Edge Computing Resource Allocation for Unmanned Aerial Vehicle Assisted Mobile Network with Blockchain Applications

Haitao Xu*, *Member, IEEE,* Wentao Huang, Yunhui Zhou, Dongmei Yang, Ming Li, *Member, IEEE,* and Zhu Han, *Fellow, IEEE,*

Abstract Mobile edge computing is becoming a major trend in providing computation capacities at the edge of mobile networks. Meanwhile, unmanned aerial vehicles (UAVs) have been considered as distinctly important integrated components to extend services coverage. In order to provide users with higher and satisfied quality of services, edge computing resources need to be allocated between edge computing stations (ECSs) and UAVs in mobile networks. However, there are significant security and privacy problems due to the open environments of ECSs and UAVs. In this paper, we propose a resource pricing and trading scheme based on Stackelberg dynamic game to optimally allocate edge computing resources between ECSs and UAVs, and blockchain technology is applied to record the entire resources trading process to protect the security and privacy. The ECSs control the resources price of the allocated edge computing resources, where the UAVs follow the price announced by the ECSs and make optimal decisions on the edge computing resources demands. Blockchain is integrated in the resource trading process to ensure the security and privacy. Numerical simulations are given to show the effectiveness of the proposed scheme.

Keyword edge computing; unmanned aerial vehicles; resource pricing; resource allocation; blockchain; Stackelberg game

I. Introduction

Recently, with the rapid development of mobile network, people's life has become more convenient. Mobile networks can provide a variety of customized services according to user needs. However, with the advances of Internet of Things (IoT), and the increase of big data, mobile network is facing a lot of new demands and challenges. The types of mobile terminals and the quantity of data traffic have been greatly raised. Even the scenarios of mobile services are gradually diversified [1], [2]. The traditional mobile network is not sufficient in supporting the increasing services requirements, and cannot support the demands of high bandwidth, low latency, and real-time communication [3], [4]. Although, cloud computing has been considered as an effective solution to deal with the problems brought by the increasing services requirements [5]–[7], there are still lots of challenges need to be solved, especially the data transfer latency problem and the energy consumption problem. As an extension of cloud computing, mobile edge computing (MEC) can be applied to mobile networks for data computation and communication [8], [9]. Compared to the other computing paradigms, MEC can provide services environment and computation capabilities at the edge of mobile networks [10]. MEC can transfer the caching data and computation tasks to the edge computing stations (ECSs) [11], [12], to make the bandwidth pressure relieved and the data processing efficiency greatly improved [13], [14]. Moreover, there is no need to transmit the services requests to the central computing stations, where it is more convenient to access the local computation and communication resources [15]–[17].

Particularly, the existing MEC based mobile networks are not applicable to the situation where the mobile users are sparely distributed. In addition, it is hoped that the MEC based mobile networks can provide assured communication in some special environments. However, under the extreme environments, such as typhoon, earthquake and other natural disasters, the MEC based mobile network will be destroyed and the communication services will be interrupted. Thus, the emergency communication techniques are needed [18], [19]. Among the various emergency communication technologies, unmanned aerial vehicles (UAVs) are becoming a widely utilized solution to improve the connectivity of mobile users, and to provide mobile services under the extreme situations, where the UAVs can solve the communication assurance issues facing the complex and changeable environments [20]–[22]. Moreover, the UAVs-assisted MEC networks can provide caching and computation services for mobile users, to support the increasing traffic requirements and the explosively increasing number of mobile users [23]–[25]. UAVs can obtain edge computing resources from the edge computing stations (ECSs) to complete more complex computation and communication tasks for mobile users, to provide mobile users with better services. The UAV-assisted MEC networks will be more broad, fast and convenient than the previous networks [26], [27].

Haitao Xu, Wentao Huang, Yunhui Zhou, and Dongmei Yang are with the Department of Communication Engineering, University of Science and Technology Beijing (USTB), Beijing, 100083 China. Corresponding Author: Haitao Xu, E-mail: {alex_xuht}@hotmail.com.

Ming Li is with Department of Computer Science and Engineering, The University of Texas at Arlington, USA. {ming.li}@uta.edu

Zhu Han is with the Department of Electrical and Computer Engineering in the University of Houston, Houston, TX 77004 USA, and also with the Department of Computer Science and Engineering, Kyung Hee University, Seoul, South Korea, 446-701. {zhan2}@uh.edu

Lots of works have been done in resource allocation problem of ECSs and UAVs [28]–[30]. However, due to the open characteristics of UAV communication and MEC paradigm, there are serious security and privacy issues in achieving edge computing resources allocation between ECSs and UAVs [31], [32]. How to maximally protect the security during the resource allocation is a secure problem needs to be solved. In the UAV-assisted MEC networks, the UAVs are always scattered distributed. Then it will be difficult to protect the security during the resource allocation using the traditional methods. The distributed digital cryptocurrency, such as the blockchain [33], can be used to protect the security and privacy for these kinds of distributed security problems. The blockchain technology has the characteristics of decentralization, unchangeable data, and high transparency, which can ensure the credibility and traceability of data information [34], [35], which has significant effect on network security and has attracted many scholars to conduct extensive research in recent years [36]–[38]. The emergence of blockchain technology provides new ideas and directions for effectively solving the security problems in the UAV-assisted MEC networks.

In this paper, we construct a UAV-assisted MEC network with blockchain applications. We mainly study the resource trading interactions between ECSs and UAVs to achieve optimal edge computing resources allocation. The ECSs allocate the edge computing resources and receive profits from the UAVs. The UAVs request the edge computing resources from the ECSs to provide mobile users with satisfied QoS. The edge computing resources trading interactions will be formulated as a Stackelberg game. Specially, using the blockchain technology to protect the security and privacy, the ECSs should pay rewards to issue the mining tasks in the blockchain, to record the trading interactions between ECSs and UAVs. The main contributions are as follows,

- We formulate the trading interactions between ECSs and UAVs as a Stackelberg game, where the ECSs are the leaders and the UAVs are the followers. The ECSs control the unit price of edge computing resources to maximize the profits earned from the UAVs. The UAVs control the amount of requested edge computing resources to maximize their objectives.
- We propose a blockchain based secure resources trading scheme in the proposed network. The ECSs work as the edge computing resources providers and the mining tasks issuers in the blockchain based network, where the UAVs are the edge computing resource requesters. The transactions information about the edge computing resources trading, including the resources demands and resources price, would be recorded in the blockchain.
- We formulate the objectives of ECSs as utility maximization problems. We employ the Lagrangian to obtain the equilibrium solutions of ECSs for resources pricing problem.
- We formulate the optimal resources demands problem of UAVs using differential game. We employ the Bellman dynamic programming to obtain the equilibrium solutions of UAVs under two situations, open loop situation and feedback situation, respectively.
- We conduct numerical simulations to evaluate the performance of the proposed scheme. The results show that the objectives optimization of ECSs and UAVs can be achieved.

The remainder of the paper is organized as follows. Section II presents a brief review of related works. System model is given in Section III, and resource allocation scheme is given in Section IV. In Section V, we analyze the solutions of the proposed Stackelberg game model. Numerical simulations are given in Section VI. Finally we conclude the work in Section VII.

II. Related Work

With lower cost and higher mobility, UAVs are playing an important role in auxiliary mobile networks. Meanwhile, reasonable resource allocation of UAV-assisted mobile networks is becoming a key role in improving the quality of communications [39]–[41]. In [39], a drone-assisted cellular network is proposed where every users can share UAVs to improve their individual uplink rates. Uplink resource allocation in terms of power and time allocation among users is investigated to optimize the uplink sum-rate. However, it is assumed that the AG channel experiences quasi-static flat fading and does not consider subcarrier allocation. In [40], a joint subcarrier and power allocation algorithm is given to solve the resource allocation problem of OFDMA uplink in UAV-assisted emergency communications. The subcarriers can be allocated among users according to the optimal solutions. However, it does not take latency and consumption into consideration. In [41], a fog computing-based drone cluster (FCSD) structure is investigated. Considering the energy consumption of UAVs, a task allocation problem that minimizes FCSD energy consumption under the constraints of delay and reliability is defined. But the algorithm does not take into account information security issues.

Now, the researchers pay attentions to the UAV-assisted MEC networks, because the UAVs can act as computation and communication relays for mobile users [42]–[44]. In [42], the UAV can collect and process the computation tasks of users. Given the services requirements of users, the energy efficiency of UAV is maximized and the energy consumption of UAV is maximized. In [43], a UAV is properly deployed to facilitate the MEC service provisioning to a set of IoT devices. Service delay of all IoT devices and UAV energy consumption are jointly optimized. However, most of the current works did not consider the security issues while deploying the UAV-assisted mobile networks. Due to the open environment of wireless transmission, the security performance in UAV-assisted MEC is important and needs to be considered [44], [45]. In [44], a secure UAV-enabled MEC system is proposed and a low-complexity iterative algorithm is designed to maximize the minimum secrecy capacity subject to latency, minimum offloading and total power constraints. In [45], the security problems for dual UAV-assisted MEC systems are investigated, where one UAV works as the offloading node to provide computing services to the devices, and the other UAV is a jammer to suppress the vicious eavesdroppers. The communication and computation resources are jointly optimized based on the proposed minimum secure computing capacity maximization problems.

