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Blockchain Meets Edge Computing: Stackelberg Game and Double Auction based Task Offloading for Mobile Blockchain

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***Abstract*—Blockchain technology is developing rapidly and has been applied in various aspects, among which there are broad prospects in Internet of Things (IoT). However, IoT mobile devices are restricted in communication and computation due to mobility and portability, so that they can't afford the high computing cost for blockchain mining process. To solve it, the free resources displayed on non-mining-devices and edge cloud are selected to construct collaborative mining network(CMN) to execute mining tasks for mobile blockchain. Miners can offload their mining tasks to non-mining-devices within a CMN or the edge cloud when there are insufficient resources. Considering competition for resource of non-mining-devices, resource allocation problem in a CMN is formulated as a double auction game, among which Bayes-Nash Equilibrium (BNE) is analyzed to figure out the optimal auction price. When offloading to edge cloud, Stackelberg game is adopted to model interactions between edge cloud operator and different CMNs to obtain the optimal resource price and devices' resource demands. The mechanism realizes improving the mining utility in mining networks while ensuring the maximum profit of edge cloud operator. Finally, profits of mining networks are compared with an existing mode which only considers offloading to edge cloud. Under the proposed mechanism, mining networks obtain 6.86% more profits on average.**

***Index Terms*—Edge computing, IoT, blockchain, resource management, task offloading.**

I. Introduction

THE Internet of Things (IoT) connects a large scale of heterogeneous devices for information exchanging and economic benefits, in which Mobile Edge Computing (MEC) is a promising solution that allows mobile devices to run demanding applications by providing computing resources. However, building trust between multiple parties in MEC is a challenge because these parties often have conflicting interests [1], [2]. To address this problem, blockchain which is a tamper proof transaction database shared by all nodes participating in a network based on a consensus protocol is introduced [3]. Features like security, transparency and decentralization allow it to be a distributed peer-to-peer network where non-trusting members can interact with each other in a verifiable manner without a trusted intermediary [4], [5]. To ensure data security in mobile commerce between mobile devices, blockchain has been integrated as an efficient security solution into establishing trust between mobile devices in a decentralized network [6].

The development of blockchain in IoT mobile applications is hindered by a major challenge brought by heavy computational process [1]. Blockchain's security relies on a proof-of-work procedure called mining, which is a difficult mathematical problem making blockchain almost impossible to be tampered with [7]. When a transaction is generated and broadcasted, it will be collected and validated by some nodes concurrently in the network, then mining nodes constantly try to find a rare random number which generates a specific hash value [8]. Mobile devices are restricted in key areas related to communication and computation such as memory, battery and processing due to design choices that guarantee their mobility [9], [10], so that they fall short to afford the high computing resources to find the value in mining process [11]. To support mining tasks execution in mobile environments for mobile devices, we suggest offloading mining tasks to edge cloud and neighbor non-mining-devices [9], [12].

Recently, several edge computing resource allocation schemes and blockchain mining task offloading models have been proposed to provide solutions. Focusing on the optimization of resource allocation and pricing between mobile users and edge cloud, Z. Xiong *et al.* proposed a Stackelberg game based economic approach for mobile devices to offload mining tasks to edge nodes in [13]. J. Wang *et al.* designed a Deep Reinforcement Learning based Resource Allocation (DRLRA) mechanism, which can adapt to different MEC environments and allocate computing resources efficiently [14]. These researches help a lot to optimize mining offloading strategies, but they only consider optimization of a single device offloading tasks to the edge cloud. Differently, we consider the optimization of mining offloading to both neighbor devices and edge cloud operator (ECO).

Since the probability of an individual miner to find a new block in due time is excruciatingly small, we suggest mobile devices in proximity interconnecting with each other to form a Collaborative Mining Network (CMN), which is like a mining

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pool [15]. Mining-devices gather their computational resources and share their hashing power in the CMN in order to smooth out their mining rewards effectively. Then they split the reward in proportion to their contribution to solving a block [16]. However, due to high mobility [17], some mining-devices may not stay in a CMN for sufficient time to contribute resources that meet the expected average mining resources. They should obtain less reward than in proportion to their contribution. Therefore, some devices with high mobility may not be profitable to mine, so that they can share their resources with neighbor mining-devices within the CMN instead of participating in mining, which we call sharing-devices. In view of competitions between mining-devices for sharing-devices' resources, we adopt a double auction method to manage mining offloading. In the auction, the BNE [18] of each mining-device's net profit is first calculated based on their values of the resources to figure out the optimal bid. Meanwhile, sharing-devices analyze BNE of their expected profits based on mining cost to obtain the optimal asking price. Then, the auction strategy is determined based on mining-devices' bids and sharing-devices' asking prices.

