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RESEARCH ARTICLE

Multi-Task Matching Mechanism Design for UAV-Assisted MEC Network With Blockchain

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ABSTRACT Mobile edge computing (MEC) is a technology deployed at the edge of mobile networks to enhance computation capabilities and reduce transmission distances. It has been extensively researched in the context of both the internet of things (IoT) and 5G communication. Recently, unmanned aerial vehicles (UAVs) have been integrated into MEC networks to create a novel architecture that utilizes line-of-sight (LOS) transmission links. In this architecture, UAVs act as relay nodes to facilitate the offloading of computing tasks from UAVs to edge computing stations (ECSs). However, the problem of creating an incentive system that guarantees the confidentiality and integrity of communication while simultaneously making it easier for UAVs and ECSs to coordinate a variety of activities remains unsolved. Consequently, this paper proposes a blockchain-based architecture for UAV-assisted MEC networks that addresses the aforementioned issues of security and privacy and investigates the problem of multi-task matching based on this architecture. A joint optimization problem is explicitly proposed to maximize both task completion rates and social welfare. Consequently, the formulated problem is decomposed into two subproblems: 1) The double auction problem, which aims to maximize societal utility and determines the winning pairs and trading price; and 2) The auction losers matching problem, which aims to increase task completion rates. Then, to identify the appropriate matching pairings and establish the trading price, a satisfaction breakeven-based double auction (SBDA) method is suggested. Sequentially, two auction losers' second selection schemes, the shortest distance (SD) and the largest difference (LD) scheme are proposed to realize second matching to enhance the task completion rate. Finally, numerical simulations are given to show the effectiveness of the proposed mechanism. Particularly, the SBDA+LD mechanism has the best system utility and overall income compared with other schemes.

INDEX TERMS Mobile edge computing, unmanned aerial vehicles, resource allocation, blockchain, multi-task offloading, matching mechanism.

I. INTRODUCTION

With the developments of Internet of Things (IoT), Mobile edge computing (MEC) tasks of smart mobile devices (SMDs), such as virtual reality (VR), augmented reality (AR), face recognition, and interactive gaming, which require low latency and high computation are attracting board attention from both academia and industry. SMDs with limited computing, storage, and battery capacity are hard to deal with compute-intensive tasks. To overcome the shortage, MEC networks with high-performance servers deployed at the edge of wireless networks have been considered a promising solution [1], [2].

However, in traditional MEC networks, due to edge servers being deployed in fixed locations, the transmission link between computation nodes and SMDs is usually non-line of sight (NLOS). Therefore, to enlarge communication coverage, enhance link transmission quality, save energy, and promote deployment flexibility, unmanned aerial vehicle (UAV) technology is introduced in MEC networks [3], [4], [5], [6]. Computation tasks can be divided into two sorts: one is executed by UAV, and the other is offloaded to MEC servers

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by UAV. In [3], the authors proposed UAV-enabled MEC architecture and found that energy consumption by processing the tasks among UAVs locally is more than offloading the tasks to the MEC server through experiments. Zhou et al. [4] investigated the weighted sum computation rates of users, the offloading times of users, the transmit power of users and UAV trajectory problems under both local computing and offloading computation tasks to MEC servers using two alternative algorithms. Akter et al. [5] focused on task-offloading, power, and computation resource allocation problems in a MEC-enabled UAV network. Authors in [6] regarded UAVs as both the computing nodes and the mobile relay stations to minimize the total energy consumption. Because of the limited battery capacity of UAVs, it is hard to deal with whole computation tasks only by UAVs. The second mode, offloading tasks to MEC servers, has been mainly considered in this article.

All the above articles studied task offloading problems by analyzing UAV trajectory, energy consumption, computation resource scheduling, bandwidth and so on. Nonetheless, they all ignored that the UAVs and MEC servers were profit-driven entities which were belonging to different camps. Due to interest-driven, much information, such as task data and trading prices, which are uploaded to edge servers may be leaked or tampered with without any security measures. Hence, how to not only motivate the communication entities to join into the process of tasks offloading but also ensure the security of communication between them becomes a hot issue.

For the first issue, in MEC networks, auction schemes as an incentive mechanism have been widely used to motivate communication entities to join in the tasks offloading [7], [8], [9]. An auction-based task offloading approach for IoT users in Edge Clouds was presented by Liu et al. [7] to address the issue of matching between edge servers and mobile users (MDs). In [8], the Federated learning (FL) paradigm and one-sided matching-based method were introduced to facilitate the trading among FL service demanders (FLSDs), UAVs, and SMDs. Authors in [9] built a UAV-to-community offloading system and regarded UAVs as computation nodes to execute computation tasks sent from SMDs. An average throughput maximization-based auction algorithm and a dynamic task admission algorithm were proposed to solve the trajectory subproblem and task scheduling subproblem, respectively.

Although these existing works have made some contributions to tasks offloading by auction mechanism, there are still some aspects that are ignored. Authors in [7] mainly focused on MEC networks without UAV-assisted. In [8], the Vickrey-Clarke-groves (VCG)-based and one-sided auction method was proposed to optimize UAV trajectory. However, the interests of sellers were neglected in the VCG auction because only by submitting bids by buyers, the utility of sellers is ignored. In [9], UAVs were regarded as computation nodes to provide edge computing services for SMDs. In fact, despite UAVs having the advantages of high mobility and self-organization, the battery capacity and computing ability of UAVs are still limited. Meanwhile, SMDs in the same community may practically have multi-tasks that need to be offloaded. Nevertheless, combinational auction, one-sided matching-based and VCG auction mentioned before are all only fit for one-to-one matching rather than many-to-many matching. Therefore, we have to consider two aspects, one is an auction between many players, and the other is multi-task matching. In the actual environment, many buyers and sellers coexist during trading. Some other auction mechanisms have been proposed to solve many-to-many matching problems in resource allocation [10], [11], [12]. In [10], a three-layer dynamic matching algorithm was proposed to solve bandwidth allocation problems among UAVs, ACC (auction control center) and users in UAV communication networks. In [11], the two-sided matching mechanism was used to give incentives to IOT users and cloudlets to maximize social welfare. Liwang et al. [12] proposed a bilateral negotiation-based future-enabled mechanism in edge computing-assisted UAV networks. The bilateral negotiation scheme is used to determine trading consensus and relevant price to maximize both the buyer's and the seller's utilities. Two-sided auction and bilateral negotiation matching schemes are executed to reach matching between multiple buyers and sellers by several quotations.

All the existing works are mainly based on the single-task satisfaction of users. In UAV networks, because each UAV may receive abundant services with various quality of service (QoS) from UE, multi-task offloading problems should be taken into account. In addition, the European Telecommunications Standards Institute (ETSI) MEC Industry Specification Group identified four typical application scenarios for MEC in [13] and [14]. It includes video stream analysis services (such as face recognition and home security surveillance), augmented reality services (such as AR and online games), IOT applications (obtaining distributed information for computation) and connected vehicles (such as autonomous driving). Meanwhile, latency and rate are also important parts of Qos of 5G traffic [15]. Report ITU M.2083-0 [16] defines the framework of IMT-2020, which present diverse usage scenario and more tasks that have the demand for low latency, high bandwidth, faster transmission rates, etc. Enhanced Mobile Broadband (eMBB), which dresses the personal multimedia service such as 3D video with a high data rate. Ultra-Reliable and Low Latency Communications (URLLC) including self-driving, industry automation and mission-critical applications have stringent requirements of latency and availability. Although all the tasks are latency-sensitive, the latency thresholds are different according to their diverse requirements.

Therefore, how to match the tasks with various QoS of UAVs with the communication computing resources of ECSs is an important issue we should consider. This prompts us to find a mechanism to solve the multi-tasks with diverse QoS requirements matching problems among multi-players.

Several related works studied task offloading issues which considered user satisfaction and system effectiveness [17],

[18], [19], [20], [21], [22]. In [17], the satisfaction ratio function was mentioned to measure the percentage of packets whose overall latency falls within the latency constraints. The value of the satisfaction ratio was between 0 and 1. Li and Wang [18] present delay and rate satisfaction for data transmission in wireless communications. The researchers mainly gave the relationship between satisfaction and latency (rate) in terms of the survey. Utility function based on user satisfaction is studied in [19], the authors solved the tasks offloading problem to maximize user service satisfaction in edge computing. In [20], the authors studied a data skew-aware approach for allocating each data block of the edge or the cloud server for processing. Chen et al. [21] proposed a multi-agent deep reinforcement learning-based framework to offload computation in a non-orthogonal multiple access (NOMA) based multi-user network.

Double auction regarded as a multi-item matching scheme is not only suitable for settling matching between multi-players but also is used to solve multi-tasks of multi-player offloading problems [22]. Recently, various double auction-based schemes have been used in multi-player and multi-task scenarios of resource allocation [23], [24], [25]. In [23], two double auction mechanisms, a truthful incentive mechanism (TIM) and an efficient design of auction (EDA) methods, were designed for resource sharing in mobile cloud computing (MCC). Sun et al. [24] proposed two kinds of double auction mechanisms to realize many-to-many mapping between edge servers and MDs and maximize the number of successful tasks. Shyuan Ng et al. [25] used a double auction mechanism to match the edge servers with computing resources to the vehicles. Meanwhile, the price was determined to complete the Coded Distributed Computing (CDC) tasks. To optimize societal welfare, Zou et al. [26] used a twofold auction-based intelligent electric vehicle (EV) charging mechanism to choose the unit price and winners. The secondary matching from auction losers was then suggested to increase the obtained rate of charging for EVs. There are two objectives of the design auction mechanism, one is motivating resource owners to join the trading process, and the other is maximizing social welfare [22]. For the problem of matching between multi-player and multi-task in UAVs-assisted MEC networks, we need to consider how to enhance social welfare and the number of successful tasks needs to be considered simultaneously. However, there is little work focusing on the problem. In this paper, we use a double auction scheme considering satisfaction to achieve task offloading and maximize social welfare, while determining the prices. Based on this, a secondary auction based on auction losers is introduced to maximize the number of pairs.

