathrm{d}}$
$c_{i,j}$	Total cost of both driving and walking
μ	Service rate in CPU cycle per bit
m_i	# of CPUs equipped at b_i
Δ_i	Parking duration of b_i
$\mathcal{X}_k^{\mathrm{h}}$	Central geo-location of h_k
λ_k	Mean workload arrival rate of h_k
$\hat{\lambda}_k$	Offloaded arrival rate per CPU of h_k
m_k	Total # of CPUs required by h_k
$z_{i,k}$	Indicator of b_i if offloads from h_k
$q_{i,j}^k$, $h_{i,j}^k$, $d_{i,j}^k$	{Queuing delay, network delay, service delay} of b_i if offloads from h_k at s_j
$c_{i,j}^k$	Energy cost of computing service
D_k	Maximum delay toleration of h_k
$C(\cdot)$	Energy cost of nearby FNs of hotspot h_k
t^{r}	Advance reservation period
$\tau_{i,j}^{\mathrm{r}}$	Parking reservation duration
p_j^{s}	Reserve price per unit time if parks at s_j
$a_{j,k}$	Offload price per CPU resource if offloads from h_k at s_j
v_i	Value of successful parking of b_i
$v_{i,j}$, $u_{i,j}$	{True valuation, utility} of b_i if parks at s_j
T_i^{w}	Maximum tolerant walking time of b_i
T_i	Maximum tolerant traveling time of b_i
$\mathcal{B}_{\mathrm{b}}$	The set of smart vehicles
$\mathcal{S}_i$	Candidate parking places of b_i
$\mathcal{B}_j$, $\mathcal{H}_j$	Candidate {vehicles, hotspots } of s_j
$\mathcal{S}_k$	Candidate parking places of h_k
M^{h}	Maximum CPUs allowed to be supported by a parked vehicle
Δ_k^{cost}, π_k	{Cost saving, profit} of h_k
π	Instantaneous profit of the FNC
p_i^b	Real payment of b_i in the auction
$\widetilde{m}_i$	Maximum # of CPUs can be provided by b_i recorded by the FNC

time t can be calculated by

$$C_j(t) = C_j - \sum_{b_i \in \mathcal{B}} \sum_{t'=1}^{t-1} x_{i,j}(t') + \sum_{b_i \in \mathcal{B}} \sum_{t'=1}^{t} y_{i,j}(t') - \sum_{b_i \in \mathcal{B}} l_{i,j}(t). \quad (4)$$

2) Vehicles: We introduce a binary indicator $w_{i,j}$ to denote the parking location of vehicle:

$$w_{i,j} = \begin{cases} 1 & \text{if } b_i \text{ is allocated to } s_j, \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

Therefore, those vehicles ($b_i \in \mathcal{B}$) with the condition $\sum_{s_j \in \mathcal{S}} w_{i,j} = 0$ are on-the-move vehicles.

For on-the-move vehicle $b_i \in \mathcal{B}$ searching for a parking slot, the current car position and the traveling destination are known as $\mathcal{X}_i^{\rm cur}$ and $\mathcal{X}_i^{\rm dest}$, respectively. Vehicle b_i can measure its average driving speed $r_i^{\rm d}$ through the historical information. In this paper, we assume that the average walking speed of human is $r^{\rm w}$ in general. Besides, we define $\Phi^{\rm r}(\cdot)$ as the distance function by city roads (similar to Manhattan distance). If vehicle b_i determines to park at place s_j, the remaining driving time and the walking time will be

$$\tau_{i,j}^{\rm d} = \Phi^{\rm r}(\mathcal{X}_i^{\rm cur}, \mathcal{X}_j^{\rm s})/r_i^{\rm d} \text{ and } \tau_{i,j}^{\rm w} = \Phi^{\rm r}(\mathcal{X}_j^{\rm s}, \mathcal{X}_i^{\rm dest})/r^{\rm w}. \quad (6)$$

Therefore, the total traveling time will be $\tau_{i,j} = \tau_{i,j}^{\rm d} + \tau_{i,j}^{\rm w}$. We define the driving energy cost as $c_{i,j}^{\rm d} = \theta \tau_{i,j}^{\rm d}$, where θ is the per unit driving energy cost. The total cost of both driving and walking can be estimated by

$$c_{i,j} = c_{i,j}^{\rm d} + \delta \tau_{i,j}, \quad (7)$$

where δ is a positive constant converting traveling time to cost.

Furthermore, we define CPU as the unit of a computing resource, which has the service rate μ (in CPU cycle per bit). A vehicle b_i can provide computing service if $m_i \neq 0$, where m_i is the number of CPUs equipped at b_i and reflects its fog capability. A vehicle b_i with $m_i \neq 0$ is a fog-capable vehicle. The parking duration of b_i is denoted by Δ_i. We assume that a parked vehicle will only serve at most one hotspot during its parking duration.

3) Hotspots: For hotspot $h_k \in \mathcal{H}$, the central geo-location is known as $\mathcal{X}_k^{\rm h}$. We assume that the FNC is capable to predict the amount of computing service requests from end users at h_k for a short period in the future, which is represented by mean workload arrival rate λ_k. We allocate the workload to each CPU evenly. That is, we have

$$\hat{\lambda}_k = \frac{\lambda_k}{m_k}, \quad (8)$$

where $\hat{\lambda}_k$ is the offloading arrival rate per CPU and m_k is the total number of CPUs required by hotspot h_k by considering its loading and delay requirements.

We introduce a binary indicator as follows:

$$z_{i,k} = \begin{cases} 1 & \text{if } b_i \text{ provides service to } h_k, \\ 0 & \text{otherwise.} \end{cases} \quad (9)$$

If vehicle b_i provides computing service to h_k ($z_{i,k} = 1$) at s_j ($w_{i,j} = 1$), the quality-of-service (QoS) can be measured in terms of service delay [24]:

$$d_{i,j}^k = q_{i,j}^k + h_{i,j}^k, \quad (10)$$

which consists of the queuing delay $q_{i,j}^k$ (CPU load) and the network delay $h_{i,j}^k$ (data deliver). Consider parallel M/G/1 processor sharing queues [25, 26], the queuing delay is

$$q_{i,j}^k = \frac{\hat{\lambda}_k m_{i,j}}{\mu - \frac{\hat{\lambda}_k m_{i,j}}{m_{i,j}}} = \frac{\hat{\lambda}_k m_{i,j}}{\mu - \hat{\lambda}_k}, \quad (11)$$

where $m_{i,j}$ is the number of CPUs provided by b_i at s_j. Note that the queuing delay in (11) increases when more CPUs are provided by a smart vehicle, which has been confirmed in the literature [27]. According to [24], the network delay is defined as

$$h_{i,j}^k = h_{j,k} = \xi \Phi^{\rm l}(\mathcal{X}_j^{\rm s}, \mathcal{X}_k^{\rm h}), \quad (12)$$

where $h_{j,k}$ is the network delay between the parking place s_j and the hotspot h_k, ξ is a scalar and $\Phi^{\rm l}(\cdot)$ is the air line distance function. The energy cost for b_i to provide such computing service for hotspot h_k is then given by [28]

$$c_{i,j}^k = \alpha \frac{\hat{\lambda}_k m_{i,j}^2}{\mu} + \beta \Phi^{\rm l}(\mathcal{X}_k^{\rm h}, \mathcal{X}_j^{\rm s}). \quad (13)$$

Furthermore, we define D_k as the maximum delay toleration of h_k. That is to say, the parked vehicle b_i can serve hotspot h_k at s_j only when $d_{i,j}^k \leq D_k$.

We assume that the FNC manages a sufficient number of nearby FNs to meet the service requirements. We define an energy cost function $C(m_k^f)$ [28] as

$$C(m_k^f) = \alpha^f \frac{\hat{\lambda}_k (m_k^f)^2}{\mu}, \quad (14)$$

where m_k^f is the number of CPUs required to be turned on at nearby FNs of hotspot h_k:

$$m_k^f = m_k - \sum_{b_i \in \mathcal{B}} \sum_{s_j \in \mathcal{S}} w_{i,j} z_{i,k} m_{i,j}. \quad (15)$$

The FNC can achieve cost saving by turning off redundant FNs when the computation workload is offloaded to the fog-capable vehicles parked at the parking places. To attract the fog-capable vehicles to the desired parking places, the FNC needs to pay a certain amount of monetary rewards for service offloading. The goal of the FNC is to minimize its cost of satisfying the demands of all end-users in all hotspots. The profit of the FNC is represented by its cost saving from offloading workloads to parked vehicles minus the total offload payments. Each on-the-move vehicle, on the other hand, aims to maximize its own utility when requesting parking reservation service. They may compete with each other for preferred parking slots. It motivates us to employ a parking reservation auction to regulate the proposed VFC system.

III. Single-round Auction Design

In this section, a single-round multi-item parking reservation auction is first presented to guide the on-the-move vehicles to the available parking places and meanwhile regulate the parked vehicles to assist the delay-sensitive computing services. In this scenario, the parking reservation auction is held once

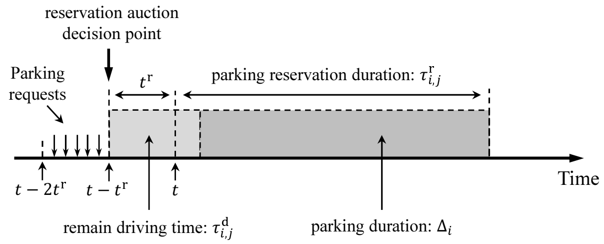


Fig. 2. Time sequence of parking reservation

every time slot and the FNC announces the corresponding offload price once in the auction. We provide the strategies of the smart vehicles. We also devise an allocation rule and a payment rule to guarantee the desired economic properties, such as incentive compatibility and individual rationality.