However, task offloading within CMN is not enough, the growing amount of mining tasks will push current CMN resource to the limit, then the mining processes will be performed with the support of ECO. In the process of mining offloading to ECO, we consider CMN as a whole, and mining-devices apply for resources from ECO through proxy in CMN. Therefore, we consider the total resources that a CMN requests from ECO and total mining profits in it. Since the non-cooperative CMNs and ECO can be assumed as intelligent decision-makers [12], [19], a two-stage Stackelberg game is adopted to model the interactions between ECO and CMNs. In the first stage, considering competitions with other CMNs and prices of ECO's resources, CMNs determine the optimal resource demands from ECO. In the second stage, ECO who aims at maximizing its profit decides upon the optimal resource price based on CMNs' resource demands.

Compared to traditional edge computing, innovations of our work lie in that mobile devices can offload their blockchain mining tasks to both neighbor devices and edge cloud. The main goal of our study is to calculate the optimal resource allocation to maximize the profits of ECO and CMN. The main contributions of this paper are summarized as follows:

- We proposed a novel resource management schema for mobile blockchain. In our schema, mobile devices in proximity aggregate computing resources to form a CMN to reduce the uncertainty of successful mining. The mining tasks of devices with limited resources can be offloaded to capable ones. Moreover, we analyze the optimal execution time of the task offloading algorithm every time a device joins or exits through simulation for adapting to the high dynamics of the IoT.
- Our mechanism supports two offloading modes. Miners can offload their mining tasks to non-mining-devices within the CMN or to edge cloud, which takes advantage of idle resources within the CMN and reduces the load on edge cloud.
- To manage resource allocation between mining-devices and sharing-devices in a CMN, we formulate the problem as a double auction game. The expected utility of two sides are formulated regarding resource value and cost, and then we calculate the BNE of the utility to obtain the optimal auction price.
- Mining offloading to ECO is developed as a price-based optimization problem to maximize the profits of ECO and CMN, in which both uniform pricing and differentiated pricing are considered. Stackelberg game is applied to model interactions between ECO and CMNs, in which we formulate the profits of both. Based on the profit function, we analyze the NE to obtain the optimal price of ECO and the most profit of CMN.

The rest of this paper is organized as follows. Section II reviews the related work. Section III presents the system model and objective formulation. A double auction algorithm for resource allocation in the CMN is presented in section IV, after which we analyze the NE of Stackelberg game between CMNs and ECO in section V. The experimental results and corresponding discussions are presented in section VI, followed by conclusions in section VII.

II. Related Work

A. Blockchain mining mechanisms

Recently, several blockchain mining mechanisms have been proposed. S. Kim *et al.* [16] presented a blockchain mining game model based on multi-leader multi-follower Stackelberg game. In the model, users are grouped into multiple distributed mining pools to gather resources while Stackelberg game is used to solve collaboration and competition issues in each mining pool and between multiple pools. L. Luu *et al.* [20] introduced a distributed computational power splitting game (CPS game) model to realize profit maximization. M. Salimitari *et al.* [21] presented a prospect theoretic approach for profit maximization in bitcoin pool mining. Since it is a big challenge for a new miner to decide which pool to join to get the most profits, they used prospect theory to calculate the miner's expected utility deriving from each pool.

These blockchain mining mechanisms have solved the optimal mining scheme of the blockchain network effectively, but it is still difficult to apply the schemes to the mobile blockchain network because mobile devices have limited communication and computation capability. However, with MEC, computation tasks can be offloaded to the edge network. We draw on their ideas for collaborative mining in the mining pool and propose a collaborative mining network CMN. Moreover, in the CMN, the devices can upload mining tasks to adjacent idle devices or edge cloud.

B. Mobile blockchain application

Blockchain has also been applied in many scenarios in IoT. To ensure the safety of mobile commerce, K. Suankaewmanee *et al.* [22] introduced MobiChain which can authenticate and record transactions between mobile applications on the blockchain to prevent tampering or repudiation. Gai *et al.* [23] proposed a permissioned blockchain edge model for smart

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grid networks to help with the privacy protection and energy security of smart grids. Furthermore, the authors presented a consortium blockchain-oriented approach to address the problem of trading information leakage in blockchain in [24]. In order to solve the insecurity issue of data outsourcing to designated data centers, P. K. Sharma *et al.* [25] put forward a novel blockchain-based distributed cloud architecture which included three layers. The device layer was used to monitor public infrastructure environments and request services. In the cloud layer, blockchain was adopted to supervise the process of data access and resource allocation. In the fog layer, they brought computing resources to the edge of the IoT network based on SDN and blockchain.

These studies have integrated blockchain into various areas of the IoT effectively. However, in mobile edge networks, the widespread application of blockchain is challenging due to limited computing and storage resources of mobile devices. To support the application of blockchain in mobile networks, we propose to offload blockchain mining tasks to the edge network.

