Multiattribute-Based Double Auction Toward Resource Allocation in Vehicular Fog Computing

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Xiting Peng, *Student Member, IEEE,* Kaoru Ota, *Member, IEEE,* and Mianxiong Dong, *Member, IEEE*

***Abstract*—Vehicular fog computing (VFC) could provide fast task processing services for vehicles. To make vehicles/fog nodes willing to buy/sell resources, a double auction mechanism considering the interests of all parties is needed. However, few works study the auction issue in VFC. Different from the existing edge-related auction which only considers the price, some non-price attributes (location, reputation, and computing power) are also important for providing fair resource allocation in VFC. In this paper, we propose a multi-attribute based double auction mechanism in VFC, which considers both the price and non-price attributes for constructing reasonable matching. To the best of our knowledge, this is the first work to consider multi-attribute based auction in VFC. Our auction mechanism could satisfy computational efficiency, individual rationality, budget balance, and truthfulness. To verify the proposed mechanism, we simulate VFC using VISSIM and extract the driving data. Experimental results show the effectiveness and efficiency of this mechanism.**

***Index Terms*—Vehicular Fog Computing (VFC), Resource Allocation, Multi-attribute Auction.**

I. INTRODUCTION

With the development of Internet of Vehicles, more and more vehicular applications are beginning to enter the lives of people, including the safety and entertainment related applications. While the emergence of numerous applications could provide innovative and convenient services for drivers, large-scale data processing is still a problem that needs to be solved. Different from traditional networks, the vehicular network has poor-quality wireless links. Therefore, moving data to the cloud for processing is not feasible in the vehicular network. Cloud-based data processing can no longer meet the requirements of massive vehicular applications.

Vehicular fog computing (VFC) is a promising way to provide fast task processing services for vehicles by offloading these tasks to fog nodes close to vehicles [1]. VFC introduces the idea of the edge computing paradigm [2] into traditional vehicular network, as a supplement to cloud computing. Different architectures of VFC have been proposed, including infrastructure-based VFC and vehicle-based VFC. Since some infrastructures, such as RSU, are not deployed in reality, vehicle-based VFC is regarded as more practical architecture. In this architecture, fog nodes refer to vehicles with remaining resources, especially slow-moving and parked vehicles. These vehicles have sufficient resources and motivations to provide services to vehicles with resource needs [3]. For the convenience of description, we refer to vehicles selling resources as vehicular fog nodes, and vehicles that need resources as client vehicles.

How to provide reasonable resource allocation is an important issue in VFC. On one hand, fog nodes need to consume their computing and storage resources when providing services. On the other hand, not all vehicles are willing to pay according to the wishes of fog nodes, which means different vehicles will pay different amounts of money for their tasks. Therefore, how to conduct fair trade between them is the key issue for providing reasonable resource allocation.

Auction is a popular way to provide fair resource allocation between buyers and sellers in the case of competition [4]. Since the interests of vehicles and fog nodes are usually inconsistent, it is better to design a double auction mechanism to consider the interests of all parties. Through double auction mechanism, the price charged from vehicles and payment for fog nodes could achieve a trade-off.

There are some works on edge-related auction mechanisms. In [5], the authors proposed a truthful auction mechanism in mobile cloud computing to achieve resource allocation between mobile devices and cloudlets. Sun *et al.* [6] considered the industrial Internet of things scenario in which the edge node is a resource-rich data center and extended the above truthful auction mechanism. However, few works study the resource auction issue in VFC scenario.

The existing edge-related auction mechanisms could not be directly used in VFC, which only consider the price information. Due to poor-quality wireless links, vehicular network has a large delay when transmitting large-scale data [7]. One fog node is difficult to provide large-scale data processing services for vehicles who are far away. Therefore, location information should be considered when determining the matching in the VFC auction. Moreover, due to different types of tasks and different computing capabilities of fog nodes, vehicles have different preferences over fog nodes. For example, vehicles want to choose fog nodes with higher capabilities when processing safety-related tasks. Therefore, other non-price attributes, such as reputation and computing capability, also need to be considered in VFC auction.

In our study, we design a multi-attribute based double auction mechanism in VFC scenario. The proposed auction mechanism not only considers the price but also considers non-price attributes when determining the winners, which could construct more reasonable matching between fog nodes and vehicles. To the best of our knowledge, this is the first work to consider the multi-attribute based auction in the VFC

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scenario. In addition, our auction mechanism could satisfy the following economic properties: computational efficiency, individual rationality, budget balance, and truthfulness [5], [8]. To verify our auction mechanism, we simulate the VFC scenario using VISSIM, an open source framework for running vehicle network simulation. Then we implement the proposed auction system by JAVA, and verify the effectiveness and efficiency of the double auction mechanism by the driving data extracted from VISSIM.

The main contributions are summarized as follows:

- We consider multi-attribute factors and propose an attribute-based matching model between fog nodes and vehicles. In our model, vehicles send task requests with bids and attribute requirements, and fog nodes process these tasks by providing their asks and attributes.
- We propose a multi-attribute based double auction mechanism which meets budget balance, truthfulness, computational efficiency, and individual rationality.
- We implement the proposed auction system by JAVA, and use the driving data extracted from VISSIM (vehicular network simulator) to verify the effectiveness and efficiency of the double auction mechanism. Experimental results show that our mechanism could meet the proposed properties.

The rest of this paper is organized as follows. Related work about the double auction mechanism and VFC is introduced in Section II. We briefly introduce the system model, auction model and the economic properties in Section III. Section IV detailed presents the proposed multi-attribute based double auction mechanism. We discuss the experimental evaluation in Section V. We conclude the paper in Section VI.

II. Related Work

A. Resource Allocation in Vehicular Fog Computing

VFC is an emerging paradigm in recent year, which introduces the idea of the edge computing paradigm into vehicular network to solve limitations (e.g., latency and transmission cost) in conventional vehicular network. Existing works on VFC architecture are mainly divided into two categories: infrastructure-based VFC which regards infrastructures close to vehicles as the fog nodes [9], and vehicle-based VFC which regards vehicles with the remaining resources as the fog nodes [1], [10]. Compared with infrastructure-based VFC which needs to deploy the additional infrastructure (e.g., Road Side Unit), vehicle-based VFC is easier to deploy. For example, Zhu *et al.* [11] proposed a VFC architecture which turns commercial fleets with predictable driving routes into fog nodes. Some applications in VFC have also been investigated, such as real-time traffic management [1] and fog-based vehicular crowdsensing [9].