A. Auction Model

The FNC acts as a *auctioneer*, who periodically holds the parking reservation auction at each time slot. An offload price $a_{j,k}$ is announced for per CPU resource provided by parked vehicles at s_j to hotspot h_k. The parking place operators are *sellers* and each of them provides homogeneous goods, namely the unoccupied parking slots. A reserve price p^s_j (minimum acceptable) is charged per unit time if the vehicle chooses to park at s_j. The on-the-move vehicles, which act as *bidders*, request for parking reservation service.

We define parking reservation point t as the beginning of parking reservation duration, as shown in Fig. 2. The reservation auction is formulated on a rolling horizon of time slot intervals and periodically starts with an advance reservation period t^{r} ahead of t. In other words, the reservation auction is held at the decision point $(t-t^{\mathrm{r}})$ periodically to reserve the parking slots up to t^{r} in advance. The advance reservation period can guarantee that those vehicles *i)* know their targeted parking places before the reserved parking duration rather than blindly search and *ii)* can directly park at their reserved parking slots when arrive. If vehicle b_i chooses to park at s_j, the parking reservation duration will be

$$\tau^{\mathrm{r}}_{i,j} = \tau^{\mathrm{d}}_{i,j} + \Delta_i - t^{\mathrm{r}}. \tag{16}$$

Then, the parking duration between arrives and departs of b_i is known as $[T^{\mathrm{in}}_{i,j}, T^{\mathrm{out}}_{i,j}]$, where $T^{\mathrm{in}}_{i,j} = t - t^{\mathrm{r}} + \tau^{\mathrm{d}}_{i,j}$ and $T^{\mathrm{out}}_{i,j} = T^{\mathrm{in}}_{i,j} + \Delta_i$. Note that vehicle i can directly park at the reserved parking slot only when its arrival time $T^{\mathrm{in}}_{i,j}$ is after the reservation point t. Thus, we have the constraint $\tau^{\mathrm{d}}_{i,j} \geq t^{\mathrm{r}}$.

The proposed reservation auction is presented as follows:

- *Step 1*: On-the-move vehicles send requests for parking reservation service to the FNC.
- *Step 2*: The FNC collects the occupancy information $C_j(t)$ and reserve prices p^s_j from parking places. And then, the FNC announces the offload price $a_{j,k}$ and the reserve price p^s_j to the smart vehicles.
- *Step 3*: The vehicles submit the bidding vectors to the FNC.
- *Step 4*: The FNC applies predefined *allocation rule* and *payment rule* to determine the parking allocation and the corresponding parking payments.

B. Strategies

1) Vehicles: Let v_i denote the value of successful parking of b_i. The utility of b_i parking at s_j is

$$u_{i,j} = v_{i,j} - \tau^{\mathrm{r}}_{i,j} p^s_j, \qquad \text{where} \tag{17}$$

$$v_{i,j} = \begin{cases} v_i - c_{i,j} + \sum\limits_{h_k \in \mathcal{H}} z_{i,k} \Delta_i (a_{j,k} m_{i,j} - c^k_{i,j}) \\ \quad \text{if } \tau^{\mathrm{d}}_{i,j} \geq t^{\mathrm{r}},\ \tau^{\mathrm{w}}_{i,j} \leq T^{\mathrm{w}}_i \text{ and } \tau_{i,j} \leq T_i, \\ 0 \quad \text{otherwise}, \end{cases} \tag{18}$$

is the true valuation. The T^{w}_i and T_i are the maximum tolerant walking time (maximum distance b_i would like to walk from the reserved parking place to the destination) and the maximum tolerant traveling time of b_i, respectively. The $v_{i,j}$ is regarded as the bidding of b_i to s_j. Besides, the constraint $\tau^{\mathrm{d}}_{i,j} \geq t^{\mathrm{r}}$ must be satisfied or else the true valuation $v_{i,j}$ will be zero. This comes from the fact that the b_i would expect to have its reserved parking space at s_j ready when it arrives. Otherwise, it will stuck at the gate or need to circle around for a while, which is not preferred by b_i. Therefore, the set of the candidate parking places of b_i is defined as

$$\mathcal{S}_i = \{s_j : v_{i,j} > 0, s_j \in \mathcal{S}\}. \tag{19}$$

Those vehicles in $\mathcal{B}$ with non-empty set of candidate parking places form the set of smart vehicles, denoted by $\mathcal{B}_{\mathrm{b}}$. Accordingly, we have the candidate vehicles of s_j as:

$$\mathcal{B}_j = \{b_i : v_{i,j} > 0, b_i \in \mathcal{B}_{\mathrm{b}}\}. \tag{20}$$

Besides, we denote $\mathcal{H}_j$ as the candidate hotspots served by the parked vehicles at s_j, where $h_{j,k} < D_k$ for $\forall h_k \in \mathcal{H}_j$. Accordingly, the candidate parking places of hotspot h_k is denoted by $\mathcal{S}_k$, where $h_k \in \mathcal{H}_j$ for $\forall s_j \in \mathcal{S}_k$.

The amount of CPU resources contributed by vehicle b_i to the FNC will depend on the benefit minus the cost. A hard constraint is that the service delay cannot surpass the maximum delay toleration D_k, that is,

$$\begin{aligned} d^k_{i,j} \leq D_k \Rightarrow \quad & \frac{\hat{\lambda}_k m_{i,j}}{\mu - \hat{\lambda}_k} + \xi \Phi^{\mathrm{l}}(\mathcal{X}^{\mathrm{s}}_j, \mathcal{X}^{\mathrm{h}}_k) \leq D_k \\ \Rightarrow \quad & m_{i,j} \leq \frac{(\mu - \hat{\lambda}_k)(D_k - \xi \Phi^{\mathrm{l}}(\mathcal{X}^{\mathrm{s}}_j, \mathcal{X}^{\mathrm{h}}_k))}{\hat{\lambda}_k} \\ \Rightarrow \quad & m_{i,j} \leq (\frac{\mu m_k}{\lambda_k} - 1)(D_k - \xi \Phi^{\mathrm{l}}(\mathcal{X}^{\mathrm{s}}_j, \mathcal{X}^{\mathrm{h}}_k)). \end{aligned} \tag{22}$$

That is to say, the FNC can use m_k, the total number of CPUs required at hotspot h_k, to control the above constraint. To integrate the parked vehicle assistance to conventional VFC system, a feasible m_k determined by the FNC becomes very important. A small m_k means heavy workload $\hat{\lambda}_k$ allocated to each CPU, which limits the number of CPUs contributed by a fog-capable vehicle subject to the constraint (22). In the proposed VFC system, we introduce a simple parameter M^{h} to indirectly determine m_k. That is, at most M^{h} CPUs per smart vehicle offered is allocated to support a hotspot h_k when parking at one of its candidate parking places $\mathcal{S}_k$. Substituting

$$\begin{aligned}\Delta_k^{\text{cost}} - \sum_{b_i\in\mathcal{B}}\sum_{s_j\in\mathcal{S}_i} w_{i,j}z_{i,k}m_{i,j}a_{j,k} =& \alpha\frac{\hat{\lambda}_k(m_k)^2}{\mu} - \alpha\frac{\hat{\lambda}_k}{\mu}(m_k - \sum_{b_i\in\mathcal{B}}\sum_{s_j\in\mathcal{S}} w_{i,j}z_{i,k}m_{i,j})^2\\ =& 2\alpha\frac{\hat{\lambda}_k m_k}{\mu}\sum\sum w_{i,j}z_{i,k}m_{i,j} - \alpha\frac{\hat{\lambda}_k}{\mu}(\sum\sum w_{i,j}z_{i,k}m_{i,j})^2 - \sum\sum w_{i,j}z_{i,k}m_{i,j}a_{j,k}\\ \geq& 2\alpha\frac{\hat{\lambda}_k m_k}{\mu}\sum\sum w_{i,j}z_{i,k}m_{i,j} - \alpha\frac{\hat{\lambda}_k m_k}{\mu}\sum\sum w_{i,j}z_{i,k}m_{i,j} - \sum\sum w_{i,j}z_{i,k}m_{i,j}a_{j,k}\\ =& \sum\sum w_{i,j}z_{i,k}m_{i,j}(\alpha\frac{\hat{\lambda}_k m_k}{\mu} - a_{j,k}) \geq 0. \end{aligned} \tag{21}$$

$m_{i,j}$ to (22) by M^{h}, we have

$$\begin{aligned} & m_k \geq \frac{\lambda_k}{\mu}[\frac{M^{\text{h}}}{(D_k - \xi\Phi^{\text{l}}(\mathcal{X}_j^{\text{s}}, \mathcal{X}_k^{\text{h}}))} + 1]\\ \Rightarrow\quad & m_k = \lceil \min_{s_j\in\mathcal{S}_k}\{\frac{\lambda_k}{\mu}[\frac{M^{\text{h}}}{(D_k - \xi\Phi^{\text{l}}(\mathcal{X}_j^{\text{s}}, \mathcal{X}_k^{\text{h}}))} + 1]\}\rceil. \end{aligned} \tag{23}$$