Recently, there are several works attempting to apply blockchain into UAV-assisted MEC networks [46]–[48]. In [46], a blockchain based secure spectrum trading system is proposed. A pricing-based mechanism is given to motivate the spectrum trading between mobile network operators and UAVs, and blockchain is utilized to improve the security and privacy during the trading process. In [47], a blockchain based data acquisition process is proposed in the UAV-enabled MEC networks. The collected data is stored securely in blockchain at mobile edge computing servers. In [48], the pricing and resource management in IoT system with blockchain-as-a-service (BaaS) and MEC is studied. A stochastic Stackelberg game with multiple leaders is proposed to the resource management and pricing problems. However, secure resource trading between the ECSs and UAVs based on blockchain technology is not considered in all the previous works. In addition, there are few researches considering the dynamic variations of users services demands in modeling the secure resources trading problem. Then, in this paper, we try to construct a blockchain based secure edge computing resources allocation scheme for the edge computing station and UAVs using Stackelberg dynamic game, considering the users services demands as the system state.

III. System Model

In this section, we firstly give out the system model in Section III-A. Then we analyze the security threats in the proposed system in Section III-B. Finally, we propose a blockchain based security framework in Section III-C.

A. System Model

We consider a UAV-assisted mobile edge computing network consisting of a number of ECSs and UAVs. The set of the ECSs is denoted by $\mathcal{M}$, $\mathcal{M} = \{1, 2, ..., M\}$, and the set of the UAVs served by ECS m is denoted by $\mathcal{N}_m$, $\mathcal{N}_m = \{1, 2, ..., N_m\}$, as shown in Figure 1. The whole network can be divided into three layers, ECS layer, UAV layer, and user layer, respectively. In ECS layer, there are multiple ECSs that are responsible for allocating edge computing resources for UAVs. They can control the trading price of the allocated edge computing resources. In UAV layer, each UAV can provide computation services for mobile users. In order to improve the quality of services (QoS) provided to mobile users, the UAVs with limited on-board resources should request edge computing resources from the ECSs. In user layer, each mobile user would upload the services requirements to the UAVs. The services requirements include the computation tasks, the communication requests, and so on. Assuming every UAV accesses to its nearest ECS, and every mobile user accesses to its nearest UAV. Then all the services requirements of mobile users can be transmitted to the UAVs, and all the UAVs can provide satisfied services to mobile users using the edge computing resources obtained from the ECSs.

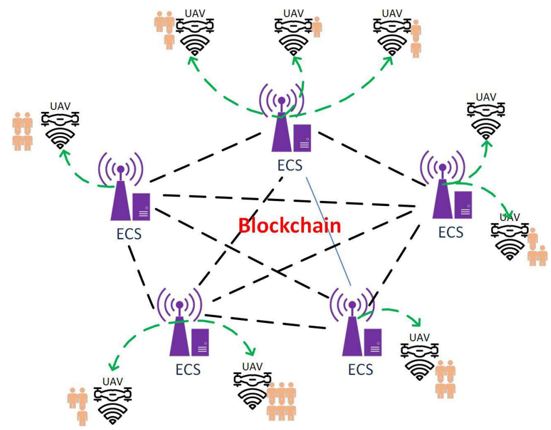

Fig. 1: System model

In the proposed system, since the UAVs should use the obtained resources from ECSs to provide the computation services to mobile users, we assume there are enough resources available in the ECSs for resources allocation. In the communication model, we assume that the up-link and down-link channels between ECSs and UAVs are symmetrical. The available transmission capacity calculated by the Shannon theorem for the allocated resources is assumed to be enough. Each UAV is responsible for gathering users services requirements from its coverage. Then, according to the amount of the services requirements gathered from the mobile users, UAVs make decisions on the edge computing resources requirements to the ECSs. In order to obtain the edge computing resources from the ECSs, the UAVs have to pay a certain amount revenue to the ECSs, The ECSs can earn profit by allocating the edge computing resources to the UAVs, through setting a appropriate trading price for the allocated edge computing resources. In the above process, the trading price of edge computing resources is an important factor in determining the resources trading behaviors and is controlled by ECSs.

B. Security Analysis

In the proposed system, we mainly focus on the edge computing resources trading between ECSs and UAVs. However, there are security and privacy issues that needs to be considered. The UAVs need to upload the resources requestments to the ECSs, which may cause security issues due to the open environment of UAVs. Meanwhile, some of the ECSs may refuse to acknowledge the receipt of the requests, which will lead to serious privacy issues. In addition, some UAVs may pretend that they haven't obtained the edge computing resources from the ECSs. In order to guarantee the security and privacy in resources trading process between UAVs and ECSs, the blockchain technology is utilized in this paper. With the blockchain technology, the resources trading between UAVs and ECSs can be written to the blockchain. Then the UAVs can obtain the edge computing resources from the ECSs in a decentralized but trustful way. Simultaneously, when the trading occurs, the optimal trading price for the allocated resources and the optimal amount of requested resources would be executed.

Based on the blockchain technology, a trusted scheme is designed for the edge computing resources trading between ECSs and UAVs. Integrated with the blockchain function into the proposed system, a "transaction" will be posted to the blockchain to announce that the trading relations are existing between ECSs and UAVs. However, as there are no sufficient resources with the UAVs to run the blockchain applications, the ECSs are chosen to run the blockchain functions. The ECSs are considered as the consensus nodes in the proposed network to run the blockchain applications, and they will record the resources trading transactions. The ECSs in the blockchain check the trading actions between ECSs and UAVs, update the transaction records, and share the transactions over the blockchain. Based on the blockchain, the system does not require a centralized process or a central unit for the resource trading between the ECSs and UAVs.

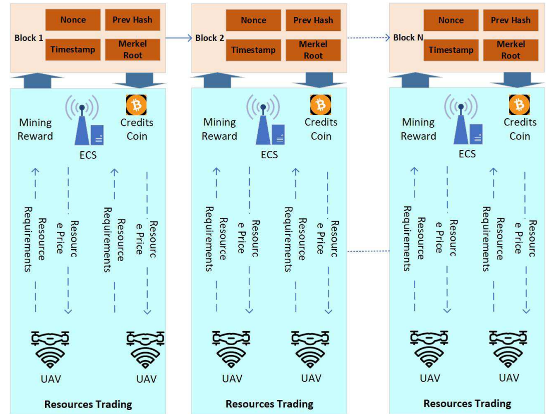

Fig. 2: Blockchain structure

C. *Blockchain based Resources Trading*

Integrated the blockchain function, there will be four roles in the proposed system, i.e., the edge computing resources requesters, the edge computing resources allocators, the mining tasks publishers and the trading block miners. The UAVs are the edge computing resources requesters in the proposed system, which control the resources requirements and obtain the edge computing resources from the ECSs. The ECSs are the edge computing resources allocators to control the trading price and to allocate the edge computing resources to the UAVs. The ECSs also work as the mining tasks publishers and the trading block miners in the blockchain system. In the blockchain based system, after controlling the resources prices and allocating the edge computing resources, the ECSs act as the blockchain nodes, submitting the trading information to the blochchain system. Based on the consensus mechanisms, the blockchain nodes verify the trading information and record the unchanged trading information in the system. The computation tasks for blockchain mining are only executed by the ECSs, because of the high computing power requirements. More details of the blockchain based resources trading scheme are given as follows.

1) Step 1: As the resources requesters, UAVs generate the edge computing resources demands $d_i(t)$. Given an initial resources price, UAVs generate the resources demands based on the services requirements from mobile users, and upload the resources demands message to ECSs.

2) Step 2: Received the resources demands from UAVs, ECSs control the resources price $p_i(t)$ to optimize the profit earned from edge computing resources allocation. ECSs broadcast the resources price and allocate the requested edge computing resources to UAVs.

3) Step 3: ECSs collect all the resources trading information $\{d(t), p(t), N\}$ at time t and issue mining tasks on the blockchain. All the transactions are structured into blocks. Each block contains a cryptographic hash to the prior blocks in the blockchain.

4) Step 4: A public blockchain among ECSs under the proof of work (PoW) based Nakamoto consensus protocol is considered. The ECSs use the credits coins to release the mining tasks, and the other ECSs in the blockchain compete to accomplish the mining tasks to write a "transaction" into the blockchain. The credits coins can be obtained from the successful mining tasks.

Based on blockchain, distributed consensus can be established before the trading records between ECSs and UAVs are written into a digital ledger. It is executed by all the collaborative ECSs based on timestamps and hash algorithms. The structure of the proposed blockchain is given in Figure 2. Each block in the proposed blockchain system contains a cryptographic hash value to the prior block. To participate in the consensus process, the ECSs are working as the miners in the proposed blockchain system. Following the works in [4], [33], [35], [48], the PoW based Nakamoto consensus protocol is considered and achieved based on the block mining of ECSs. Here, credits coins are defined as new cryptocurrency for the edge computing resources trading. Once the ECSs successfully solve the PoW puzzle, they will win the credits coins. During edge computing resources pricing and allocation, the trading records are stored in the blockchain, and the blockchain-inspired distributed consensus mechanisms are achieved. The edge computing resources trading records will be encrypted and structured into the blocks based on distributed consensus mechanisms.