As an emerging paradigm, existing works in VFC mainly focus on its architecture [10]. Few works investigated the resource allocation issue, which limits the development of VFC. Feng *et al.* [12] designed a job scheduling method according to ant colony optimization. In [13], the authors proposed an adaptive resource scheduler for Fog Centers, which can maximize system efficiency. However, these works do not consider how to incentive vehicles and fog nodes to participate in resource sharing. The design of an efficient incentive mechanism in VFC scenario is still a great challenge.

B. Auction Mechanisms in Vehicular Network and Edge Computing

Nowadays, auction issues in traditional vehicular network have received the attentions from the academia. In [14], the authors proposed a VCG-based reverse auction scheme for cloud-based vehicular network, which can only meet the properties of truthfulness and individual rationality. Kumar *et al.* [15] studied the spectrum handoff issues in cognitive radio vehicular network, and proposed a game theoretic auction theory approach to select the optimal network for spectrum handoff. In [16], [17], the authors studied the energy trading of electric vehicles, and proposed the efficient auction mechanisms to incentive electric vehicles in the two-layer vehicle-to-grid (V2G) system. However, these works study the auction mechanisms in traditional cloud-based vehicular network and do not consider the auction issues in the vehicular fog computing scenario which contain many fog nodes with different interests.

Although there is little work to design auction mechanisms in VFC, some auction mechanisms in other edge computing scenarios have been proposed [18], such as mobile cloud computing [5], [19] and industrial Internet of things [6]. Sun *et al.* [6] considered industrial Internet of things scenario in which the edge node is a resource-rich data center and proposed a double auction scheme which can fit one-to-many scenario (one edge server can serve multiple devices). However, this auction mechanism cannot be applied to the VFC since vehicular fog nodes have fewer resources. In [20], the authors solved the resource auction problem at the edge/cloud levels. However, it cannot meet the property of truthfulness. Kiani *et al.* [21] introduced a hierarchical mobile edge computing which contains different types of cloudlets and proposed a resource allocation mechanism with two-time scale. However, this mechanism takes a long time, which is not suitable for rapid changes of the network topology in VFC. In [19], the authors proposed an incentive-compatible auction mechanism in mobile cloud computing. Then they extended it and proposed two auction mechanisms which can meet desirable properties according to different needs [5].

Note that the above works only consider the price factor when determining the winners, which could not be directly used in the VFC. As discussed in the introduction, due to the poor-quality wireless links which limit the range of data transmission among vehicles [22] and different types of tasks in the vehicular network which need to choose different fog nodes based on the task requirements, some non-price attributes, such as location, reputation and computing capability, also need to be considered in VFC auction. Therefore, in this paper, we consider these important non-price attributes to construct more reasonable matching between vehicles and fog nodes when designing the double auction mechanism for VFC scenario.

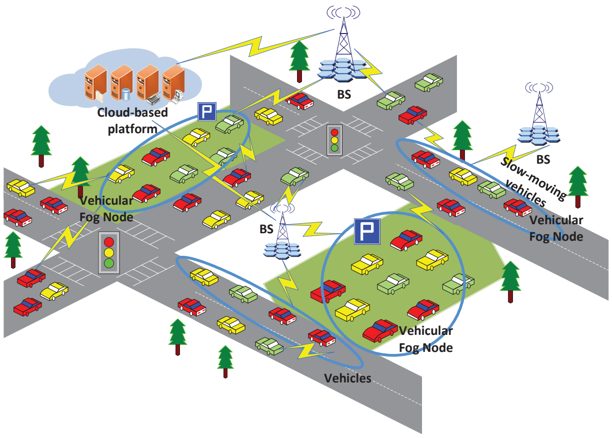


Fig. 1: The Architecture of Vehicular Fog Computing

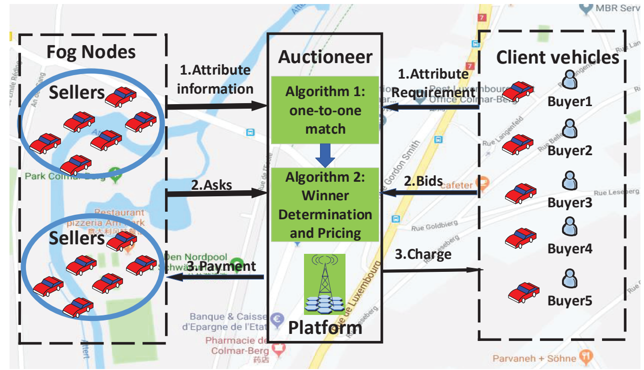


Fig. 2: The Multi-attribute based Double Auction Framework for Vehicular Fog Computing

III. Problem Formulation

In this section, we will introduce the system model, auction model, and the design objective of the auction mechanism.

A. System Model

As depicted in Fig.1, VFC system includes a cloud-based platform, some base stations (BSs), and massive vehicles serving as vehicular fog nodes (sellers) or client vehicles (buyers). Due to the limitation of transmission distance, a vehicular fog node can only provide services for its neighboring client vehicles. Therefore, we divide the VFC system into some subsystems according to the coverage of a base station, and the auction is performed among vehicles covered by the same base station [11]. The base station, a trusted third party, can be used as an auctioneer to determine winners. In our model, the base station only needs to perform the auction process (such as matching and pricing), but it does not need to provide the resources for executing client vehicles' tasks. Note that we only consider that one fog node can only serve one vehicle at a time because the vehicular fog node has limited resources.

To construct more reasonable matching between vehicular fog nodes and client vehicles, we consider the non-price attributes in this paper. We choose three kinds of important attributes as the examples and explain the rationality of using them in the VFC auction mechanism. Note that it is easy to extend to other attributes. If we want to add one attribute, the auction system will notify client vehicles to submit their attribute requirements and fog nodes to submit their attribute values before the auction process begins.

(A.) Location: The poor-quality wireless links make the vehicular fog nodes can only serve the nearby vehicles [23], [24]. Therefore, the location should be considered when establishing the matching between them in the VFC auction scenario.

(B.) Reputation: It is difficult to ensure vehicles can honestly publish or perform tasks. For example, some sellers may forge calculation results or reduce the performing speed, which affects the buyer's service experience. Therefore, a reputation system is needed to ensure trust services.

(C.) Computing Power: Client vehicles have different requirements for the execution time of different tasks. For example, some safety-related tasks need to be processed in a very short time, which need more computing power. On the contrary, vehicles do not have such high requirements for entertainment-related tasks. Therefore, computing power also needs to be considered to provide flexible services for different needs of vehicles.