The other issue is the security of information during the whole trading. If the trading information (such as bidders, prices, utilities of sellers and buyers) is uploaded to the edge servers without any security measurements, it may be leaked or tampered easily by other edge competitors. In the MEC network consider multi-task, to obtain more income, each buyer and seller may gain more offloading chances by tampering with data. This is bound to become a normal transaction behavior that cannot be carried out. To guarantee the reliability of trading information, blockchain, as a distributed digital cryptocurrency technology, has been used in edge computing in recent years [24], [27], [28], [29], [30], [31]. In [27], a proof of work (PoW)-based blockchain network was proposed to allocate cloud/fog computing resources. In [28], the authors investigated the integrated blockchain and edge computing system and discussed some potential problems which need to be solved before the system's widespread deployment. Such as its scalability enhancement, self-organization, resource management, etc. In [29], since UAVs were regarded as aerial BSs, a mobile blockchain structure was proposed to maximize system payoffs in the blockchain-as-a-service (BaaS)-MEC model. In [30], ECSs, regarded as blockchain nodes, were applied to record trading information and ensure security and privacy during the resource trading process in UAVs-assisted MEC networks. However, [27], [28], [29], [30] does not consider the auction mechanism to maximize social welfare in blockchain-based networks. In [31], an iterative double-sided auction scheme was proposed to realize the edge computing resource trading between ECSs and IoT devices to maximize social welfare. In [24], authors proposed a blockchain mechanism with the delegated proof of stake (DPoS) consensus [32] based double auction scheme to maximize the number of successful tasks. However, due to the auction mechanisms proposed in [24] and [31] not considering the satisfaction of tasks with diverse QoS demands [19], the bid of the buyer could not reflect real value, meanwhile, the benefit of buyers and sellers could not be guaranteed.

In this paper, we introduce blockchain technology to ensure the security and privacy of trading between UAVs and ECSs in UAV- assisted MEC networks. A task satisfaction-based double auction mechanism is proposed to maximize social welfare and motivate UAVs and ECSs to join the computing process. We approach the task-matching issue differently than previous works to increase both the completion rates of the union tasks and the social welfare activities.

The contributions of this paper are summarized as follows:

- We formulate multi-task offloading in UAV-assisted MEC networks as a matching process, where the UAVs are the buyers, which are providing rewards, and the ECSs are the sellers, with plenty of computing resources. The matching issue, whose goal is to maximize both social welfare and union task completion rates, was then proposed under several limitations, including the limitation of the idle computing power of ECSs and UAVs for various tasks that need to be processed. The problem is a mixed-integer programming problem, which is an NP-hard problem that cannot be solved by a polynomial algorithm [33].
- We divide the problem into two subproblems to obtain an ideal matching technique. A satisfaction breakeven-based double auction (SBDA) system with budget balance, individual rationality, and truthfulness solves

the first subproblem known as the double auction problem. The scheme is proposed to maximize social welfare and to determine the trading price synchronously. The second subproblem, which is referred to sequentially as the auction loser's secondary matching problem, tries to boost the completion rate of union tasks by recommending the shortest distance (SD) scheme and the largest different (LD) scheme. The output of the first subproblem, such as the unfinished jobs, idle computer resources, and trade prices, serves as the input for the second subproblem.

- We conduct numerical simulations to evaluate the performance of the proposed matching mechanism. We first show the SBDA scheme satisfies individual rationality, budget balance, and truthfulness. Then, we compare the social welfare of SBDA with BDA and TIM to illustrate the effectiveness of the SBDA auction. We also offer a system effectiveness study to assess the combined technique that has been suggested. The findings indicate that SBDA+LD achieved more winning buyer-seller pairs and overall revenues than TIM, BDA, SBDA, and SBDA+SD, respectively.
- We propose a Blockchain-based resource trading scheme in UAV-assisted MEC networks to perform multi-task offloading. Edge computing stations with powerful computing capabilities are both computing /communication/ storage nodes and blockchain nodes. All transaction information, such as the smart contract, the resource demands and the auction information is recorded in the blockchain nodes.

The rest of the paper is organized as follows. Section II introduces the system model. The satisfaction function, auction model, and the formulation of the multi-task matching problem are proposed in Section III. The proposed formulated problem is divided into two subproblems in Section IV. We propose a smart contract-based joint matching mechanism that combines double auction and auction losers' secondary selection to solve the optimization subproblem, respectively. Numerical simulations are given in Section V. Finally, the paper is concluded in Section VI.

II. SYSTEM MODEL

The network structure and channel model are described in Section II-A and Section II-B, respectively.

A. NETWORK STRUCTURE WITH BLOCKCHAIN

UAVs can be expressed as $\{1, 2, \ldots, v, \ldots, Vl\}, v \in V$, where the amount of the UAVs is Vl; and ECSs can be expressed as $\{1, 2, \ldots, e, \ldots, El\}$, where the amount of the ECSs is El. In addition, slicing networks technology [17] provides us with an effective method to improve system capacity, as different tasks could be processed parallelly without interference in each ECS. Furthermore, tasks are divided into many different types for their different quality of service (QoS) levels. According to their QoS constraints, the tasks are represented by $\{1, 2, \ldots, k, \ldots, Kl\}, k \in K$, where the number of types of the tasks is Kl.

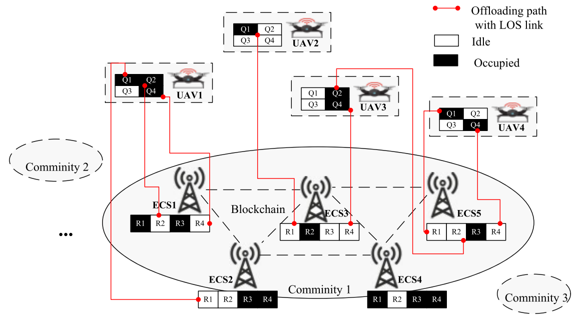

FIGURE 1. Network structure with blockchain.

Besides, the UAV regarded as the buyer wants to be allocated some computing and communication resources from ECSs that are regarded as the seller and the auctioneer as well. Therefore, the edge server does not only select suitable buyers and allocate resources to them but also records trading information and auction results, such as bidder, asks price, buying price and selling price.

For UAVs, they receive a large number of tasks from User Equipment (UEs) simultaneously. For community t, the tasks are denoted as a task indicator vector with a binary variable. It is expressed as $Q^t = \{Q_1; Q_2; \ldots; Q_{Vl}\}$, which is a $Vl \times Kl$ matrix. Hence, every UAV has multiple options to offload tasks. It may choose the nearest edge server or the ECS that has more remaining resources. Using the auction method, in the same community, the UAVs could buy resources from ECSs by submitting various bids, according to the different distances between UAVs and ECSs or the amount of computing and communication tasks of UAVs. The bid matrix of UAVs is represented as $B^t = \{B_1; B_2; \ldots; B_{Vl}\}$. For UAV v, whose task indicator vector is $Q_v = \{q_{v,1}, q_{v,2}, q_{v,k}, \ldots, q_{v,Kl}\}$, has task k to be processed $q_{v,k} = 1$, otherwise $q_{v,k} = 0$. Meanwhile, the bid of the UAV v is $B_v = \{b_{v,1}, b_{v,2}, b_{v,e}, \ldots, b_{v,El}\}$, which is the row v of the bid matrix B.

For ECSs, the tasks are presented as applications (apps) for describing simplification. The application indicator vector with a binary variable is defined as $R^t = \{R_1; R_2; \ldots; R_{El}\}$, which is a $El \times Kl$ matrix. Meanwhile, we assume every ECS gives every different UAV the same ask price that is determined by its remaining resources and computing ability itself. Therefore, the ask vector is defined as $A^t = \{a_1, a_2, \ldots, a_{El}\}$, which is a $1 \times El$ matrix.

For example, the ECS e's app indicator vector is described as $R_e = \{r_{e,1}, r_{e,2}, r_{e,k} \ldots r_{e,Kl}\}$, which is the row e of the app matrix. If the app k of ECS e is idle $r_{e,k} = 0$, otherwise $r_{e,k} = 1$; and the asking price of the ECS e is a_e, which is the element e of the asking matrix. As seen in Fig. 1, for example, five ECSs and four UAVs are deployed in community 1. The UAVs with limited resources need to offload tasks to the ECSs. The UAVs regarded as buyers submit their bids to the ECSs to purchase computing resources from them. The ECSs regarded as sellers are not only the server nodes but also the auctioneers. They received the bids and chose suitable buyers to improve their revenue. The matching mechanism is used to solve the problem. Through matching, we can see that Task1, Task2 and Task4 in UAV1 are deployed in ECS 1 and ECS 2, respectively. As for ECS5, there are three idle applications including R1, R2 and R4. R1 and R4 are allocated to UAV4, and R2 is allocated to offer service for Task2 of UAV3.

Nevertheless, during the trading, all the information and results might be tampered with or falsified because of competition among sellers. To enhance reliability and primary, a blockchain mechanism is introduced into the structure of the network. Edge servers are not only sellers and auctioneers but also blockchain nodes, which verify and record trading information. The DPos consensus algorithm on the blockchain allows for the execution of a smart contract that contains all the data and outcomes from the previous section.