C. Edge computing resource allocation

Now that compute-intensive mining tasks can be offloaded to the edge cloud, we further consider resource allocation strategies in the edge and CMN. The edge computing resource allocation problem has also interested some researchers recently. Several approaches have been proposed to provide solutions: resource auction [26], [27], game theory [28]–[30], Deep Reinforcement Learning (DRL) [31], [32], etc.

Considering resource auction, Y. Jiao *et al.* [26] investigated an auction mechanism in the mobile blockchain to maximize social welfare. The social welfare was described as the profit of the whole blockchain network. Each time miners decided upon their bids, the system selected winners until social welfare decreased. N. C. Luong *et al.* [27] proposed a deep-learning-based auction method for edge computing resource allocation. They constructed a multi-layer neural network architecture to provide solution of the optimal auction. Yang *et al.* [31] designed a real-time adaptive schema for computational resource allocation to support task offloading of mobile users based on DRL. Tan *et al.* [32] invented a DRL-based multi-time-scale framework, which jointly optimizes communication, caching, and computational design issues to achieve the optimal cost effectiveness of vehicle networks. Gai *et al.* [33] designed the Energy-Aware Heterogeneous Cloud Management model and proposed an adaptive solution to address the task offloading problem for reducing the computation costs.

Game theory has also already been extensively applied to optimize the problem of edge computing resource allocation. Z. Xiong *et al.* put forward a two-stage Stackelberg game model in [28] to acquire the optimal price-based resource management between mobile devices and edge cloud service provider in mobile blockchain. In [30], two data offloading mechanisms among multiple mobile users based on game theory were proposed. The multi-item auction (MIA) based data offloading approach was designed from the perspective of mobile operator who wanted to maximize his revenue. And for the mobile subscriber aiming at minimizing the payment, they proposed a congestion game (COG) based data offloading approach. X. Chen *et al.* [29] adopted a game theoretic approach to address the challenges of choosing between local computing and cloud computing.

These recent researches have achieved excellent results and introduced innovations well worth adopting. On the basis of existing resource allocation optimization strategies, we take both the mining benefits of CMN and edge cloud as the optimization goal, to adapt to our scenario. Besides, different from these existing researches on mining strategies in edge network, we support mining offloading not only to edge clouds, but also to neighbour devices to take advantage of idle device resources within the CMN and reduce communication delays.

III. System Model

A. Network Model

As shown in Fig. 1, we consider a scenario with an ECO and several CMNs $\mathcal{M} = \{1, \ldots, M\}$ in a mobile blockchain. CMN i is consisted of multiple mobile devices $\mathcal{N}_{\rangle} = \{1, \ldots, N_i\}$ which are arranged according to the time of joining CMN, and the available resources of mobile devices in it are set to $\mathcal{C}^i = \{c_1, \ldots, c_{N_i}\}$. Note that the collection is dynamic, N_i will change when a device joins or exits the CMN. As mentioned before, there are both mining-devices and sharing-devices in the CMN. We use $\mathcal{M}^i = \{1, \ldots, M_i\}$ to describe mining-devices in CMN i. Mining-devices can apply for resources from ECO through the edge broker or from sharing-devices within the CMN to offload their mining tasks. In order to reduce transmission costs, the mining task is preferentially offloaded to sharing-devices within the CMN through an auction mechanism which will be detailed in section 3.2. Considering different CMNs, let $\mathcal{R} = \{r_1, \ldots, r_M\}$ denote the expected average resources for mining of different CMNs. Only if resources in a CMN can't reach the expected value, the edge broker in it requests resources for mining-devices from ECO. Therefore, a CMN's resource demand from ECO is the expected mining resources minus the resources it owns, defined as $y_i = \max(M_i r_i - \sum_{j \in \mathcal{N}_{\rangle}} c_j, 0)$. Obviously, there is a limit that $r_i \in [\underline{r_i}, \overline{r}], \forall i \in \mathcal{M}$, where $\underline{r_i}$ is the average resources of mobile devices in CMN i and $\overline{r}$ is the maximum resources can be provided by ECO.

The generation of a new block consists of two stages: mining and consensus. In the mining process, miners compete to mine to create a new block. Let $\omega = \{\omega_1, \ldots, \omega_M\}$ denote the miner number vector of CMNs such that the possibility of a CMN successfully mining can be expressed as its hashing power

$$h_i(r_i, \mathbf{r}_{-i}) = \frac{M_i r_i}{\sum_{j \in \mathcal{M}} M_j r_j}, h_i > 0, \tag{1}$$

in which $\sum_{j \in \mathcal{M}} h_j = 1$. After a valid block is mined, it is instantaneously propagated across the network for verification to complete the consensus process. If the propagation and verification time is too long, the mined block will become an orphaned block which is abandoned by blockchain. Here, we set miner i's block propagation delay as $\tau_i^p = \frac{t_i}{\gamma \cdot c}$, where t_i is