At the begin of each auction round, vehicles dynamically join a sub-auction system using different identities (vehicular fog node or client vehicle) and register with the auctioneer within the communication range using their personal information (ID, type of the vehicle, location, reputation and computing capabilities). At the same time, the information about all vehicular fog nodes will be distributed to each client vehicle under the same sub-auction system.

At the bid submission phase, each client vehicle computes its bids for all vehicular fog nodes, which are different values according to sellers' attributes (resources) and the buyer's preferences (the calculation method is shown in Section III-B). At the same time, the client vehicles also submit minimum attribute requirements in order to construct reasonable matching. Similarly, the vehicular fog nodes submit their asks to the auctioneer. After receiving the bids and asks, the auctioneer executes the auction algorithm and determines the winners based on information provided by buyers and sellers. The concrete auction process is shown in Fig. 2.

B. Auction Model

Considering m vehicular fog nodes provide resources for n client vehicles, we model our problem as a single-round double auction:

- Let $\mathcal{B} = \{b_1, b_2, ..., b_n\}$ be the set of client vehicles (buyers), and $|\mathcal{B}| = n$. We denote minimum attribute requirements of i-th buyer as $\boldsymbol{q_i^b} = \{(q_i^{11}, q_i^{12}), q_i^2, q_i^3, ..., q_i^k\}$, where q_i^{11} and q_i^{12} represent the location and acceptable distance with a vehicular fog node, while q_i^2, q_i^3, and q_i^k represent the acceptable reputation, computing power, and the requirement of k-th attribute.
- Similarly, $\mathcal{S} = \{s_1, s_2, ..., s_m\}$ is m vehicular fog nodes (sellers). $\boldsymbol{q_j^s} = (q_j^1, q_j^2, q_j^3, ..., q_j^k)$ are the attribute values owned by the j-th vehicular fog node, which represent location, reputation, computing power, and the value of k-th attribute respectively.

- For each b_i, its bids for every seller s_j is $\boldsymbol{H_i} = (h_i^1, h_i^2, ..., h_i^m)$. As different fog nodes have different attributes (resources), buyers are willing to pay different prices. Moreover, buyers have preferences over these attributes according to tasks, which can be defined as the attribute weights $\omega_i = (\omega_i^1, \omega_i^2, \omega_i^3, ..., \omega_i^k)$. For example, buyers processing safety-related tasks will give a larger weight to reputation. Based on attributes of fog nodes and attribute weights, one buyer could give different bids for sellers. We could compute the weights based on the attribute requirements $\boldsymbol{q_i^b}$, and assign greater weight for the attribute which has more demand.
- For all sellers in $\mathcal{S}$, they give asks according to their resources, which is defined as $A = (A_1, A_2, ..., A_m)$. A seller requests the same ask for different buyers since it provides all resources for one client vehicle in one round.

According to resource attributes $\boldsymbol{q_j^s}$ of the fog node (obtained from the auctioneer) and the buyer's attribute weights $\omega_i = (\omega_i^1, \omega_i^2, \omega_i^3, ..., \omega_i^k)$, the buyer b_i could compute the valuation $V_i^j(\omega_i, q_j^s)$ for having services from the fog node s_j:

$$V_i^j(\omega_i, q_j^s) = \Phi_i + \omega_i^1 * (d_c - d(q_i^{11}, q_j^1)) + \sum_{a=2}^{k} \omega_i^a * q_j^a \quad (1)$$

where Φ_i is the fixed valuation. d_c is the diameter of the base station's coverage and $d(\cdot, \cdot)$ is the distance between the buyer and the seller. Note that these attribute values should be mapped to a unified non-dimensional interval firstly.

As a truthful auction mechanism, we will ensure that a buyer/seller has the maximum utility if it submits the bid h_i^j and ask A_j which are equal to the true valuation $V_i^j(\omega_i, q_j^s)$ and cost $C_j(q_j^s)$ for providing the resources (the proof is shown in Section IV-D). $C_j(q_j^s)$ is fixed, which will not change even if this seller s_j provides services for different buyers. Based on bids/asks, the auctioneer determines winning client vehicles $\mathcal{B}_w$ and vehicular fog nodes $\mathcal{S}_w$. Then it will determine the price P_i^b charged from b_i and the reward P_j^s for s_j. We define U_{ij}^b as the utility of the buyer b_i if this vehicle is matched with s_j and U_j^s as the utility of s_j:

$$U_{ij}^b = \begin{cases} V_i^j(\omega_i, q_j^s) - P_i^b; , & \text{if } b_i \in \mathcal{B}_w \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

$$U_j^s = \begin{cases} P_j^s - C_j(q_j^s), & \text{if } s_j \in \mathcal{S}_w \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

C. Economic Properties and Design Objective

A feasible and fair double auction mechanism usually meets the following basic properties:

- Individual Rationality: Individual rationality means the bid of a winning buyer should be greater than the charge ($h_i^j \geq P_i^b$) and the ask of a winning seller should be less than the payment ($A_j \leq P_j^s$).
- Computational Efficiency: The muti-attribute based double auction mechanism is computational efficiency if it has polynomial time complexity.
- Budget Balance: Total payments that the auctioneer pays to winning fog nodes should be less than total prices that the auctioneer charges from winning buyers.
- Truthfulness: As a truthful buyer/seller, it will honestly provide its bid/ask which is equal to its valuation/cost. However, it is reasonable to assume that the buyer/seller is selfish, and the buyer/seller has the enough motivation to increase its utility by submitting a bid/ask different from its true valuation/cost, which will affect the fairness of the auction. Therefore, our mechanism must ensure: the buyer/seller could obtain the maximum utility if they honestly provide a bid/ask which is equal to its valuation/cost. That means $\forall b_i \in \mathcal{B}, U_i^b$ is maximum when the bid $H_i = V_i$, and $\forall s_j \in \mathcal{S}, U_j^s$ is maximum when the ask $A_j = C_j$, where U_i^b is a vector representing the utilities of client vehicle i when it is matched by each fog node and V_i is the true valuations when client vehicle i is served by each fog node.

Moreover, system efficiency also needs to be considered for constructing an efficient auction mechanism. Since fog nodes have different resources and client vehicles have different resource requirements, it is better to increase resource utilization as much as possible on the basis of meeting buyers' needs. Therefore, we choose resource utilization (allocate more resources to the buyer who has higher requirements) as the measurement of system efficiency.

Although an auction mechanism that meets these five properties is a perfect auction mechanism, unfortunately, there is no double auction mechanism can satisfy these five properties at the same time [5], [8]. Therefore, we design a feasible auction mechanism that can strictly satisfy the first four properties, which can provide a fair and reasonable auction environment. At the same time, our mechanism can partly ensure system efficiency by allocating reasonable weights, as described in the following section.

