Blockchain-based Resource Trading in Multi-UAV Edge Computing System

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***Abstract*—Unmanned aerial vehicle (UAV) assisted mobile edge computing (MEC) systems have emerged as a promising technology with the capability to expand terrestrial networks. UAVs, working as edge computing nodes and mobile base stations, can be deployed closer to user equipment (UEs). However, with the rapid increase of UEs, the scarcity of spectrum resources and computing resources has become a critical challenge for future mobile communication systems. Additionally, the inherent characteristics of wireless transmission and untrusted broadcasting pose significant security and privacy concerns for multi-UAV networks. To address these issues, this paper presents a blockchain-based resource trading mechanism (BRTM) and a double auction-based resource trading algorithm (DARA) for multi-UAV edge computing systems. It combines blockchain technology with double auction theory to ensure the security and fairness of resource trading. The relations between UEs and UAVs as a two-stage Stackelberg game is formulated and a pricing-based incentive strategy is proposed. The proposed scheme encourages active participation from both UEs and UAVs while maximizing the sum of their utilities. The security assessment and numerical outcomes show that the proposed method is effective and outperforms other benchmark schemes.**

***Index Terms*—Unmanned aerial vehicle (UAV), mobile edge computing (MEC), blockchain, resource trading, double auction theory.**

I. Introduction

A. Background

In recent years, the proliferation of mobile devices and the increasing demand for real-time and data-intensive applications have posed significant challenges to traditional cloud computing infrastructure. To address these challenges, Mobile edge computing (MEC) has emerged as a promising paradigm that brings computation, storage, and networking capabilities closer to the network edge. In MEC, user equipment (UEs) can purchase spectrum and computing resources and then offload computational tasks to a closer edge computing node for further execution. By leveraging the computational resources of edge servers, MEC reduces latency, enhances application performance, and enables the efficient delivery of services to end-users. However, terrestrial network coverage is limited in remote areas, including mountains and islands, as well as areas affected by earthquakes. In this context, unmanned aerial vehicle (UAV) assisted MEC have emerged as a promising technology with the capability to expand terrestrial networks. In this case, high-altitude platforms (HAPs) and UAVs are introduced into the system. HAPs, situated at stratospheric altitudes, possess extensive coverage capabilities and substantial payload capacities [1]–[3]. On the other hand, UAVs exhibit limited coverage, but excel in mobility and flexible deployment, making them suitable as airborne base stations and edge computing nodes [3]–[5].

Despite Multi-UAV MEC have attracted broad interests from industry and academia for various types of aerial access Internet of Things (IoT) network applications, there are still some key challenges that need to be addressed. On one hand, in UAV-assisted networks, each UAV has limited spectrum and computational resources, so it is necessary to design a reasonable joint resource trading mechanism to ensure the effective use of resources and prevent selfish behavior. On the other hand, the inherent characteristics of wireless transmission and untrusted broadcasting pose significant security and privacy issues for Multi-UAV networks. Ensuring the integrity of resource transaction information against tampering is thus a critical aspect that necessitates careful consideration within such a system.

Focusing on improving resource utilization and fairness of transactions, auction theory has been used to solve the resource transaction problem of wireless networks in recent years. Auction theory serves as the fundamental mechanism for the allocation of resources, price determination, and decision-making processes. It offers a well-structured approach that promotes efficient and equitable resource allocation between users and service providers.

Moreover, to guarantee the security of resource trading and enhance the trust of parties involved, blockchain-based wireless networks emerge as a promising solution. Blockchain is an innovative distributed ledger technology, which functions in a peer-to-peer decentralized fashion, allowing transactions to be efficiently recorded among multiple participants in a verifiable and permanent manner without the need for a central authority. The utilization of blockchain technology offers the potential for executing resource trading within a decentralized, clear, and secure marketplace.

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B. Related Work

To facilitate the usage of spectrum resources, cognitive radio systems have been proposed to enable efficient and dynamic use of spectrum and have emerged as a promising solution to the spectrum scarcity challenge [6], [7]. Lakew *et al.* [8] investigate a dynamic heterogeneous aerial access IoT (AAIoT) network consisting of a HAP, multiple UAVs, and internet of things devices (IoTDs). Then they solve the problem of resource allocation of the network thus maximizing the service satisfaction for IoTDs while minimizing total energy consumption. Xiaobin et al. [9] propose a hybrid Stackelberg game for managing communication and computation resources. Hu *et al.* [10] apply contract theory to solve the problem of optimal bandwidth pricing for multiple UAV operators at a macro base station (BS), incentivizing both parties to engage in resource trading.

In recent years, blockchain technology [11], [12] has received increasing attention from researchers due to its decentralized, tamper-proof, transparent and traceable features. Initially, blockchain technology emerged from Bitcoin, but it has evolved to encompass the field of mobile computer networks. The authors of [13] extensively study the potential of blockchain for spectrum sharing and identified several scenarios for its productive implementation. Furthermore, how to motivate the miners to participate in blockchain receives increasing interests. Guo *et al.* [14] investigate a incentive mechanism under the edge-computing-enabled blockchain to encourage the participation of blockchain. They formulate a two stage Stackelberg game model to optimize the utility of miners and edge service provider. Qiu *et al.* [15] propose a consortium blockchain-enabled spectrum trading framework to improve transaction security without relying on third parties. In addition, the authors investigate two pricing schemes, including nonuniform pricing and uniform pricing. Wang *et al.* [16] propose a consortium blockchain for vehicular edge computing to secure the resource sharing process between service requesters and vehicles. Additionally, a contract-based incentive mechanism is developed to motivate vehicles to help offload tasks from service requesters. Ling *et al.* [17] propose a blockchain radio access network to develop a large self-organized RAN by virtually combining multiple entities without relying on a highly powerful network center. Wang *et al.* [18] propose a blockchain-aided distributed access control scheme for UAV computing networks to realize autonomous management of identity, attributes and access policies for UAVs. In addition, to overcome the challenges posed by high communication complexity and scalability in blockchain, the authors perform a committee election utilizing Verifiable Random Function (VRF) and implement optimization through sharding.

Auction theory was originally used in the field of economics. In recent years, auction theory has been an effective way to solve the resource trading problem [19], [20]. In order to designate the most suitable user based on user reputations, the authors introduce a selection methodology grounded in the fixed price incentive scheme (RSFP) [21]. Zhu *et al.* [22] present BISA, a blockchain-based two-stage secure spectrum intelligent sensing and sharing auction mechanism, to guarantee secure spectrum auction. The authors design a unit-utility-based auction algorithm (UUA), which allocates the spectrum resources of primary users (PU) auctions to secondary users (SU) to maximize the utility of SUs. To address the problem of multi-unit spectrum auction, an ascending-price progressive auction algorithm (APA) is proposed [23], which introduces Pareto optimality as the measurement for evaluating the efficiency. Ji *et al.* [24] propose a reverse auction-based incentive mechanism (RAIN) for mobile crowdsensing systems to optimize the composition of workers in the system meanwhile reducing the long-term system cost.

C. Motivation and Contributions

The above works do not take account of the joint trading of spectrum and computing resources in Multi-UAV MEC scenarios. Moreover, the transaction mechanism of blockchain-based multilayer airborne networks has not been sufficiently explored, which is crucial in the context of heterogeneous networks.

Motivated by the aforementioned observations, in this paper, we exploit the blockchain technology to devise a secure resource trading and sharing mechanism. In order to optimize the pricing of UAVs' spectrum and computing resources, and the amount of UE required resources, we establish a two stage Stackelberg game to achieve optimal results for both UAVs and UEs. Furthermore, we maximize the social welfare by employing the double auction method. Comparing with the previous works, the contributions of this paper can be summarized as follows:

- In this paper, we investigate a multi-UAV edge computing system, comprising of a HAP, multiple UAVs, and multiple UEs with varying quality of service (QoS) demands. The integration of HAP and UAVs in an edge computing framework presents an innovative solution to address the growing demand for high-quality and low-latency services in various applications, such as disaster response, surveillance, and communication in remote or densely populated areas.
- We propose a blockchain-based resource trading mechanism (BRTM) to address security risks. The UAVs are responsible for block generation by means of mining, while the HAP collects information regarding UAVs and user equipment service requirements and devises a bidding strategy. Then the auction outcomes are documented in a smart contract and added to the blockchain.
- We propose a pricing-based incentive mechanism to encourage resource trading between UAVs and UEs. UAVs serve as sellers with the authority to price their spectrum and computing resources, while UEs act as buyers by specifying the desired resource quantity and providing compensation to UAVs. To address the allocation concerns arising between UAVs and user equipment clusters (UECs), we introduce a double auction-based resource trading algorithm (DARA) that maximizes social welfare by matching UECs with UAVs, taking account of the private information and geographic locations of both parties.

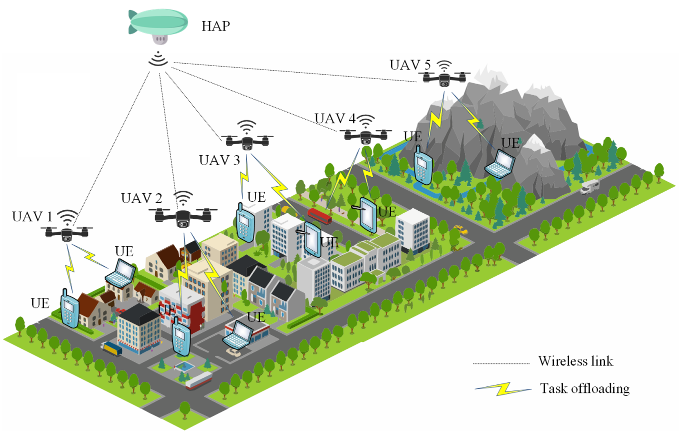

Fig. 1. System model.