B. CHANNEL MODEL

The air-to-ground (A2G) channel model with many LOS links is used in our system [34]. In the system, the height of UAVs is more than 50 meters, and the edge servers are fixed up on higher areas, such as the top of a tree or a building roof. In addition, we assume the uplink and downlink channels between UAVs and ECS are symmetrical. Therefore, in community t, the path loss function $PL^t_{v,e}$ can be defined by:

$$PL^t_{v,e} = 30.9+(22.25-0.5\log_{10}h)\log_{10}w^t_{v,e}+20\log_{10}f_c, \tag{1}$$

where h represents the height of the UAV, $w^t_{v,e} = ||n^t_v - m^t_e||$ is the distance between the UAV v (location is n^t_v) and the ECS e (location is m^t_e). And the carrier frequency is denoted as f_c.

Since UAVs in the same community share the same frequency, the interference of ECS e, I^t_e, can be described as:

$$I^t_e = \sum_{v' \in V, v' \neq v} P \cdot 10^{-PL^t_{v',e}/10}. \tag{2}$$

And then, $\gamma^t_{v,e}$, which is defined as the received signal to interference plus noise ratio (SINR), is expressed as:

$$\gamma^t_{v,e} = \frac{P \cdot 10^{-PL^t_{v,e}/10}}{I^t_e + N_o}, \tag{3}$$

where P is the transmission power of UAV, N_o is the additive white Gaussian noise (AWGN). Therefore, when carrier bandwidth is f_e, the achieved transmission rate of each community [35] is defined as:

$$Rate^t_{v,e} = f_e \log_2(1+\gamma^t_{v,e}). \tag{4}$$

III. THE FORMULATED PROBLEM

In this work, we consider the matching problem between edge servers and UAVs to maximize social welfare and the union task completion rate. Using a suitable matching scheme, each UAV could offload tasks to the edge servers that have enough computing resources. Thus, we may fix computing nodes. Meanwhile, more tasks of UAVs could be processed, and more idle resources of edge servers could be utilized to achieve shorter computing time and a higher transmission rate by the edge server-assisted UAV networks compared with other networks.

In Section III-A, we propose the task satisfaction function. The auction model and multi-task matching problem are shown in Sections III-B and III-C, respectively.

A. TASK SATISFACTION FUNCTION

Assuming the diverse service rate $Rate^t_{v,e}$, given in (4), is the same. In addition, L_k is the data size, the link bandwidth is f_e, $Tcomm$ is the transmitting time, and $Tcomp$ is the computing time depend on the computing ability of the MEC server base (to simplify, we assume it has sufficient computing power). Consequently, the transmitting latency between the UVA v and the ECS e for the task $kT^t_{v,e}(k)$ is expressed as:

$$T^t_{v,e}(k) = Tcomm + Tcomp = \frac{L_k}{Rate^t_{v,e}} + Tcomp. \tag{5}$$

And then, the latency satisfaction for task k is defined as a negative exponential function [18], which is shown in (6). Correspondingly, the total latency satisfaction between UVA u and ECS e is described in (7).

$$S^t_{v,e}(k) = \begin{cases} 1, & T^t_{v,e}(k) \leq T_{thr,k} \\ \dfrac{2}{9} + \dfrac{7}{9}e^{-\varepsilon t \cdot (T^t_{v,e}(k) - T_{thr,k})} & T^t_{v,e}(k) \geq T_{thr,k} \end{cases}, \tag{6}$$

$$S^t_{v,e} = \frac{1}{Kl}\sum_{k \in K} S^t_{v,e}(k), \tag{7}$$

where εt is the latency satisfaction factor, $T_{thr,k}$ is the threshold of latency, Kl is the number of service types.

B. AUCTION MODEL

In the article, the auction model is designed as a double auction because multiple sellers and buyers are considered. In community t, to determine whether the UAV v is chosen by ECS e and the ECS e i s chosen by UAV v, binary variables $x^t_{v,e}$ and $y^t_{e,v}$ are defined in (8) and (9), respectively. $x^t_{v,e} \in X^t$, X^t is the choosing vector of buyers. And $y^t_{e,v} \in Y^t$, Y^t is the allocation vector of sellers.

$$x^t_{v,e} = \begin{cases} 1, & \text{if the ECS } e \text{ is chosen by the UAV } v, \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

$$y^t_{e,v} = \begin{cases} 1, & \text{if the UAV } v \text{ is chosen by the ECS } e, \\ 0, & \text{otherwise,} \end{cases} \tag{9}$$

where $x^t_{v,e} = 1$ means the UAV v chooses ECS e as its partner, if $x^t_{v,e} = 0$, otherwise. Similarly, $y^t_{e,u} = 1$ indicate that the ECS e receives the request from UAV v, and then UAV v could offload the task to the ECS e, if $y_{e,u} = 0$, otherwise. Specifically, as shown in Fig.1, idle app 1 of ECS 5 is allocated to task 1 of UAV 4, $x^1_{4,5} = 1, y^1_{5,4} = 1$.

TABLE 1. Key notation setting.

Notation	Meaning
T	Set of communities
V	Set of UAVs (buyers)
E	Set of ECSs (sellers)
K	The types of tasks
Q^t	Task indicator vector of buyers
R^t	Application indicator vector of buyers
B^t	Bid vector of buyers
A^t	Ask vector of buyers
X^t	Choosing vector of buyers
Y^t	Allocation vector of sellers
$S^t_{v,e}$	Satisfaction of buyers
U^t_v	Utility of buyers
U^t_e	Utility of sellers
U^t_s	Utility of communities
Pb^t	Payoff of winning buyers
Ps^t	Payment of winning sellers
N^t	The number of winning pairs
V^t_{win}	Set of winning buyers
E^t_{win}	Set of winning sellers

Furthermore, the binary decision variables $q^t_{v,k}$ and $r^t_{u,k}$ are defined in (10) and (11), which are mentioned in the network structure part, are derived to indicate whether the task k of UAV v has to be offloaded and whether the app k of ECS e is idle, respectively.

$$q^t_{v,k} = \begin{cases} 1, & \text{if the task } k \text{ of UAV} v \text{ need to be excuted,} \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

$$r^t_{e,k} = \begin{cases} 1, & \text{otherwise,} \\ 0, & \text{if the app } k \text{ of ECS} e \text{ is idle,} \end{cases} \tag{11}$$

where $q^t_{v,e} = 1$ means the task k of the UAV v needs to be executed, if $q^t_{v,e} = 0$, otherwise. Similarly, $r^t_{e,k} = 0$ means the app k of the ECS e is idle, if $r_{e,k} = 1$, otherwise.

To achieve efficient communication, for each UAV, it is necessary to submit a reasonable bid according to the QoS of the tasks. We use satisfaction functions rather than random numbers to determine the bid of UAVs. Meanwhile, the asking price reflects the seller's real cost due to offer applications. Only telling the truth may generate more revenue for both buyers and sellers.

For buyers, it would not be possible to get more benefits by increasing the bids since a higher bid means more payment given to the sellers. If the bid is more than the true value of the tasks, the buyer's revenue would be negative. On the contrary, if the buyer decreases the bid, it could lose the opportunity to join in the trading. Accordingly, we assume the bid from buyer v to seller e is denoted as $b^t_{v,e}$, which is given by satisfaction $S^t_{v,e}$. Therefore, basing the buyer's bid submission approach on its real valuation is the best course of action. Therefore, the bid of the buyer v is the same as the valuation of the task $val^t_{v,e}$ in the auction model.

For sellers, the best value of the asking price a^t_e is the same as the real cost of a computing or communication task c^t_e. No seller could get more benefit from improving or reducing its ask price because the higher ask price could make it be refused by buyers, and the lower ask price would make its revenue less than the real cost of itself.

In addition, the payment provided by the buyer to the seller and the payoff received by the seller are defined as $Pb^t_{v,k}$ and $ps^t_{e,k}$, respectively. In the following, several key definitions of double auction could be given.

Definition 1: (***The Utility of UAV*** u): *The utility of UAV v in the community t is defined as the difference between the valuation of tasks and the payment. Thus, the utility of the UAV v (buyer) can be described as*:

$$U^t_v = \sum\nolimits_{\forall e \in E} \sum\nolimits_{\forall k \in K} \left(val^t_{v,e} - pb^t_{v,k}\right) x^t_{v,e} y^t_{e,v} q^t_{v,k}. \tag{12}$$

In (12), for the buyer v,the utility is mainly determined by the difference between true valuation $val^t_{v,e}$ and payment $Pb^t_{v,k}$. If the price disparity is negative, the update utility via completing tasks would be negative as well. It means that the buyer will refuse the service.

Definition 2: (***The utility of ECS***e): *The utility that ECS e in the community t obtains by providing service is denoted as the difference between the payoff received and the cost. Thus, the utility of ECS e (seller) can be expressed as below*:

$$U^t_e = \sum\nolimits_{v \in V} \sum\nolimits_{\forall k \in K} (ps^t_{e,k} - c^t_e) x^t_{v,e} y^t_{e,v} r^t_{e,k}. \tag{13}$$

Definition 3: (***Social Welfare***): *The social welfare of a community is the key index for evaluating the effectiveness of a system. In the paper, the social welfare of the community t is defined as follow*:

$$U^t_s = \sum\nolimits_{\forall u \in U} U^t_u + \sum\nolimits_{\forall e \in E} U^t_e. \tag{14}$$

C. PROBLEM FORMULATION

In this work, we consider the task and app matching problem in edge server-assist UAV networks to maximize. To enhance both the social welfare of the whole community and the union completion rate of tasks.