To achieve the maximum utility when parking at s_j, the b_i needs to select its serving hotspot and the corresponding optimal number of offered CPUs:

$$\begin{aligned} &\{h_{k^*}, m_{i,j}^*\} = \arg\max_{m_{i,j}}(a_{j,k}m_{i,j} - c_{i,j}^k), h_k \in \mathcal{H}_j\\ \text{s.t.}\quad & m_{i,j} \in \{1, \cdots, m_i\},\\ & m_{i,j} \leq \frac{(\mu - \hat{\lambda}_k)(D_k - \xi\Phi^{\text{l}}(\mathcal{X}_j^{\text{s}}, \mathcal{X}_k^{\text{h}}))}{\hat{\lambda}_k}, \forall h_k \in \mathcal{H}_j. \end{aligned} \tag{24}$$

Note that it is possible for b_i that any offer will give it negative utility due to insufficient compensation from the FNC. In such a case, the b_i chooses to park at s_j without providing offload service. Let $z_{i,k^*} = 1$ and $\sum_{h_k\neq h_{k^*}} z_{i,k} = 0$, the bidding valuation $v_{i,j}$ can be calculated by (18). Therefore, the bidding vector of b_i to s_j is represented as $\{v_{i,j}, h_{k^*}, m_{i,j}^*\}$.

2) FNC: With the service aid of parked vehicles, the cost saving at h_k will be

$$\Delta_k^{\text{cost}} = C(m_k) - C(m_k^f). \tag{25}$$

Therefore, the FNC's instantaneous profit is represented as

$$\pi = \sum_{h_k\in\mathcal{H}} \pi_k = \sum_{h_k\in\mathcal{H}}(\Delta_k^{\text{cost}} - \sum_{b_i\in\mathcal{B}}\sum_{s_j\in\mathcal{S}_i} w_{i,j}z_{i,k}m_{i,j}a_{j,k}), \tag{26}$$

where π_k is the profit of hotspot h_k.

We would like to guarantee the non-negative profit for each hotspot by (21).

Therefore, we have

$$a_{j,k} \leq \alpha\frac{\hat{\lambda}_k m_k}{\mu}, \forall h_k \in \mathcal{H}. \tag{27}$$

On the other hand, to attract those fog-capable vehicles that park at s_j and meanwhile provide computing services to hotspot h_k, the FNC needs to guarantee that the desired vehicles will have positive utilities here, that is,

$$a_{j,k}m_{i,j} - \alpha\frac{\hat{\lambda}_k m_{i,j}^2}{\mu} - \beta\Phi^{\text{l}}(\mathcal{X}_k^{\text{h}}, \mathcal{X}_j^{\text{s}}) > 0. \tag{28}$$

Note that at most M^{h} CPUs are allowed to support a hotspot per smart vehicle. Moreover, we would like to design the offload price so that the parked vehicle can gain more utility when it offers more CPUs to VFC. We first observe that the quadratic function in the above constraint is an upside-down parabola with respect to $m_{i,j}$. Let $m_{i,j} = 1$, we have

$$a_{j,k} > \alpha\frac{\hat{\lambda}_k}{\mu} + \beta\Phi^{\text{l}}(\mathcal{X}_k^{\text{h}}, \mathcal{X}_j^{\text{s}}). \tag{29}$$

We should guarantee its symmetry axis to be greater than or equal to M^{h}, that is,

$$-\frac{a_{j,k}}{2(-\alpha\frac{\hat{\lambda}_k}{\mu})} \geq M^{\text{h}} \Rightarrow a_{j,k} \geq \frac{2\alpha\hat{\lambda}_k M^{\text{h}}}{\mu}. \tag{30}$$

Therefore, the offload price $a_{j,k}$ is constrained by

$$a_{j,k} > \max\{\alpha\frac{\hat{\lambda}_k}{\mu} + \beta\Phi^{\text{l}}(\mathcal{X}_k^{\text{h}}, \mathcal{X}_j^{\text{s}}), \frac{2\alpha\hat{\lambda}_k M^{\text{h}}}{\mu}\}. \tag{31}$$

In the single-round auction, the FNC can announce fixed offload price $a_{j,k}$ subject to the constraints (27)(31).

C. Allocation Rule

The objective of the allocation rule is to maximize the aggregate utility of the smart vehicles in $\mathcal{B}_{\text{b}}$:

$$\begin{aligned} w_{i,j}^* = \arg\max_{w_{i,j}} & \sum_{b_i\in\mathcal{B}_{\text{b}}}\sum_{s_j\in\mathcal{S}} w_{i,j}(v_{i,j} - \tau_{i,j}^{\text{r}}p_j^s),\\ \text{s.t.}\quad & w_{i,j} \in \{0,1\}, \forall b_i \in \mathcal{B}_{\text{b}}, \forall s_j \in \mathcal{S}\\ & \sum_{s_j\in\mathcal{S}} w_{i,j} \leq 1, \forall b_i \in \mathcal{B}_{\text{b}}\\ & \sum_{b_i\in\mathcal{B}_{\text{b}}} w_{i,j} \leq C_j(t), \forall s_j \in \mathcal{S}\\ & w_{i,j}(v_{i,j} - \tau_{i,j}^{\text{r}}p_j^s) \geq 0. \end{aligned} \tag{32}$$

Lemma 1. *The allocation problem* (32) *can be modified as a maximum weight b-matching problem in a weighted bipartite graph (WBG).*

Proof. In a *weighted bipartite graph*, the vertices can be decomposed into two disjoint sets U and V such that every edge with an associated weight connects a vertex in U to the other in V. A maximum weighted b-matching problem in a WBG is defined as a matching where the sum of the weights of all edges in the matching has a maximal value and each vertex in U matches at least 1 and at most $b(v)$ vertices in V. In the allocation problem (32), we construct a WBG $G = (U, V, E)$ with two disjoint sets, the set of parking places $U = \mathcal{S}$ and the set of smart vehicles $V = \mathcal{B}_{\text{b}}$. The weight $A(b_i, s_j)$ of the edge connecting s_j and b_i represents the utility of b_i if parks at s_j. Parking place s_j matches at most $C_j(t)$ smart vehicles since its parking slot inventory at time t is $C_j(t)$. And a smart vehicle can be assigned to one parking slot. In this way, the problem (32) is modified as a maximum weight b-matching problem in WBG. □

Lemma 2. *The allocation problem* (32) *is a maximum weight perfect bipartite matching (MWPBM) problem.*

Proof. To fits classic 1-matching problem, we duplicate the original WBG $G = (U, V, E)$ to a new WBG $G' = (U', V, E')$, where $U' = \{U_1, \cdots, U_M\}$, $U_j = \{s_{j,1}, \cdots, s_{j,C_j(t)}\}$ and $s_{j,n}$ is the n-th parking slot of parking place s_j. An identical weight is assigned between the parking slots in the same place and a vertex in V, that is, $A(b_i, s_{j,n}) = A(b_i, s_j)$. Furthermore, by adding some virtual vertexes and virtual edges, we transform G' to a complete WBG $G'' = (U'', V', E'')$ to satisfy the conditions that $|U''| = |V'| = \max\{\sum_{s_j \in \mathcal{S}} C_j(t), |\mathcal{B}_{\mathrm{b}}|\}$ and every vertex in U'' is connected to every vertex in V'. For those virtual vertexes, the weighted of the link is changed to be zero. In this way, we aims to find a matching of G'' where every vertex in $(U'' \cup V')$ is incident to exactly one edge. Therefore, the allocation problem (32) become a MWPBM problem. □

Lemma 3. *The allocation problem* (32) *has a complexity of* $O(N^3)$.

Proof. We know that classic Kuhn-Munkres (KM) algorithm (also known as Hungarian algorithm) [29, 30] can be exploited to solve MWPBM problem, which has the complexity of $O(N^3)$. In addition, the transformation proposed above has a complexity of $O(N^2)$. Therefore, the allocation problem (32) can be solved with the complexity of $O(N^3)$. □

Specifically, we find out that the advance reservation period t^{r} can be used as a parameter to control the frequency of the reservation auction. A small period means high auction frequency, which indirectly restricts the number of participant smart vehicles in each auction and therefore the complexity can be reduced.

D. Payment Rule

The goal of the payment rule is to satisfy the desired economic properties in a socially optimal manner subject to the reserve price constraint. Vickrey Clarke Groves (VCG) mechanism is widely used in auction design that gives bidders an incentive to bid their true valuations. We modify the VCG mechanism with Clarke pivot payments [31]. Let $\{w_{i,j}\}$ and $\{\hat{w}_{i,j}\}$ be the allocation results of problem (32) with and without b_i's participation, respectively. Then, the payment for b_i to its parking place s_j can formally be written as

$$p_i^b = \begin{cases} \tau_{i,j}^{\mathrm{r}} p_j^s + \sum\limits_{b_l \neq b_i} \sum\limits_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s) \\ \qquad - \sum\limits_{b_l \neq b_i} \sum\limits_{s_o \in \mathcal{S}} w_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s) \\ \qquad \text{if } b_i \text{ wins a parking reservation at } s_j, \\ 0, \qquad \text{if } b_i \text{ loses the auction.} \end{cases} \tag{33}$$

Note that the marginal harm each vehicle cause to other bidders is non-negative according to the VCG mechanism, therefore, the reserve price required by the parking places can be guaranteed.