- The impact of the number of UEs and UAVs, the total available resources of UAV and the computational task size are analyzed in the simulation. The simulation results demonstrate that the proposed DARA scheme is effective in providing incentives and outperforms other benchmark schemes concerning the evaluated performance parameters.

D. Organization

The rest of this article is organized as follows. The system model is introduced in Section II. In Section III, we present the BRTM. In Section IV, we present a pricing-based incentive mechanism and formulate the utility functions for UEs and UAVs. The solution for the optimal resources trading and DARA are given in Section V. Numerical results and analysis are shown in Section VI. Finally in Section VII, we conclude the paper.

II. System Model

A. System Model

The system model is shown in Fig. 1. We consider a Multi-UAV MEC consisting of three layers: the UE layer, the UAV layer and the HAP layer. The UE layer comprises devices with limited power and computing capacity, which request spectrum resources and computing resources from the UAV layer and then offload the computing tasks to UAV. In the UAV layer, UAVs are characterized by easy deployment, flexible mobility and autonomous operation, which can bring them closer to the users. Therefore, the UAVs are deployed as aerial base stations, which allows them to provide spectrum resources and computing resources to the user equipment clusters (UECs) at the edge of the network. Meanwhile, the HAP layer acts as an auctioneer to collect necessary data from both UAVs and users, in order to determine the optimal matching strategy between the user clusters and UAVs, and to ultimately complete the auction. The main notations used in this paper are listed in Table I.

Table I
Notations and Definitions

Notations	Definitions
$\mathcal{M}$/ M	Set of UEs/ number of UEs
$\mathcal{N}$/ N	Set of UAVs/ number of UAVs
$\mathcal{K}$/ K	Set of UECs/ number of UECs
B_j	The available spectrum resources of UAV
F_j	The available computing resources of UAV
b_{ij}	The spectrum resource sold form UAV j to UE i
f_{ij}	The computing resource sold form UAV j to UE i
p_j	The spectrum resource price of UAV j
f_{ij}	The computing resource price of UAV j
U_{ij}^{UE}	The utility of UE i from UAV j
U_{ij}^{UAV}	The utility of UAV j
U_{sw}	The social welfare of system
g_{ij}	The channel power gain between UE i and UAV j
P_m	The transmission power of UE
δ^2	Noise power spectral density
T_1	Maximum tolerated transmission delay
T_2	Maximum tolerated execution delay
w_i	Task size in bits of UEs
v_i	CPU cycles needed to execute a bit of UE's task
d_{ki}	The distance from the UAV j to the UEC k
u_j	The speed of UAV j

B. System Assumption

In this model, we assume that multiple UAVs are randomly distributed within the coverage area of the HAP. The set of all UAVs is denote by $\mathcal{N} = [1, 2, ..., N]$. In addition, without loss of generality, there are M UEs randomly deployed in the service area of the HAP, where the set of all UEs is denote by $\mathcal{M} = [1, 2, ..., M]$. UEs are clustered into K UECs according to their respective locations. The set of all UECs is denote by $\mathcal{K} = [1, 2, ..., K]$. The HAP can be deployed in a fixed position in the stratosphere [25] and its height to the ground be fixed as H_h. The horizontal position of HAP is expressed as $l_h = (x_h, y_h)$. In addition, for simplicity, it is assumed that all UAVs are deployed above the HAP's coverage area at a height of H_j. The horizontal location of UAV j is represented by $l_j = (x_j, y_j)$. Similarly, the horizontal location of the UE $i \in \mathcal{N}$ is represented by $l_i = (x_i, y_i)$. The horizontal location of the center of UEC k is represented by $l_k(x_k, y_k)$. We define B_j and F_j to be the available spectrum resources and computing resources of UAV j, respectively.

To facilitate the implementation of computation offloading, UEs are required to procure spectrum resources and computing resources from the UAVs. Let B_j and F_j be the available spectrum resource and computing resource of UAV j, respectively. We make the assumption that the unit price of spectrum for UAV j is denoted as p_j, while the quantity of spectrum sold UAV j to UE i is b_{ij}. Similarly, we define the purchase strategy of computing resource from UAV is f_{ij}, with q_j denoting the corresponding price set by the UAV. We assume that all UAVs and UEs are rational and self-interested. For UE i, in order to

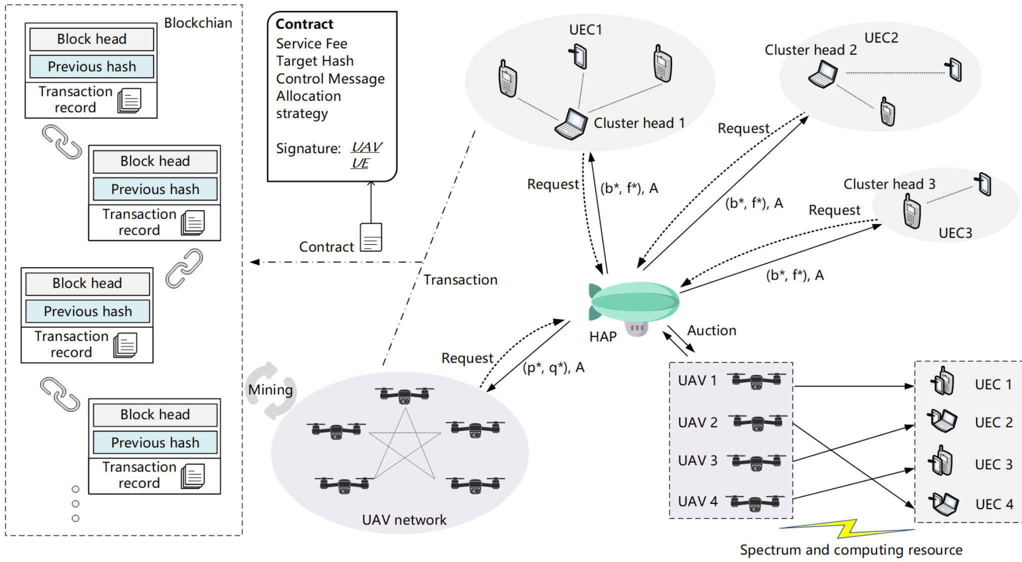

Fig. 2. Framework of Blockchain-based Resource Trading Mechanism.

maximize its utility U_{ij}^{UE}, it needs to choose the appropriate UAV for connection and determine its own optimal purchase strategy b_{ij}^* and f_{ij}^*. At the same time, for UAV j, it needs to propose the optimal pricing p_j^* and q_j^* to maximize its utility U_j^{UAV}.

In order to satisfy both parties in the trade, the resource trading scheme should maximize the utilities of both UAVs and UEs as much as possible. Therefore, we use social welfare to denote the effect of resource trading, which can be expressed as

$$\max U_{sw} = \sum_{i=1}^{M}\sum_{j=1}^{N} U_{ij}^{UE} + \sum_{j=1}^{N} U_j^{UAV}. \tag{1}$$

C. Security Threats

There are also significant trust issues that could threaten the security and privacy of the system due to the untrustworthy broadcast nature and wireless transmission of the multi-UAV-based network.

1) External attackers: External attackers are unauthorized entities with the capability to intercept communications across public channels while actively manipulating the system through the alteration or replay of messages. These entities possess the potential to commandeer an UAV within the network, consequently acquiring access to sensitive information and assuming the identity of a participant for the execution of a cloning attack.

2) Malicious UE: After the resource is allocated, a malicious UE may pretend that it has not received resource and refuses to pay, resulting in a loss for the system and other legitimate users.

3) Malicious UAV: A malicious UAV may publish untrue information about spectrum resources and computing resources, thus enhancing its own effectiveness by deceiving UEs.

III. Blockchain-based Resource Trading Mechanism

In this section, we propose BRTM to solve the potential security threats from malicious UEs and malicious UAVs mentioned in the previous section. In addition, we provide a detailed description of the framework and resource transaction process of BRTM.

A. Blockchain and Mining

In this paper, we use blockchain technology to improve system security. The framework of BRTM is shown in Fig. 2. Specifically, we integrate UAVs into a blockchain network. In order to ensure the authenticity and accuracy of transactions, UAVs aggregate transaction records during a certain time, and then encrypt and digitally sign these records. As shown in the figure, we use a smart contract to represent the transaction, which includes signature of UAV, signature of UE, service frees, terms of service, etc. All transactions are packaged into a block, which contains a block head, previous hash, a transaction set and other information.

Similar to that in Bitcoin, the UAVs in the blockchain engage in competition to generate a block by solving the Proof of Work (PoW) problem. Each UAV calculates the hash value of its block based on a random nonce value φ, timestamp, current Block Data, previous block hash and so on, which can be written as

$$Hash(\varphi + PrevHash + Data + Timestamp) \leq Target, \tag{2}$$

where the $Target$ is a number that can be adjusted by the system term to control the speed of finding out the specific nonce value φ. Each hash calculation to solve the puzzle can be considered a separate binomial trial.