IV. Resources Allocation Scheme

In this section, we firstly propose a resources leasing mechanism for ECSs and UAVs in Section IV-A. Then we give out the dynamic state of services demand from mobile users in Section IV-B. Finally, a blockchain based framework is proposed for secure resources trading problem in Section IV-C and a Stackelberg dynamic game framework is presented for resources allocation problem in Section IV-D.

A. *Resources Leasing Mechanism*

In this section, we will design a resources leasing mechanism to motivate the ECSs to allocate the edge computing resources to the UAVs. Based on the proposed scheme, the UAVs can obtain the edge computing resources form the ECSs to provide mobile users with enhanced QoS, and the ECSs can obtain a certain amount of profit from the allocated resources.

Here, the UAVs, which are responsible for the payments of edge computing resources, are stands for the UAVs, the UAV operators or the operators. Then we can say that the UAVs should pay the ECSs for the allocated edge computing resources. Therefore, a mechanism is given in this section to facilitate the trading of edge computing resources between ECSs and UAVs.

For the ECSs, they can receive the edge computing resources requirements from the UAVs. The ECSs provide the edge computing resources to the UAVs based on requirements, and obtain the payments for the allocated resources from the UAVs. Let $p_i(t)$ denote the unit price of the edge computing resources provided to UAV i at time t, $d_i(t)$ denote the resources demands from UAV $i \in N$ at time t. Then, the objective of each ECS is to maximize the profit obtained from the edge computing resources trading, which can be denoted by the following function,

$$U_{ECS}(t) = \sum_{i=1}^{N} \gamma_i p_i(t) d_i(t), \tag{1}$$

where γ_i is the possibility that the resources trading between UAVs and ECSs can be written into a valid block. Through setting an appropriate trading price $p_i(t)$ for UAV $i \in N$ at time t, each ECS can attract more UAVs to require edge computing resources.

For the UAVs with limited on-board resources, they require the edge computing resources from the ECSs based on the services requirements of mobile users. They can earn revenue for the services provided to the mobile users. The revenue function of UAV i at time t is given as follows,

$$U_i(t) = r_i(t)x_i(t) - \gamma_i p_i(t) d_i(t). \tag{2}$$

Based on (2), we can find that the revenue function of each UAV is composed by two parts. The fist part is given by $r_i(t)x_i(t)$, which is the revenue earned from the provided services, where $r_i(t)$ is the price of services, and $x_i(t)$ is the services requirements of mobile users. The services requirements are the services demands of mobile users that need to be completed by the UAVs, which include the computing tasks, communication requests, and so on. The second part of revenue function is $p_i(t)d_i(t)$, which is the payments for the allocated edge computing resources from ECSs.

As the UAVs use the edge computing resources from the ECSs to provide services to the users, the UAVs should increase the edge computing resources requirements as the users' demands increase. The payments of the allocated edge computing resources will become very high for UAVs, if there are massive demands need to be satisfied. Then, the objective function of UAV i during the observation time $[0,T]$ can be expressed as,

$$\max_{d_i(t)} J_i(t) = \max_{d_i(t)} \left\{ \int_0^T [r_i(t)x_i(t) - \gamma_i p_i(t) d_i(t)] e^{-\tau t} dt + g_i x_i(T) \right\}, \tag{3}$$

where $g_i x_i(T)$ is the terminal cost of each UAV at the final observation time T. $e^{-\tau t}$ is the discount factor, and τ is the discount rate.

B. Dynamic Services Requirements of Mobile Users

As given in the above subsection, we use $x_i(t)$ to denote the services requirements of mobile users. For each UAV $i \in N$, it trys to provide the services to mobile users with the edge computing resources from the ECSs. The UAVs which have more computing resources can served more mobile users. Meanwhile, the services requirements of mobile users will be affected by the unit price of services. Based on the above assumptions, we use a differential equation to describe the evolution of users services demands in UAV i [49], which is given as follows,

$$dx_i(t) = \left[\mu_i r_i^{\alpha_i}(t) + \upsilon_i d_i^{\beta_i}(t) + \delta_i x_i(t)\right] dt, \tag{4}$$

where $r_i(t)$ is the unit price of services, with the weighted parameter μ_i. As the linear pricing mechanism is an effective policing mechanism that influences users' behaviors towards a more efficient operating point, we use the linear pricing mechanism to formula the relationship between the unit price $r_i(t)$ and the services requirements $x_i(t)$. Then the unit price of services could be a linear function of services requirements $x_i(t)$, i.e., $r_i(t) = \varphi_i x_i(t)$. Based on the linear pricing relationship, the method of income calculation is more simple, intuitive and convenient. $d_i(t)$ is the edge computing resources of UAV i obtained from ECS, with the weighted parameter υ_i, which can be considered as the resources capacity of UAV i at time t. The users services demands are defined referring to the Cobb-Douglas function [49] that models well these elasticity aspects. It is assumed that mobile users can obtain the information of services price $r_i(t)$ and services capacity $d_i(t)$ provided by UAV i. Compared to the UAV with lower resources capacity, there will be more mobile users accessing the UAV with larger resources capacity. δ_i is the users departure rate. α_i and β_i are elasticity coefficient of services demands state. Based on (4), the evolution of users services demands are mainly influenced by two factors, the unit price $r_i(t)$ of the provided services and the capacity $d_i(t)$ of edge computing resources.

C. Miners Cost

In this subsection, we will discuss the blockchain-based framework for the proposed system, as given in Figure 2. In order to motivate the ECSs to run the mining function and to execute the blockchain application, mining rewards are given to the ECSs. The ECSs compete against each other in the mining to be the first one to solve the PoW puzzle and receive the mining rewards. Based on the blockchain technology, if the transaction is validated and written into a block, the ECS that firstly completes the mining task can obtain the mining rewards. The ECS that firstly mines the mining tasks collects the real-time information of transactions between ECSs and UAVs. It records the payments given by the UAVs, the price of allocated resources and the amount of allocated resources by the ECSs. It transmits the trading-related information among all the nodes in the blockchain. Then, the transaction is written into the blockchain, and the ECS that successfully mines the mining tasks can win the mining rewards. Meanwhile, the ECS winning the mining rewards can also obtain some transaction coins, which can be considered as credits coins in the blockchain system. The ECSs need to pay a certain amount of credits coins to publish the mining tasks every time. Without the credits coins, the ECSs cannot publish the mining tasks in the blockchain and the transactions between ECSs and UAVs cannot be conducted. Let $\phi(t)$ denote the cost of ECS for publishing the mining tasks in the blockchain, which is given as follows,

$$\phi(t) = \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p_i(t)} \right]. \tag{5}$$

In (5), the cost function is composed by two components. The first component is the mining rewards denoted by ψ. The second part, $\pi_i \frac{d_i(t)}{p_i(t)}$, is the payment of credits coins for publishing the mining tasks, where π_i is the coefficient between the credits coins and task scale, and $\frac{d_i(t)}{p_i(t)}$ is the task scale of ECS for the transactions with UAV i. During the trading process, if the price is high, the willingness to require the edge computing resources of ECSs will be reduced and the transactions need to be recorded will be decreased. Meanwhile, if more resources are purchased by the UAVs, more transactions need to be recorded in the blockchain. Then we use $\frac{d_i(t)}{p_i(t)}$ to denote the task scale of ECS for the transactions with UAV i. Then the objective function of ECS given in (1) should be changed to a function of profit minus payment, as follows,

$$U_{ECS}^{'}(t) = \sum_{i=1}^{N} \gamma_i p_i(t) d_i(t) - \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p_i(t)} \right]. \tag{6}$$

In (6), the objective function of ECS mainly consists of two parts. One part is the profit obtained from the allocated edge computing resources, which is denoted by (1). The second part is the cost of ECS for publishing the mining tasks in the blockchain, as given in (5). As the control variable for (1) and (5) are both the unit price $p_i(t)$, the control variable of (6) is the same.

D. Stackelberg Game Framework

In Section IV-A, a resources leasing mechanism to motivate the ECSs to allocate the edge computing resources to the UAVs. Based on the proposed scheme, the ECSs can obtain a certain amount of profit from the allocated resources, and the UAVs can obtain the edge computing resources form the ECSs to provide mobile users with enhanced QoS. Setting an appropriate resources price, the ECSs try to optimize their profits from the allocated resources. With the allocated edge computing resources, the UAVs try to optimize their utilities earned from the provided services. It is obvious that game theory can be used to analyze the optimized problems of ECSs and UAVs, where ECSs and UAVs can be both considered as rational game players during the resources trading process. During the trading process, the ECSs firstly broadcast the resources price to the UAVs, and the UAVs control their resources requirements according to the price. Thus, the resources trading between ECSs and UAVs can be formulated using Stackelberg game.