E. Economic Analysis

Theorem 1. *The proposed auction is incentive compatible.*

Proof. In a truthful auction, all bidders are incited to voluntarily reveal their true valuation for the items they are bidding. Let V_i be the true valuation vector of b_i and V_{-i} be the valuation vectors of other smart vehicles $\mathcal{B}_{\mathrm{b}} \backslash \{b_i\}$. When V_i and V_{-i} are submitted, the utility of b_i can be calculated using the payment rule (33):

$$\begin{aligned} u_i &= \sum_{s_j \in \mathcal{S}} w_{i,j} v_{i,j} - p_i^b \\ &= \sum_{s_j \in \mathcal{S}} w_{i,j}(v_{i,j} - \tau_{l,j}^{\mathrm{r}} p_j^s) + \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} w_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s) \\ &\qquad - \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s). \end{aligned} \tag{34}$$

When V_i' and V_{-i} are submitted, the utility of b_i is

$$\begin{aligned} u_i' &= \sum_{s_j \in \mathcal{S}} w_{i,j}' v_{i,j} - p_i^b \\ &= \sum_{s_j \in \mathcal{S}} w_{i,j}'(v_{i,j} - \tau_{l,j}^{\mathrm{r}} p_j^s) + \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} w_{l,o}'(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s) \\ &\qquad - \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s). \end{aligned} \tag{35}$$

Since $\{w_{i,j}\}$ maximizes the total profit defined by (32), we have

$$\begin{aligned} &\sum_{s_j \in \mathcal{S}} w_{i,j}(v_{i,j} - \tau_{l,j}^{\mathrm{r}} p_j^s) + \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} w_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s) \\ \geq &\sum_{s_j \in \mathcal{S}} w_{i,j}'(v_{i,j} - \tau_{l,j}^{\mathrm{r}} p_j^s) + \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} w_{l,o}'(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s). \end{aligned} \tag{36}$$

By subtracting the term $\sum\limits_{b_l \neq b_i} \sum\limits_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau_{l,o}^{\mathrm{r}} p_o^s)$ from both sides of the inequality, we get $u_i \geq u_i'$, which means that the incentive compatible property is held. □

Theorem 2. *The proposed auction is individually rational.*

Proof. The utility of the sellers and buyers should be no less than zero. Each agent participating in the auction can expect a non-negative utility. According to the payment rule (33), we observe that the per unit payment from each parked vehicle is greater than the reserved price announced by sellers since $p_i^b / \tau_{i,j}^{\mathrm{r}} \geq p_j^s$ if b_i wins a parking reservation at s_j. That is, the sellers can achieve non-zero utility. Besides, we consider the utility of b_i in (34) and have

$$\begin{aligned} u_i &= \sum_{s_j \in \mathcal{S}} w_{i,j}(v_{i,j} - \tau^{\mathrm{r}}_{l,j} p^s_j) + \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} w_{l,o}(v_{l,o} - \tau^{\mathrm{r}}_{l,o} p^s_o) \\ &\quad - \sum_{b_l \neq b_i} \sum_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau^{\mathrm{r}}_{l,o} p^s_o) \\ &\geq \sum_{b_l \in \mathcal{B}_{\mathrm{b}}} \sum_{s_o \in \mathcal{S}} w_{l,o}(v_{l,o} - \tau^{\mathrm{r}}_{l,o} p^s_o) \\ &\quad - \sum_{b_l \in \mathcal{B}_{\mathrm{b}}} \sum_{s_o \in \mathcal{S}} \hat{w}_{l,o}(v_{l,o} - \tau^{\mathrm{r}}_{l,o} p^s_o) \geq 0, \end{aligned} \tag{37}$$

which shows individual rationality of buyers. □

Theorem 3. *The proposed auction has budget balance.*

Proof. We know that the FNC can achieve a non-negative profit of each hotspot when announces the offload price subject to the constraint (27). Besides, the parking places can charge at least reserve price from the parked vehicles when the proposed payment rule (33) is employed. Therefore, *budget balance* is held in the proposed auction. □

IV. Multi-round Auction with Dynamic Offload Pricing

We have proposed a single-round parking reservation auction, where fixed offload price is announced subject to the constraints (27)(31) by the FNC. Although we have derived the feasible region of the offload price, the optimal choice of the offload price is still unknown. In general, it is challenging to get a closed form of the optimal offload price given the proposed auction structure. Nevertheless, the offload price can be improved through iterative update process in a multi-round setting. Apparently, some hotspots can transfer their CPU resources provided by parked vehicles to other hotspots with a more appropriate offload price so that the total profit of the FNC is increased. In this section, we provide a multi-round multi-item parking reservation auction with offload pricing update to increase the profit of the FNC. The overall description of the proposed multi-round auction is shown in Fig. 3. An observation stage is employed at the end of each round of the reservation allocation. Besides, we propose intra-parking place pricing and inter-parking place pricing for the profit improvement of the FNC. The multi-round auction is considered as a replacement of the single-round auction. That is to say, the whole auction procedure in Fig. 3 will be completed at a single decision point, where the final parking allocation and the corresponding parking payments are determined. The winners have their reserved parking slots by playing this one-shot multi-round auction.

A. Observation Stage

To address the offload pricing to regulate both the biddings of the smart vehicles and the allocation results, the FNC needs to know the private information of those smart vehicles, such as the value of successful parking v_i, the actual parking duration Δ_i, total cost of both driving and walking $c_{i,j}$. According to (17)(18), we have

$$v_{i,j} = v_i - c_{i,j} + \Delta_i z_{i,k}(a_{j,k} m_{i,j} - c^k_{i,j}). \tag{38}$$

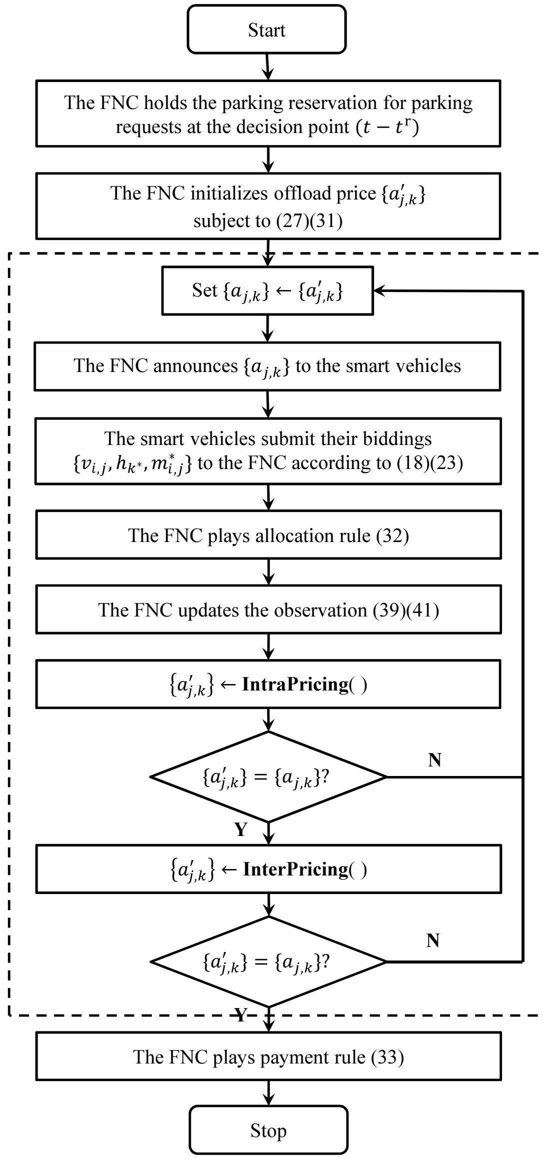


Fig. 3. Flow chart of the proposed multi-round auction with offload pricing

In each round of the reservation auction, the values of $v_{i,j}$ and $(a_{j,k} m_{i,j} - c^k_{i,j})$ are known to the FNC from their bidding vectors. We know that a solution to a system of two-variable linear equations can be derived from a two equation set. Therefore, the FNC can calculate the values of $(v_i - c_{i,j})$ and Δ_i with two different $a_{j,k}$:

$$\begin{cases} v_i - c_{i,j} = \frac{v'_{i,j} z_{i,k}(a_{j,k} m_{i,j} - c^k_{i,j}) - v_{i,j} v_{i,j}}{z_{i,k}(a_{j,k} m_{i,j} - c^k_{i,j}) - z'_{i,k'}(a'_{j,k'} m'_{i,j} - c^{k'}_{i,j})}, \\ \Delta_i = \frac{v_{i,j} - v'_{i,j}}{z_{i,k}(a_{j,k} m_{i,j} - c^k_{i,j}) - z'_{i,k'}(a'_{j,k'} m'_{i,j} - c^{k'}_{i,j})}. \end{cases} \tag{39}$$

That is to say, the private information of vehicles can be observed by the FNC by applying offload pricing update after two rounds of the auction.