Upon discovery of a valid proof of work, the fastest UAV assumes the role of a leader and disseminates the block along with the corresponding nonce value to other UAVs for scrutiny

Algorithm 1 Consensus Algorithm

```
The Leader UAV broadcast the block data to other UAVs.
for each UAV do
    Audit the data received;
    if the data received is verified to be correct then
        Broadcast a True result to other UAVs for mutual supervision and verification;
    else
        Broadcast a False result to other UAVs for mutual supervision and verification;
    end if
    Compare its result with others and send a reply back to the leader UAV;
end for
The leader UAV receives all replies;
if all UAVs agree with the new block then
    The leader UAV sends records containing block data and digital signatures to other UAVs for storage.;
else
    The leader UAV sends block data to UAVs who disagree once again for audit;
end if
Discard the block that is not successfully verified.
```

and validation. If the other UAVs reach a consensus on the legitimacy of the block, the informational content within this new block is systematically appended to the blockchain in a sequential and chronological manner. Subsequently, the fastest UAV receives returns in the form of virtual coins.

B. Blockchain Consensus

In order to ensure agreement among UAVs on the validity of transactions and the order in which transactions are added to the blockchain, we consider a distributed consensus algorithm, which is presented in Algorithm 1. The consensus process is shown is Fig. 3.

The leader UAV first broadcasts the block data to other UAVs for audit. The block data contains information such as timestamps and nonce value φ, etc. For each UAV, it first audits the received block data. If the received data is verified to be correct, the UAV will send a *True* result to the other UAVs. Otherwise, the UAV will send a *False* result to other UAVs. It then compares its results with those of other UAVs and generates a response consisting of the received audit results, the audit results, the comparison results, and the UAV signature. Finally, each UAV sends a reply to the leader UAV.

For the leader UAV, it collects and checks replies from all other UAVs. If all UAVs agree with the new block, the leader UAV will send records containing block data and digital signatures to other UAVs for storage. Otherwise, the leader UAV will send block data to UAVs who disagree once again for audit. Eventually, unsuccessfully verified blocks will be discarded.

C. Overview of BRTM

The main entities in the model are introduced in detail as follows:

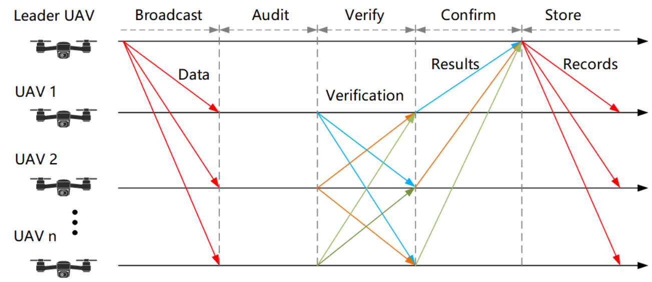

Fig. 3. Consensus process.

1) UAV: UAVs are the providers of spectrum and computing resources, as well as important edge computing nodes. The UAVs provide computing and spectrum resources to UEs with optimal resource trading strategies. At the same time, they act as miners and maintain the blockchain network by solving PoW problems.

2) UE: UEs are the purchasers of resources, and they form multiple UECs. Each UE sends their information to the HAP and the double auction method is then used to match suitable UAVs and UECs.

3) HAP: HAP is the trusted authority of the system and exists as the auctioneer of the auction mechanism. HAP collects information from UAVs and UEs and completes the auction operation. The HAP collects information about the UAVs and UEs and then gets the allocation scheme for UAVs and UEs through a double auction. HAP periodically broadcasts a smart contract that contains the results of the allocation as well as HAP's digital signature.

In the phase of BRTM, the participating UE first sends the maximum transmission delay T_i^{off} and maximum calculation delay T_i^{com} to the HAP. At the same time, the UAVs upload their private resource information to HAP. Subsequently, the computation server in HAP calculate the optimal purchase strategy (p_j^*, q_j^*) for each UAV and the optimal purchase strategy (b_{ij}^*, f_{ij}^*) for each UE. This proactive measure safeguards against self-interested individuals manipulating information to augment their individual revenue at the expense of the collective interest.

When each UE receives the optimal purchase policy, it will send some auction requests to the UAVs. The auction request of UE i can be expressed as follows:

$$Req_{UE_i} = E_{PB_i}((b_{ij}^*, f_{ij}^*)||Cert_i||Sig_{UE_i}||Ts_{UE_i}), \quad (3)$$

where $E_{PB_i}(\cdot)$ is the encryption function, (b_{ij}^*, f_{ij}^*) is the set of best bids of UE i, certificate $Cert_i$ is used to check the validity of the identity, Ts_{UE_i} is the timestamp for request generation.

After receiving broadcast information, UAV j initially verifies identity through the scrutiny of digital signatures and certificates. Subsequently, it selects the UEC that provides it with the greatest utility to make an auction request. The auction request of UAV j can be expressed as follows:

$$Req_{UAV_j} = E_{PB_i}((p_j^*, q_j^*)||Cert_j||Sig_{UAV_j}||Ts_{UAV_j}), \quad (4)$$

where (p_j^*, q_j^*) is the auction bid selected by UAV j, certificate $Cert_j$ is used to check the validity of the identity, Sig_{UAV_j} is the signature of UAV and Ts_{UAV_j} is the timestamp for request generation.

Subsequently, a double auction method is employed to resolve the allocation quandary between the UAV and the UEC. Once the UAVs have received bids from the UEs, they construct their preference lists in a descending order based on utility. They evaluate their performance lists and identify the top-ranked UEC as a prospective candidate, subsequently initiating a trade request with the users associated with that particular UEC. Similarly, each UEC formulates its own preference list in a descending order, considering the utility as the key criterion.

After the auction is completed, the HAP will respond to UAVs and UEs with matching results A_{ij}. The response can be expressed as follows:

$$Rsp_{HAP_i} = E_{PB_{HAP_i}}(O^*||Cert_{HAP}||Sig_{HAP}||Ts_{HAP}||A_{ij}),$$
$$O^* = (b^*_{ij}, f^*_{ij}, p^*_j, q^*_j). \tag{5}$$

where $Cert_{HAP}$ is the certificate of HAP, Sig_{HAP} is the signature of HAP and Ts_{HAP} is timestamp.

When the transaction is completed, the UAV j uploads the transaction record to the blockchain network, which can be expressed as follows:

$$R_{UAV_i} = E_{PB_{UAV_i}}(O^*||Cert_j||Sig_{UAV_j}||Ts_{UAV_j}||A_{ij}). \tag{6}$$

After all those operation, the auction coins will be transferred from the wallet address AD_{UE_i} of UE i to the wallet address AD_{UAV_j} of UAV j.

D. Security Analysis

The security of the BRTM is analyzed as follows.

1) Avoiding the risks from intermediary: Unlike traditional transaction mechanisms that must rely on a trusted intermediary, our proposed BRTM uses a blockchain-based distributed storage solution. This allows BRTM to avoid the risks from intermediary, such as denial of service attacks, privacy leakage and a single point of failure.

2) Transaction traceability: In our proposed BRTM, transactions are traceable. After a transaction is completed, the transaction record and the traders' information are permanently stored in the blockchain. The real identity of the illegal operator can be found by checking the public ledger from anonymous certificate Cert and registered ID.

3) Secure transactions: In BRTM, before transactions are stored in the blockchain, they must be publicly audited and authenticated. After the data is stored in the blockchain, the packed data is formed into a chained structure by a hashing algorithm. The latter block includes the hash value of the preceding block. Due to the one-way and tamper-proof nature of the hashing algorithm, it is impossible for attackers to forge or tamper transactions.

IV. Design of the Pricing-Based Incentive Mechanism

In this section, we design the pricing-based incentive mechanism for the system. We first establish the utility function of the UAV and the UE, and then consider the interaction process between the UAV and UEs as two-stage Stackelberg game problem.

A. The utility of UE

In our system, there are multiple UAVs and UEs, and all UAVs and UEs have similar utility function. For simplicity, we consider the relationship between the UAV j and the UEC k with K UEs. In the phase of BRTM, UE i engages primarily in two processes: the acquisition of spectrum resources and the procurement of computing resources. Then the utility function of UE i with respect to UAV j as follows:

$$U^{UE}_{ij}(b_{ij}, f_{ij}, p_j, q_j) = S_{ij}(b_{ij}, f_{ij}) - C_{ij}(b_{ij}, f_{ij}, p_j, q_j), \tag{7}$$

where $S_{ij}(b_{ij}, f_{ij})$ denotes the satisfaction about spectrum resources and computing resources, and $C_{ij}(b_{ij}, f_{ij}, p_j, q_j)$ denotes the cost of purchasing spectrum resources and computing resources.