In this paper, the resources trading between ECSs and UAVs is modeled as a two-stage Stackelberg game, where the ECSs are the leaders, which control the unit price of the edge computing resources provided to the UAVs. The ECSs also work as the mining tasks publishers and the trading block miners in the blockchain system. The UAVs are the followers, which optimize the resources requests to the ECSs, limited by resources price controlled by the ECSs. The optimization problems for ECSs and UAVs are given as follows.

1) Optimization problems of ECSs: For the ECSs, they should make decisions on the resources price $p_i(t)$ to maximize the profit function, which is given as follows,

$$U_{ECS}^{'}(t) = U_{ECS}(t) - \phi(t), \tag{7}$$

where the unit price $p_i(t)$ is the control variable for the ECSs. The game problem of ECSs can be written as follows,

***Problem** 1:* **(Leader's Game):**

$$\begin{aligned} \max_{p_i(t)} \quad & U_{ECS}^{'}(t) \\ \text{s. t.} \quad & 0 \le p_i(t) \le \tilde{p}_i. \end{aligned} \tag{8}$$

2) Optimization problems of UAVs: For the UAVS, they should control their edge computing resources demands $d_i(t)$ to optimize their objectives. The objectives of the UAVs are given by (3), with a dynamic system state given by (4). Therefore, the game problem for UAVs can be given as follows,

***Problem** 2:* **(Follower's Game):**

$$\begin{aligned} \max_{d_i(t)} \quad & J_i(t) \\ \text{s. t.} \quad & dx_i(t) = f_i(t,x)dt, \end{aligned} \tag{9}$$

where $f_i(t,x) = \mu_i r_i^{\alpha_i}(t) + \upsilon_i d_i^{\beta_i}(t) + \delta_i x_i(t)$.

UAVs tend to achieve their maximum utilities while ECSs focus on getting the most profits. Hence, to adjust the demand of edge computing resources and the price for the allocated edge computing resources, a Stackelberg dynamic game can be formed. The ECSs who are the leaders first announce the unit price of the allocated edge computing resources to the UAVs (followers). Based on the price declared by the ECSs, the followers make decisions on the expected edge computing resources. After the demands are uploaded to the ECSs, the ECSs decide the optimal price to obtain the maximum profit. The Stackelberg equilibrium ensures the utilities of ECSs are maximized given that the UAVs generate their resources requirements to maximize the profit. The objectives of the proposed Stackelberg game are to find Stackelberg equilibriums for both ECSs and UAVs. The UAVs can find their optimal resources demands and the ECSs can optimally set a proper resources price. The Stackelberg equilibrium can be written as follows.

***Definition** 1: For the edge computing station, the service price $p_i^*(t)$ is the Stackelberg equilibrium, if the following* *inequality holds for all service price $p_i(t) \neq p_i^*(t)$,*

$$U_{ECS}^{'}(p_i^*(t), d_i^*(t), t) \geq U_{ECS}^{'}(p_i(t), d_i^*(t), t). \tag{10}$$

***Definition** 2: For the UAV i, the resource demands $d_i^*(t)$ is the Stackelberg equilibrium, if the following inequality holds for all service price $d_i(t) \neq d_i^*(t)$,*

$$J_i(d_i^*(t), p^*(t), t) \geq J_i(d_i(t), p^*(t), t). \tag{11}$$

V. Equilibrium Analysis

In this section, on the basis of the Stackelberg game model proposed in Section IV-D, we analyze the performance of the game model and calculate the Stackelberg equilibriums for ECSs and UAVs to obtain the optimal resources price and demands between ECSs and UAVs. Based on the proposed framework, we will firstly analyze the equilibrium of UAVs in Section V-A, then the optimal resources price will be given to maximize the ECSs utilities in Section V-B.

A. Equilibrium of UAVs

We first consider the equilibrium solutions of UAVs, in which the UAVs pay the ECSs for the allocated edge computing resources at a price level $p(t)$ to maximize their own individual utilities non-cooperatively. In this section, the resources price is uniform, which means the ECSs charge the UAVs with the same price. Given the resources price $p(t)$, we can find the optimal resources demands of UAVs using Bellman dynamic programming. Before analyzing the equilibrium solutions, one definition is first given for Bellman dynamic programming, as follows.

***Definition** 3: The optimal resource demand $\{d_i^*(t)\}$ of UAV i is an open-loop equilibrium to the problem in (3), and $\{x_i^*(t), 0 \leq t \leq T\}$ is the corresponding optimal trajectory of users' demand, if there exists a costate function $\Lambda_i(t)$ such that the following equations are satisfied,*

$$d_i^*(t) = \arg\max \left\{ J_i(t) + \Lambda_i(t)\dot{x}_i(t) \right\}, \tag{12}$$

$$\dot{\Lambda}_i(t) = -\frac{\partial \left[J_i(t) + \Lambda_i(t)\dot{x}_i(t) \right]}{\partial x_i(t)}, \tag{13}$$

where $\dot{x}_i(t) = \frac{dx_i(t)}{dt}$ and $\dot{\Lambda}_i(t) = \frac{d\Lambda_i(t)}{dt}$.

In order to simplify the expression of **Definition** 3, we replace (12) with Hamiltonian function as follows,

$$d_i^*(t) = \arg\max\{H_i(t, x_i(t))\}, \tag{14}$$

$$\dot{\Lambda}_i(t) = -\frac{H_i(t, x_i(t))}{\partial x_i(t)}, \tag{15}$$

where,

$$H_i(t, x_i(t)) = J_i(t) + \Lambda_i(t)\dot{x}_i(t). \tag{16}$$

Based on **Definition** 3, each UAV controls its resources demands to maximize its individual utility function. Next, we analyze the existence and uniqueness of the open-loop equilibrium for each UAV.

***Theorem** 1: There exists a unique open loop equilibrium for each UAV in **Problem 2**.*

Proof: Based on **Definition** 3, in order to get the open loop equilibrium solutions for UAVs, we first need to calculate the partial derivative to the Hamiltonian function, and let the partial derivative to be zero. We have the partial derivative of Hamiltonian function as follows,

$$\frac{\partial H_i(t, x_i(t))}{\partial d_i(t)} = -\gamma_i p_i(t) + \Lambda_i(t)\beta_i\nu_i d_i^{\beta_i - 1}(t). \tag{17}$$

Based on (15) and (16), $\Lambda_i(t)$ can be given by the following differential equation,

$$-\dot{\Lambda}_i(t) = 2\varphi_i x_i(t) + \Lambda_i(t)\left[\alpha_i \mu_i \varphi_i^{\alpha_i} x_i^{\alpha_i - 1}(t) + \delta_i \right]. \tag{18}$$

Then the optimal resources demands of UAVs can be obtained using the above differential equations (17) and (18). The optimal resources demands of each UAV is controlled by the resources price announced by the ECS. The optimal resources demands of each UAV is also a function of users services requirements. Especially, under the open-loop situation, the optimal resources demands of each UAV depend on the initial services requirements of mobile users $x_i(t = 0)$ and vary with the time t. Now we have proved that there exists a unique open loop equilibrium for each UAV. ■

Further, based on the partial derivative of the Hamiltonian function, we have,

$$-\gamma_i p_i(t) + \Lambda_i(t)\beta_i\nu_i d_i^{\beta_i - 1}(t) = 0, \tag{19}$$

and we can obtain the equilibrium solutions for UAVs to control their resources demands by solving (19). The unique equilibrium solution for UAV i to control its resources demands is given as follows,

$$d_i(t) = \left[\frac{\gamma_i p_i(t)}{\Lambda_i(t)\beta_i\nu_i} \right]^{\frac{1}{\beta_i - 1}}. \tag{20}$$

To eliminate information non-uniqueness in the derivation of Nash equilibrium, we can also obtain the equilibrium solutions of UAVs to satisfy the feedback equilibrium property. In the feedback situation, the information structures of UAVs follow closed-loop perfect state pattern, and the optimal strategies of UAVs become the functions of initial users services demands $x_i(t = 0)$, the current users services demands $x_i(t)$ at time t, and the current time t. A definition of value function for analyzing the equilibrium solutions of UAVs under feedback situation is given as follows.

***Definition** 4: The optimal resource demand $\{\widetilde{d}_i^*(t)\}$ of UAV i is a feedback equilibrium to the problem in (3), if there exists a continuously differentiable value function $V_i(t, x)$ such that the following equations are satisfied,*

$$\begin{aligned} -\frac{\partial V_i(t, x)}{\partial t} &= \left[\varphi_i x_i^2(t) - \gamma_i p_i(t)\widetilde{d}_i^*(t) \right] e^{-\tau t} \\ &+ \frac{\partial V_i(t, x)}{\partial x} \left[\mu_i r_i^{\alpha_i}(t) + \upsilon_i(\widetilde{d}_i^*(t))^{\beta_i} + \delta_i x_i(t) \right]. \end{aligned} \tag{21}$$

Calculating the partial derivative for $\widetilde{d}_i(t)$ in (21), we can obtain the optimal resource demands of UAV i under feedback situation as follows,

$$\widetilde{d}_i^*(t) = \left[\frac{\gamma_i p_i(t)}{\frac{\partial V_i(t, x)}{\partial x} e^{\tau t}\beta_i\nu_i} \right]^{\frac{1}{\beta_i - 1}}. \tag{22}$$

The existence and uniqueness of equilibrium solutions under feedback situation for the proposed game can be given as follows.