Firstly, the utility of the whole community is the same as the social welfare, which is regarded as an indicator of evaluating the performance of auction schemes. Specifically, the whole utility of communities is determined by every community's social welfare, which is inflected by the sum of the utility of both buyers and sellers located in the community. Therefore, choosing a suitable matching strategy to form pairs between buyers and sellers may enhance the social welfare of each community. Moreover, total social welfare would be improved.

Secondly, we focus on how to increase the completion rate of tasks, which is determined by the number of matching pairs. We define the task completion rate of UAVs and the app completion rate of ECSs, respectively. And then the completion rate of tasks is denoted. Considering the community t, the task completion rate of UAVs, η_v^t, and the application completion rate of ECSs, η_e^t, can be represented by (15) and (16), respectively.

$$\eta_v^t = \frac{\sum_{e\in E}\sum_{v\in V}\sum_{k\in K} y_{e,v}^t * x_{v,e}^t * q_{v,k}^t}{\sum_{v\in V}\sum_{k\in K} q_{v,k}^t}, \tag{15}$$

$$\eta_e^t = \frac{\sum_{v\in V}\sum_{e\in E}\sum_{k\in K} x_{v,e}^t * y_{e,v}^t * r_{v,k}^t}{\sum_{e\in E}\sum_{k\in K} r_{e,k}^t}, \tag{16}$$

In (15) and (16), the denominator represents the total number of tasks of UAVs that desire to be processed and the total idle applications of ECSs, respectively. Meanwhile, the numerator is the number of tasks that are executed by ECSs and the number of applications occupied by UAVs, respectively. In the article, both completion rates are used to indicate the effectiveness of the system. The union task completion rate, which is determined by the number of successful tasks and the number of apps allocated, is given by:

$$\eta^t = \sigma\eta_v^t + (1-\sigma)\eta_e^t. \tag{17}$$

Where σ is the weight factor of the completed rates that is related to the difference between the task completion rate and the app completion rate. The goal of task offloading is to increase both the social welfare of the whole community and the union completion rate of tasks. For the community t, U_s^t represents social welfare and η^t represents the union task completion rate. We also consider the task completion rate as the ratio of offloading tasks. To maximize the income of community t is to maximize the result of social welfare multiplied by the ratio of offloading tasks. Therefore, the problem we want to solve is repressed as below:

$$\max_{\mathbf{x},\mathbf{y},\mathbf{Q},\mathbf{R}} \sum_{t\in T} U_s^t \eta^t, \tag{18}$$

$$s.t.\ \sigma \in (0,1), \tag{18a}$$

$$x_{v,e}^t, y_{e,v}^t, q_{v,k}^t, r_{e,k}^t \in \{0,1\}, t \in \mathrm{T}, \tag{18b}$$

$$\mathbf{x} = \{x_{v,e}^t, \forall v \in V, e \in E, t \in T\}, \tag{18c}$$

$$\mathbf{y} = \{y_{e,v}^t, \forall e \in E, v \in V, t \in T\}, \tag{18d}$$

$$\mathbf{Q} = \{q_{v,k}^t, \forall v \in V, k \in K, t \in T\}, \tag{18e}$$

$$\mathbf{R} = \{r_{e,k}^t, \forall e \in E, k \in K, t \in T\}, \tag{18f}$$

$$\forall v \in V, e \in E, val_{v,e}^t = b_{v,e}^t, c_e^t = a_e^t, \tag{18g}$$

$$\forall e\in E, k\in K, 0 \le \sum_{e\in E}\sum_{k\in K} x_{v,e}^t * y_{e,v}^t * r_{v,k}^t < Kl, \tag{18h}$$

$$\forall v\in V, k\in K, 0 \le \sum_{v\in V}\sum_{k\in K} y_{e,v}^t * x_{v,e}^t * r_{v,k}^t < Kl. \tag{18i}$$

Where the constraint (18a) can ensure that the value of the completion rate is between 0 and 1. In the constraint (18b), $x_{v,e}^t, y_{e,v}^t, q_{v,k}^t$ and $r_{e,k}^t$ are the binary decision variables, where $x_{v,e}^t$ is used to indicate whether the ECS is chosen by UAV as its partner, and $y_{e,v}^t$ is leveraged to indicate the ECS will allocate its resource to UAV to process tasks, $q_{v,k}^t$ denote whether the task k of UAV needs to be solved, and $r_{e,k}^t$ denote whether the app of ECS is idle. In addition, constraints (18c) and (18d) describe the decision $\mathbf{x}^t$ and $\mathbf{y}^t$ are related to the binary decision variable $x_{v,e}^t$ and $y_{e,v}^t$, respectively. The constraints (18e) and (18f) denote the number of tasks of the UAVs and the number of apps of the ECSs. Constraint (18g) can ensure each bid and ask price are based on UVA's satisfaction and true valuation of the resource by edge service. Furthermore, in the constraint (18h), although multiple bids are submitted by the UAV v, each task can win only one ECS at most. It means that the total number of successful tasks for UAV v could not be above Kl. Constraint (18i) can ensure no more than Kl tasks can be received by every ECS.

The optimization problem in (18) with the corresponding constraints (18a) - (18i) is a mixed-integer programming problem [31], which is an NP-hard problem that could not be solved by a polynomial algorithm. Because the weight factor σ is not the important factor, we let $\sigma = 0.5$. The problem is still hardly solved by the enumeration method. The branch and bound (BB) algorithm, proposed by Land and Doig [36], has been widely used to solve mixed-integer programming problems. However, determining the appropriate bound is hard in multi-task and multi-player scenarios in the MEC network at this stage. Meanwhile, we notice that it is similar to the multiple knapsack problem.

IV. MATCHING MECHANISM

To solve the optimization problem described in (18), we divided the problem into two sub-problems: (1) the double auction problem for determining the winning pairs and trading price by maximizing the social welfare; and (2) the auction loser matching problem for improving the task completion rate. Furthermore, security and privacy need to be considered. Therefore, we propose a smart contract-based joint matching mechanism that combines double auction and auction losers' secondary selection to solve the optimization subproblems, respectively. The joint mechanism is presented in Section IV-A. The satisfaction generation method (SGS) is proposed in Section IV-B. And then, we give out a satisfaction-breakeven-based double auction to maximize the social welfare in Section IV-C. Finally, we match more tasks from auction losers to improve the task completion rate using the auction losers' secondary selection schemes named SD and LD, which are given in Section IV-D.

A. SMART CONTRACT-BASED JOINT MECHANISM

Edge computing tasks cannot be carried out without any security precautions since edge servers could simply leak or tamper with any information generated while trading. Our suggested solution, which is expressed in a smart contract, incorporates blockchain technology to address the issue. The method's execution is depicted in Fig. 2, and the specifics are given as follows:

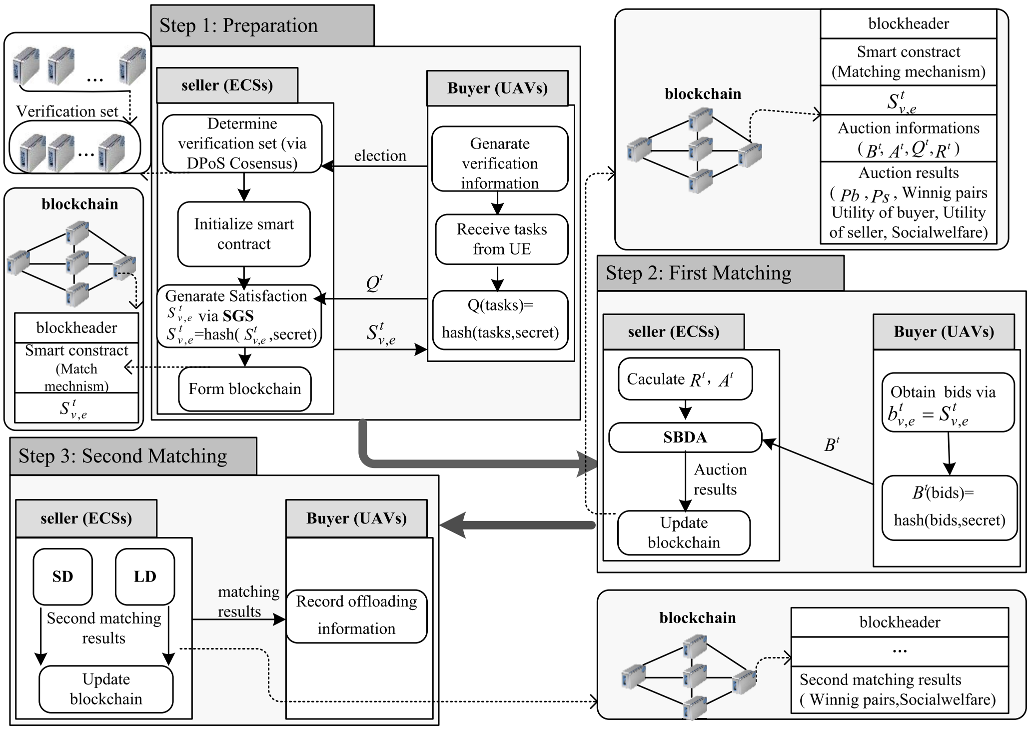

FIGURE 2. Overview of the proposed twice-matching method that considers satisfaction and using blockchain.

1) STEP1 (PREPARATION)

First of all, the buyer UAVs, as well as the token holders, elect the honest edge servers as blockchain nodes. The verification set of sellers is formed using DPOS (Delegated Proof of Stake), which is an improved consensus mechanism to ensure the effective running of networks. Each verifier elected by buyers will perform the match process. Meanwhile, buyers receive the tasks from the user equipment to form the task indicator vector Q^t.