The channel power gain can be determined by the distance between the UE and the UAV. Then, the channel power gain between UE i and the UAV j can be expressed as

$$g_{ij} = \rho_0 d_i^{-2} = \frac{\rho_0}{(H_j^2 + ||l_i - l_j||^2)^{-2}}, \tag{8}$$

where ρ_0 is the channel power gain at the reference distance of d_0 = 1 m and H_j is the altitude of the UAV j. Then the transmission rate of UE i and the UAV can be expressed as

$$r_{ij} = b_{ij}\log_2(1 + \frac{p_m g_{ij}}{\delta^2}), \tag{9}$$

where p_m is the transmission power of UE i, and δ^2 is the noise power spectrum density. Therefore, the transmission delay of UE i to offload its task to UAV j can be computed as

$$t^{off}_{ij} = \frac{w_i}{r_{ij}} = \frac{w_i}{b_{ij}\log_2(1 + \frac{p_m g_{ij}}{\delta^2})}, \tag{10}$$

where w_i is the task data bits. Then, the UAV uses computing resources f to execute the task data bits from UE i. Let v_i be the CPU cycles needed to execute a bit of UE's task. The task execution delay for UAV j can be denoted by t^{com}_{ij}, can be obtained as

$$t^{com}_{ij} = \frac{w_i v_i}{f_{ij}}. \tag{11}$$

The resource satisfaction S_{ij} should be increasing functions of b_{ij} and f_{ij}. In addition, the satisfactions need to take into account its own real demands. To represent the transmission delay demands and computation delay demands of UE, we employ the notation T^{off}_i and T^{com}_i, where $T^{off}_i \in [0, T_1]$ and $T^{com}_i \in [0, T_2]$. Here, T_1 represents the maximum tolerated transmission delay, while T_2 represents the maximum tolerated execution delay. Similar to [15], we use the logarithmic function to model satisfactions, and it can be expressed as

$$\mathrm{S}_{ij}(b_{ij}, f_{ij}) = \alpha_i \log_2(1 + \frac{T^{off}_i}{t^{off}_{ij}}) + \beta_i \log_2(1 + \frac{T^{com}_i}{t^{com}_{ij}}), \tag{12}$$

where α_i and β_i are satisfaction parameters.

In general, the cost is proportional to the purchase quantity of UE. Note that p_j and q_j are the prices of spectrum resources and computing resources for UAV j, respectively. Then C_{ij} can be modeled as

$$C_{ij}(b_{ij}, f_{ij}, p_j, q_j) = p_j b_{ij} + q_j f_{ij}. \tag{13}$$

Therefore, the utility of UE i from UAV j can be given by

$$\begin{aligned} &U_{ij}^{UE}(b_{ij}, f_{ij}, p_j, q_j) \\ &= \alpha_i \log_2(1 + \frac{T_i^{off} b_{ij} \log_2(1 + \frac{p_m g_{ij}}{\delta^2})}{w_i}) - p_j b_{ij} \\ &\quad + \beta_i \log_2(1 + \frac{T_i^{com} f_{ij}}{w_i v_i}) - q_j f_{ij}. \end{aligned} \tag{14}$$

B. The utility of UAV

For UAV j, there are three processes it is mainly involved in, namely, moving to the center of the UEC k to provide spectrum resources to the UEs, calculating tasks offloaded by the UEs, and mining as a miner to generate blocks.

Let $\mathcal{B}$ denote the bandwidth vector of UEC with $\mathcal{B} = [b_1, b_2, ..., b_K]^T$, and $\mathcal{F}$ denote the computing resource vector of UEC with $\mathcal{F} = [f_1, f_2, ..., f_K]^T$. Then, the utility function of UAV j from UEC k can be defined as

$$\begin{aligned} &U_{kj}^{UAV}(\mathcal{B}, \mathcal{F}, p_j, q_j) \\ &= R_{kj}(\mathcal{B}, \mathcal{F}, p_j, q_j) + \Pi_j^b - C_{kj}^{UAV}, \end{aligned} \tag{15}$$

where R_{kj} is the revenue from the sale of spectrum resources and computing resources, Π_{kj} is the mining revenue and C_{kj}^{UAV} is the cost of UAV j.

The revenue R_{ij} from the sale of resources by UAV j is the sum of the costs of all UEs in UEC k. Mathematically, R_{kj} can be expressed as

$$R_{kj}(\mathcal{B}, \mathcal{F}, p_j, q_j) = \sum_{i=1}^{K} (p_j b_{ij} + q_j f_{ij}). \tag{16}$$

Let f_j' denote the computing resource of UAV j for mining. Then the hash computing force occupied by UAV j in the whole network is θ_j, which can be expressed as

$$\theta_j = \frac{f_j'}{\sum_{n \in N} f_n'}. \tag{17}$$

The probability of UAV j in solving the PoW problem is denoted by ρ_j. It is assumed that the miner's solution to the PoW problem follows a Poisson distribution with a compliance parameter λ. Thus, ρ_j can be expressed as $\rho_{\mathrm{j}} = \theta_j e^{-\lambda t_j}$, where t_j represents the computing delay, which is related to the block size π.

During the blockchain network maintenance process, the mining revenue Π_j^b of UAV j is composed of three distinct components: the fixed reward R_f, the performance reward R_p, and the participant reward R_ε [26].

The fixed reward is a predetermined amount of cryptocurrency that is paid out to the miner for every successfully mined block. The fixed reward R_f of a blockchain can be viewed as a decay function with a half-life of T, which can be expressed as

$$R_f = R_f^{\max}(\frac{1}{2})^{\frac{t}{T}}. \tag{18}$$

The performance reward R_p is positively correlated with the size of the generated block, which can be expressed as

$$R_p = r\pi, \tag{19}$$

where r is an evaluation factor. The participant reward R_ε depends on the degree of participation in the computing process, which can be expressed as

$$R_\varepsilon = \varepsilon \theta_j, \tag{20}$$

where ε is an evaluation factor.

Similar to [26], the rewards Π_j^b in the process of block generation can be expressed as follows

$$\begin{aligned} \Pi_j^b &= \rho_{\mathrm{j}}(R_f + R_p) + R_\varepsilon \\ &= \big(R_f^{\max}(\frac{1}{2})^{\frac{t}{T}} + r\pi\big) \frac{e^{-\lambda t_j} f_j'}{\sum_{n \in N} f_n'} + \frac{\varepsilon f_j'}{\sum_{n \in N} f_n'}. \end{aligned} \tag{21}$$

According to [27] and [28], let the energy consumption coefficient of UAV j denoted by δ_i, and it depends on the UAV's chip. The computing power of UAV for computing task of all UEs and PoW problem can be defined as

$$P_{ij}^{loc} = \delta_i F_j^3. \tag{22}$$

When UAV j is linked to user cluster k, it needs to fly to the center of the user cluster. The flight distance of the UAV can be expressed as

$$d_{kj} = \sqrt{{H_j}^2 + ||l_j - l_k||^2}. \tag{23}$$

Let t_{kj}^{fly} denote the delay of the UAV flying, which depends on the distance between the UAV j and the UE and the speed of the UAV u_j. t_{kj}^{fly} can be expressed as

$$t_{kj}^{fly} = \frac{d_{kj}}{u_j}. \tag{24}$$

With reference to [27], the energy consumed by the UAV flight is $E_{kj}^{fly} = \frac{1}{2}\varphi_j m_j t_{kj}^{fly} {u_j}^2$, where φ_j is the flight energy consumption parameter and m_j is the weight of UAV j. Therefore, the energy consumed by the UAV flight can be computed as

$$E_{kj}^{fly} = \frac{1}{2}\varphi_j m_j u_j d_{kj}. \tag{25}$$

Since the output data is very small, the communication-related energy consumption of the UAV is much smaller than the computational and flight energy consumption, and thus can be ignored [29], [30]. We consider that the energy consumption of UAV mainly consists of computational and flight energy consumption in this paper. For the sake of simplicity, we use computing power to capture the computing cost. Therefore, the total cost for computing and flying can be defined as

$$C_{kj}^{UAV} = \sigma_j \delta_i F_j^3 + \frac{1}{2}\tau_j \varphi_j m_j u_j d_{kj}, \tag{26}$$

where $0 < \sigma_j < 1$ and $0 < \tau_j < 1$ are the normalized weights of computing and flying costs.

Therefore, the utility function of UAV j from UEC k can be written as follow

$$\begin{aligned}
&U_{kj}^{UAV}(\mathcal{B},\mathcal{F},p_j,q_j)\\
&=\sum_{i=1}^{K}(p_j b_{ij}+q_j f_{ij})-\sigma_j\delta_i F_j^3-\frac{1}{2}\tau_j\varphi_j m_j u_j d_{kj}\\
&\quad+\left(R_f^{\max}(\frac{1}{2})^{\frac{t}{T}}+r\pi\right)\frac{e^{-\lambda t_j}f_j'}{\sum_{n\in N}f_n'}+\frac{\varepsilon f_j'}{\sum_{n\in N}f_n'}.
\end{aligned} \tag{27}$$

C. Stackelberg Game

When UAV j sells spectrum and and computing resources to UEC k, the goal of the UEC is to maximize the total UE utility, and the goal of UAV j is to maximize its utility U_{kj}^{UAV}. We formulate the interaction between UAV j and UEC k as an two-stage Stackelberg game problem. The optimal solution of this resource allocation problem is expressed as $Q_{kj}^*=(\mathcal{B}^*,\mathcal{F}^*,p_j^*,q_j^*)$, where $\mathcal{B}^*$ is the optimal bandwidth vector with $\mathcal{B}^*$ = $[b_{1j}^*,b_{2j}^*,...,b_{Kj}^*]$ and $\mathcal{F}^*$ is the optimal computing resource vector with $\mathcal{F}^*$ = $[f_{1j}^*,f_{2j}^*,...,f_{Kj}^*]$. We define UAV j as the leader and UEs as followers in the game model. In the first stage, the UAV j sets the resource price p_j and q_j. In the second stage, each UE determines its spectrum and computing resource quantity b_{ij}^* and f_{ij}^* according to the price of UAV's resources. The optimization problems in each stage can be described as follows.