IV. Multi-attribute based Double Auction Mechanism

The proposed multi-attribute based double auction mechanism (MADA) includes three main stages: Matching Stage, Assignment Stage, and Winner Determination and Pricing Stage. We will introduce these three stages in detail and demonstrate that the proposed auction mechanism could satisfy the basic properties in this section.

A. Attributes based Buyer-Seller Matching

The first step of the buyer-seller matching is to build the connection between client vehicles and vehicular fog nodes based on the attributes since not all fog nodes could meet client vehicles' requirements. Moreover, our design objective includes increasing resource utilization as much as possible on the basis of meeting buyers' needs. Therefore, we should set a reasonable weight for every connection to construct the optimal matching between them.

In this paper, we model our problem as a weighted bipartite graph to represent the matching. The vertices are buyers and sellers, and the edges represent whether the sellers can provide

Algorithm 1: One-to-One Assignment Algorithm

Input: Weighted Bipartite Graph $T = (\mathcal{B} \cup \mathcal{S}, \mathcal{B} \leftrightarrow \mathcal{S})$
Output: One-to-One Assignment M

1 Adding some virtual vertices and edges with a weight of -1 to T to make it a balanced bipartite graph $T^{'}$.
2 Setting the initial labelling $l()$ for every vertex in $T^{'}$:
3 **for** *each* $b_i \in \mathcal{B}$ **do**
4 | $l(b_i) = max_{s_j \in S}\{\lambda(b_i, s_j)\}$
5 **end**
6 **for** *each* $s_j \in \mathcal{S}$ **do**
7 | $l(s_j) = 0$
8 **end**
9 Generating the equality graph $T_l^{'}$ which meets:
10 $T_l^{'} = \{(b_i, s_j) : l(b_i) + l(s_j) = \lambda(b_i, s_j)\}$
11 Selecting a random matching M in $T_l^{'}$;
12 "Result" is a boolean variable; "$L \subset \mathcal{B}$, $R \subset \mathcal{S}$" are the sets of unsaturated and saturation points of "M" when the Hungarian algorithm terminates, respectively.
13 $Result$, L, $R \leftarrow$ Hungarian algorithm (M, $T_l^{'}$);
14 **if** *Result* == *True* **then**
15 | $M \leftarrow$ Remove the virtual vertices and edges in M;
16 | **return** M;
17 **end**
18 **else**
19 | $\beta_l = \min_{b_i \in L, s_j \in \mathcal{S}-R}\{l(b_i) + l(s_j) - \lambda(b_i, s_j)\}$;
20 | updating the labelling:
21 | $l^{'}(u) = \begin{cases} l(u) - \beta_l, & u \in L \\ l(u) + \beta_l, & u \in R \\ l(u), & others \end{cases}$
22 | updating the equality graph $T_l^{'}$ based on the new labelling. Go to line 11.
23 **end**

services to the buyers. Then we set a reasonable weight for each edge to ensure assigning a larger weight to an edge who connects a buyer with greater requirements and a seller with more resources. Therefore, our design objective can be converted to find the maximum weighted matching in a weighted bipartite graph.

1) Constructing the Unweighted Bipartite Graph: We say b_i and s_j have a matching ($b_i \leftrightarrow s_j$) if the resources of s_j is greater than the requirements of b_i. Based on the matching between them, we can construct an unweighted bipartite graph $T = (\mathcal{B} \cup \mathcal{S}, \mathcal{B} \leftrightarrow \mathcal{S})$, where $\mathcal{B}$ and $\mathcal{S}$ are two sets of vertices representing n vehicles and m vehicular fog nodes, respectively. $\mathcal{B} \leftrightarrow \mathcal{S}$ represents the matching between them.

A buyer b_i has the minimum attribute requirements $\boldsymbol{q_i^b}$, and s_j has the resources $\boldsymbol{q_j^s}$. If there exists a matching ($b_i \leftrightarrow s_j$) between b_i and s_j, they should meet the non-price attribute constraints:

$$(d(q_i^{11}, q_j^1) \leq q_i^{12}) \cap (q_j^2 \geq q_i^2) \cap (q_j^3 \geq q_i^3) \cap \cdots \quad (4)$$

where q_i^{11} and q_i^{12} represent the location and acceptable distance with a vehicular fog node, while q_i^2 and q_i^3 represent the acceptable reputation and computing power. Similarly, q_j^1, q_j^2, and q_j^3 are the attribute values owned by the j-th vehicular fog node, which represent location, reputation and computing power respectively. After satisfying the above constraints, we can establish the unweighted matching (coined as an edge) between b_i and s_j.

2) Setting the Weight for Each Edge: According to our design objective, we want to allocate more resources to the buyer who has higher demand for providing better services. Therefore, we define the weight as the product of the buyer's requirements and the seller's resources if there exists a matching between them, which could ensure assigning a larger weight to an edge who connects a buyer with greater demand and a seller with more resources. Then we give the definition of the weight $\lambda(b_i, s_j)$ for an edge ($b_i \leftrightarrow s_j$):

$$\lambda(b_i, s_j) = (d_c - q_i^{12}) * (d_c - d(q_i^{11}, q_j^1)) + \sum_{a=2}^{k} q_i^a * q_j^a \quad (5)$$

Then we can obtain the weighted bipartite graph $T = (\mathcal{B} \cup \mathcal{S}, \mathcal{B} \leftrightarrow \mathcal{S})$ by setting the weight for every matching.

B. One-to-One Assignment by the Weighted Bipartite Graph

We have converted the problem of maximizing resource utilization into finding the maximum weighted matching in a weighted bipartite graph by setting reasonable weights. In this section, we use the idea of Kuhn-Munkres (KM) algorithm to find maximum weighted matching from weighted bipartite graph $T = (\mathcal{B} \cup \mathcal{S}, \mathcal{B} \leftrightarrow \mathcal{S})$. The concrete procedure is shown in Algorithm 1: Firstly, we add some virtual vertices and edges with the weights of "-1" (which means it is not a normal matching) to T to make it a balanced bipartite graph $T^{'}$. Secondly, we set the initial labelling $l(\cdot)$ for every vertex, and generate the equality subgraph $T_l^{'}$ which meets the equation in line 10 of Algorithm 1:

$$T_l^{'} = \{(b_i, s_j) : l(b_i) + l(s_j) = \lambda(b_i, s_j)\} \quad (6)$$

Thirdly, we execute the Hungarian algorithm (Line 13) to find the perfect matching (maximum weighted matching) in $T_l^{'}$. If there is no perfect matching, we will relax the labelling (Line 18-21) for introducing new edges into $T_l^{'}$ and repeat this algorithm until we find the perfect matching M. After relaxing the labelling, the original feasible edge is still feasible, and the edge that was not feasible becomes a feasible edge now, which means we can definitely find the perfect matching after performing multiple relaxations. For each edge ($b_i \leftrightarrow s_j$) in M, it means the task from vehicle b_i can be processed by the vehicular fog node s_j.