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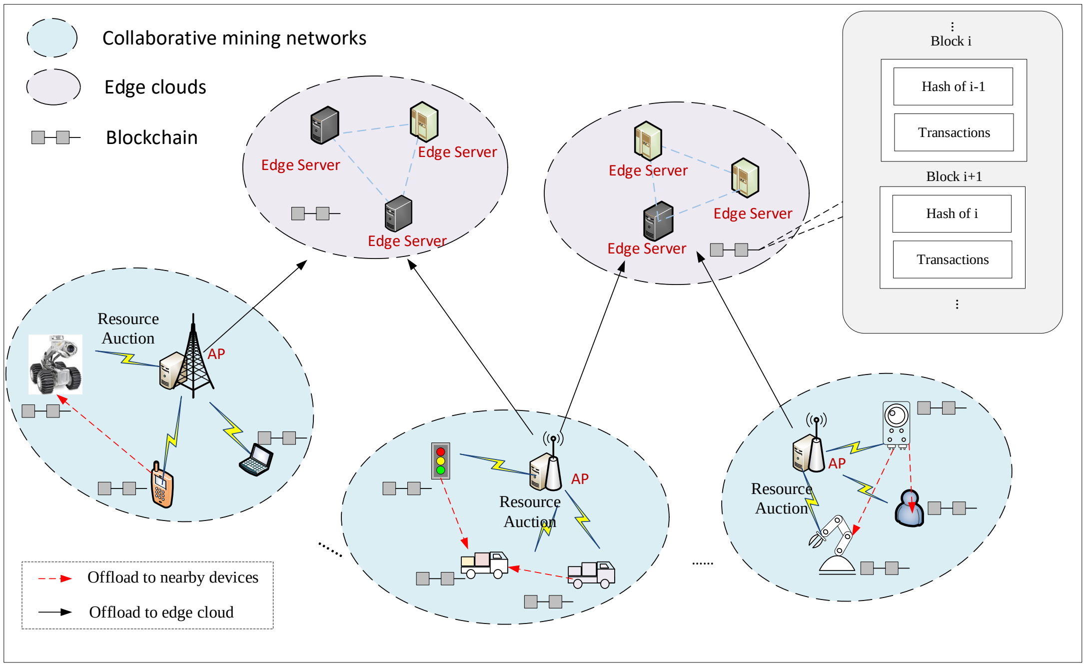

Fig. 1. Mobile blockchain with two mining offloading modes: offloading to neighbor devices and edge cloud.

the number of transactions in the block, γ is the network scale-related parameter, and c is the average effective channel capacity of each link [34]. As the verification and PoW computing time for a transaction requires a fixed amount of computation, the time is assumed linear to the number of transactions in the block [35], expressed as $\tau_i^v = l \cdot t_i$, where l is a parameter determined by network scale and the average verification speed of nodes. Considering that the generation of new blocks follows a Poisson process , miner i's orphaning probability can be approximated as $P_o(t_i) = 1 - e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)}$ with a process parameter λ referring to the complexity of mining a block. Obviously, the probability of CMN i successfully mining to generate a block is

$$P_i(r_i, M_i, t_i) = h_i \times (1-P_o(t_i)) = \frac{M_i r_i}{\sum_{j\in\mathcal{M}} M_j r_j} e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)}. \tag{2}$$

CMN i successfully mining will gain a corresponding mining reward. The reward consists of a fixed reward R and a commission reward defined as rt_i, in which t_i represents the number of its mining transactions and r is the reward for unit transaction (reward rate). Additionally, it is charged for using resources of ECO. Therefore, CMN i's utility is formulated as

$$\begin{aligned} U_i^M &= (R+rt_i)\frac{M_i r_i}{\sum_{j\in\mathcal{M}} M_j r_j} e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)} \\ &- (M_i r_i - \sum_{j\in\mathcal{N}_\rangle} c_j)p_i - \sum_{j\in\mathcal{N}_\rangle} B_j^i c_j, \end{aligned} \tag{3}$$

where p_i is ECO's unit resource price to CMN i, and the cost for device j in CMN i using unit resource is defined as B_j^i.

After successful mining, mining-devices split the reward in proportion to their contributed resources to solve the block. Moreover, we impose certain penalties on those who leave the CMN before providing enough mining resources that meet the expected average mining resources r_i, and reward the excess. So the expected profit of mining-device k in CMN i is formulated as

$$U_{k,i}^m = \frac{c_k^{'}}{c_k^{'} + \sum_{j\neq k} c_j} E - (r_i - c_k^{'})\rho_i - c_k^{'} B_k^i, \tag{4}$$

where $E = \frac{(R+rt_i)M_i r_i}{\sum_{j\in\mathcal{M}} M_j r_j} e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)} - (M_i r_i - \sum_{j\in\mathcal{N}_\rangle} c_j)p_i$, $c_k^{'}$ is the number of resources actually used for mining before the node exits and ρ_i is the penalty coefficient in CMN i set according to the market. We can see that some mobile devices with tiny resources and high mobility may not be profitable. So when a new device joins the CMN, it first estimates the mining profit regarding its resources. If it is not profitable, it can choose to share its resources to high-capacity devices.