In the first stage, the game of the UAV aims at addressing problem $P1$:

$$P1:\ \max_{p_j,q_j}\ U_{kj}^{UAV}(\mathcal{B},\mathcal{F},p_j,q_j) \tag{28}$$
$$\text{s.t.}\quad p_j\geq 0, q_j\geq 0, \tag{29}$$
$$\sum_{i=1}^{K}f_{ij}+f_j'=F_j, \tag{30}$$
$$\sum_{i=1}^{K}b_{ij}\leq B_j. \tag{31}$$

In the second stage, the game of the UE i aims at addressing problem $P2$:

$$P2:\ \max_{b_{ij},f_{ij}}\ U_{ij}^{UE}(b_{ij},f_{ij},p_j,q_j) \tag{32}$$
$$\text{s.t.}\quad b_{ij}\geq 0, \tag{33}$$
$$f_{ij}\geq 0. \tag{34}$$

Definition 1. *Let p_j^* and q_j^* be a solution for Problem 1 and $\mathcal{B}^*$ and $\mathcal{F}^*$ denotes a solution for Problem 2. The point ($\mathcal{B}^*$, $\mathcal{F}^*$, p_j^*, q_j^*) is an Stackelberg equilibrium (SE) for the two-stage Stackelberg game if for any ($\mathcal{B}$, $\mathcal{F}$, p_j, q_j), the following conditions are satisfied:*

$$U_{kj}^{UAV}(\mathcal{B}^*,\mathcal{F}^*,p_j^*,q_j^*)\geq U_{kj}^{UAV}(\mathcal{B},\mathcal{F},p_j,q_j), \tag{35}$$
$$U_{ij}^{UE}(b^*,f^*,p_j^*,q_j^*)\geq U_{ij}^{UE}(b,f,p_j,q_j). \tag{36}$$

From the definition, we can see that a two-stage iterative is required to reach an SE. First, UAV j releases its own price of spectrum and computing resources. Then each UE calculate its optimal bandwidth b_{ij}^* and computing resource f_{ij}^* by solving the problem 2. Finally, the UAV j resets its own price to p_j^* and q_j^* by solving the problem 1. In the following, the optimal bandwidth and computing resource strategy of the UE i is first analyzed, and then the optimal price strategy of the UAV to the UE i is calculated.

V. Solution for optimal resources trading

In this section, we first give the detailed solution of proposed two-stage Stackelberg game problem. Then a double auction based resource trading algorithm is proposed to solve the allocation problems between UAVs and UECs.

A. Optimal resource purchase strategy

When an UAV j sells spectrum and computing resources to an UEC k, the target of UE i is to maximize its utility. It is important to note that if UE i is unable to purchase spectrum resources, it will not be able to offload tasks and therefore will not need to purchase computing resources. Consequently, we introduce a parameter $\chi_{ij}\in\{0,1\}$, where $\chi_{ij}=1$ if $b_{ij}^*>0$, and $\chi_{ij}=0$ otherwise. Then the optimal computing resource f_{ij}^* is replaced with $f_{ij}^*=\chi_{ij}f_{ij}^*$.

With reference from (14), the problem 2 can be formulated as follows

$$\begin{aligned}
\max_{b_{ij},f_{ij}}\ &\alpha_i\log_2(1+\frac{T_i^{off}b_{ij}\log_2(1+\frac{p_m g_{ij}}{\delta^2})}{w_i})-p_j b_{ij}\\
&+\beta_i\log_2(1+\frac{T_i^{com}f_{ij}}{w_i v_i})-q_j f_{ij}
\end{aligned} \tag{37}$$
$$\text{s.t.}\quad b_{ij}\geq 0, \tag{38}$$
$$f_{ij}\geq 0. \tag{39}$$

Theorem 1. *For a certain UE whose utility function satisfies (14), there exists a unique Nash equilibrium point.*

Proof. The first partial derivatives of the utility function U_{UE_i} about b_{ij} and f_{ij} are calculated.

$$\begin{aligned}
&\frac{\partial U_{ij}^{UE}(b_{ij},f_{ij},p_j,q_j)}{\partial b_{ij}}\\
&=\frac{\alpha_i T_i^{off}\log_2(1+\frac{p_m g_{ij}}{\delta^2})}{\ln 2\left(w_i+T_i^{off}b_{ij}\log_2(1+\frac{p_m g_{ij}}{\delta^2})\right)}-p_j,
\end{aligned} \tag{40}$$

and

$$\frac{\partial U_{ij}^{UE}(b_{ij},f_{ij},p_j,q_j)}{\partial f_{ij}}=\frac{\beta_i T_i^{com}}{\ln 2\,(w_i v_i+T_i^{com}f_{ij})}-q_j. \tag{41}$$

Then the second partial derivatives of the U_{ij}^{UE} are calculated as followed.

$$\begin{aligned}
A=&\frac{\partial^2 U_{ij}^{UE}(b_{ij},f_{ij},p_j,q_j)}{\partial b_{ij}^2}\\
=&-\frac{\alpha_i(T_i^{off}\log_2(1+\frac{p_m g_{ij}}{\delta^2}))^2}{\ln 2\left(w_i+T_i^{off}b_{ij}\log_2(1+\frac{p_m g_{ij}}{\delta^2})\right)^2}<0,
\end{aligned} \tag{42}$$

$$B=\frac{\partial^2 U_{ij}^{UE}(b_{ij},f_{ij},p_j,q_j)}{\partial b_{ij}\partial f_{ij}}=0, \tag{43}$$

and

$$C = \frac{\partial^2 U_{UE_i}\left(b_{ij}, f_{ij}, p_j, q_j\right)}{\partial f_{ij}^2} = -\frac{\beta_i (T_i^{com})^2}{\ln 2 \left(w_i v_i + T_i^{com} f_{ij}\right)^2} < 0. \tag{44}$$

Since $AC - B^2 > 0$ and $A < 0$, both the maximum value of utility function and Nash equilibrium exist. □

From Theorem 1, The original $P2$ can be decoupled into $P2a$ and $P2b$.

$P2a:$

$$\max_{b_{ij}} \ \alpha_i \log_2\left(1 + \frac{T_i^{off} b_{ij} \log_2\left(1 + \frac{p_m g_{ij}}{\delta^2}\right)}{w_i}\right) - p_j b_{ij} \tag{45}$$

$$\text{s.t.} \quad b_{ij} \geq 0. \tag{46}$$

$P2b:$

$$\max_{f_{ij}} \ \beta_i \log_2\left(1 + \frac{T_i^{com} f_{ij}}{w_i v_i}\right) - q_j f_{ij} \tag{47}$$

$$\text{s.t.} \quad f_{ij} \geq 0. \tag{48}$$

From (40) and (42), it is observed that the function (45) is a concave function over b_{ij}. In addition the constraint $b_{ij} \geq 0$ is affine. Therefore, it can be solved by solving the Karush-Kuhn-Tucher (KKT) conditions.

Theorem 2. *For a given bandwidth price p_j, the optimal b_{ij}^* for the bidding strategy for UE i can be given by*

$$b_{ij}^* = \begin{cases} \frac{\alpha_i}{p_j \ln 2} - \frac{w_i}{\pi_i}, & \text{if } p_j < \frac{\alpha_i \pi_i}{w_i \ln 2}, \\ 0, & \text{if } p_j \geq \frac{\alpha_i \pi_i}{w_i \ln 2}. \end{cases} \tag{49}$$

where $\pi_i = T_i^{off} \log_2\left(1 + \frac{p_m g_{ij}}{\delta^2}\right)$.

Proof. Refer to Appendix A. □

Since T_i^{off} is the maximum transmission delay to meet UE's requirements, there is a minimum purchase quantity when the UE i purchases spectrum resources. With simple calculation we can derive the optimal bandwidth is $\frac{w_i}{\pi_i}$ in order to ensure $t_{ij}^{off} > T_i^{off}$. Then we can get the final result of optimal b_{ij}^*

$$b_{ij}^* = \begin{cases} \frac{\alpha_i}{p_j \ln 2} - \frac{w_i}{\pi_i}, & \text{if } p_j < \frac{\alpha_i \pi_i}{w_i 2 \ln 2}, \\ \frac{w_i}{\pi_i}, & \text{if } \frac{\alpha_i \pi_i}{w_i 2 \ln 2} \leq p_j < \frac{\alpha_i \pi_i}{w_i \ln 2}, \\ 0, & \text{if } p_j \geq \frac{\alpha_i \pi_i}{w_i \ln 2}. \end{cases} \tag{50}$$

where $\pi_i = T_i^{off} \log_2\left(1 + \frac{p_m g_{ij}}{\delta^2}\right)$.

Similar to the solution for optimal bandwidth b_{ij}^*, we can easily observe that the function (47) is concave with respect to the variable f_{ij}. In addition, the constraint $f_{ij} \geq 0$ is affine. The optimal computing resource problem can also be solved by applying the KKT condition.