Based on the above steps, we could obtain the maximum weighted matching "M", which is the one-to-one assignment ($s_j = M(b_i)$) between fog nodes and client vehicles. In the next section, we will show how to design a reasonable winner determination and pricing scheme based on one-to-one assignment "M".

C. Winner Determination and Pricing

In the previous step, algorithm 1 outputs one-to-one assignment "M". Since part of assignments between buyers and

Algorithm 2: Winner Determination and Pricing

Input: The matching set M, the candidate client vehicles $\mathcal{B}_c$ and vehicular fog nodes $\mathcal{S}_c$ in M

Output: The winning buyers $\mathcal{B}_\omega$ and sellers $\mathcal{S}_\omega$; the charge P^b and payment P^s

1 Sorting all buyers in $\mathcal{B}_c$ according to the bids by an descending order: $h_{i_1}^{M(i_1)} \geq h_{i_2}^{M(i_2)}$...;
2 Sorting all sellers in $\mathcal{S}_c$ according to the asks by an ascending order: $A_{j_1} \leq A_{j_2}$...;
3 Searching for the largest g (Aligned Boundary) from the first element in sorted buyers/sellers: $h_{i_g}^{M(i_g)} \geq A_{j_g}$;
4 Searching for the largest a from the (g+1)th buyer such that $h_{i_a}^{M(i_a)} \geq A_{j_g}$ and the largest b from the (g+1)th seller such that $h_{i_g}^{M(i_g)} \geq A_{j_b}$;
5 $(\theta, \eta) \leftarrow (a-1, g-1)$ or $(g-1, b-1)$: Choosing one pair with more matchings from $(\mathcal{B}_{a-1}, \mathcal{S}_{g-1})$ and $(\mathcal{B}_{g-1}, \mathcal{S}_{b-1})$; // $\mathcal{B}_{a-1}$ means first "$a-1$" elements in sorted $\mathcal{B}_c$
6 The subscript of Boundary Pair: $(\theta, \eta) \leftarrow (\theta+1, \eta+1)$
7 // Pricing
8 $P^b \leftarrow h_{i_\theta}^{M(i_\theta)}, P^s \leftarrow A_{j_\eta}$;
9 $\mathcal{B}_\omega \leftarrow$ Choosing the first "$\theta-1$" elements in sorted $\mathcal{B}_c$;
10 $\mathcal{S}_\omega \leftarrow$ Choosing the first "$\eta-1$" elements in sorted $\mathcal{S}_c$;
11 $\mathcal{B}_\omega, \mathcal{S}_\omega \leftarrow$ Removing all buyers/sellers who do not have the matching in $\mathcal{S}_\omega$/$\mathcal{B}_\omega$;
12 **return** $(\mathcal{B}_\omega, \mathcal{S}_\omega, P^b, P^s)$

sellers do not have a consistent price, these assignments do not represent final winners. Therefore, a reasonable winner determination and pricing algorithm is needed. McAfee double auction is a classical auction mechanism to price the homogeneous items. However, the simple pricing which does not consider the assignments between buyers and sellers will miss some winning buyers/sellers. Therefore, we refer to another truthful and computationally efficient pricing scheme [8].

The core idea of our pricing algorithm is shown as follows: We firstly sort the bids of buyers in descending order and asks of sellers in ascending order for finding the aligned boundary (Line 3). Then we fix the aligned boundary of one part (buyer or seller) and relax the boundary of another part for finding the extended boundary pairs, which have more candidate buyers and sellers. The boundary pair with more matchings will be regarded as the final price boundary. The concrete process is shown in Algorithm 2.

D. Theoretical Analysis

We will prove that our scheme satisfies the properties of individual rationality, computational efficiency, budget balance, and truthfulness.

Theorem 1. *MADA satisfies individual rationality.*

Proof. As shown in Line 1 and 2 of Algorithm 2, we sort the buyers and sellers by the descending and ascending order, and the winning buyers/sellers are the first "$\theta-1$/$\eta-1$" elements in sorted $\mathcal{B}_c$/$\mathcal{S}_c$. That means each winning buyer has the higher bid $h_i^{M(i)}$ than the charge $P^b = h_{i_\theta}^{M(i_\theta)}$, and each winning seller has the lower ask A_j than the payment $P^s = A_{j_\eta}$, which can ensure the individual rationality. □

Theorem 2. *MADA is budget-balance for the auctioneer.*

Proof. The muti-attribute based double auction mechanism meets the property of budget balance if the total rewards that the auctioneer pays to all winning fog nodes are not less than the total price the auctioneer charges from all winning client vehicles. For each b_i and the corresponding s_j, the utility that the auctioneer could obtain is $P_i^b - P_j^s = P^b - P^s \geq 0$. Therefore, the overall utilities of the auctioneer are greater than zero, which can meet the property of budget balance. □

Theorem 3. *The total time complexity of MADA is polynomial in the order of $O(\chi^3)$, where χ is the larger one of m and n.*

Proof. In the Matching stage, we need to set the weight between each buyer and seller. Therefore, the time complexity is $O(nm)$. In the Assignment stage, the KM algorithm always can be achieved in the time complexity of $O(\chi^3)$ [25], where χ is $\max\{m, n\}$. In the final stage, the sorting operations need a time complexity of $O(\chi \log(\chi))$. Then the searching operation needs a time complexity of $O(\psi)$, where ψ is less than $\min\{m, n\}$. Finally, the removing operations need to traverse each buyer/seller before the boundary pair, which needs a time complexity of $O(\psi^2)$. Therefore, the total time complexity of MADA is polynomial in the order of $O(\chi^3)$. □

Theorem 4. *our mechanism can ensure the truthfulness, which means the buyer/seller could not improve its utility by providing a bid/ask which is not equal to its real valuation.*

Proof. Firstly, we prove that buyers/sellers cannot submit fake attributes. Location can be obtained from GPS, which is easy to detect if they submit a fake location [26]. As for the reputation, it is evaluated by another entity (buyers/sellers). When a fog node completed a client vehicle' task, the client vehicle will evaluate the fog node in terms of execution time and accuracy of the results. Similarly, the fog node will evaluate the client vehicle in terms of payment time. Then these information (score) will be uploaded to a reputation server, and the distributed auctioneers will download and update this information in time. Therefore, they cannot modify it since reputation information cannot be controlled by themselves. Computing power is related to the type of vehicles, which will be provided when registering with the auction system. Since the type of vehicles is difficult to fake, it is easy to ensure drivers will submit the real computing power based on the registration information. Therefore, buyers/sellers cannot submit fake attributes. Then the matching and assignment algorithm will output a deterministic and bid/ask-independent assignment results, which means the changing of bids/asks will not affect assignment results.