B. Mining offloading model

In this subsection, a double auction model is adopted for mining offloading within the CMN, and mining offloading to ECO is modeled as a Stackelberg game.

1) Mining offloading within CMN: Considering the competition among mining-devices, we adopt a double auction [36], [37] method for resource sharing between mobile devices in CMN.

In the double auction, each mining-device (buyer) i decides a bid for unit resource indicated as b_i. Each sharing-device (seller) j has a maximum amount of resources available defined as R_j, and the asking price for unit resource is given as s_j. Since the mining profit function of a single mobile device is convex in the resource quantity, gaining more mining resources will definitely bring more profit. So we assume that the resource demand of the mining-device is always more than any sharing-device's resource supply. Then, the bids, asking prices and resources available information are all sent to the edge broker who manages auction process.

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TABLE I
SYMBOL SUMMARY

Symbol	Definition
$\mathcal{M}$	The set of CMNs.
$\mathcal{N}_{\rangle}$	The mobile devices in a CMN.
c_j^i	The resources of mobile device j in CMN i.
r_i	The expected average mining resources of CMN i.
t_i	The transaction number of CMN i.
λ	The complexity of mining a block.
γ	The network scale-related parameter.
c	The average effective channel capacity of each link.
l	The reciprocal of the average verification speed of nodes.
R	The fixed reward for mining.
r	The reward for unit transaction (reward rate).
U_i^M	CMN i's net profit from mining.
$U_{k,i}^m$	Mobile device k's net profit from mining in CMN i.
U^{ECO}	The net profit of ECO.
p_i	The price of ECO's unit resource to CMN i.
B	The cost of using unit resource on ECO.
B_j^i	The cost of using unit resource on device j.
u^b	Mining-device i's utility from unit auctioned resource.
u^s	Sharing-device j's profit from selling unit resource.
b_i	Mining-device i's bid for unit resource.
s_j	Sharing-device j's asking price for unit resource.

Assuming that there are n buyers bidding for m sellers' resources. To ensure all the sellers profitable, we find the intersection point before which sellers' asking prices are lower than buyers' bids. So bids of the n buyers are arranged in descending order as $b_1 \geq b_2 \geq \cdots \geq b_n$, and asking prices of the m sellers are arranged in ascending order as $s_1 \leq s_2 \leq \cdots \leq s_m$. If a value k satisfying the condition $b_k \geq s_k$ and $b_{k+1} < s_{k+1}$ can be found, there are successful matches in the auction. To match the supply and resource demand [38], the sellers before k are arranged in ascending order of resource supplies as $R_{1'} \leq R_{2'} \leq \cdots \leq R_{k'}$. Then the auction price between buyer k and seller k' is determined to $(s_{k'} + b_k)/2$. After making the deal, the two are removed from the market and the other participants repeat the above process. When there is no k satisfying the condition, the edge broker informs the remaining sellers and buyers to reconsider their prices. If there are only sellers remaining after the auction, all buyers and the remaining sellers open a new round of auctions.

Obviously, the profit of buyer k is $u_b = v_k - (s_{k'} + b_k)/2$, and the profit of seller k' is $u_s = (s_{k'} + b_k)/2 - B_{k'}$, where v_k is the value that unit auctioned resource can create to buyer k and $B_{k'}$ is seller k''s cost of unit computing resource.

Since the buyers do not bid at the same time, they can not know the price strategy of others. And the match result will not be known until auction ends. So it is a static game of incomplete information and BNE exists. In accordance with Harsanyi's theory [36], BNE is generally analyzed to obtain the expected utility maximization with incomplete information in traditional auctions as

$$E(u) = (v_i - b_i)P_{win}(b_i), \tag{5}$$

where $P_{win}(b_i)$ is buyer i's probability of winning the auction, v_i is the expected profit from unit auctioned resource and b_i is his bid for unit resource.

As the buyers aim at maximizing their expected profits by giving the optimal bids, the optimization problem can be described as

$$\mathbf{P1}: \max_{\mathbf{b}_i} \quad u^b(\mathbf{b}_i(\mathbf{v}_i)) = (v_i - b_i(v_i)) \cdot P\{b_i \geq s_j(B_j)\}. \tag{6}$$

The sellers focus on figuring out the optimal asking price to maximize their expect profits, so the optimization problem can be formulated as

$$\mathbf{P2}: \max_{\mathbf{s}_j} \quad u^s(\mathbf{s}_j(\mathbf{B}_j)) = (s_j(B_j) - B_j) \cdot P\{b_i(v_i) \geq s_j\}. \tag{7}$$

2) Mining offloading to ECO: ECO is profitable by charging the CMNs for using its resources. So its net profit is given as revenue from CMNs getting rid of calculation cost

$$U^{ECO} = \sum_{i \in \mathcal{M}} (p_i - B)(M_i r_i - \sum_{j \in \mathcal{N}_{\rangle}} c_j), \tag{8}$$

where B is the cost for performing unit work on edge cloud.