However, $(v_i - c_{i,j})$ can only be observed when $a_{j,k}$ is updated and h_k is selected by b_i at s_j. To further increase the observation efficiency, we apply an indirect observation. Let $A_{i,j} = z_{i,k}(a_{j,k} m_{i,j} - c^k_{i,j})$ and $A_{i,j'} = z_{i,k'}(a_{j',k'} m_{i,j'} -$

Algorithm 1 Intra-parking Place Pricing (**IntraPricing**)

Require: $\{a_{j,k}\}$, $\{\pi_k\}$.
Initialization: Set $\Delta\pi \leftarrow 0$.
Sort $h_k \in \mathcal{H}$ by π_k in ascending order.
for each hotspot h_k **do**
  for each candidate parking place $s_j \in \mathcal{S}_k$ **do**
    for each candidate hotspot $h_{k'} \in \mathcal{H}_j \backslash \{h_k\}$ **do**
      Set $\mathcal{M}$ to be the unique set of $\{m_{i,j}\}$, $\forall w_{i,j} z_{i,k'} = 1$.
      Set $m \leftarrow \min(\mathcal{M})$.
      Calculate new offload price $a'_{j,k}$ according to (44).
      Calculate new profits π'_k and $\pi'_{k'}$ according to (45)(46).
      Set $\Delta\pi' \leftarrow [(\pi'_k + \pi'_{k'}) - (\pi_k + \pi_{k'})]$.
      if $\Delta\pi < \Delta\pi'$ **then**
        Set $\Delta\pi \leftarrow \Delta\pi'$, $s_{j^*} \leftarrow s_j$, $a^* \leftarrow a'_{j,k}$.
      end if
    end for
  end for
  if $\Delta\pi \neq 0$ **then**
    Set $\{a'_{j,k}\} \leftarrow \{a_{j,k}\}$.
    Set $a'_{j^*,k} \leftarrow a^*$.
    exit and **output** $\{a'_{j,k}\}$
  end if
end for
output $\{a'_{j,k}\}$

$c^{k'}_{i,j'}$). We have

$$\begin{aligned} & v_{i,j} - v_{i,j'} \\ =& (v_i - c_{i,j} + \Delta_i A_{i,j}) - (v_i - c_{i,j'} + \Delta_i A_{i,j'}) \\ =& \Delta_i (A_{i,j} - A_{i,j'}) + c_{i,j'} - c_{i,j}. \end{aligned} \tag{40}$$

Similarly, $(c_{i,j'} - c_{i,j})$ and Δ_i can be observed when either $a_{j,k}$ or $a_{j',k'}$ is updated and either h_k is selected by b_i at s_j or $h_{k'}$ is selected by b_i at $s_{j'}$:

$$\begin{cases} c_{i,j'} - c_{i,j} = \frac{(v'_{i,j} - v'_{i,j'})(A_{i,j} - A_{i,j'}) - (v_{i,j} - v_{i,j'})(A'_{i,j} - A'_{i,j'})}{(A_{i,j} - A_{i,j'}) - (A'_{i,j} - A'_{i,j'})}, \\ \Delta_i = \frac{(v_{i,j} - v_{i,j'}) - (v'_{i,j} - v'_{i,j'})}{(A_{i,j} - A_{i,j'}) - (A'_{i,j} - A'_{i,j'})}. \end{cases} \tag{41}$$

In addition, we know that the number of CPUs equipped in the smart vehicles can be measured by the offered CPUs in the bidding vectors iteratively. The FNC records the maximum number of CPUs provided by the smart vehicle b_i by:

$$\widetilde{m}_i = \max\{\widetilde{m}_i, \max_{s_j \in \mathcal{S}_i} m_{i,j}\}, \tag{42}$$

where $\widetilde{m}_i$ is initialized by 0.

B. Intra-parking Place Pricing

Consider the allocation results of each single-round reservation auction, some CPUs of the smart vehicles parking at s_j have been offered to hotspot $h_{k'}$. The FNC will expect to attract those offered CPUs from $h_{k'}$ to h_k at the same parking place s_j by increasing the offload price $a_{j,k}$ if the total profit is thereby increased. In the same parking place s_j, b_i will change its choice by selecting h_k instead of h_k if

$$\begin{aligned} & a_{j,k} m_{i,j} - c^k_{i,j} > a_{j,k'} m_{i,j} - c^{k'}_{i,j} \\ \Rightarrow \quad & a_{j,k} > \frac{c^k_{i,j} - c^{k'}_{i,j}}{m_{i,j}} + a_{j,k'}. \end{aligned} \tag{43}$$

Therefore, we update the offload price by:

$$a'_{j,k} = \min_{b_i \in \mathcal{B}_\mathrm{b}} \{ \frac{c^k_{i,j} - c^{k'}_{i,j}}{m_{i,j}} \} + a_{j,k'}. \tag{44}$$

Algorithm 2 Inter-parking Place Pricing (**InterPricing**)

Require: $\{C_j(t)\}$, $\{\pi_k\}$, $\{w_{i,j}\}$, $\{z_{i,k}\}$.
Initialization: Set $\pi \leftarrow \sum \pi_k$, $\widetilde{\pi} \leftarrow \pi$.
Sort $h_k \in \mathcal{H}$ by π_k in ascending order.
for each hotspot h_k **do**
  Update $C_j(t)$ according to current allocation result.
  for each candidate parking place $s_j \in \mathcal{S}_k$ **do**
    Set $\mathcal{B}'_j \leftarrow \mathcal{B}_j \backslash \{b_i : w_{i,j} = 1 \vee \widetilde{m}_i = 0, \forall b_i \in \mathcal{B}_j\}$.
    if $C_j(t) > 0$ and all Δ_i and $(c_{i,j'} - c_{i,j})$ have been observed for $\forall b_i \in \mathcal{B}'_j$, $w_{i,j'} = 1$ **then**
      Set $\{a(i)\} \leftarrow Inf$.
      for each vehicle $b_i \in \mathcal{B}'_j$ **do**
        Calculate new offload price $a'_{j,k}$ according to (49)(50).
        Set $a(i) \leftarrow a'_{j,k}$.
      end for
      Sort $\mathcal{B}'_j$ by $a(i)$ in ascending order.
      Set $\{w'_{i,j}\} \leftarrow \{w_{i,j}\}$, $\{z'_{i,k}\} \leftarrow \{z_{i,k}\}$
      for each vehicle $b_i \in \mathcal{B}'_j$ **do**
        if $C_j(t) > 0$ and $a(i) \neq Inf$ **then**
          Set $a'_{j,k} \leftarrow a(i)$.
          Let $s_{j'}$ for $w'_{i,j'} = 1$, $h_{k'}$ for $z_{i,k'} = 1$.
          Set $w'_{i,j'} \leftarrow 0$, $w'_{i,j} \leftarrow 1$, $z'_{i,k'} \leftarrow 0$, $z'_{i,k} \leftarrow 1$.
          Set $\{C_j(t)\} \leftarrow \{C_j(t)\} - 1$.
          Set $\mathcal{B}''_j \leftarrow \{b_i : w'_{i,j} = 1 \wedge z'_{i,k} = 0 \wedge \widetilde{m}_i \neq 0, \forall b_i \in \mathcal{B}_j\}$.
          for each vehicle $b_{i''} \in \mathcal{B}''_j$ **do**
            Let $h_{k''}$ for $z_{i'',k''} = 1$.
            if $a'_{j,k} m_{i'',j} - c^k_{i'',j} > a'_{j,k''} m_{i'',j} - c^{k''}_{i'',j}$ **then**
              Set $z'_{i'',k''} \leftarrow 0$ and $z'_{i'',k} \leftarrow 1$.
            end if
          end for
          Calculate new profits π' according to (26) that subject to $\{w'_{i,j}\}$ and $\{z'_{i,k}\}$.
          if $\widetilde{\pi} < \pi'$ **then**
            Set $\widetilde{\pi} \leftarrow \pi'$, $s_{j^*} \leftarrow s_j$, $a^* \leftarrow a'_{j,k}$.
          end if
        end if
      end for
    end if
  end for
  if $\widetilde{\pi} \neq \pi$ **then**
    Set $\{a'_{j,k}\} \leftarrow \{a_{j,k}\}$, $a'_{j^*,k} \leftarrow a^*$.
    exit and **output** $\{a'_{j,k}\}$
  end if
end for
output

In this way, the profits of h_k and $h_{k'}$ become

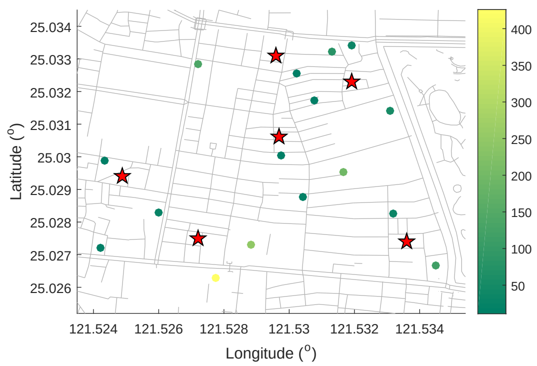
$$\begin{aligned} \pi'_k =& C(m_k) - C(m^f_k - \sum_{b_i \in \mathcal{B}_\mathrm{b}} w_{i,j} z_{i,k'} m_{i,j}) \\ & - \sum_{b_i \in \mathcal{B}_\mathrm{b}} \sum_{s_{j'} \in \mathcal{S}_i \backslash \{s_j\}} w_{i,j'} z_{i,k} m_{i,j'} a_{j',k} \\ & - \sum_{b_i \in \mathcal{B}_\mathrm{b}} w_{i,j} (z_{i,k} + z_{i,k'}) m_{i,j} a'_{j,k}, \end{aligned} \tag{45}$$

$$\begin{aligned} \pi'_{k'} =& C(m_{k'}) - C(m^f_{k'} + \sum_{b_i \in \mathcal{B}_\mathrm{b}} w_{i,j} z_{i,k'} m_{i,j}) \\ & - \sum_{b_i \in \mathcal{B}_\mathrm{b}} \sum_{s_{j'} \in \mathcal{S}_i \backslash \{s_j\}} w_{i,j'} z_{i,k'} m_{i,j'} a_{j',k'}, \end{aligned} \tag{46}$$

respectively.