Theorem 3. *For a given computing resource price q_j, the optimal f_{ij}^* for the bidding strategy for UE i can be given by*

$$f_{ij}^* = \begin{cases} \frac{\beta_i}{q_j \ln 2} - \frac{w_i v_i}{T_i^{com}}, & \text{if } q_j < \frac{\beta_i T_i^{com}}{w_i v_i 2 \ln 2}, \\ 0, & \text{if } q_j \geq \frac{\beta_i T_i^{com}}{w_i v_i \ln 2}. \end{cases} \tag{51}$$

Proof. Similar to the proof of Theorem 2. Due to space limitations, we omit it here. □

When UE i purchases computing resource, it should be guaranteed that t_i^{com} is less than T_i^{com}. When $t_{ij}^{com} = T_i^{com}$, we can derive that the minimum computing resource purchase is $\frac{W_i V_i}{T_i^{com}}$. Considering the parameter χ_{ij}, we can obtain the expression for the final f_{ij}^*

$$f_{ij}^* = \begin{cases} \frac{\beta_i}{q_j \ln 2} - \frac{w_i v_i}{T_i^{com}}, & \text{if } q_j < \frac{\beta_i T_i^{com}}{w_i v_i 2 \ln 2} \ \textit{and} \ b_{ij}^* \neq 0, \\ \frac{w_i v_i}{T_i^{com}}, & \text{if } \frac{\beta_i T_i^{com}}{w_i v_i 2 \ln 2} \leq q_j < \frac{\beta_i T_i^{com}}{w_i v_i \ln 2}, \\ & \quad \textit{and} \ b_{ij}^* \neq 0, \\ 0, & \text{if } q_j \geq \frac{\beta_i T_i^{com}}{w_i v_i \ln 2} \ \textit{or} \ b_{ij}^* = 0. \end{cases} \tag{52}$$

B. Optimal pricing strategy

In this subsection, we analyze the optimal pricing strategy of UAV when associated with UEC k. By substituting (50) and (52) into (27), the Problem 1 can be expressed as follows

$$\begin{aligned} \max_{p_j, q_j} \ & U_{kj}^{UAV}(\mathcal{B}, \mathcal{F}, p_j, q_j) \\ = & \sum_{i=1}^{K} \left(p_j b_{ij}^* + q_j f_{ij}^*\right) - \sigma_j \delta_i F_j^3 - \frac{1}{2} \tau_j \varphi_j m_j u_j d_{kj} \\ & + \left(R_f^{\max} \left(\frac{1}{2}\right)^{\frac{t}{T}} + r\pi\right) \frac{e^{-\lambda t_j} f_j'}{\sum_{n \in N} f_n'} + \frac{\varepsilon f_j'}{\sum_{n \in N} f_n} \end{aligned} \tag{53}$$

$$s.t. \quad p_j \geq 0, q_j \geq 0, \tag{54}$$

$$\sum_{i=1}^{K} f_{ij} + f_j = F_j, \tag{55}$$

$$\sum_{i=1}^{K} b_{ij} \leq B_j. \tag{56}$$

Each UE in the system is associated with segmented function b_{ij}^* and f_{ij}^* with respect to p_j and q_j, while also having different T_i^{off} and T_i^{com}. Given these intricacies, resolving (53) poses a formidable challenge. To address this issue and reduce the algorithmic complexity, we propose a genetic algorithm (GA) based resource pricing algorithm, which is presented in Algorithm 2.

Firstly, we create an initial population of G UAVs. Inspired by the principles of genetics, we postulate that each UAV has two chromosomes, with each chromosome being encoded using a ten-bit binary code. The coding values of chromosomes are used to map the purchase price of two resources.

In each iteration, first, the fitness $\mathcal{F}_j$ of each UAV is calculated, where the UAV's fitness is equal to its utility. The total fitness $\mathcal{F}_{sum}$ is then obtained by summing up the fitness of all UAVs. Selection, crossover, and mutation operations are then performed to obtain new populations. In the selection operation, a total of G^0 UAVs are selected from the primitive population with the probability of selection being proportional to its fitness. In the crossover operation, each UAV conducts a single point crossing with a certain probability P_c, and the offspring is generated by exchanging the code at a random point in the coding string over the $\frac{1}{2}G^0$ pairs of UAVs. In

Algorithm 2 GA Based Resource Pricing Algorithm

Input hereditary algebras L, the GA related parameters { G, P_c, P_{mu} }, $\mathcal{B}$, $\mathcal{F}$.
Create a Initial population of G UAVs, and each UAV is represented by two chromosomes;
for i = 1:L **do**
  Calculate the fitness of each UAV as $\mathcal{F}_j$ and total fitness of the population as $\mathcal{F}_{sum}$;
  Select the parent chromosomes randomly with a probability proportional to their fitness $\mathcal{F}_j/\mathcal{F}_{sum}$;
  Generate offspring by applying a single-point crossover operation with a probability P_c and a simple mutation operation with a probability P_{mu};
  Replace some of the low fitness chromosomes from the original population to form a new generation of UAV population;
end for
Find the individual in the population with the highest fitness value and record its corresponding fitness value. Then the optimal pricing strategy can be obtained $(p_j^*, q_j^*) = \arg\max_{p,q} \mathcal{F}_j(p_j, q_j)$;
Output the best pricing strategy p_j^* and q_j^*.

the mutation operation, each bit of the coding string of each chromosome executes a mutation operation with probability P_{mu}. After these operations, the fitness of each UAV is recalculated, and low fitness UAVs are replaced by high fitness ones. The program continues until the number of genetic generations reaches L.

Finally, calculate the fitness of the last generation UAV, and the optimal pricing strategy (p_j^*, q_j^*) can be obtained from the UAV with the highest fitness. Thus, the optimal pricing strategy can be rewritten as

$$(p_j^*, q_j^*) = \arg\max_{p,q} F_j(p_j, q_j). \tag{57}$$

In our proposed GA-Based resource Pricing Algorithm, selection, crossover and mutation operations are performed independently and randomly. The new population is related only to its parent population and the genetic operation operator, and not to the generations preceding its parent population. Thus we can describe our algorithm as a Markov chain with the following theorem of global convergence:

Theorem 4. *Genetic algorithm with optimal preservation operation converges to the global optimal solution.*

Proof. The theoretical proof of Theorem 4 is given in [31]. □

In our algorithm, we keep the optimal solution at any stage of each population and place it in the next population, which complies with Theorem 4. Therefore, our proposed GA-Based resource Pricing Algorithm can eventually converge to the optimal solution.

Algorithm 3 DARA Algorithm

Input: Set of UAVs $\mathcal{N}$, set of UECs $\mathcal{M}$, $\mathcal{K}$;
Output: Matching matrix Z_{ij}
Initialize: Matching matrix $Z_{ij} \leftarrow 0(i \in [1, M], j \in [1, N])$, Allocation matrix of UAV $A_j \leftarrow 0(j \in [1, N])$, Allocation matrix of UE cluster $E_i \leftarrow 0(i \in [1, K])$, Candidate matrix $C_j \leftarrow 0(j \in [1, N])$;
Calculate the optimal resource trading strategy $O_{ij}^* = (\mathcal{B}^*, \mathcal{F}^*, p_j^*, q_j^*)$ for all UAVs and UEs;
for j = 1:N **do**
  Sort the utility of UAV j in descending order, and obtain L_j^{UAV} = Descending sort (U_{kj}^{UAV});
end for
for k = 1:L **do**
  Sort the utility of UE cluster k in descending order, and obtain L_k^{UEC} = Descending sort ($\sum_{i=1}^{K} U_{ij}^{UE}$);
end for
while $\sum_{j=1}^{N} A_j \neq N$ **do**
  for j = 1:N **do**
    while $A_j \neq 0$ and $C_j == 0$ **do**
      $C_j \leftarrow i = \arg FirstRank(L_j^{UAVj})$;
      if $E_{C_j} == 1$ **then**
        $C_j \leftarrow 0$, $L_j^{UAV'} \rightarrow Delete(UEC_i)$;
      end if
    end while
  end for
  for j = 1:N **do**
    if $C_j == C_{j'} (j' \neq j)$ **then**
      if $Rank(L_j^{UEC}) > Rank(L_k^{UEC'})$ **then**
        $C_{j'} \leftarrow 0$, $L_j^{UAV'} \rightarrow Delete(UEC_k)$;
      else
        $C_j \leftarrow 0$, $L_j^{UAV} \rightarrow Delete(UEC_k)$;
      end if
    end if
  end for
  for j = 1:N **do**
    if $C_j \neq 0$ **then**
      $A_j \leftarrow 1$, $E_{C_j} \leftarrow 1$, $Z_{C_j,j} \leftarrow 1$;
    end if
  end for
end while

C. Double Auction Based Resource Trading Algorithm

In order to solve the allocation issues between UAVs and UECs, a double auction based resource trading algorithm (DARA) is proposed, which is shown in Algorithm 3.

First, initialize the parameters associated with the DARA. The auction matching results can be represented by matrix Z_{ij}, i.e., Z_{ij} = 1 purports that UAV j sells spectrum resources and computing resources to UEC i, and Z_{ij} = 0 indicates that UAV j cannot trade with UEC i. The allocation matrix of UAV and UEC are expressed as A_j $(j \in [1, N])$ and E_i $(i \in [1, K])$. In addition, C_j is the candidate matrix of UAV, and represents the best candidate for UAV in a certain period.