***Theorem** 2: The value function $V_i(t,x)$ admits a solution that satisfies,*

$$V_i(t,x) = \left[A_i(t)x + B_i(t)\right] e^{-\tau t}, \tag{23}$$

where $A_i(t)$ and $B_i(t)$ are given by,

$$\frac{dA_i(t)}{dt} = \left[1 + \delta_i + \mu_i \varphi_i^{\alpha} x_i^{\alpha-1}(t)\right] A_i(t) + \varphi_i x_i(t), \tag{24}$$

$$\begin{aligned} \frac{dB_i(t)}{dt} =& \frac{\gamma_i p_i(t)(\beta_i A_i(t)-1)}{\beta_i A_i(t)} \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{1}{\beta_i - 1}} \\ &+ \tau B_i(t). \end{aligned} \tag{25}$$

Proof: Based on the value function given in (23), we have,

$$\begin{aligned} \frac{\partial V_i(t,x)}{\partial t} e^{\tau t} =& \frac{dA_i(t)}{dt} x - \tau A_i(t) x \\ &+ \frac{dB_i(t)}{dt} - \tau B_i(t), \end{aligned} \tag{26}$$

$$\frac{\partial V_i(t,x)}{\partial x} e^{\tau t} = A_i(t). \tag{27}$$

Then, we have the optimal resources demands of UAV i under feedback situation as follows,

$$\widetilde{d}_i^*(t) = \left[\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right]^{\frac{1}{\beta_i - 1}}. \tag{28}$$

and the differential value function in (21) can be given as follows,

$$\begin{aligned} &- \frac{dA_i(t)}{dt} x_i(t) + \tau A_i(t) x_i(t) - \frac{dB_i(t)}{dt} + \tau B_i(t) \\ &= A_i(t) \left[\mu_i r_i^{\alpha_i}(t) + \upsilon_i \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{\beta_i}{\beta_i - 1}} + \delta_i x_i(t)\right] \\ &+ \left[\varphi_i x_i^2(t) - \gamma_i p_i(t) \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{1}{\beta_i - 1}}\right] \\ &= A_i(t) \left[\mu_i \varphi_i x_i^{\alpha_i}(t) + \upsilon_i \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{\beta_i}{\beta_i - 1}} + \delta_i x_i(t)\right] \\ &+ \left[\varphi_i x_i^2(t) - \gamma_i p_i(t) \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{1}{\beta_i - 1}}\right]. \end{aligned} \tag{29}$$

If the above equation is satisfied, we have,

$$\frac{dA_i(t)}{dt} = \left[1 + \delta_i + \mu_i \varphi_i^{\alpha} x_i^{\alpha-1}(t)\right] A_i(t) + \varphi_i x_i(t), \tag{30}$$

$$\begin{aligned} \tau B_i(t) - \frac{dB_i(t)}{dt} =& A_i(t) \upsilon_i \left(\frac{p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{\beta_i}{\beta_i - 1}} \\ &- \gamma_i p_i(t) \left(\frac{\gamma_i p_i(t)}{\beta_i \nu_i A_i(t)}\right)^{\frac{1}{\beta_i - 1}}, \end{aligned} \tag{31}$$

Hence, **Theorem 2** follows. ■

Based on the outcome of **Theorems** 1 and 2 obtained above, we present a dynamic game based algorithm for UAVs to control their resources demands, which is sketched in Algorithm 1. The proposed algorithm returns the open-loop equilibrium solutions and feedback equilibrium solutions for UAVs on the basis of resources demands as their output. First, we initialize and calculate all the necessary parameters.

Algorithm 1: Dynamic Resource Demands Control Algorithm

Input: Unit price $p_i(t)$ for the allocated edge computing resources controlled by ECSs
Output: The optimal resources demands $d_i(t)$ of each UAV

```
Initialization: The initialization parameters in objective function (3) and system state function (4);
The ECSs set the initial price for the allocated edge computing resources, and send the price for all UAVs in its coverage;
The UAVs compute the resources demands based on the initial price set by the ECSs;
for j ∈ M do
    for i ∈ N do
        Obtain the optimal resources demands under open-loop situation using (20);
        Obtain the optimal resources demands under feedback situation using (28);
    end
end
Return the optimal resources demands of UAVs;
```

Then, we compute the optimal resources demands in terms of open-loop solutions and feedback solutions according to the proposed game framework. Finally, the optimal resources demands for UAVs under two kinds of situations are obtained. The main computational complexity of Algorithm 1 lies in obtaining the open loop equilibrium solutions and feedback e-quilibrium solutions for UAVs. The total number of operations for obtaining the optimal strategies under open-loop situation and feedback situation is both MN. Thus, the complexity order is calculated as $O(MN)$.

B. Equilibrium of ECSs

In this section, the equilibrium solutions to **Problem 1** will be discussed. As the optimal strategies to Problem (1), $p^*(t)$ are a set of resources price for UAVs to control their resources demands. Every UAVs will be announced an rational price for the allocated edge computing resources controlled by the ECSs. In order to find the equilibrium solutions of ECSs, we first try to prove the optimization problem given in **Problem 1** is a concave function.

***Theorem** 3: The objective function for ECSs in **Problem 1** is a concave function.*

Proof: Please refer to Appendix A. ■

We consider the uniform pricing model for ECSs. Based on the uniform pricing model, the resources price is uniform, and the ECSs charge the UAVs with the same price. Therefore, the purchase of each ECS is to set up an optimal resources price for UAVs to maximize its profit. The optimal resources price of each ECS can be given as follows.

***Theorem** 4: A set of control vectors $p^*(t)$ for ECSs in **Problem 1** exists.*

Proof: Based on **Theorem** 3 given in the above, the optimization problem in **Problem 1** is a convex optimization

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problem. Thus, we can deal with the optimization problem by solving its dual problem. The Lagrangian for the optimization problem in **Problem 1** can be written as,

$$\begin{aligned}\mathsf{L}(t) = &\sum_{i=1}^{N} \gamma_i p^*(t) d_i(t) - \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p^*(t)}\right] \\ &- \lambda \left[p^*(t) - \tilde{p}\right],\end{aligned} \tag{32}$$

where λ is the dual variable associated with the constraint $0 \leq p^*(t) \leq \tilde{p}$. By taking the derivative of (32), we have,

$$\frac{\partial \mathsf{L}(t)}{\partial p^*(t)} = \sum_{i=1}^{N} \gamma_i d_i(t) + \sum_{i=1}^{N} \left[\pi_i \frac{d_i(t)}{(p^*(t))^2}\right] - \lambda = 0. \tag{33}$$

Let the partial derivative to be zero, we have,

$$p^*(t) = \left[\frac{\sum_{i=1}^{N} \pi_i d_i(t)}{\lambda - \sum_{i=1}^{N} \gamma_i d_i(t)}\right]^{\frac{1}{2}}. \tag{34}$$

Substituting the constraint $0 \leq p^*(t) \leq \tilde{p}$ into the above equation, we can find that the dual variable follows the below equation,

$$\lambda = \sum_{i=1}^{N} \left(\frac{\pi_i}{\tilde{p}^2} + \gamma_i\right) d_i(t). \tag{35}$$

Substituting (35) into the partial derivative of Lagrangian, we can find the optimal price for the allocated edge computing resources, which is denoted as follow,

$$p^*(t) = \left[\frac{\sum_{i=1}^{N} \pi_i d_i(t)}{\sum_{i=1}^{N} (\frac{\pi_i}{\tilde{p}^2} + \gamma_i) d_i(t) - \sum_{i=1}^{N} \gamma_i d_i(t)}\right]^{\frac{1}{2}}. \tag{36}$$

Hence **Theorem 4** follows. ■

Algorithm 2: Dynamic Optimal Price Control Algorithm

Input: The optimal resources demands $d_i(t)$ of each UAV;
Output: The optimal price $p_i(t)$ for the allocated edge computing resource controlled by ECSs;

Initialization: The initialization parameters in objective function (8);
The ECSs receive the resources demands from all UAVs in its coverage;
The ECSs compute the optimal price for the allocated edge computing resources with the resource demands from all UAVs;
for $j \in \mathcal{M}$ **do**
    Obtain the optimal price for the allocated edge computing resources using (36);
end
After that, the ECSs send the optimal price to the miners. The miners update the price and broadcasts the price to the UAVs. The transactions information between ECSs and UAVs are recorded on the blockchain.