We try to find a parking place s_{j^*} and a hotspot h_{k^*} so that the FNC can achieve maximum profit by applying new

(a) Street layout in OpenStreetMap



(b) Parking places and hotspots

Fig. 4. Selected region of Da'an district, Taipei city

offload price a_{j^*,k^*} according to (44), that is,

$$\{s_{j^*}h_{k^*}\} = \max_{s_j,h_k}[(\pi'_k + \pi'_{k'}) - (\pi_k + \pi_{k'})],$$
$$\text{s.t.} \quad (\pi'_k + \pi'_{k'}) - (\pi_k + \pi_{k'}) > 0. \tag{47}$$

The overall description of the intra-parking place pricing is shown in Algorithm 1. Note that the hotspot with less profit has higher priority to update its offload price to its candidate parking places.

C. Inter-parking Place Pricing

Moreover, the offered CPUs can also be transferred between different parking places if the offload price is further increased. We propose an inter-parking place pricing when the intra-parking place pricing could not reach any profit improvement.

For parking place s_j, we exclude those smart vehicles from $\mathcal{B}_j$, which have been allocated to s_j or have zero number of CPUs observed by the FNC, that is,

$$\mathcal{B}'_j \leftarrow \mathcal{B}_j \backslash \{b_i : w_{i,j} = 1 \vee \widetilde{m}_i = 0, \forall b_i \in \mathcal{B}_j\}. \tag{48}$$

We consider those candidate parking places of h_k, $s_j \in \mathcal{H}_j$, which have non-empty parking slot inventory $C_j(t)$ updated by the current allocation result, and have full observation of Δ_i and $(c_{i,j'} - c_{i,j})$ for $\forall b_i \in \mathcal{B}'_j, w_{i,j'} = 1$.

To attract the fog-capable vehicle b_i from $s_{j'}$ to s_j and meanwhile transfer its serving hotspot from $h_{k'}$ to h_k when s_j still has parking slot inventory, we need to guarantee that $u_{i,j} \geq u_{i,j'}$. Derived from (17)(18), we have

$$a_{j,k} \geq \frac{\tau^{\mathrm{r}}_{i,j}p^s_j - \tau^{\mathrm{r}}_{i,j'}p^s_{j'} + c_{i,j} - c_{i,j'}}{\Delta_i m_{i,j}} + \frac{c^k_{i,j} - c^{k'}_{i,j'}}{m_{i,j}} + a_{j',k'}. \tag{49}$$

If $h_{k'}$ doesn't exist, then it reduces to

$$a_{j,k} \geq \frac{\tau^{\mathrm{r}}_{i,j}p^s_j - \tau^{\mathrm{r}}_{i,j'}p^s_{j'} + c_{i,j} - c_{i,j'}}{\Delta_i m_{i,j}} + \frac{c^k_{i,j}}{m_{i,j}}. \tag{50}$$

Moreover, we find that those smart vehicles, which have been allocated to s_j and have none-zero number of CPUs observed by the FNC, may change their serving hotspots to h_k due to the update of $a_{j,k}$. Therefore, we need to consider the new choices of those smart vehicles, denoted by

$$\mathcal{B}''_j \leftarrow \{b_i : w_{i,j} = 1 \wedge z_{i,k} = 0 \wedge \widetilde{m}_i \neq 0, \forall b_i \in \mathcal{B}_j\}, \tag{51}$$

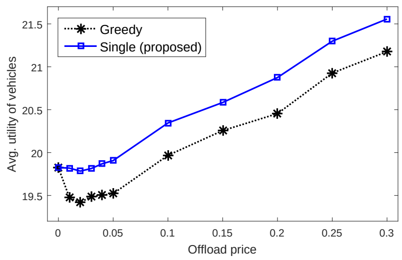
according to (24). The overall description of the inter-parking place pricing is shown in Algorithm 2.

So far, we have fully introduced the proposed multi-round auction with offload pricing as shown in Fig. 3. Note that non-negative profit of each hotspot can be achieved in the single-round auction by applying the offload price according to the constraints (27) (31), as discussed in Section III-E. In the multi-round auction, the FNC announces new offload price each time, which can improve its total profit. Therefore, budget balance is also held in the proposed dynamic auction.

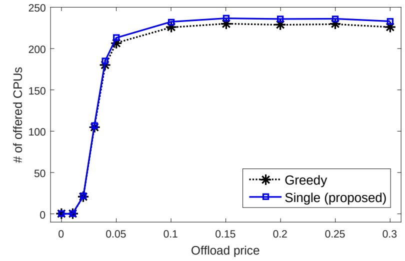
V. Simulation Results

In this section, simulation results are provided to verify the performance of the proposed VFC. As shown in Fig. 4(a), we select a partial region of Da'an district, Taipei city, as the map for simulations. The street layout of the selected region is obtained from the OpenStreetMap (OSM) database. The parking census in the selected region is available from "Data. Taipei" platform [32]. Fig. 4(b) shows the locations of parking places and hotspots. In the selected region, each dot scattered on the street layout represents the location of a parking place and the color bar on the right displays the capacity of those parking places. Specifically, we select 6 hotspots according to the crowd density of the selected region, as marked by red pentastars in Fig.4(b). The ratio of parking slot inventory available and reserved for smart vehicles in each parking place follows the standard uniform distribution. Unconnected vehicles are not allowed to use these reserved spaces and therefore will not impact the auctions. The current car position and the traveling destination are also initialized by following the 2D uniform distribution in the whole map. The key simulation parameters are listed in Table II. Specifically, we assume that the parking valuation v_i is proportional to the parking duration Δ_i, namely $v_i = 10\Delta_i$ in our simulations. We compare four approaches: 1) *Conventional*, without the aid of parked vehicles; 2) *Greedy*, in which the vehicles are allocated according to greedy allocation instead of the proposed allocation rule; 3) *Single*, the proposed single-round auction; 4) and *Multiple*, the proposed multi-round auction. The greedy allocation rule is defined that the available parking slots are allocated to the smart vehicles with larger bidding value $v_{i,j}$, and the allocation order following the parking value. The offload price of both *Single* and *Multiple* is initialized to be the minimum of the constraints (27)(31).

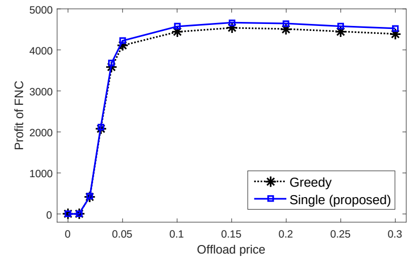
We first present the performance versus the offload price in Fig. 5, where the FNC announces the same and fixed offload price between parking places and hotspots. In Fig. 5(a), we



(a) Avg. utility of vehicles

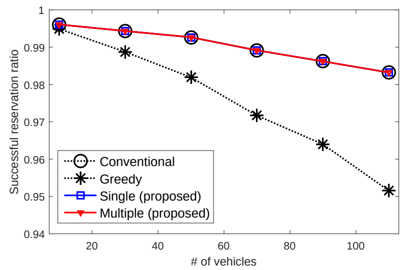


(b) # of offered CPUs

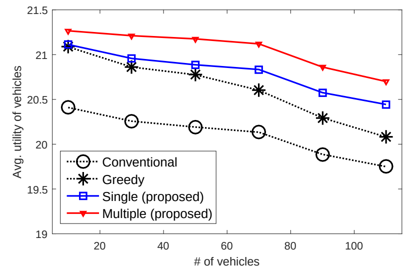


(c) Profit of FNC

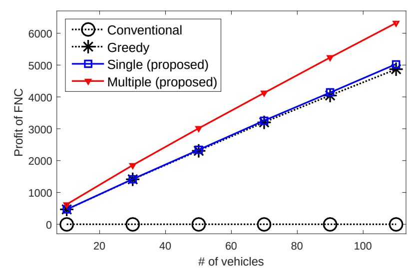
Fig. 5. Performance versus the offload price: $N = 100$.