And then, sellers' ECSs determine the satisfaction $S^t_{v,e}$ via SGS (satisfaction generating scheme), which calculates the satisfaction according to the channel quality and the number of tasks. $S^t_{v,e}$ is not only stored in block nodes but also encrypted and given back to the buyer. For buyers, the task indicator vector Q^t encrypted is sent to sellers.

2) STEP 2(FIRST MATCHING)

After receiving the satisfaction value, buyers will decrypt the value $S^t_{v,e}$ and make it equal to the bids. Through encrypting the bids, we get the bid matrix B^t, which is also sent to the seller. Meanwhile, the sellers first calculate the asking price A^t and app indicator vector R^t. And then, the first matching is executed by SBDA to find suitable buyers and sellers to achieve maximum social welfare. Auction results that include the payment and payoff price, the winning pairs, and the utility of the buyer and seller are stored in blockchain nodes as smart contracts.

3) STEP3 (SECOND MATCHING)

Because the bid of buyers and the asking price of sellers may be lower or higher than the average ask price, respectively, some tasks are ignored after SDBA executes the first matching. There is a possibility to enhance the number of successful tasks by finding more tasks from auction losers. The prices that are determined by SBDA could be used as input parameters in the second matching. Therefore, we introduce the auction losers' secondary selection schemes, the shortest distance (SD) scheme, and the largest difference (LD) scheme, to improve the number of tasks processed in the networks. After that, the results are also stored on blockchain nodes in the form of a smart contract. The matching results are sent back to buyers.

B. SATISFACTION GENERATING

In edge computing, a task offloading scheme considering the service satisfaction of users could motivate buyers to join in matching to improve their utilities. Because it is a true representation of the will for buyers to submit bid prices according to their satisfaction. Firstly, UAVs send task requests received for UEs (user equipment) to edge servers. And then, the edge server calculates the path loss, the achieved transmission rate, and the transmitting latency by eq. (1)-(5). At last, the satisfaction values for UAVs, which are associated with the channel quality and the number of tasks, are determined by eq. (6)-(7). Higher channel quality would lead to higher satisfaction, which means a higher bid

Algorithm 1 Satisfaction Generating scheme (SGS)

Input: Q^t, Vl, El, Kl, h, $w^t_{v,e}$, f_c, f_e, P, N_o, L_k, εt, $T_{thr,k}$;
Output: $S^t_{v,e}$;

Calculate the pathloss between UAVs and ECSs using eq. (1);
for each UAV **do**
  for each ECS **do**
    Calculate the interference between UAVs and ECSs using eq. (2) - (3);
    Determine the achieved transmission rate per unit bandwidth $Rate^t_{v,e}$ using eq. (4);
   for each task **do**
    Determine the latency of every task using eq. (5);
    Determine satisfaction of each task using eq. (6);
    Obtain total satisfaction of UAV $S^t_{v,e}$ using eq. (7) according to Q;
   end for
  end for
end for
return

price. Meanwhile, the buyer would submit a higher bid price if there were more tasks to be processed. Algorithm 1 gives us more details about the scheme.

C. SATISFACTION BREAKEVEN-BASED DOUBLE AUCTION

The breakeven-based double auction technique is first described in this part, along with details on how to perform the matching of buyers and sellers and how to calculate the payoffs given by the buyer and the payment received by the seller. The individual logic, financial stability, and veracity of the suggested SBDA scheme will next be demonstrated.

The SBDA is carried out in two steps, which are as follows: Choosing the best buyers and sellers from the candidate sets is step one, and step two is the selection of the winning buyers and sellers from the candidate sets.

To determine the buyer set and the seller set, we first sort the ask prices in ascending order, which is shown as A^a (line 1 in Alg. 2), and obtain the median asking price $\bar{a}$, which is also the breakeven point (line 2 in Alg. 2). Only asking price less than $\bar{a}$ are retained. Secondly, the original bid matrix, B, is determined by the satisfaction of UAVs, which is given by the Satisfaction Generating Scheme.

Only elements of $B(b_{v,e})$ greater than the breakeven point $\bar{a}$ could be retained, other elements would be ignored. Therefore, the bid matrix of candidate UAVs, B_r, may be determined (line 4 in Alg. 2). In the winning buyer-seller pair decision part, we first pick out the maximize element of B_r, which is regarded as $b^{\max}_{v,e}$, whose row is buyer v, and col is seller e. And then, the task of buyer v, q_v,would be obtained from Q (lines 5- 7 in Alg.2).The winning buyer may obtain one or more sellers. On the condition that the buyer v only obtains the seller e, the winning seller e is set as $e*$. For

Algorithm 2 Satisfaction Breakeven-based Double Auction mechanism (SBDA)

Input: B^t, A^t, R^t, Q^t, Kl
Output: V^t_{win}, E^t_{win}, Pb^t, Ps^t, B^t, A^t, R^t, Q^t, $U^t_v U^t_e$, U^t_s, N^t

1: Sort the elements in A in ascending order: $A^a = \{a_{e_1}, a_{e_2}, \ldots a_{e_{El}}\}$;
2: Calculate the median ask price of seller, which is regarded as $\bar{a}$;
3: Determine ask price of ECS candidate: $A_r = A^a \backslash \{a_{e_{av+1}}, a_{e_{av+2}}, \ldots a_{e_{El}}\}$;
4: Determine the bid matrix of candidate UAVs: B_r, according to $b_{v,e} > \bar{a}$;
5: **while** $b^{\max}_{v,e} > \bar{a}$ **do**
6: Find the maximum element of B_r, which is regarded as $b^{\max}_{v,e}$, whose row is buyer v, and col is seller e;
7: Obtain the tasks of buyer v from Q^t;
8:   **for** each task k **do**
9:   **if** buyer v only wins one seller **then**
10:    $e* = e$, $e*$ is the winning seller;
11:    Compare with other buyer's bids whose tasks including k, find the highest losing bid, $pb^t_{v_i,k}$, which is regarded as payoff;
12:   **else** buyer v wins more than one seller **then**
13:    List candidate seller set;
14:    finding the maximum value of the highest losing bid of candidate sellers to determine the best seller $e*$ and the highest losing,bid, $pb^t_{v,k}$;
15:   **end if**
16:   Update X^t, Y^t according to eq. (8) - (9);
17:   Update Q^t, R^t according to eq. (10) - (11);
18:   Update the number of winning pairs $N^t = N^t + 1$;
19:   Update Payoff of winning buyers: $Pb^t = Pb^t \cup pb^t_{v_i,k}$;
20:   Find the payment price received by seller $ps^t_{e*,k} = \bar{a}$, then $Ps^t = Ps^t \cup ps^t_{e*,k}$;
21:   Update the utility of buyers U^t_v and U^t_e using eq. (12)-(13);
22:   Update the social welfare: U^t_s using eq. (14);
23:   **If** $v \notin V_{win}$ **then**
24:    $V_{win} = V_{win} \cup v$;
25:   **end if**
26:   **If** $e \notin E_{win}$ **then**
27:    $E_{win} = E_{win} \cup e*$;
28:   **end if**
29:   **end for**
30: Updating B_r;
31: **end for**
32: **return** V^t_{win}, E^t_{win}, Pb^t, Ps^t, B^t, A^t, R^t, Q^t, $U^t_v U^t_e$, U^t_s, N^t

each task of the buyer, we may assign the second-highest bid of candidate buyers as the payoff price $pb^t_{v,k}$ (lines 9-11 in Alg. 2). The highest losing price regarded as a payoff has been used in related work [22].

On the condition of more than one seller, the buyer v obtains more than one seller. We first list the candidate seller set. Secondly, for each task of the buyer, through finding the maximum difference between each candidate seller's ask and every competition buyer's bid to confirm the best seller $e*$ that will help the buyer achieve the highest utility (lines 12-15 in Alg. 2). Simultaneously, $ps^t_{e*,k}$ is regarded as $\bar{a}$, the utility of buyers and sellers, the choosing/allocation vector, admission the number of tasks N^t, task indicator matrix Q and app indicator matrix R, the winning buyer set V_{win} and seller set E_{win} are all Updating (lines 16-27 in Alg. 2). Subsequently, we remove the bids of the buyer (set the value of it to 0: $b^t_{v,e} = 0$) whose task has been processed and repeat the above matching progress.

In the following, we will prove the proposed SBDA is not only individually rational but also budget-balanced and truthful.

Lemma 1: SBDA is individually rational.

Proof: After the auction, if each buyer and seller will benefit, it means that the proposed SBDA mechanism is individually rational.

For each buyer, there are two choices: 1) Joining in the trade. In this situation, the payoff price is the highest losing, which is equal to or less than the bid. Therefore, the difference between bid and payoff (such as: $b^t_{v,e} - pb^t_{v,k}$) is always greater than or equal to zero. 2) Rejected by the auctioneer. If the buyer loses the chance to take part in the trade, it means that its bid is smaller or that no task needs to be processed. In this situation, the buyer pays nothing, and its utility is zero.

For each seller, there are also two situations: 1) Joining in the trade. If the asking price of the seller is lower enough ($a_{e*} \leq \bar{a}$), the payoff of $e*$ is equals to $\bar{a}$. Therefore, the utility is always greater than zero. 2) Rejected by the auctioneer. It indicates that the vendor lost the auction and that there is no utility. In conclusion, SBDA is individually rational.

Lemma 2: SBDA satisfies budget-balanced.