Based on **Theorems** 3 and 4, we present a dynamic optimal price control algorithm for ECSs to maximize the profit function given in (8). Given the dynamic resources demands of UAVs based on Algorithm 1, the ECS can control the resources price for the allocated edge computing resources to maximize its profit earned from UAVs. As every UAV has two kinds of resources demands, the open-loop situation and feedback situation, respectively, there will also be two optimal price for ECSs to allocate the edge computing resources. The main computational complexity of Algorithm 2 lies in obtaining the optimal pricing strategies for the allocated edge computing resources using (36). The total number of operations for obtaining the optimal price is M. Thus, the complexity order is calculated as $O(M)$.

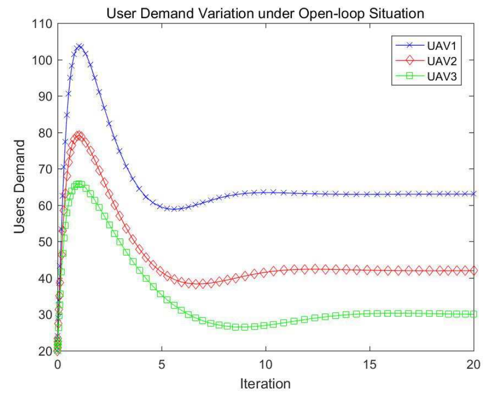

Fig. 3: Users demands variations with 3 UAVs under open-loop situation

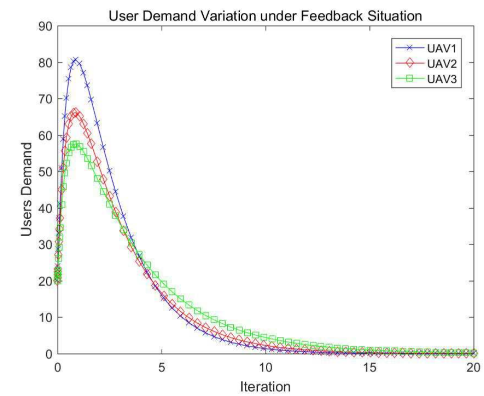

Fig. 4: Users demands variations with 3 UAVs under feedback situation

VI. Numerical Simulations

In this section, we conduct simulation experiments and evaluate the performance of the proposed dynamic resource allocation scheme. Firstly, we introduce the simulation scene and specific experimental parameters. Then, the optimal solutions for UAVs to control their resources demands are analyzed under open-loop situation and feedback situation, respectively. And the optimal strategy of ECS to control the price for the allocated edge computing resources is also discussed.

A. Simulation Setting

A UAV-assisted mobile network with one ECS and multiple UAVs is considered in this section. In the proposed system,

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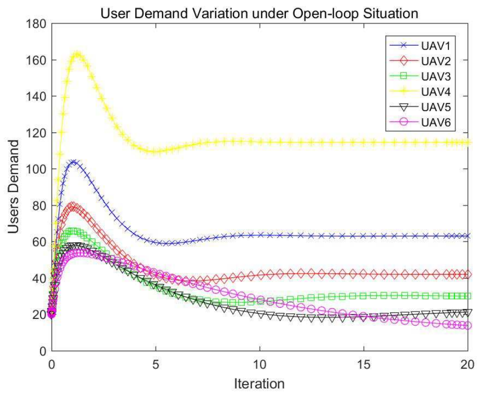

Fig. 5: Users demands variations with 6 UAVs under open-loop situation

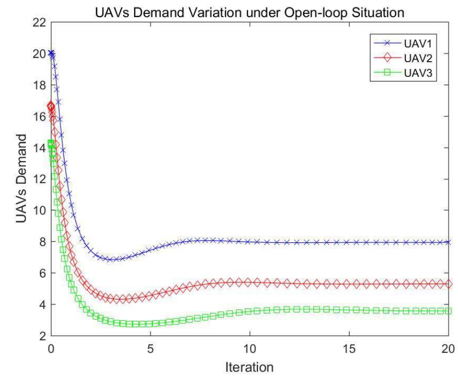

Fig. 7: Required resources of 3 UAVs under open-loop situation

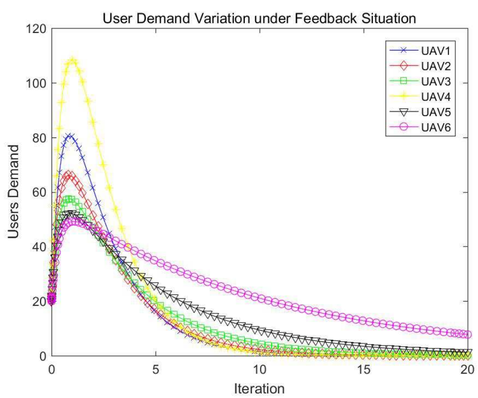

Fig. 6: Users demands variations with 6 UAVs under open-loop situation

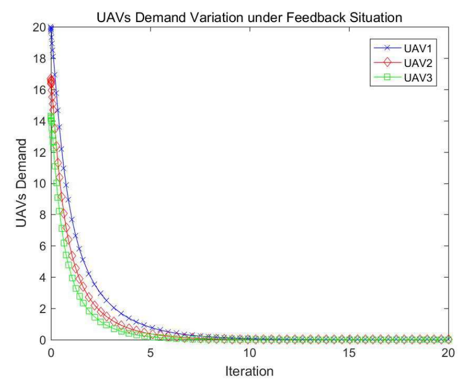

Fig. 8: Required resources of 3 UAVs under feedback situation

the UAVs require the edge computing resources from the ECS to provide mobile users with satisfied services. The ECS allocates the edge computing resources to the UAVs to earn profit. Meanwhile, the ECS should pay the mining reward for the transactions between ECS and UAVs. The optimal strategies of requested resources for UAVs will be given under two different situations, open-loop situation and feedback situation, respectively, which are mainly affected by the services demands from mobile users. As the followers of the Stackelberg game, the optimal strategies for requested resources of UAVs will be analyzed with a initial price of edge computing resources announced by the ECS, where the resources price is assumed to be constant and same for all UAVs. In this simulations, the resources price is set to be 2 unit/resources. After the UAVs make decisions on the required resources, the ECS will control the resources price to maximize its profit, where the possibility that the resource transactions between ECS and UAVs can be written into a valid block is assumed to be 100%. The other parameters setting for simulations are given in TABLE I.

B. Performance Discussion

Firstly, we investigate the variations of users services demands under two kinds of situations, open-loop situation and feedback situation, respectively. The variations of users services demands are given by the state variable $x_i(t)$, and are shown in Figures 3, 4, 5, and 6. The services demands under open-loop situation are given in Figures 3 and 5, where Figures 4 and 6 are the services demands under feedback situation. Figures 3 and 4 are the services demands in the proposed UAV-assisted MEC network with 3 UAVs. We can find that, at the beginning of the game, the mobile users increase their services demands to obtain the relevant services from UAVs. As more and more users services are satisfied, the services demands decrease and converge to an equilibrium value. Under the feedback situation, the services demands first increase and then quickly drop to zero. In Figures 5 and 6, we double the number of UAVs from 3 to 6, and obtain the services demands under open-loop situation and feedback situation, respectively. We can find that the number of UAVs will not affect the

TABLE I: Simulation Parameters Setting

Parameters	UAV1	UAV2	UAV3
α_i	2	2	2
β_i	2	2	2
μ_i	0.5	0.4	0.3
ν_i	0.5	0.6	0.7
δ_i	-0.5	-0.4	-0.3
φ_i	0.001	0.0015	0.002
π_i	0.2	0.3	0.5
$\tilde{p}_i$	5	10	15

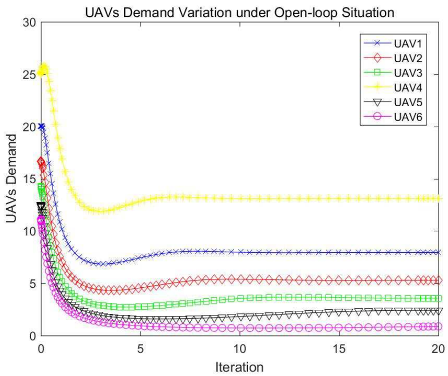

Fig. 9: Required resources of 6 UAVs under open-loop situation

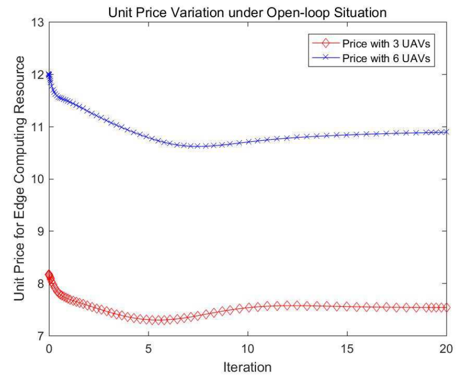

Fig. 11: Optimal pricing strategy of ECS under open-loop situation

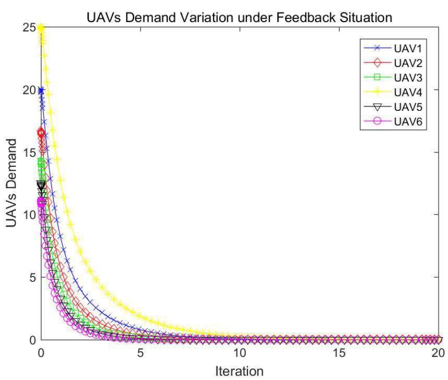

Fig. 10: Required resources of 6 UAVs under feedback situation

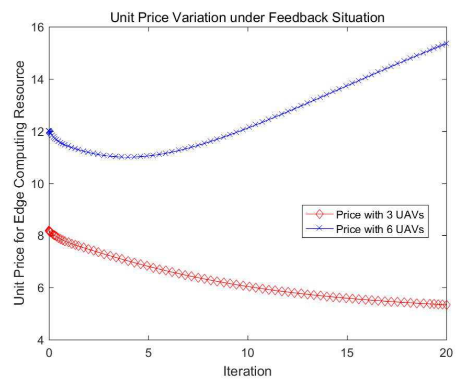

Fig. 12: Optimal pricing strategy of ECS under feedback situation

services demands in the proposed system, where the services demands of UAV1, UAV2 and UAV3 are the same with the previous results.