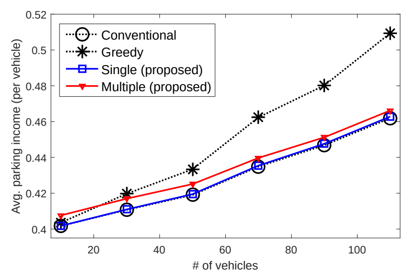
(a) Successful reservation ratio



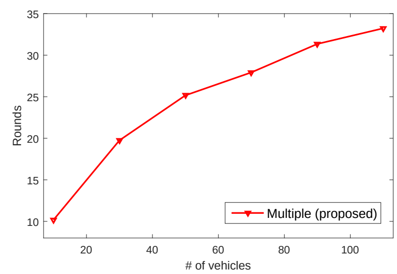
(b) Avg. utility of vehicles



(c) Profit of FNC



(d) Avg. parking income (per vehicle)



(e) # of rounds

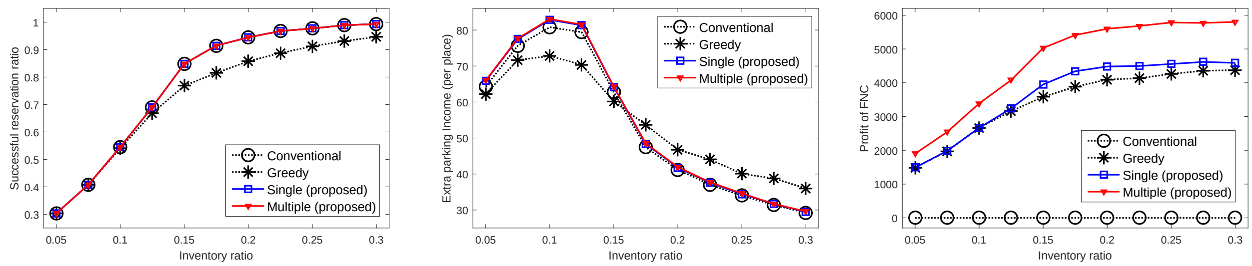
Fig. 6. Performance versus the number of smart vehicles.

TABLE II
LIST OF KEY SIMULATION PARAMETERS

α^f, α, β, ξ	0.8, 0.6, 0.4, 0.001
δ, θ	10, \$0.5/km
p_j^s	unif(\$2, \$3)
μ, λ_k	1MB/s, unif(5MB/s, 20MB/s)
m_i, M^{h}	unif(0, 5), 5
D_k	unif(10ms, 50ms)
r^{w}, r_i^{d}	3.5km/h, unif(10km/h, 30km/h)
t^{r}, Δ_i	0.01h, unif(0.5h, 5h)
T_i^{w}, T_i	0.2h = 12min, 0.15h = 9min

observe that the average utility of vehicles increases against the offload price because the compensation from the FNC becomes larger. Specifically, the fluctuation at lower offload price is because the maximum offered CPUs allowed to support a hotspot per smart vehicle increase accordingly as the offload price grows and therefore the smart vehicles reselect their serving hotspots and the number of offered CPUs. Nevertheless, their average utility increased steadily at higher offload price because of limit number of equipped CPUs. We also find out that higher offload price can attract more parked vehicles to provide their CPUs in Fig. 5(b). *Single* outperforms *Greedy* by attracting more CPUs for service offloading and cost saving. Nevertheless, the profit of the FNC is not always increasing due to the unnecessary offload payments, as shown in Fig. 5(c). The overpriced offload payment makes no increment to the number of offered CPUs and decreases the profit of the FNC. This suggests an optimal choice of offload price exists and therefore we propose *Mulitiple* to improve the profit of the FNC with offload price update. In general, the benefit of *Single* is relatively insignificant due to the same and fixed offload price, which is used to compensate for the fog service cost of parked vehicles. Therefore, different offload price should be announced to attract those smart vehicles to park at proper parking spaces. Nevertheless, the analysis on single-round mechanism serves as the foundation for us to understand the effect of offload price on the allocation in the proposed auction.

In Fig. 6, we show the performance versus the number of smart vehicles. The successful reservation ratio of vehicles in Fig. 6(a) is calculated by the number of those vehicles, which have been successfully allocated to the unoccupied parking slots, over the number of smart vehicles. We observe that the allocation ratio decreases against the number of vehicles due



(a) Successful reservation ratio (b) Extra parking income per parking place (c) Profit of FNC

Fig. 7. Performance versus the inventory ratio of parking places: $N = 100$.

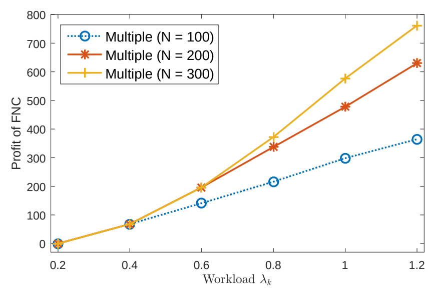


Fig. 8. Profit of the FNC versus workload arrival rate.

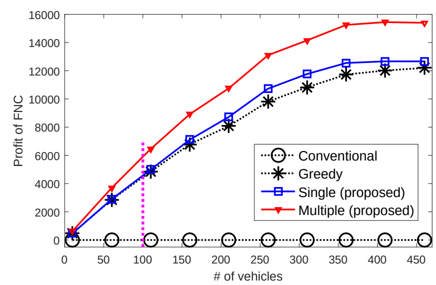


Fig. 9. Profit of the FNC versus the number of smart vehicles.

to the limited parking slots. *Greedy* causes a great loss of successful parking reservation when the number of vehicles is more than 100. However, both *Single* and *Multiple* can satisfy almost all of the smart vehicles. The decline in Fig. 6(b) indicates the intensified competition of the smart vehicles for preferred parking slots. Nevertheless, *Single* achieves better average utility of vehicles comparing with *Conventional* and *Greedy*. *Multiple* further improves the average utility of vehicles from *Single* due to the increase of the offload price in the proposed multi-round setting. In Fig. 6(c), we observe that the proposed smart VFC framework outperforms *Conventional* in terms of FNC's profit since *Conventional* doesn't deliver any cost saving for the FNC. The multi-round auction achieves significant profit improvement of the FNC from *Single* by applying the proposed intra-parking place pricing and the inter-parking place pricing. Comparing with *Conventional* as shown in Fig. 6(b) and Fig. 6(d), we observe that the proposed smart VFC framework guarantees the benefits of vehicles subject to the reserve price constraint and meanwhile provide additional income to the parking places. In Fig. 6(d), the maximum average parking income per vehicle is achieved by *Greedy*, which means that the utility of the parked vehicles will be degraded accordingly as we observed in Fig. 6(b). Besides, we find out that the average utility of vehicles, the profit of the FNC and the average parking income per vehicle in *Multiple* is better than both *Conventional* and *Single*. That is to say, the proposed system with multi-round auction provides a win-win solution to all auction players. Fig. 6(e) shows the number of round of *Multiple*. We further increase the number of smart vehicles from 110 to 230 and observe that the complexity is bounded in 40. That is to say, the complexity of *Multiple* will not always increase with the number of smart vehicles due to the limited parking slots in the real world.

The shortage of available parking spaces will intensify the competition among the smart vehicles bidding for preferred parking slots. To illustrate this phenomenon, the performance versus the inventory ratio of parking places is shown in Fig. 7. In Fig. 7(a), the successful reservation ratio of the smart vehicles generally increases with more available parking spaces as we expect. Due to the heuristic of myopic choice at each stage, *Greedy* could not make full use of limited parking resources comparing with the proposed allocation rule. We define the extra parking income of a parking place as the sum of the parking payment minus the reserve price of each smart vehicle parking there. In Fig. 7(b), the extra parking income per place firstly increases and then decreases versus the inventory ratio. Under the shortage of available parking spaces, higher inventory ratio allows more successful reservations of the smart vehicles and therefore the parking places will get more extra parking income. However, the extra parking income decreases when parking places are sufficient. We know that the proposed payment rule charges each parked vehicle the marginal harm they cause to other bidders so that the incentive compatibility can be guaranteed. Therefore, less competition under sufficient parking places also leads to less extra parking income. We observe that both *Single* and *Multiple* outperforms *Greedy* in terms of extra parking income under the shortage of parking spaces. In Fig. 7(c), the profit of the FNC increases due to more assisted CPUs from more successful parked vehicles. That is to say, the profit of the FNC is constrained by the limited parking spaces.

To further evaluate the upper bound of the profit of the FNC, we illustrate the profit of the FNC versus the same and fixed workload arrival rate of the hotspots in Fig. 8, where N is the number of smart vehicles. We observe that increasing number of smart vehicles could not increase the profit of the FNC when the workload arrival rate is small. That is because the profit of the FNC, which is represented by its cost saving from offloading workloads to parked vehicles minus the total offload payments, is bounded due to the finite CPU demands of hotspots. Moreover, by adopting the dynamic offload pricing in the proposed multi-round auction, the FNC could not increase its profit any more when the increased offload payment could not be covered by the improved cost saving. We also show that the profit of the FNC is bounded versus the number of smart vehicles in Fig. 9.

VI. Conclusion

In this paper, a smart VFC system combining both PVA and smart parking is proposed to guide the on-the-move vehicles to the available parking places to provide PVA service while satisfying their parking demands. We formulate the fog-aware smart parking problem as a maximum weight b-matching problem and the optimal allocation can be derived in polynomial time. Given this result, we theoretically prove that the proposed auction design guarantees incentive compatibility, individual rationality, and budget balance. The simulation results confirm the performance improvement from the proposed design comparing with conventional and greedy approaches, especially when the parking demand is huge. We also find out that the proposed system with multi-round auction provides a win-win solution to the FNC, the smart vehicles, and the parking places.