According to (50), (52) and Algorithm 2, we can calculate

Table II
PARAMETER SETTING IN THE SIMULATION

Parameters	**Values**
Number of UAVs N	[3, 5, 7]
Number of UEs M	[5, 50]
Transmission power of UE P_m	1 W
The available spectrum resources of UAV B_j	[5, 25] MHz
The available computing resources of UAV F_j	[5, 25] GHz
Noise power spectral density δ^2	-110 dBm/Hz
Rayleigh fading parameter ρ_0	1
The speed of UAV u_j	5 m/s
Maximum tolerated transmission delay T_1	[0.5, 1] s
Maximum tolerated execution delay T_2	[0.5, 1] s
Task size in bits of UEs w_i	[1, 1.9] Mbits
CPU cycles needed to execute a bit of UE's task v_i	[1000, 1300]

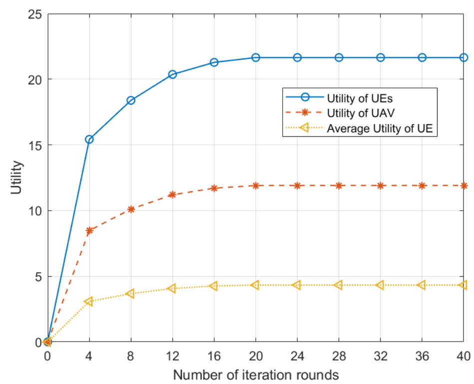

Fig. 4. Utility vs. number of iteration rounds

the optimal resource trading strategy $Q_{ij}^* = (\mathcal{B}^*, \mathcal{F}^*, p_j^*, q_j^*)$ of for all UAVs and UEs through a two-stage iteration process. In the auction theory, the higher bidder is more likely to get the auction item. The objective of UAV j is to maximize its utility, while the UEC i aims to maximize its own utility as well. Consequently, Then each UAV constructs a list L^{UAV} based on the descending order of utilities offered by different UECs, while each UEC builds a list L^{UEC} according the descending order of utilities provided by different UAVs.

If any UAV has not been matched to an UEC, each unmatched UAV browses its own list L_{UAV}, and update the highest ranked unmatched UEC as its new candidate (lines 10-17). In the event that two UAVs share the same candidate UEC k, the candidates of UAVs that rank higher in the UE cluster list L^{UEC} are preserved, while the remaining candidates are rejected (lines 18-26). Subsequently, UAVs are paired with their respective candidates, and the parameters A_j, E_i and Z_{ij} are updated concurrently (lines 27-31). This process is repeated until all UAVs have been successfully matched.

VI. NUMERICAL RESULTS AND ANALYSIS

In this section, we numerically evaluate the effectiveness of the proposed scheme. We consider a network topology encompassing a spatial dimension of 1000 meters by 1000 meters. The network architecture comprises a single HAP, multiple UAVs, and multiple UEs, with UAVs and UEs being randomly distributed across the network's spatial expanse. The simulations are conducted utilizing Python 3.8 on a server equipped with an Intel Core i7-10700F CPU and an NVIDIA GeForce RTX 3060 GPU. The pertinent system parameters are detailed in Table II.

Initially, we validate the convergence of the resource pricing algorithm. Then, we assess the influence of the total available spectrum of UAV and the total available computing resources of UAV, as well as the maximum tolerable transmission delay of UE, the maximum tolerable computing delay of UE, computational task size, and number of UEs on the system performance. Finally, in order to evaluate the effectiveness of our proposed DARA, we compare it with four baseline algorithms, including random selection algorithm (RSA), fixed price incentive scheme (RSFP), seller favorable algorithm (SFA) and greedy allocation algorithm (GAA).

- RSA: Within the framework of the RSA, each UAV randomly selects a UEC to provide the service. Then the prices of spectrum and computing resources are computed based on the Starkelberg game.
- RSFP: Within the framework of the RSFP, the price of spectrum and computing resources is fixed for each UAV, and these prices are based on the total number of resources available to the UAV itself.
- SFA: Within the framework of the SFA, we prioritize maximizing the sum of the utility of the UAVs. Each UAV chooses the UEC that maximizes its benefit to provide service. When multiple UAVs select a UEC at the same time, the UAV with the larger benefit gets the right to serve that UEC.
- GAA: Within the framework of the GAA, the UECs are sorted in descending order according to their optimal utilities. Then, the UECs are sequentially assigned a UAV that minimizes their cost of purchasing resources.

We first explore the resource pricing process between a UAV and a UEC containing 5 UEs. Fig. 4 shows the utility of UEs, utility of UAV and average utility of UEs under increasing iteration rounds. Evidently, there is an initial rapid ascent in all three utilities, followed by a gradual stabilization phase. This trend signifies that the UEs are successfully aligning their actions with the instructions of the UAV leader. Notably, convergence among the three utilities is achieved after approximately 20 iterations, signifying an equilibrium state in utility optimization for both the UAV leader and UE followers. Our analysis demonstrates that our proposed GA based pricing algorithm is effective and has good convergence.

In Fig. 5 we explore the effect of total available spectrum resource of UAV and maximum tolerated transmission delay T_1 on the price of spectrum resource and utilities. It is noteworthy that we employ the term "total revenue" to represent the aggregation of utilities extended to both the UAV and the UEs. In general, as the total available spectrum resource of UAV increase, the price of spectrum resources decreases while the total revenue increases, as can be seen from Fig. 5(a) and Fig. 5(b). This is because as the total available spectrum resources

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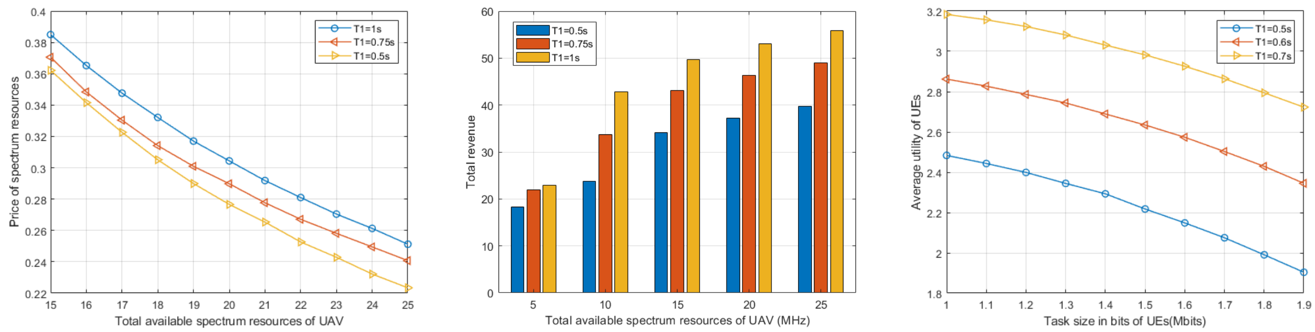
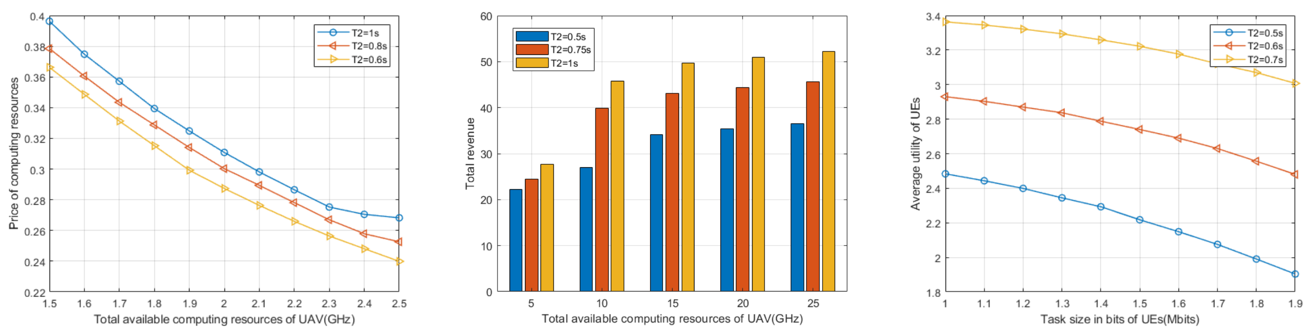


(a) (b) (c)

Fig. 5. The impact of maximum tolerated transmission delay T_1. (a) Impact of the total available spectrum resources on price of spectrum resources for different value of T_1 (T_2 = 0.6). (b) Impact of the total available spectrum resources on total revenue for different value of T_1(T_2 = 0.6). (c) Impact of the task size in bits of UEs an average utility for different value of T_1 (T_2 = 0.6).



(a) (b) (c)

Fig. 6. The impact of maximum tolerated execution delay T_2. (a) Impact of the total available computing resources on price of computing resources for different value of T_2 (T_1 = 0.5). (b) Impact of the total available computing resources on total revenue for different value of T_2 (T_1 = 0.5). (c) Impact of the task size in bits of UEs an average utility for different value of T_2 (T_1 = 0.5).

increase, UEs can purchase more spectrum resources. When the UAV reduces the price of spectrum resources relatively, the UEs tend to buy more resources in order to increase their benefits, and thus the benefits for both parties can increase.