Next, we analyze the strategies of UAVs for the required edge computing resources. Because the unit price for the allocated edge computing resources is assumed to be a fixed value, the impact of price on UAVs decision-making is temporarily ignored. Based on the services demands, the UAVs would require the edge computing resources from the ECS to provide satisfied services to mobile users. The variations of required resources for each UAV are shown in Figures 7, 8, 9 and 10, respectively. Figures 7 and 9 show the required edge computing resources of UAVs under open loop situation, where Figures 8 and 10 are the equilibrium strategies under feedback situation. Since the UAVs don't know how much resources are needed to meet the services demands from mobile users at the beginning of the game, each UAV requires a large amount of edge computing resources from the ECS to meet the possible services demands. As the game goes on, the amount of the required edge computing resources by each UAV would be decreased to a stable equilibrium value based on the actual needs of mobile users. The amount of required edge computing resources vary according to the users services demands. More edge computing resources are needed by the UAVs with more users services demands. As we assume there is enough edge computing resources in the ECS for resource allocation, when we double the number of UAVs in the proposed system, we can find that the number of UAVs will not affect the amount of required edge computing resources, as given in Figures 9 and 10.

As the leader of the proposed Stackelberg dynamic game, after the UAVs make decisions on the requirements of edge computing resources, the ECS would re-allocate the unit price of the allocated edge computing resources to maximize its profit based on (8). The equilibrium solutions of ECS are shown in Figures 11 and 12, which are the optimal pricing strategies under open-loop situation and feedback situation, respectively. For the optimal pricing strategy of ECS under open loop situation, the price goes down at the beginning. After 5 iterations, the unit price increases and converges to a stable value. Because the number of UAVs can affect the profit obtained from the allocated edge computing resources and the payments for the miners, the number of UAVs could affect the pricing strategies of ECS, as shown in Figure 11. When the number of UAVs are doubled, the unit price given in the blue line is higher than the unit price in red line, which means the ECS would set a higher price for the allocated edge computing resources, when the number of UAVs are increased. Under the feedback situation, the optimal pricing strategies of ECS with 3 UAVs keeps going down until it converges. When the number of UAVs is doubled to 6, the ECS reduces the unit price at the beginning. After 5 iterations, the ECS' strategy is

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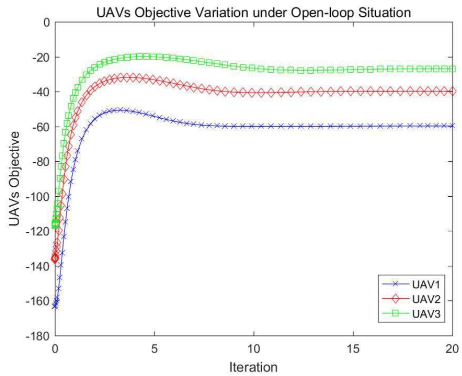

Fig. 13: Objective of 3 UAVs under open-loop situation

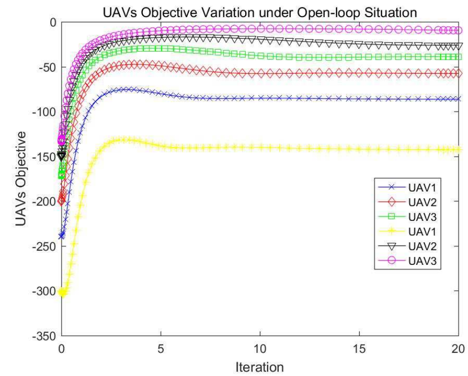

Fig. 15: Objective of 6 UAVs under open-loop situation

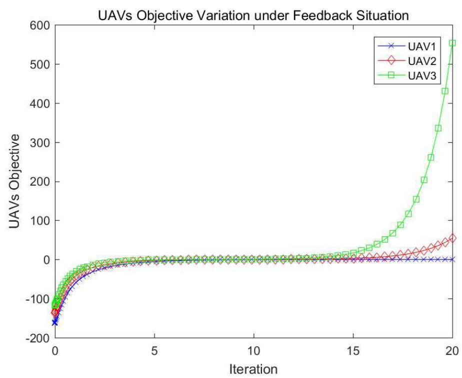

Fig. 14: Objective of 3 UAVs under feedback situation

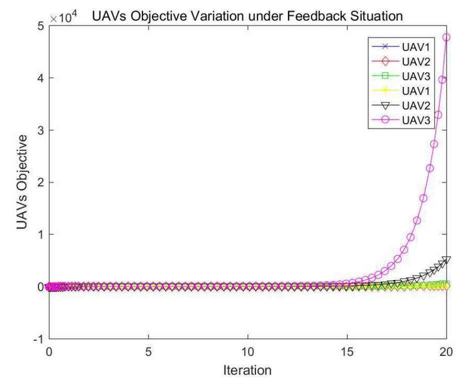

Fig. 16: Objective of 6 UAVs under feedback situation

to raise the resources price to earn more profit.

Given the equilibrium strategies of UAVs and ECS, we can obtain the optimal objectives of UAVs, and the optimal profit of ECS, respectively. Figures 13 and 14 are the objectives of UAVs under open-loop situation and feedback situation, where the number of UAVs is 3. Under open loop situation, it is shown that the objectives of UAVs can quickly converge to a stable value. Under the feedback situation, the objectives can keep steady at the beginning, and then quickly increase to a maximum value. When the number of UAVs is increased from 3 to 6, the objectives of UAVs are decreased, as shown in Figures 15 and 16. When the number of UAVs is increased, the ECS will set a higher price value for the allocated edge computing resources, then the UAVs would cost more for the same amount of edge computing resources and the objectives would be decreased.

The profit of ECS for allocating the edge computing resources are given in Figures 17 and 18. As shown in the Figures, the profit of ECS would converge to a stable value quickly under two kinds of situations. But under the feedback situation, the profit would decrease to zero, because the UAVs decrease their resources demands to zero. The value of rewards paid for the miners would also affect the profit of ECS. If the ECS set a larger value for the rewards, the profit earned by the ECS would be lower. We can also find that the number of UAVs in the system will affect the profit of ECS. When the number of UAVs is increased, the ECS can obtain more profit from the UAVS.

Finally, we show the convergence of payments to the miners under two kinds of situations. For different payments, we consider that the reward ψ paid for the miners are 1, 10, 20. From Figure 19, we first observe that the payments to the miners with different reward under open-loop situation. We can observe that the payment to the miners after the convergence is larger when the reward is higher. The payment with reward value 20 is the highest as it has the largest reward value compared with other situations. From Figure 20, we can also observe the same phenomenon. Under the feedback situation, as the reward value is higher, the payment to the miners is greater.

VII. Conclusion

In this paper, a UAV assisted mobile edge computing network is researched, and a novel resource pricing and allocation scheme is proposed to solve the edge computing resource allocation problem in the proposed network. The resource pricing and allocation problem is formulated as a Stackelberg game, where the leader is the ECS and the followers are the UAVS. Based on the proposed framework, the ECS can achieve optimal edge computing resource pricing, where the resources can be optimally allocated among the UAVS. The security problem during the resource allocation process is also considered and solved through the blockchain techniques.