Proof: The auction is regarded as satisfying budget-balanced under the condition that the total payback of all buyers is larger than or equal to the total payment of sellers. The payout for each successful buyer is the highest lost bid, which is higher than $\bar{a}$. Meanwhile, for each winning seller, the payment is $\bar{a}$. The sum of the payoff is greater than the sum of the payment ($\sum\limits_{v_i \in E_{win}} pb^t_{v_i,k} > \sum\limits_{e_j \in E_{win}} ps^t_{e_j,k}$). Therefore, the proposed SBDA scheme satisfies budget-balanced.

Lemma 3: SBDA obeys truthfulness.

Proof: Monotonicity and criticality are crucial in demonstrating an auction's veracity. On the one hand, with the enhancement of the bid, the buyer may have a better chance of being accepted by the seller. Hence, our proposed SBDA mechanism is monotonic. However, because the payment price is equal to the highest losing bid, no further profit will be generated immediately if the bid exceeds the highest losing bid. The utility of the buyer will not change, and the highest losing bid is going to be a critical point. On the other hand, for sellers, a higher ask price means a lesser winning chance and a lower ask price means more possibilities accepted by the auctioneer. It is in accord with the monotony. Nonetheless, the payment of the winning seller $e*$ is $\bar{a}$ and the difference between payment and ask price is unchanged. It means a greater ask could bring no more utility for the seller, and the critical point exists. Consequently, the best strategy for both buyers and sellers is, to tell the truth. It means the bid and asking prices submitted by buyers and sellers must reflect their true demands. In our proposed SBDA auction, submitting a bid is equal to the satisfaction which denotes the true valuation of the buyer, such as $b^t_{v_i,e_j} = S^t_{v_i,e_j}$. For every seller, the asking price is its true will. Therefore, SBDA follows truthfulness.

D. AUCTION LOSER SECOND SELECTION SCHEME

The task completion rate, which considers both the number of successful tasks of UAVs and the number of applications of ECSs, is a significant indicator of system effectiveness. To enhance the union completion rate of tasks, the second selection schemes, SD (shortest distance) matching and LD (largest difference) matching methods based on auction losers are proposed.

Algorithm 3 SD (Shortest Distance)

Input: $B^t, A^t, R^t, Q^t, dist^t, Kl, U^t, N^t, Pb^t, Ps^t$
Output: N^t, U^t, Q^t, R^t

```
for each task k do
    Determine candidate sells whose app k is idle;
    Determine candidate buyers whose task k is unaccepted;
    for each candidate sells e do
        determine the buyer v,whose distance to the candidate seller e is minimum and the difference between buyer and sell is positive;
        update Q^t, R^t;
        update: N^t = N^t + 1;
        update: U^t = U^t + (B^t(v,k) - A^t(e)) + (pb^t_{v,k} - ps^t_{e,k});
    end for
end for
return N^t, U^t, Q^t, R^t
```

In the SD matching scheme, as shown in Alg. 3, every losing buyer selects ECS nearby to process its task k. The matching method is based on which seller is the nearest one whose app k is idle. In the other scheme, LD matching, as shown in Alg. 4, distance is not the key factor in selecting the buyer-seller pairs. We focus on the difference between bids and asks obtained by a double-based auction. By finding out the largest difference between the ask and bid of losers to find more matching pairs from buyers and sellers. Both schemes obey the un-decreasing utility rule, so there is no social welfare reduction due to the introduction of the second matching method.

Algorithm 4 LD (Largest Difference)

Input: B^t, A^t, R^t, Q^t, $dist^t$, Kl, U^t, N^t, Pb^t, Ps^t
Output: N^t, U^t, Q^t, R^t

```
for each task k do
    Determination candidate sells whose app k is idle;
    Determination candidate buyers whose task k is unaccepted;
    for each candidate sells e do
        determine the buyer v, the difference between whose bid price and the candidate seller e's ask price is maximum;
        update Q, R;
        update: N^t = N^t + 1;
        update: U^t = U^t + (B^t(v, k) − A^t(e)) + (pb^t_{v,k} − ps^t_{e,k});
    end for
end for
return N^t, U^t, Q^t, R^t
```

V. SIMULATION RESULTS AND ANALUSIS

A. SIMULATION PARAMETERS

To analyze the performance of the proposed joint mechanism, we consider a UAV-assisted network with three communities. Considering the limited battery capacity, the range of communication transmission is limited. Every community includes a hovering zone with several flying UAVs ($UAV \in [5, 50]$) and an edge server zone (a circle area, radius $r = 0.2km$) with several ECSs ($ECS \in [5, 50]$).

As seen in Fig. 3, in community 1, 20 ECSs are deployed on an edge server with UAVs hovering over the area. We assume the location of ECSs is generated randomly in the edge server zone with a uniform distribution.

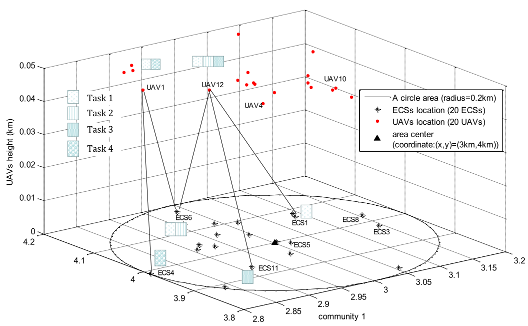

FIGURE 3. Simulation network scenario.

Meanwhile, all the UAVs are flying at a fixed height ($h = 50m$) in a hovering zone with uniform distribution too. For both ECSs and UAVs, task types are considered 4, 6, 8 and 10, respectively. In the last section, to observe how the strategy improves system performance over time, we assume the probability of UVA arrivals following a Poisson distribution and consider one minute as a timeslot. Thus, one day is divided into three periods based on the number of UAV arrivals. The first period is from 0 am to 6 am, the second period is from 6 am to 6 pm, and the third period is from 6 pm to 0 am.

TABLE 2. Parameters of the proposed mechanism.

Symbol	Parameter	Value
f_c	Carrier frequency	2GHz
f_e	Carries bandwidth	20MHz
N_o	Gaussian noise power	10^9W
P	Transmit power of Each UAV	5W
$Tcomp$	Computing time	0.1ms
L_k	Data size per task	300k, 300k, 400k, 500k
$T_{thr,k}$	Threshold of latency per task	2ms, 4ms, 4ms,5ms
σ	Weight factor of the completed rates	0.5
r	Radius of edge server zone	0.2km
h	Flying height of UAV	50m
λ_{time}	Expectation and variance of Poisson distribution of UAVs arrival	5, 25, 45

The expectation and variance of Poisson distribution of UAV arrivals for different periods, λ_{time}, are set as 5, 25 and 45, respectively. The related simulation parameters are described in Table 1.

To illustrate the effectiveness of the proposed joint mechanism, satisfaction breakeven-based double auction and second selection (SBDA+LD), We contrast the procedure with the methods that are given below:

- TIM (truthful incentive mechanism): The method includes two stages, candidate determination and pricing and candidate elimination, respectively. Because the mechanism only considers a single task, through auctioning, every winning buyer has a one-to-one mapping with only one seller. It will result in a small number of winning pairs. This auction mechanism may be suitable for a single-task scenario.
- Only BDA: The mechanism is widely used in multi-buyer and multi-seller matching problems to enhance system utility. Without considering the satisfaction of the buyer, buyers could submit higher bids, which are beyond their true value, to offload more tasks in multi-task networks.
- SBDA: To submit a true bid to realize the auction, we propose a BDA scheme considering the satisfaction of buyers by the SGS algorithm, which has been described in Algorithm 1.
- SBDA+SD: After executing the SBDA auction, we offload more tasks by finding the shortest distance between the locations of loser sellers and buyers. In the meantime, the winning pairs obtained by the second matching scheme need to obey the rule of non-negative utility.

B. INDIVIDUAL RATIONALITY AND BUDGET-BALANCE

With the change in the number of winning pairs, the changes in bids, payoffs, payments, and asks are shown in Fig. 4. No matter how many successful pairs there are in the system.

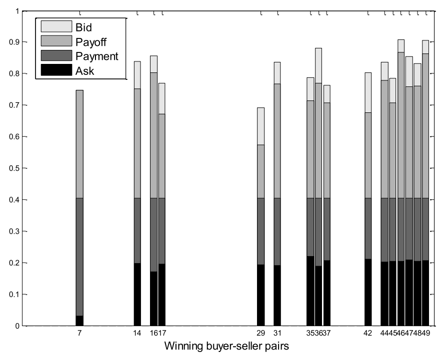

FIGURE 4. Individual rationality and budget balance.

We can see that the reward for each successful buyer is always lower than their bid, while the payoff for each successful sale is always higher than their asking price. Consequently, the proposed satisfaction-breakeven-based auction mechanism is based on individual rationality. Additionally, winning sellers received less money overall than winning buyers demanded overall. Therefore, the SBDA mechanism ensures a balanced budget. Hence, through the double auction, a reasonable payoff and payment are determined. Meanwhile, the winning buyer-seller pairs are selected from the candidate buyers and sellers as well. Hence, the results show that the proposed mechanism is individual rationality and budget balance.

C. TRUTHFULNESS

We select several buyers and sellers to observe how their utilities change as their bids and asking prices change. For instance, the red marker designated as the key point in Figures 5(a) and 5(b) represents the correct valuation. For buyer 9, the point appears when the bid is 0.8474. When the bid price is less than the value, the buyer will lose the accepted chance, and its utility is zero. When the bid is greater than 0.8474, no matter how to enhance the bid, the utility is equal to 0.1306. For seller 14, the critical point appears when the asking price is 0.2726 and the utility is 0.0941. Similar to the buyer, when the asking price is lower than its true valuation (0.2726), the seller will always win. However, its utility does not increase as the asking price decreases. The seller will lose the auction and its utility is zero if the asking price exceeds the critical point value. It indicates that neither a buyer nor a seller could increase or decrease the bid or the asking price to make themselves more useful. Therefore, the results show the proposed mechanism is truthfulness.