Furthermore, it can also see from Fig. 5(a) and Fig. 5(b) that the incremental of T_1 leads to a increase in the price of spectrum resource and total revenue. This is because that a prolonged T_1 engenders a reduced demand for spectrum resources, thereby affording a surplus of adequately provisioned spectrum resources. Appropriately increasing the price of spectrum resources can satisfy users with higher delay satisfaction while making the UAVs generate more revenue from the sale of spectrum resources. In Fig. 5(c), the average utility of UEs decreases as the Task size in bits of UES increase. This is because the larger the size of the UE's task, the more spectrum resources the user needs to purchase to meet the latency requirements, which results in less utility to the UE.

Fig. 6 shows the impact of the total available computing resource and maximum tolerated execution delay T_2 on the price of computing resources and utilities. From Fig. 6, it can be seen that as the total available computing resources of UAV increase, the price of computing resources decreases and the total revenue increases. In addition, as the maximum tolerated execution delay T_2 of the UEs increases, the price of the computing resources decreases, and at the same time the total revenue and the average utility of UEs increase.

In Fig. 7, we explore the impact of the number of UAVs and the number of the UEs on the utilities. When the number of UAVs increases, the resources in the system increase, and therefore the social welfare, the total utility of UEs and the average benefits of UEs increase. Note that with the number of UAVs greater than the number of UEs, some of the UAVs will be idle and not selling resources. As can be seen in Fig. 7(a) and Fig. 7(b), as the number of users increases social welfare and the total utility of the UEs rise rapidly and then at a lower rate. Fig. 7(c) shows that as the number of users increases the average utility of UEs keeps decreasing. This is because when the number of UEs in the system is small, the available resources can satisfy the demands of most UEs, and as the number of users increases, the utilization of the resources keeps increasing. When the number of UEs is large and keeps increasing, spectrum and computational resources become strained, resulting in the inability to satisfy the needs of partial UEs and a decrease in the percentage of UE participation.

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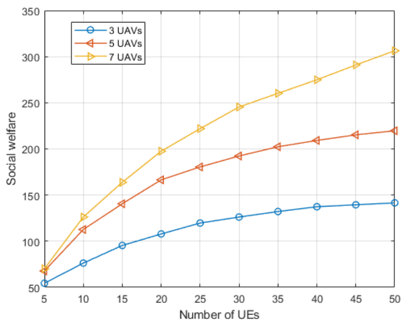
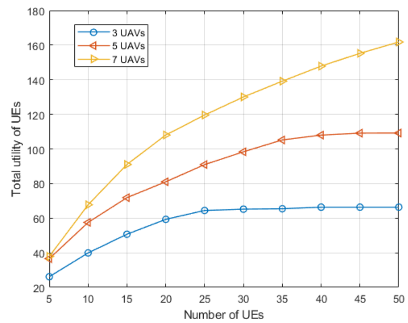
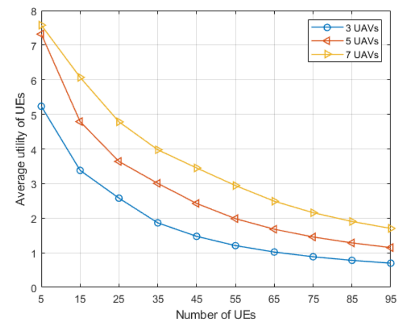


(a)



(b)



(c)

Fig. 7. The impact of the number of UAVs. (a) Impact of the number of UEs on social welfare for different numbers of UAVs. (b) Impact of the number of UEs on total utility of UEs for different numbers of UAVs. (c) Impact of the number of UEs on average utility of UEs for different numbers of UAVs.

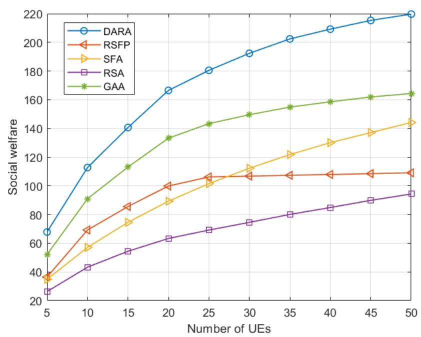


Fig. 8. Social welfare vs. number of UEs

Fig. 8 shows the social welfare of different methods with the different numbers of UEs. We contemplate a system replete with 5 UAVs. When the number of UEs is relatively small, the social welfare of all methods increase rapidly. As the number of UEs increases to a larger number, the spectrum resources and computing resources become scarce. The system load reaches an upper limit, resulting in a less significant change in social welfare. From the Fig. 8, it is evident that our proposed DARA method outperforms RSA by 131.5% to 141.3%, RSFP by 79.5% to 101.8%, SFA by 51.7% to 89.1% and GAA by 30.2% to 35.8% in terms of social welfare. This superiority arises from the fact that, in the RSA, the UAV randomly selects a UEC to sell resources, resulting in the worst social welfare. In RSFP, fixed prices paid by UEs and fixed amounts of computing and spectrum resources lead to a rigid resource distribution, not adaptable to UE demand. Although the SFA maximizes UAV benefits, it does not guarantee optimal matching of UECs to UAVs for their best benefits. In addition, GAA only achieves maximizing the utilities of each UEC while ignoring the impact of the allocation strategy on the utilities of UAVs. Therefore, as the number of UEs increases, our proposed DARA achieves the highest social welfare when compared to other benchmarks.

VII. Conclusion

In this paper, we first propose the BRTM for Multi-UAV edge computing system to address the possible security risks. The framework of BRTM and the process of resource trading are described in detail. Then, to motivate the UAV and UEs to engage in resource trading and maximize social welfare, we propose a pricing-based incentive mechanism. Additionally, to solve the optimal resource purchase strategy, the DARA is designed. We formulate the resource pricing between UAVs and UEs as a two-stage Stackelberg game problem and match the UAV and UE by auction theory. The impact of the number of UEs and UAVs, the total available resources of UAV and the computational task size are analyzed in the simulation. Besides, Numerical results depicts that our proposed method achieves higher social welfare than other benchmark methods.

Appendix A
Proof of the Theorem 2

The problem 2a is a convex optimization problem, it is easy to construct the Lagrangian function. Then, we can convert the original problem into solving the dual problem. The Lagrangian function of this problem is given by

$$\begin{aligned}\mathcal{L}\left(b_{ij},\eta\right) =&\alpha_i \log_2\left(1+\frac{T_i^{off} b_{ij}\log_2(1+\frac{p_m g_{ij}}{\delta^2})}{w_i}\right)\\&-p_j b_{ij}+\eta b_{ij},\end{aligned} \quad (58)$$

where η is the negative dual variable associates with the constraints $b_{ij} \geq 0$.

The dual function is given as to find the maximum value of the Lagrangian function, which is defined as $\mathcal{V}(\eta) = \max \mathcal{L}(b_{ij},\eta)$ with $b_{ij} \geq 0$. The dual optimization problem is given as $\min \mathcal{V}(\eta)$ with $\eta \geq 0$. The optimal solution should satisfy the following KKT conditions:

$$\begin{aligned}&\frac{\partial \mathcal{L}\left(b_{ij},\eta\right)}{\partial b_{ij}}\\&=\frac{\alpha_i T_i^{off}\log_2(1+\frac{p_m g_{ij}}{\delta^2})}{\ln 2\left(w_i+T_i^{off} b_{ij}\log_2(1+\frac{p_m g_{ij}}{\delta^2})\right)}-p_j+\eta=0 \quad (59)\\&s.t.\quad \eta \geq 0, b_{ij} \geq 0, \quad (60)\\&\qquad \eta b_{ij}=0. \quad (61)\end{aligned}$$

From (59), we can derive

$$b_{ij} = \frac{\alpha_i}{(p_j - \eta)\ln 2} - \frac{w_i}{T_i^{off}\log_2(1 + \frac{p_m g_{ij}}{\delta^2})}. \quad (62)$$

We adopt the counterfactual approach, assuming that $b_{ij} = 0$ when $p_j < [\alpha_i \pi_i / (w_i \ln 2)]$, where $\pi_i = T_i^{off}\log_2(1 + \frac{p_m g_{ij}}{\delta^2})$. Then, from (62), it follows $p_j = [\alpha_i \pi_i / (w_i \ln 2)] + \eta$. Since $\eta \geq 0$, it can be deduced that $p_j \geq [\alpha_i \pi_i / (w_i \ln 2))]$, which contradicts the presumption. Therefore, $b_{ij} \neq 0$ when $p_j < [\alpha_i \pi_i / (w_i \ln 2)]$. From (61), it follows $\eta = 0$. Therefore, the optimal solution in this set of p_j can be defined as

$$b_{ij} = \frac{\alpha_i}{p_j \ln 2} - \frac{w_i}{\pi_i}, \text{ if } p_j < \frac{\alpha_i \pi_i}{w_i \ln 2}. \quad (63)$$

Assume that $b_{ij} > 0$ when $p_j \geq [\alpha_i \pi_i / (w_i \ln 2)]$. Then from (61), it can be derived that $\eta = 0$. Let $b_{ij} > 0$ and $\eta = 0$, we can get $p_j < [\alpha_i \pi_i / (w_i \ln 2)]$ from (62), which contradicts the presumption. The optimal solution in this set of p_j can be defined as

$$b_{ij} = 0, \text{ if } p_j \geq \frac{\alpha_i \pi_i}{w_i \ln 2}. \quad (64)$$

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