CMN tends to achieve its maximum utility while ECO focuses on getting the most profits. Hence, to adjust the demand of computation resources and the price for using them, this process is modeled as Stackelberg Game. ECO who is the leader first declares the prices for unit resource to CMNs (followers). Based on other CMNs' strategies and the prices announced from ECO, the followers decide their expected mining resources. Then, according to the state of resource allocation, ECO provides the optimal price to obtain the maximum profit.

The objective of CMN i is to maximize its own utility by choosing the optimal mining resource size for given price p_i set by the ECO. Mathematically, this problem can be described as

$$\mathbf{P3}: \max_{r_i} U_i^M(r_i, \mathbf{r}_{-i}, p_i) = (R + rt_i)\frac{M_i r_i}{\sum_{j \in \mathcal{M}} M_j r_j} e^{-\lambda(\frac{t_i}{\gamma c} + lt_i)} - (M_i r_i - \sum_{j \in \mathcal{N}_{\rangle}} c_j)p_i - \sum_{j \in \mathcal{N}_{\rangle}} B_j^i c_j. \tag{9}$$

The goal of ECO is to maximize its revenue obtained from renting computation resources to mobile devices. Mathematically, the optimization problem at ECO's side can be expressed as

$$\mathbf{P4}: \max_{\mathbf{p} \geq 0} \quad U^{ECO}(\mathbf{p}, \mathbf{r}) = \sum_{i \in \mathcal{M}} (p_i - B)(M_i r_i - \sum_{j \in \mathcal{N}_{\rangle}} c_j), \tag{10}$$

note that p_i can be uniform or different meaning that pricing can adapt to different demands of CMNs for resources.

IV. OFFLOADING WITHIN CMN BASED ON DOUBLE AUCTION

In this section, on the basis of the double auction model presented in section 3.2.1, we calculate the BNE to acquire the optimal auction strategy in CMN.

In a round of mining, mobile devices first carry out the auction process to offload mining tasks to neighbour devices. After that, the remaining mining tasks will be offloaded to the edge cloud. Since the network is dynamic, we consider

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to balance the algorithm overhead and wait time of newly joining devices and set the process to non-preemptive. When the number of newly joining devices for mining in the CMN reaches N_f, these newly added devices execute the proposed algorithm and perform a new round of mining.

The sellers do not bid at the same time, when a new sharing-device joins the CMN, it announces the asking price to mining-devices. When a sharing-device exits, the profit it obtains is the number of resources it provides by auction price. To simplify the process, we premise that all mining-devices (buyers) and sharing-devices (sellers) give prices with a linear strategy. Before buyer i participates in the auction, it first considers the resource value as part of its bid, presented as

$$b_i = \eta_b + \xi_b \times v_i, \tag{11}$$

where $v_i = \frac{c_i}{\sum_{j\in\mathcal{N}_\rangle} c_j}E + \rho$ obtained from (4) is miner i's possible profit from unit auctioned resource, and η_b and ξ_b are the fixed parameters. And seller j considers the cost as part of its asking price, presented as

$$s_j = \eta_s + \xi_s \times B_j, \tag{12}$$

and η_s and ξ_s are the fixed parameters.

According to the history of transaction records, it is supposed that the permitted maximum auction price in the market is P_{max} and the permitted minimum auction price is P_{min}. So unit cost and profit from unit resource follow uniform distribution

$$B_i \sim \mathcal{U}[P_{min}, P_{max}], v_i \sim \mathcal{U}[P_{min}, P_{max}]. \tag{13}$$

Thus, s_j and b_i follow

$$\begin{aligned} &s_j \sim \mathcal{U}[\eta_s + \xi_s P_{min}, \eta_s + \xi_s P_{max}], \\ &b_i \sim \mathcal{U}[\eta_b + \xi_b P_{min}, \eta_b + \xi_b P_{max}]. \end{aligned} \tag{14}$$

Considering the property of uniform distribution and the definition of auction price, (6) and (7) can be further transformed into

$$\begin{aligned} \mathbf{P1}^{'} : &\max_{\mathbf{b}_i}\{v_i - \frac{1}{2}[b_i + E(s_j(B_j) \mid b_i \geq s_j(B_j))]\} \\ &\cdot P\{b_i \geq s_j(B_j)\}. \end{aligned} \tag{15}$$

$$\begin{aligned} \mathbf{P2}^{'} : &\max_{\mathbf{s}_j}\{\frac{1}{2}[s_j + E(b_i(v_i) \mid b_i(v_i) \geq s_j)] - B_j\} \\ &\cdot P\{b_i(v_i) \geq s_j\}. \end{aligned} \tag{16}$$