Then we will prove that the changing of bids/asks will not affect the pricing stage. We use the proof of sellers' truthfulness as the example, and the truthfulness of buyers can be proved in similar ways. We define $\tilde{A}_{M(i)}$ as an ask different from the cost and $A_{M(i)}$ is equivalent to the cost $C_{M(i)}$. $\tilde{U}^s_{M(i)}$ and $U^s_{M(i)}$ represent their utilities respectively. We will discuss the following two cases separately:

1) $\tilde{A}_{M(i)} > A_{M(i)}$: There are four sub-cases.

- The seller $s_{M(i)}$ is the winner when submitting both $\tilde{A}_{M(i)}$ and $A_{M(i)}$. Without loss of generality, we assume the boundary pair is (b_{i_g}, s_{j_b}) when submitting $A_{M(i)}$ for auction. Note that another boundary pair (b_{i_a}, s_{j_g}) has the similar deduction processes. We define y, x as the position numbers of $s_{M(i)}$ and the corresponding buyer b_{i_x}, where $A_{j_y} = A_{M(i_x)}$. Similarly, $\tilde{y}$ is the position number of $s_{M(i)}$ when submitting $\tilde{A}_{M(i)}$, where $\tilde{A}_{M(i)} = \tilde{A}_{j_{\tilde{y}}}$ and $\tilde{y} > y$. Therefore, we have : $A_{j_y} < \tilde{A}_{j_{\tilde{y}}} < A_{j_b}$ or $A_{j_y} < A_{j_b} < \tilde{A}_{j_{\tilde{y}}}$.
For the first situation, we have: ① $y < \tilde{y} < g < b$; ② $g < y < \tilde{y} < b$; ③ $y < g < \tilde{y} < b$. For the sub-case ①, it will not affect the ask at/behind position g, which can obtain the same aligned boundary g and boundary pair. For the sub-case ②, since $h_{i_y} \leq h_{i_{g+1}} < A_{j_{g+1}} \leq A_{j_y} \leq A_{j_{y+1}}$ in the original order (submitting $A_{M(i)}$) and $s_{j_{y+1}}$ in the original order will be moved to the position y when submitting $\tilde{A}_{M(i)}$, position g is still the aligned boundary ($h_{i_g} \geq A_{j_g}$, $h_{i_{g+1}} < A_{j_{g+1}}$). Therefore, we can obtain the same g and boundary pair since $h_{i_g} \geq A_{j_b} > \tilde{A}_{j_{\tilde{y}}}$. Sub-case ③ has the same deduction process as sub-case ②.
For the second situation, we have: ① $y < g < b < \tilde{y}$; ② $g < y < b < \tilde{y}$. For the sub-case ①, we have $h_{i_g} \geq A_{j_b} \geq A_{j_{g+1}}$ and $h_{i_{g+1}} < A_{j_{g+1}} < A_{j_{g+2}}$ since the boundary pair is (b_{i_g}, s_{j_b}). When submitting $\tilde{A}_{j_{\tilde{y}}}$, $s_{j_{g+1}}$ and $s_{j_{g+2}}$ will be moved to position g and $g+1$. Therefore, position g is still the aligned boundary since $h_{i_g} \geq A_{j_{g+1}}$ and $h_{i_{g+1}} < A_{j_{g+2}}$. Since $h_{i_g} \geq A_{j_b}$ and $h_{i_g} < A_{j_{b+1}}$, the boundary of seller is located at position $b-1$ when we fix the boundary of buyer (Line 4 in Algorithm 2), which could not include the new ask $\tilde{A}_{j_{\tilde{y}}}$ into final winners. Therefore, this sub-case is impossible. We could derive the same result for the sub-case ②.
Therefore, we could obtain the same boundary pair when $\tilde{A}_{M(i)} > A_{M(i)}$. The seller will be paid the same price P^s and these two asks have the same utility: $\tilde{U}^s_{M(i)} = U^s_{M(i)} = P^s - C_{M(i)}$.
- $s_{M(i)}$ only wins when submitting $\tilde{A}_{M(i)}$; If the ask $\tilde{A}_{M(i)}$ wins and we submit a bid $A_{M(i)}$ which is less than $\tilde{A}_{M(i)}$, it must be a winning seller as discussed in the first sub-case. Therefore, this sub-case is impossible.
- $s_{M(i)}$ only wins when submitting $A_{M(i)}$; $U^s_{M(i)} \geq 0 = \tilde{U}^s_{M(i)}$ since the seller only wins when submitting $A_{M(i)}$.
- $s_{M(i)}$ is not the winner when submitting both $\tilde{A}_{M(i)}$ and $A_{M(i)}$; In this sub-case, $\tilde{U}^s_{M(i)} = U^s_{M(i)} = 0$.

2) $\tilde{A}_{M(i)} < A_{M(i)}$: there are also four sub-cases.