D. EFFECTIVENESS ANALYSIS OF PROPOSED MATCHING MECHANISM

In this part, we present the system's effectiveness by comparing the proposed joint matching mechanism SBDA+LD with SBDA, SBDA+SD, and baseline scheme TIM and BDA.

Firstly, we observe the change in the utility of buyers (UAVs) and sellers (ECSs) with the introduction of the user satisfaction function. The total utility of UAVs utilizing the

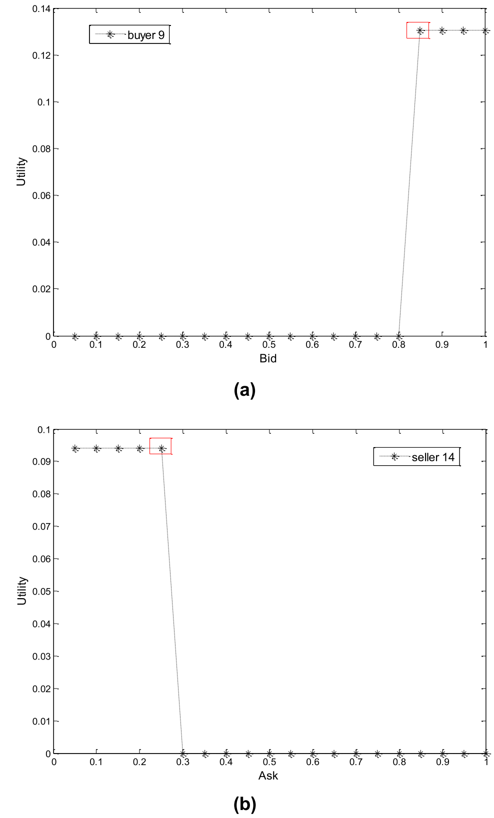

FIGURE 5. Truthfulness of buyers and sellers. (a) Buyer $V_i \in V_{win}$. (b) Seller $e_j \in E_{win}$.

SBDA method is shown in Fig. 6(a) to be comparatively steady. This is because the number of ECSs (20 ECSs) remains constant while the number of UVAs is increasing from 5 to 50.

Because the BDA, without considering user satisfaction, will make the UAV submit a greater bid to obtain the chance of acceptance, it results in a greater bid that may be beyond the buyer's true value. Thus, with the increasing number of UAVs, more tasks of buyers with exorbitant bids (for the buyer, the payoff price is greater than the true value) will be offloaded. It means the total utility of buyers will decrease.

In addition, with the increasing number of buyers, more competitors joining the auction leads to a lower difference between the bid price and the highest losing. It implies that when the number of buyers rises, their overall utility may decline. Due to the same ask price rule, Fig. 6(b) shows us that the total utility of sellers is similar for both SBDA and BDA, with the amount of UAV increasing. The number of unused ECS apps is constant because the number of sellers is fixed (20 ECS).

When the number of UAVs approaches 30, the number of jobs offloaded by ECSs will rarely rise due to the restricted processing power of these systems. Meanwhile, the payment price received by the seller is defined as the average ask; hence, the asking price is defined relatively simply. But the bid is only slightly smaller than the highest losing bid. As a result, the buyer experiences less disparity between the task

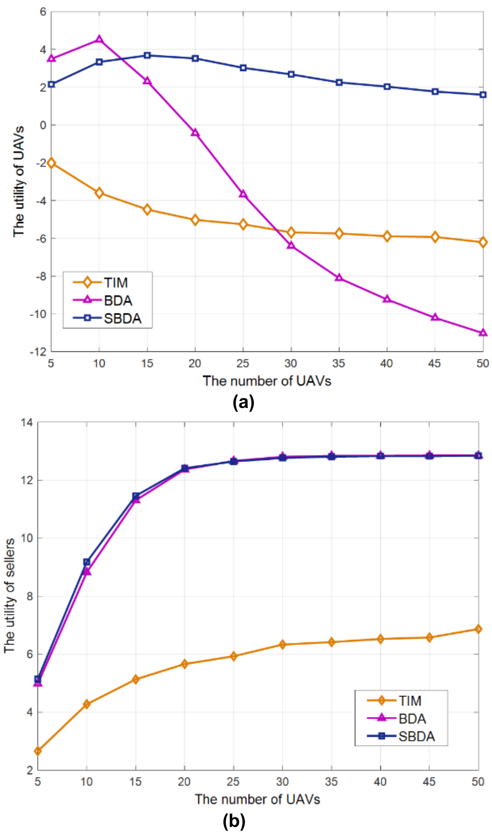

FIGURE 6. The utility of UAVs and ECSs. (a) Fixed number of ECSs. (b) Fixed number of UAVs.

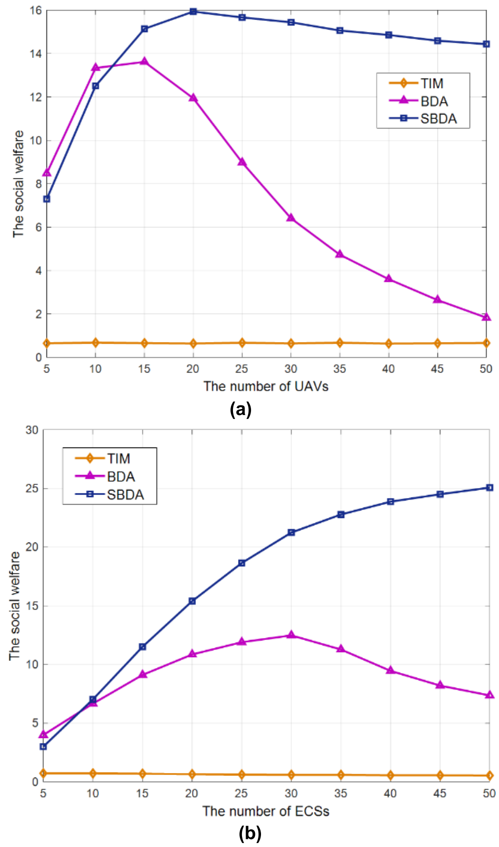

FIGURE 7. Comparison the difference of social welfare under scenario of fixed number of ECS and fixed number of UAV, respectively. (a) Fixed number of ECS. (b) Fixed number of UAV.

assessment and the payoff. Additionally, the gap between the price paid and the actual cost is typically larger for the seller.

It implies that each buyer's utility is often lower than each seller's utility. Besides, because the TIM algorithm only considers the single-task offloading problem, the utility of buyer and seller is relatively lower than in the other two schemes.

Secondly, we present social welfare, the average completion rate of tasks, and the total number of winning pairs under two scenarios: a fixed number of ECSs (20 ECSs) and a fixed number of UAVs (20 UAVs). In Fig. 7, due to only considering the single task, the social welfare of each community using TIM is the lowest. In Fig. 7(a), the social welfare of BDA increases first, and then it decreases after the number of UAVs exceeds 15. Since the number of ECSs is fixed at 20, offloading more tasks without considering their true value would lower the utility of the buyer. It results in lower social welfare compared with SBDA. For SBDA, social welfare increases when the number of UAVs is smaller than 20. Once beyond 20, more UAVs could not bring more revenue. In Fig. 7(b), because the number of UAVs is fixed (total tasks are unchanged), more ECS deployed in the system means more candidate sellers. Through BDA, UAVs may choose as many suitable partners as possible to offload their tasks. As we have seen, the social welfare of SBDA increases faster than that of BDA. In addition, when the number of ECSs goes beyond 30, the social welfare of BDA decreases because more buyers with exorbitant bids join in the trading.

The number of winning pairs is shown in Fig. 8. It can be seen that more pairs appear when more UAVs or ECSs join our system. When there are 50 UAVs, as shown in Fig. 8(a), the proposed SBDA+LD and SBDA+SD methods each produce roughly 46.48% and 46.02% more winning pairings than SBDA. In Fig. 8(b), with the number of ECSs increasing, more candidate computing resources provide more matching chances. Since the number of tasks for UAVs is fixed, more computing resources result in more winning pairs. The winning pairs obtained by SBDA+LD and SBDA+SD improve more rapidly than SBDA. When the number of ECSs is about 50, the winning pairs are almost close to the same value. Besides, the greatest advantage of the joint mechanism appears when the number of ECSs is similar to the number of UAVs.

In Fig. 9, the average completion rate of tasks and apps in each community is the lowest using TIM. The joint matching mechanisms (SBDA+LD, SBDA+SD) have excellent performance. SBDA+LD and SBDA+SD obtain similar average completion rates, which are greater than BDA and SBDA.

In Fig. 9(a), when a few tasks are needed to be offloaded, almost all of those tasks will be offloaded. It means that

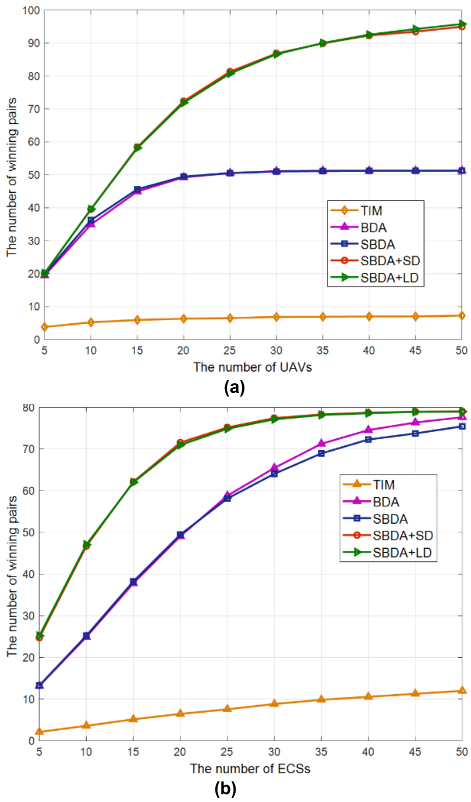

FIGURE 8. Comparison the difference of the number of winning pairs under scenario of fixed number of ECS and fixed number of UAV, respectively. (a) Fixed number of ECSs. (b) Fixed number of UAVs.