Further, $P\{b_i \geq s_j(B_j)\}$ and $E(s_j(B_j) \mid b_i \geq s_j(B_j))$ can be calculated as (17) and (18).

$$P\{b_i \geq s_j(B_j)\} = P\{B_j \leq \frac{b_i - \eta_s}{\xi_s}\} = \frac{b_i - (\eta_s + \xi_s P_{min})}{(P_{max} - P_{min})\xi_s}, \tag{17}$$

$$\begin{aligned} E\{s_j(B_j) | b_i \geq s_j(B_j)\} &= \frac{\int_{\eta_s+\xi_s P_{min}}^{b_i} \frac{1}{(P_{max}-P_{min})\xi_s} x dx}{P\{b_i \geq s_j(B_j)\}} \\ &= \frac{1}{2}(b_i + \eta_s + \xi_s P_{min}). \end{aligned} \tag{18}$$

Finally, by substituting the above two formulas into (15) we can achieve the final form of $\mathbf{P1}^{'}$

$$\begin{aligned} \mathbf{P1}^{''} : &\max_{\mathbf{b}_i}\{v_i - \frac{1}{2}[b_i + \frac{1}{2}(b_i + \eta_s + \xi_s P_{min})]\} \\ &\cdot \frac{b_i - (\eta_s + \xi_s P_{min})}{(P_{max} - P_{min})\xi_s}. \end{aligned} \tag{19}$$

Similarly, $\mathbf{P2}^{'}$ can be further simplified to

$$\begin{aligned} \mathbf{P2}^{''} : &\max_{\mathbf{s}_j}\{\frac{1}{2}[s_j + \frac{1}{2}(s_j + \eta_b + \xi_b P_{max}))] - B_j\} \\ &\cdot \frac{(\eta_b + \xi_b P_{min}) - s_j}{(P_{max} - P_{min})\xi_b}. \end{aligned} \tag{20}$$

We derive the first order and second order derivatives of the above two equations, finding that the two problems are concave. Let the first derivatives be 0, and we can obtain

$$b_i = \frac{2v_i + (\eta_s + \xi_s P_{min})}{3}, \tag{21}$$

$$s_j = \frac{2B_j + (\eta_b + \xi_b P_{max})}{3}. \tag{22}$$

By substituting (11), (14) into (21), (22), the equilibrium point can be obtained.

$$\eta_s = \frac{P_{min}}{12} + \frac{P_{max}}{4}, \xi_s = \frac{2}{3}, \tag{23}$$

$$\eta_b = \frac{P_{max}}{12} + \frac{P_{min}}{4}, \xi_b = \frac{2}{3}. \tag{24}$$

Finally, we obtain the optimal bid and asking price as listed below. We can see that the buyer gives its optimal bid linear to the value and the optimal asking price of seller is linear to the cost.

$$b_i^* = \frac{2v_i}{3} + \frac{P_{min}}{4} + \frac{P_{max}}{12}, \tag{25}$$

$$s_j^* = \frac{2B_j}{3} + \frac{P_{max}}{4} + \frac{P_{min}}{12}. \tag{26}$$

To sum up the auction model in section 3.2.1 and the optimization problems above, a resource auction algorithm in CMN is presented in Algorithm 1.

V. Offloading between CMN and ECO based on Stackelberg Game

In this section, on the basis of the Stackelberg game model presented in section 3.2.2, we analyze the performance of the game model and calculate the NE to obtain the optimal resource allocation and pricing between ECO and CMNs.

A. *Offloading Algorithm*

Given the utility function defined in (9) and (10), we now analyze the performance of the Stackelberg game. The strategic game can be formulated as $\Gamma = \langle \mathcal{M}, (r_i)_{i\in\mathcal{M}}, (u_i)_{i\in\mathcal{M}} \rangle$, in which the players are M CMNs. $(r_i)_{i\in\mathcal{M}}$ denotes the set of strategies (number of mining resources) of CMNs, and $(u_i)_{i\in\mathcal{M}}$ denotes the utility functions. We refer to the game as a multi-user noncooperative offloading game. Considering that if CMNs can compute a strategy profile in which no CMN can

Algorithm 1: Resource auction in CMN Algorithm.

Input : Value profile of buyers $v = (v_1, v_2, \ldots, v_n)$.
Cost and resource supply tuple of sellers $S = \{(B_1, R_1), \ldots, (B_m, R_m)\}$.
Permitted maximum price P_{max}.
Permitted minimum price P_{min}.