- $s_{M(i)}$ is the winner when submitting both $\tilde{A}_{M(i)}$ and $A_{M(i)}$. we also assume the boundary pair is (b_{i_g}, s_{j_b}) when submitting $A_{M(i)}$. Therefore, we have $\tilde{A}_{j_{\tilde{y}}} < A_{j_y} < A_{j_b}$. Then we have: ① $\tilde{y} < y < g < b$; ② $\tilde{y} < g < y < b$; ③ $g < \tilde{y} < y < b$. For the sub-case ①, it will not affect the ask at/behind position g, which can obtain the same g and boundary pair. For the sub-case ②, we have $h_{i_g} \geq A_{j_g} \geq A_{j_{g-1}}$ in the original order. When submitting $\tilde{A}_{M(i)}$, s_{j_g} will be moved to position $g+1$. If $h_{i_{g+1}} \geq A_{j_g}$, $g+1$ will be the new aligned boundary since $h_{i_{g+2}} < h_{i_{g+1}} < A_{j_{g+1}}$. Since $A_{j_g} \leq h_{i_{g+1}} < A_{j_{g+1}}$, the new boundary of seller will be located at position $g+1$ (s_{j_g} is moved to position $g+1$). Therefore, the new payment $\tilde{P}^s = A_{j_g} \leq A_{j_b} = P^s$. If $h_{i_{g+1}} < A_{j_g}$, the position g is still the aligned boundary and the boundary pair is still (b_{i_g}, s_{j_b}). For sub-case ③, it will not affect the ask before position g, which can obtain the same g and boundary pair. Overall, we could obtain a new payment $\tilde{P}^s \leq P^s$ or the same price $\tilde{P}^s = P^s$ when the boundary pair has not changed. Therefore, the new utility $\tilde{U}^s_{M(i)} = \tilde{P}^s - C_{M(i)} \leq U^s_{M(i)}$.
- $s_{M(i)}$ only wins when submitting $\tilde{A}_{M(i)}$. Since $s_{M(i)}$ only wins when submitting $\tilde{A}_{M(i)}$, we could obtain a new payment $\tilde{P}^s = A_{\tilde{j}_{\eta}}$, which is less than $A_{M(i)} = C_{M(i)}$ since $s_{M(i)}$ loses by submitting $A_{M(i)}$. Therefore, we have $\tilde{U}^s_{M(i)} = \tilde{P}^s - C_{M(i)} \leq 0 = U^s_{M(i)}$.
- $s_{M(i)}$ only wins when submitting $A_{M(i)}$. This sub-case is similar to the second sub-case when $\tilde{A}_{M(i)} > A_{M(i)}$.
- $s_{M(i)}$ is not the winner when submitting both $\tilde{A}_{M(i)}$ and $A_{M(i)}$. In this sub-case, $\tilde{U}^s_{M(i)} = U^s_{M(i)} = 0$.

Considering the above situations, we always have the $U^s_{M(i)} \geq \tilde{U}^s_{M(i)}$, which can prove that sellers cannot improve its utility by providing a fake ask. The truthfulness of buyers can be proved in similar ways. □

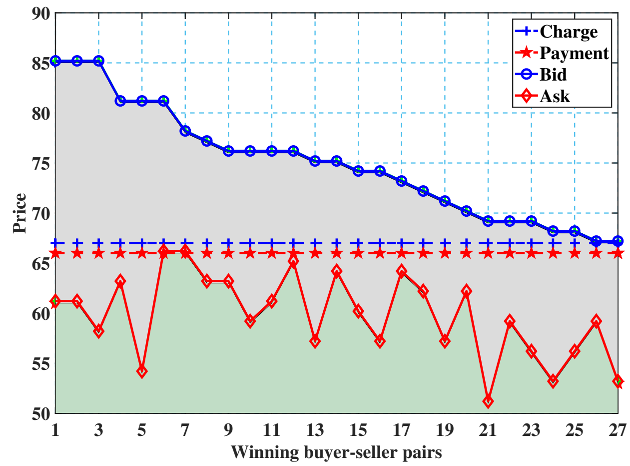
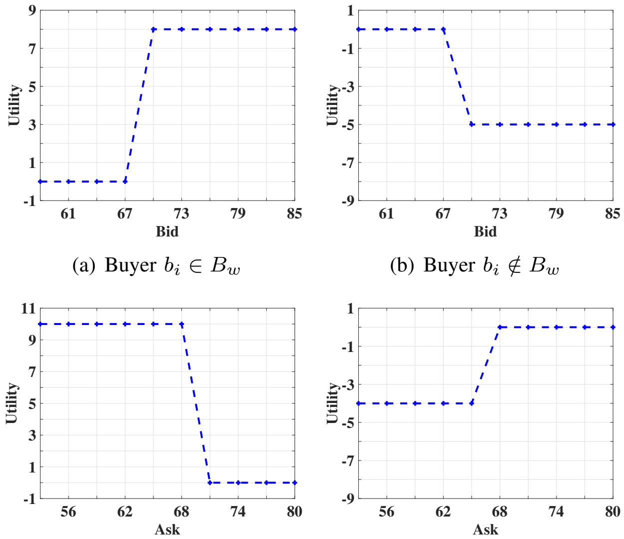


Fig. 3: The Individual Rationality and Budget Balance

V. Evaluation

A. Experiment Setup

We simulate the VFC using VISSIM, a classic open source framework for vehicular network simulation. It can analyze the operation of urban traffic and public transportation under various traffic conditions. With VISSIM, we can construct different scales of vehicular network, and obtain the driving data in real time, such as location, speed, vehicle type, power, and



(a) Buyer $b_i \in B_w$ (b) Buyer $b_i \notin B_w$

(c) Seller $s_j \in S_w$ (d) Seller $s_j \notin S_w$

Fig. 4: Truthfulness of buyers and sellers

so on. We initialize the Luxembourg map and randomly load multiple vehicles to implement the scenario of the vehicular network. After the simulator has been running for a while, we select an urban-intersection with a radius of $500m$ in this map and extract the driving data (location, speed, and vehicle type/power) of vehicles driving in this urban-intersection at this moment.

Then we divide these vehicles into two types (client vehicles and vehicular fog nodes) based on the driving speed and vehicle type/power. It is reasonable since fog nodes always refer to vehicles with the remaining resources, especially slow-moving and parked vehicles in VFC architecture. We consider three attributes (location, reputation, and computing power) in our auction system. Since reputation could not be obtained from VISSIM, we randomly generate them in our experiment. In practice, the auctioneer has enough ability to collect the reputation using another server in real time [27].

In our experiments, we select 150 client vehicles and 150 vehicular fog nodes from the candidate vehicles, and record their attributes. The bids and asks are computed based on these attributes. We also vary the number of buyers or sellers for evaluating the performance of the auction mechanism under different number of buyers/sellers. We conduct multiple experiments on the window PC with 64-bit intel-core i5-6200U CPU at 2.3 GHz and 8 GB memory, and average the experimental results. The experimental setting and parameters are shown in Table I.