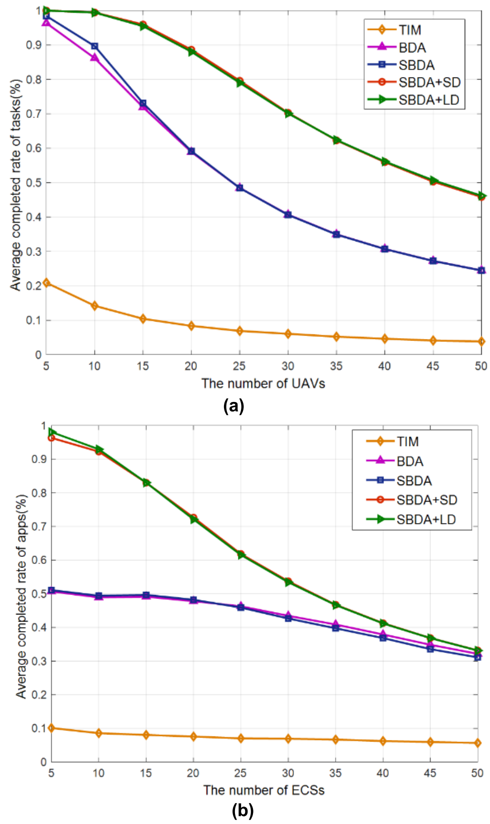

FIGURE 9. Comparison the difference of average completed rate of tasks and apps under scenario, respectively. (a) Fixed number of ECSs (b) Fixed number of UAVs.

the average completion rate of tasks is close to 100%. With the increasing use of UAVs, the completion rate of tasks in SBDA+LD is slightly higher than in SBDA+SD. When the number of UAVs is about 20 to 35, the maximum difference in completion rate appears between SBDA+LD and SBDA. The average completed rate of tasks goes up to 37.5% higher than using SBDA. In Fig. 9(b), for SBDA, the completed rate of apps is close to 50% when a few buyers exist in the system. This means that about half of the computing resources could not be utilized.

For the joint matching mechanism SBDA+LD, the completed rate of apps is close to 100% because of the second matching method, which executes the secondary matching from the auction loser.

All the results shown above mean the proposed joint matching mechanism, considering the secondary selection, has a significant influence on task offloading utilization and social welfare when the number of ECSs is less than or equal to the number of UAVs. Hence, it is practical and significant to use our proposed matching scheme to offload tasks in multi-task UAV networks.

Thirdly, we mainly focus on the two joint matching schemes, SBDA+SD and SBDA+LD, to analyze their system effectiveness. System effectiveness includes not only social welfare but also the union task completion rate. Fig. 10 shows the difference in system utility between SBDA+SD and SBDA+LD. When the number of UAVs is similar to the number of ECS (ECS = 20), we can find the best value point. In this situation, the system utility of SBDA+LD and SBDA+SD is 19.0766 and 18.5444, respectively. The system utility of SBDA+LD is 2.87% higher than SBDA+SD. Hence, SBDA+LD is the most superior of our proposed matching schemes (SBDA+LD and SBDA+SD).

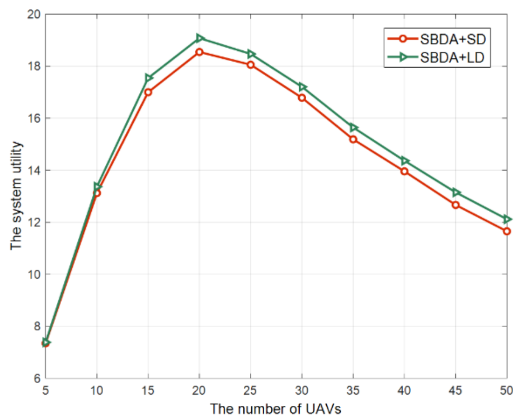

FIGURE 10. System efficiency.

At last, we discuss the overall income of the system and the number of winning pairs. Given the system, which includes three communities, in every community, the number of ECSs is unchanged (ECSs = 20) and the number of UAVs

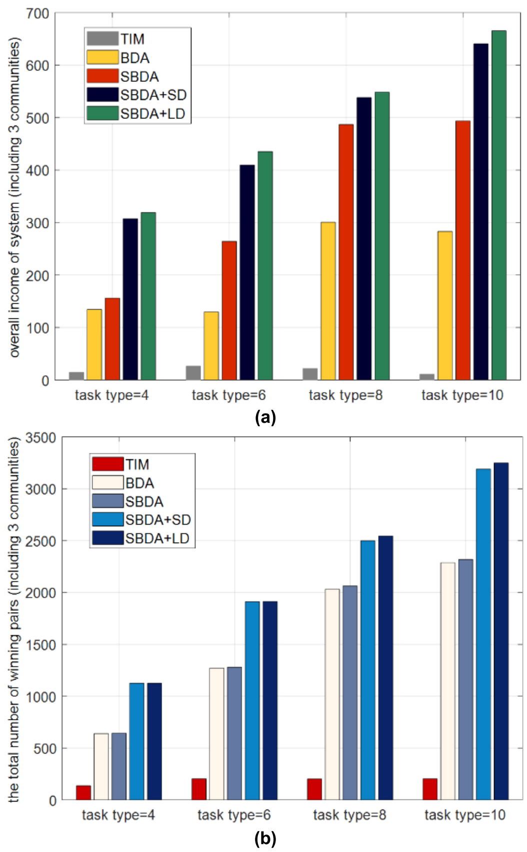

FIGURE 11. **Comparison overall income of system and the number of winning pairs (including 3 communities) under various number of task type via TIM, BDA, SBDA, SBDA+LD, SBDA+SD. (a) Overall income of entire system. (b) The total number of winning pairs.**

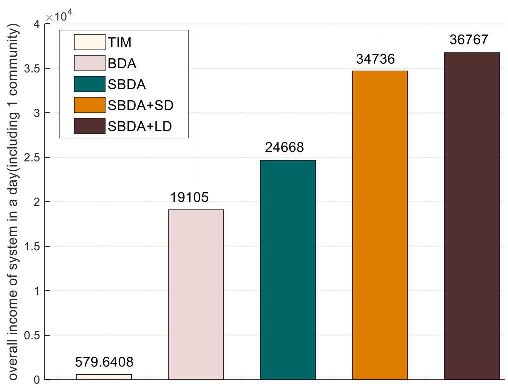

FIGURE 12. **Comparison overall income of system in a day(1440 time slots) among various methods (TIM, BDA, SBDA, SBDA+LD, SBDA+SD).**

is 5 to 50. We take the number of task types as 4, 6, 8, or 10, for example, to analyze the variation tendency of system effectiveness. Fig. 11 shows that SBDA+LD performs the best among these methods. Take task type = 10, for example. The overall incomes achieved by SBDA+LD are 5000%, 93.83%, 11.09%, and 1.90% higher than TIM, BDA, SBDA, and SBDA+SD, respectively. The total number of winning buyer-seller pairs given by SBDA+LD is 1485%, 42.06%, 40.10%, and 1.85% greater than TIM, BDA, SBDA, and SBDA+SD, respectively. We assume the probability of UAV arrivals follows the Poisson distribution and regard one minute as a timeslot. Fig. 12 shows the difference in the overall income of one community in a day under various methods. The income achieved by the SBDA+LD is 361.87%,92.45%,49.05% and 5.85% higher than TIM, BDA, SBDA and SBDA+SD, respectively.

VI. CONCLUSION

In the paper, the multi-task offloading problem in UAV-assisted MEC networks is investigated. Firstly, we build the network structure with blockchain to ensure all data is untampered and the whole process of trading is safe.

Subsequently, we propose an optimization problem to maximize the system's effectiveness, including social welfare and union task completion rates. To solve the problem, we divided it into two subproblems. An SBDA double auction scheme considering satisfaction has been proposed to solve the first matching to maximize social welfare and also determine the payoff and payment price. And then, two auction losers' secondary selection schemes that are based on the largest difference and shortest distance between loser buyers and sellers have been applied to enhance social welfare and increase the union completion rate of tasks.

The simulation results show that the proposed joint matching mechanism, especially SBDA+LD, significantly enhances the system effectiveness compared with the other four methods in multi-task UAV-assisted communication networks with only a small number of ECSs deployed.

The UAVs-assisted MEC network is suitable for multi-task IOT communication scenarios. Such as virtual reality (VR), augmented reality (AR), face recognition, and interactive gaming, which require low latency and high computation, coexist in the network. The result of this paper shows that the proposed SBDA+LD method is fit for the UAVs-assisted MEC network with only a small number of ECSs deployed. Building more ECSs means increasing costs. Therefore, the method has certain practical value. The mobility of UAVs is simplified in the paper. In the future, we expect to design a multi-task offloading method that considers the trajectory of UAVs to minimize energy consumption, reduce latency and improve the data rate in MEC networks.

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