Acknowledgment

This work was supported by the Ministry of Science and Technology under Grant MOST 105-2221-E-002-014-MY3, 105-2221-E-001-003-MY3 and the Academia Sinica under Thematic Research Grant.

References

[1] H. Shah-Mansouri and V. W. Wong, "Hierarchical fog-cloud computing for iot systems: A computation offloading game," *IEEE Internet of Things Journal*, 2018.

[2] Y.-H. Hung and C.-Y. Wang, "Fog micro service market: Promoting fog computing using free market mechanism," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2018, pp. 1–6.

[3] Y.-J. Ku, D.-Y. Lin, C.-F. Lee, P.-J. Hsieh, H.-Y. Wei, C.-T. Chou, and A.-C. Pang, "5g radio access network design with the fog paradigm: Confluence of communications and computing," *IEEE Communications Magazine*, vol. 55, no. 4, pp. 46–52, 2017.

[4] Y.-Y. Shih, W.-H. Chung, A.-C. Pang, T.-C. Chiu, and H.-Y. Wei, "Enabling low-latency applications in fog-radio access networks," *IEEE network*, vol. 31, no. 1, pp. 52–58, 2017.

[5] C. Huang, R. Lu, and K.-K. R. Choo, "Vehicular fog computing: architecture, use case, and security and forensic challenges," *IEEE Communications Magazine*, vol. 55, no. 11, pp. 105–111, 2017.

[6] N. Liu, M. Liu, W. Lou, G. Chen, and J. Cao, "Pva in vanets: Stopped cars are not silent," in *INFOCOM, 2011 Proceedings IEEE*. IEEE, 2011, pp. 431–435.

[7] N. Liu, M. Liu, G. Chen, and J. Cao, "The sharing at roadside: Vehicular content distribution using parked vehicles," in *INFOCOM, 2012 Proceedings IEEE*. IEEE, 2012, pp. 2641–2645.

[8] F. Malandrino, C. Casetti, C.-F. Chiasserini, C. Sommer, and F. Dressler, "The role of parked cars in content downloading for vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 9, pp. 4606–4617, 2014.

[9] Z. Su, Y. Hui, and S. Guo, "D2d-based content delivery with parked vehicles in vehicular social networks," *IEEE Wireless Communications*, vol. 23, no. 4, pp. 90–95, 2016.

[10] Z. Su, Q. Xu, Y. Hui, M. Wen, and S. Guo, "A game theoretic approach to parked vehicle assisted content delivery in vehicular ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 7, pp. 6461–6474, 2017.

[11] D. C. Shoup, "Cruising for parking," *Transport Policy*, vol. 13, no. 6, pp. 479–486, 2006.

[12] Y. Geng and C. G. Cassandras, "New "smart parking" system based on resource allocation and reservations," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1129–1139, 2013.

[13] B. Zou, N. Kafle, O. Wolfson, and J. J. Lin, "A mechanism design based approach to solving parking slot assignment in the information era," *Transportation Research Part B: Methodological*, vol. 81, pp. 631–653, 2015.

[14] T. N. Pham, M.-F. Tsai, D. B. Nguyen, C.-R. Dow, and D.-J. Deng, "A cloud-based smart-parking system based on internet-of-things technologies," *IEEE Access*, vol. 3, pp. 1581–1591, 2015.

[15] T. Lin, H. Rivano, and F. Le Mouël, "A survey of smart parking solutions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 12, pp. 3229–3253, 2017.

[16] J. Liu, J. Wan, B. Zeng, Q. Wang, H. Song, and M. Qiu, "A scalable and quick-response software defined vehicular network assisted by mobile edge computing," *IEEE Communications Magazine*, vol. 55, no. 7, pp. 94–100, 2017.

[17] K. Zhang, Y. Mao, S. Leng, Y. He, and Y. ZHANG, "Mobile-edge computing for vehicular networks: A promising network paradigm with predictive off-loading," *IEEE Vehicular Technology Magazine*, vol. 12, no. 2, pp. 36–44, June 2017.

[18] Z. Zhou, P. Liu, Z. Chang, C. Xu, and Y. Zhang, "Energy-efficient workload offloading and power control in vehicular edge computing," in *Wireless Communications and Networking Conference Workshops (WCNCW), 2018 IEEE*. IEEE, 2018, pp. 191–196.

[19] A. O. Kotb, Y.-C. Shen, X. Zhu, and Y. Huang, "iparker - a new smart car-parking system based on dynamic resource allocation and pricing," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 9, pp. 2637–2647, 2016.

[20] E. Simhon, C. Liao, and D. Starobinski, "Smart parking pricing: A machine learning approach," in *Computer Communications Workshops (INFOCOM WKSHPS), 2017 IEEE Conference on*. IEEE, 2017, pp. 641–646.

[21] L. Zhang and Y. Li, "A game-theoretic approach to optimal scheduling of parking-lot electric vehicle charging," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4068–4078, 2016.

[22] "SFpark." [Online]. Available: http://sfpark.org/

[23] "LA ExpressPark." [Online]. Available: http://www.laexpresspark.org/

[24] H. Zhang, Y. Xiao, S. Bu, D. Niyato, F. R. Yu, and Z. Han, "Computing resource allocation in three-tier iot fog networks: A joint optimization approach combining stackelberg game and matching," *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1204–1215, 2017.

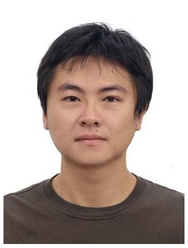
[25] A. Gandhi, M. Harchol-Balter, R. Das, and C. Lefurgy, "Optimal power allocation in server farms," in *ACM SIGMETRICS Performance Evaluation Review*, vol. 37, no. 1. ACM, 2009, pp. 157–168.

[26] Z. Liu, M. Lin, A. Wierman, S. H. Low, and L. L. Andrew, "Geographical load balancing with renewables," *ACM SIGMETRICS Performance Evaluation Review*, vol. 39, no. 3, pp. 62–66, 2011.

[27] S. W. Ko, K. Han, and K. Huang, "Wireless networks for mobile edge computing: Spatial modeling and latency analysis," *IEEE*

Transactions on Wireless Communications, pp. 1–1, 2018.
[28] H. Zhang, Y. Xiao, S. Bu, D. Niyato, R. Yu, and Z. Han, "Fog computing in multi-tier data center networks: A hierarchical game approach," in *Communications (ICC), 2016 IEEE International Conference on*. IEEE, 2016, pp. 1–6.
[29] H. W. Kuhn, "The hungarian method for the assignment problem," *Naval Research Logistics (NRL)*, vol. 2, no. 1–2, pp. 83–97, 1955.
[30] J. Munkres, "Algorithms for the assignment and transportation problems," *Journal of the society for industrial and applied mathematics*, vol. 5, no. 1, pp. 32–38, 1957.
[31] N. Nisan, T. Roughgarden, E. Tardos, and V. V. Vazirani, *Algorithmic game theory*. Cambridge university press, 2007.
[32] Taipei city government, "Data. Taipei." [Online]. Available: http://data.taipei/opendata/datalist/listDataset

Yi Zhang received the B.S. degree in software engineering from Software College, Xiamen University (XMU), China, in 2014. He received the M.S. degree from Graduate Institute of Communication Engineering (GICE), National Taiwan University (NTU), Taipei, Taiwan, in 2016. He has been an assistant engineer in Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences (CAS), during 2016-2017. He is currently pursuing the Ph.D. degree in GICE at NTU. His primary research areas include wireless communication, game theory and optimization theory.



Chih-Yu Wang received the B.S. and Ph.D. degrees in electrical engineering and communication engineering from National Taiwan University (NTU), Taipei, Taiwan, in 2007 and 2013, respectively. He has been a visiting student in University of Maryland, College Park in 2011. He joined Academia Sinica, Taipei, Taiwan in 2014. He is currently an Associate Research Fellow in Research Center for Information Technology Innovation. His research interests include game theory, wireless communications, social networks, and data science.

Hung-Yu Wei received his B.S. degree in electrical engineering from National Taiwan University (NTU) in 1999. He received his M.S. and Ph.D. degrees in electrical engineering from Columbia University, in 2001 and 2005, respectively. He was a summer intern at Telcordia Applied Research in 2000 and 2001. He was with NEC Labs America from 2003 to 2005. He joined Department of Electrical Engineering at the National Taiwan University in July 2005. He is currently a Professor with the Department of Electrical Engineering and Graduate Institute of Communication Engineering at National Taiwan University. His research interests include broadband wireless communications, fog computing, cross-layer design for wireless multimedia, IoT, and game theoretic models for networking. He has been actively participating in NGMN, IEEE 802.16, 3GPP, OpenFog Consortium, and IEEE P1934 standardization activities.

He was the recipient of the Recruiting Outstanding Young Scholar Award from the Foundation for the Advancement of Outstanding Scholarship in 2006, NTU Excellent Teaching Award in 2008, K. T. Li Young Researcher Award from ACM Taipei Chapter and IICM in 2012, CIEE Excellent Young Engineer Award in 2014, and Wu Ta You Memorial Award from Ministry of Science and Technology in 2015. He was the chair of IEEE Vehicular Technology Society Taipei Chapter during 2016-2017. He is currently the Secretary of IEEE P1934 Working Group. He also serves as an Associate Editor for IEEE IoT journal.