B. Individual Rationality/Budget Balance

Individual rationality means the winning buyers will not pay the charges more than their bids, and the winning sellers will not obtain the payment less than their asks. Therefore, we run the auction mechanism between 50 client vehicles and 50 vehicular fog nodes, and output the final charges and payments, as shown in Fig. 3. The abscissa represents the i-th winning buyer-seller pair, and the ordinate represents the

TABLE I: Experimental Setting and Parameters

Parameters	Value
Vehicular network Simulator	VISSIM
The duration time of simulator	30 mins
The radius of simulation area	500m
Number of vehicles in simulation area	1000
Running by	Windows PC
Auction system implementation	JAVA
Number of client vehicles (n)	150
Number of vehicular fog nodes (m)	150
The range of bid/ask	(50, 100]
The value of attributes	(50, 100]
The range of weights	(0, 1]

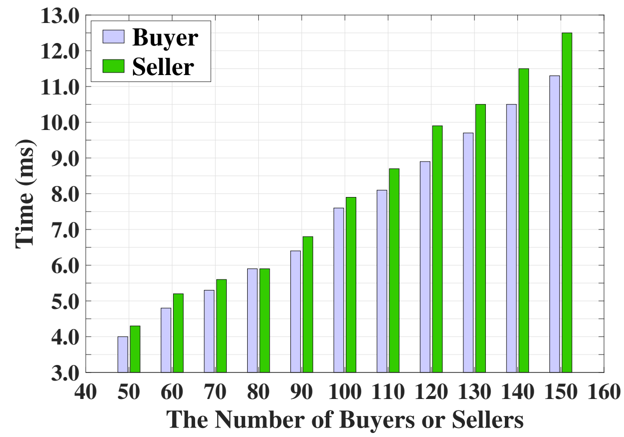


Fig. 5: Computational Complexity

price. We can see that the bid of the winning buyer is always higher than the final charge, and the ask is always less than the final payment, which can prove the individual rationality.

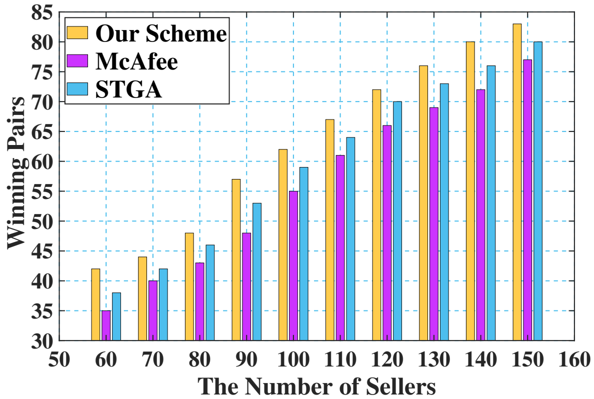
As for the budget balance, we can see that the line representing the charge is higher than the line representing the payment. Therefore, the auctioneer will obtain additional income from the auction, which can prove the budget balance.

C. Truthfulness

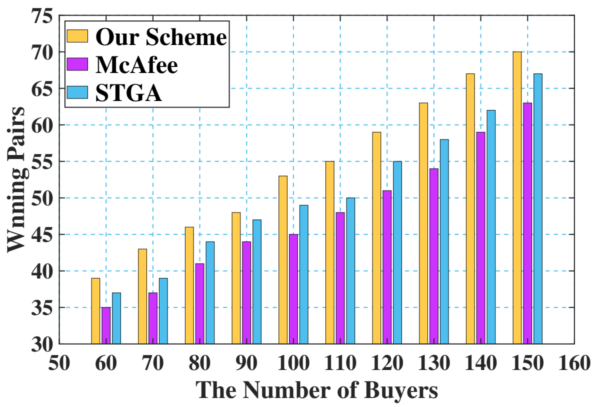
We verify the truthfulness of the proposed multi-attribute double auction mechanism by the following experiments, as an auxiliary way to theoretical analysis (Section IV-D). We randomly select a buyer/seller from the final winning set and a buyer/seller who is not in the winning set. Then we change the bid/ask of this buyer/seller, containing the value greater than and less than the true valuation/cost. To provide a consistent environment for comparison, we keep all parameters unchanged in addition to the bid/ask of this buyer/seller.

Fig. 4 shows utilities when buyers/sellers provide different bids/asks. Fig. 4(a) is the result when b_i is the final winning buyer. We can see that b_i has the maximum utility when it bids by the true valuation (76), and other bids will not bring more utilities. Fig. 4(b) shows the utilities when b_i is not the final winning buyer. The maximum utility of b_i is zero since they are not the final winner if it truthfully submits the bid (64). Although it can be the final winner when it changes the bid, it also cannot obtain the utility which is greater than zero.

Fig. 4(c) and Fig. 4(d) are two cases of sellers. From Fig. 4(c) and Fig. 4(d) we can see that these sellers have the



(a) Comparison under Different Number of Sellers



(b) Comparison under Different Number of Buyers

Fig. 6: Performance under Different Number of Buyers/Sellers

maximum utilities when they offer the real cost (59, 71). In summary, we can verify the truthfulness of our mechanism.

D. Computational Complexity

We evaluate the impact of the number of buyers/sellers on running time by choosing a different number of buyers/sellers. In this experiment, we fix buyers/sellers at 100 and change the number of sellers/buyers from 50 to 150, respectively. Fig. 5 shows the results of the running time under a different number of buyers/sellers. The purple bar shows the running time when we fix the sellers, and the other is the results when we fix the buyers. We can see that both of them have a polynomial computation time, which can show the stability of our system under different scale of data.

E. Performance Comparison with Other Auction Mechanisms

We compare the proposed mechanism with McAfee auction and another edge-related double auction mechanism (STGA). To provide a consistent comparison environment, we use same dataset and parameters when running these mechanisms. We use the number of winning pairs as the performance metric to conduct the comparative experiment, as described in Section IV-C. we fix the number of buyers/sellers at 100 and vary the number of sellers/buyers from 60 to 150, respectively. The compare results are shown in Fig. 6(a) and Fig. 6(b), where the yellow bar represents the winning pairs of our system, the blue bar represents the STGA, and the pink bar represents the McAfee auction. We can see that our scheme always has more winning pairs than other auction mechanisms, which can show the superiority of the proposed system's performance.

VI. Conclusion

In our study, we design a multi-attribute based double auction mechanism in VFC scenario. The proposed auction mechanism not only considers the price but also considers non-price attributes when determining the winners. In addition, our auction mechanism could satisfy the following economic properties: computational efficiency, individual rationality, budget balance, and truthfulness. To verify our auction mechanism, we simulate the VFC scenario using VISSIM (a framework for running vehicle network simulation), and extract the driving data (location, speed, and vehicle type/power) of vehicles for the auction. Experimental results show the effectiveness and efficiency of our auction mechanism. In the future work, we will study dynamic/online auction mechanism, which allows client vehicles and vehicular fog nodes to join the auction process in real time.

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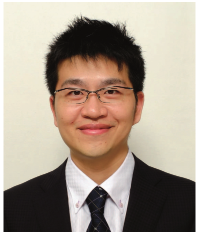

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