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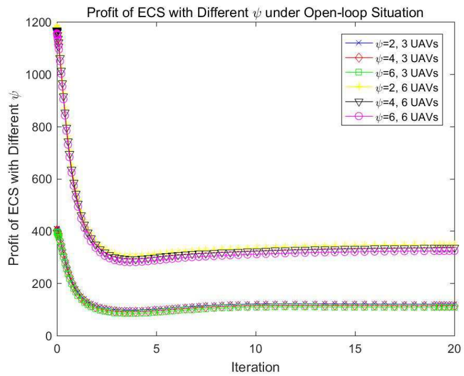

Fig. 17: Profit of ECS with different ψ under open-loop situation

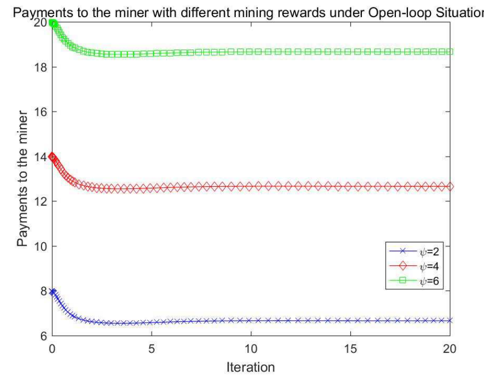

Fig. 19: Payments to the miners with different ψ under open-loop situation

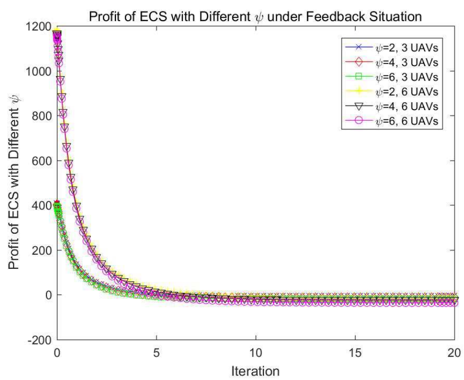

Fig. 18: Profit of ECS with different ψ under feedback situation

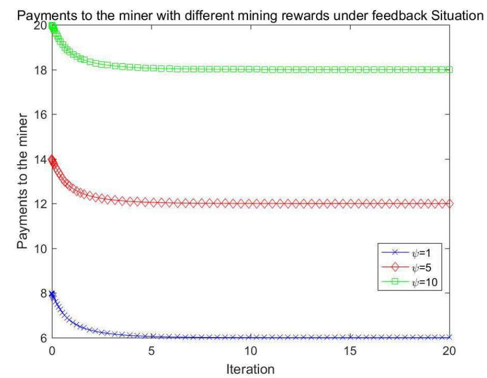

Fig. 20: Payments to the miners with different ψ under feedback situation

VIII. Acknowledgement

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Appendix A
Proof of Theorem 3

Assuming there are two sets of resources price that can satisfy the objective function given in **Problem 1**, which are denoted by $\{p_i(t)\}$ and $\{q_i(t)\}$ respectively. For a constant $\lambda, (0 < \lambda < 1)$, we have,

$$
\begin{aligned}
&U_{ECS}^{'}(\lambda p_i(t) + (1-\lambda) q_i(t)) \\
&= \sum_{i=1}^{N} \left[\lambda p_i(t) + (1-\lambda) q_i(t)\right] \gamma_i d_i(t) \\
&- \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{\lambda p_i(t) + (1-\lambda) q_i(t)}\right].
\end{aligned} \tag{37}
$$

Substituting $\{p_i(t)\}$ and $\{q_i(t)\}$ into the objective function, we have,

$$
\begin{aligned}
\lambda U_{ECS}^{'}(p_i(t)) =& \lambda \sum_{i=1}^{N} \gamma_i p_i(t) d_i(t) \\
&- \lambda \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p_i(t)}\right],
\end{aligned} \tag{38}
$$

$$
\begin{aligned}
(1-\lambda) U_{ECS}^{'}(q_i(t)) =& (1-\lambda) \sum_{i=1}^{N} \gamma_i q_i(t) d_i(t) \\
&- (1-\lambda) \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{q_i(t)}\right].
\end{aligned} \tag{39}
$$

Then we have,

$$
\begin{aligned}
&\lambda U_{ECS}^{'}(p_i(t)) + (1-\lambda) U_{ECS}^{'}(q_i(t)) \\
&= \lambda \sum_{i=1}^{N} \gamma_i p_i(t) d_i(t) - \lambda \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p_i(t)}\right] \\
&+ (1-\lambda) \sum_{i=1}^{N} \gamma_i q_i(t) d_i(t) \\
&- (1-\lambda) \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{q_i(t)}\right].
\end{aligned} \tag{40}
$$

Calculating (37) and (40), we have,

$$
\begin{aligned}
&U'_{ECS}(\lambda p_i(t) + (1-\lambda)q_i(t)) \\
&- \left[\lambda U'_{ECS}(p_i(t)) + (1-\lambda)U'_{ECS}(q_i(t))\right] \\
&= \sum_{i=1}^{N} \left[\lambda p_i(t) + (1-\lambda)q_i(t)\right]\gamma_i d_i(t) \\
&- \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{\lambda p_i(t) + (1-\lambda)q_i(t)}\right] \\
&- \lambda \sum_{i=1}^{N} \gamma_i p_i(t) d_i(t) + \lambda \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{p_i(t)}\right] \\
&- (1-\lambda) \sum_{i=1}^{N} \gamma_i q_i(t) d_i(t) \\
&+ (1-\lambda) \sum_{i=1}^{N} \left[\psi + \pi_i \frac{d_i(t)}{q_i(t)}\right] > 0,
\end{aligned}
\tag{41}
$$

which means the objective function is a concave function. Hence, Theorem follows.

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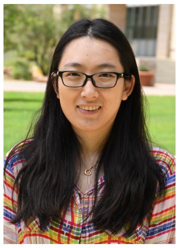
Haitao Xu (M’16) received the B.S. degree in communication engineering from Sun Yat-Sen University, China, in 2007, the M.S. degree in communication system and signal processing from University of Bristol, UK, in 2009, and the Ph.D. degree in communication and information system from University of Science and Technology Beijing, China, in 2014.

From 2014 to 2016, he was with the Department of Communication Engineering, University of Science and Technology Beijing, Beijing, China, as a Post-doc. Currently, he is an associate professor with the Department of Communication Engineering, University of Science and Technology Beijing, Beijing, China. His research interests include wireless resource allocation and management, wireless communications and networking, dynamic game and mean field game theory, big data analysis, and security. Dr. Xu has co-edited a book titled Security in Cyberspace and co-authored over 50 technical papers. He has been serving in the organization teams of some international conferences, e.g. CCT2014, CCT2015.

Wentao Huang was born in Chengdu, China, in 1988. From 2006 to 2010, he studied in Sichuan Normal University and received his bachelor’s degree in 2010. From 2012 to 2015, he studied in Beijing University of Aeronautics and Astronautics and received his Master degree in 2011. Currently, he studies Ph.D. in University of Science and Technology Beijing. His research interests include Optical fiber communications and computers.

Yunhui Zhou was born in Sichuan, China, in 1993. Currently, she is a Ph.D. student of University of Science and Technology Beijing. Her research interests include satellite network, artificial intelligence and IoT.

Dongmei Yang was born in HanDan,China, in 1974. Currently, she is a Ph.D. student of University of Science and Technology Beijing. Her research interests include application of artificial intelligence in self-organizing low-orbit constellation, satellite communication, IoT and 5G technology. She is currently working in World Telecom Satellite Technology Limited as CEO and senior software engineer.



Ming Li received the B.E. degree in Electrical Engineering from Sun Yat-sen University, China, in 2007, the M.E. degree in Electrical Engineering from Beijing University of Posts and Communications, China, in 2010, and the Ph.D. degree in Electrical and Computer Engineering from Mississippi State University, Starkville, in 2014, respectively. She is currently an assistant professor in the Department of Computer Science and Engineering, The University of Texas at Arlington. Her research interests include mobile computing, internet of things, security, and privacy-preserving computing. Her work won Best Paper Awards in Globecom 2015 and DASC 2017, respectively. She received the NSF CAREER Award in 2020 and is a member of the IEEE and the ACM.

Zhu Han (S'01-M'04-SM'09-F'14) received the B.S. degree in electronic engineering from Tsinghua University, in 1997, and the M.S. and Ph.D. degrees in electrical and computer engineering from the University of Maryland, College Park, in 1999 and 2003, respectively.

From 2000 to 2002, he was an R&D Engineer of JDSU, Germantown, Maryland. From 2003 to 2006, he was a Research Associate at the University of Maryland. From 2006 to 2008, he was an assistant professor at Boise State University, Idaho. Currently, he is a John and Rebecca Moores Professor in the Electrical and Computer Engineering Department as well as in the Computer Science Department at the University of Houston, Texas. His research interests include wireless resource allocation and management, wireless communications and networking, game theory, big data analysis, security, and smart grid. Dr. Han received an NSF Career Award in 2010, the Fred W. Ellersick Prize of the IEEE Communication Society in 2011, the EURASIP Best Paper Award for the Journal on Advances in Signal Processing in 2015, IEEE Leonard G. Abraham Prize in the field of Communications Systems (best paper award in IEEE JSAC) in 2016, and several best paper awards in IEEE conferences. Dr. Han was an IEEE Communications Society Distinguished Lecturer from 2015-2018, AAAS fellow since 2019 and ACM distinguished Member since 2019. Dr. Han is 1% highly cited researcher since 2017 according to Web of Science. Dr. Han is also the winner of 2021 IEEE Kiyo Tomiyasu Award, for outstanding early to mid-career contributions to technologies holding the promise of innovative applications, with the following citation: "for contributions to game theory and distributed management of autonomous communication networks."