Bidding profile $\mathbf{b} = \varnothing$.
Asking price profile $\mathbf{s} = \varnothing$.
Auction result tuple $\mathbf{r} = \varnothing$.
set $i = 1, j = 1$.
while $i \leq n$ **do**
  $b_i = \frac{2v_i}{3} + \frac{P_{min}}{4} + \frac{P_{max}}{12}$.
  $\mathbf{b} = \mathbf{b} \cup b_i,\ i = i + 1$.
end
while $j \leq m$ **do**
  $s_j = \frac{2B_j}{3} + \frac{P_{max}}{4} + \frac{P_{min}}{12}$.
  $\mathbf{s} = \mathbf{s} \cup s_i,\ j = j + 1$.
end
Sort **b** in descending order and get $\mathbf{b} = (b_{(1)}, \ldots, b_{(n)})$.
Sort **s** in ascending order and get $\mathbf{s} = (s_{(1)}, \ldots, s_{(m)})$.
while ***b*** $\neq \varnothing$ ***and s*** $\neq \varnothing$ **do**
  if *value* k *satisfies the condition* $b_{(k)} \geq s_{(k)}, b_{(k+1)} < s_{(k+1)}$ **then**
    Sort $(R_{(1)}, R_{(2)}, \ldots, R_{(k)})$ in ascending order, and get $(R_{(1')}, R_{(2')}, \ldots, R_{(k')})$.
    $p_k = \frac{(s_{(k')} + b_{(k)})}{2}$.
    $\mathbf{b} = \mathbf{b} \setminus b_{(k)}$, $\mathbf{s} = \mathbf{s} \setminus s_{(k')}$.
    $\mathbf{r} = \mathbf{r} \cup (b_{(k)}, s_{(k')}, p_k)$.
  else
    break
  end
end

Output: Auction result tuple
$\mathbf{r} = \{(b_{(1)}, s_{(1')}, p_1), \ldots, (b_{(k)}, s_{(k')}, p_k), \ldots\}$.

further increase its utility overhead by changing its strategy, there is a pure NE in the game.

Definition 1. *For the strategic game* Γ*, given the price vector set by ECO* $\boldsymbol{p}^* = (p_1^*, p_2^*, \ldots, p_M^*)$*, no CMN can increase its utility overhead by unilaterally changing its strategy under strategy profile* $\boldsymbol{r}^* = (r_1^*, r_2^*, \ldots, r_M^*)$*,* $\boldsymbol{r}^*$ *is the unique NE, i.e.,*

$$U_i^M(r_i^*, \boldsymbol{r}_{-i}^*, p_i^*) > U_i^M(r_i, \boldsymbol{r}_{-i}^*, p_i^*), \forall r_i \in \mathcal{R}. \tag{27}$$

Based on the NE of the mining resources in game Γ, ECO (leader) can optimize its pricing strategy to maximize its profit defined in (10).

Definition 2. *Given the NE of the mining resources in game* Γ*, a strategy profile* $\boldsymbol{p}^* = (p_1^*, p_2^*, \ldots, p_M^*)$ *is the optimal price, if at* $\boldsymbol{p}^*$*, ECO can't further increase its profit by unilaterally changing its strategy, i.e.,*

$$U_i^{ECO}(\boldsymbol{p}^*, \boldsymbol{r}^*) > U_i^{ECO}(\boldsymbol{p}, \boldsymbol{r}^*), \forall \boldsymbol{p} > 0. \tag{28}$$

To sum up, the Stackelberg game based offloading algorithm between CMN and ECO is detailed in Algorithm 2.

Algorithm 2: Mining offloading between CMN and ECO Algorithm.

CMN set $\mathcal{M} = \{1, 2, \ldots, M\}$.
$\mathbf{r}^* = \varnothing,\ \mathbf{p}^* = \varnothing$.
for *each* $i \in \mathcal{M}$ **do**
  r_i^*=0, p_i^*=0.
end
for *each* $i \in \mathcal{M}$ **do**
  CMN i calculates r_i^* according to (42).
  if $r_i \in [\underline{r_i}, \overline{r}]$ **then**
    $\mathbf{r}^* = \mathbf{r}^* \cup r_i^*$.
  end
end
for *each* $i \in \mathcal{M}$ **do**
  ECO calculates p_i^* based on $\mathbf{r}^*$.
  $\mathbf{p}^* = \mathbf{p}^* \cup p_i^*$.
end

Output: Optimal resource price $\mathbf{p}^*$ and optimal mining resource strategy $\mathbf{r}^*$.

B. Analysis of the NE for the offloading game between CMN and ECO

We consider two modes of ECO's pricing: uniform pricing and differentiated pricing. Next, the existence of the optimal mining resources and the optimal prices in these two modes will be proved.

1) Uniform pricing: Under uniform pricing, ECO charges the same price p for different users, so we can replace p_i with p in (9) and (10).

Theorem 1. *The NE in game* $\Gamma = \langle \mathcal{M}, (r_i)_{i\in\mathcal{M}}, (u_i)_{i\in\mathcal{M}} \rangle$ *exists.*

Proof. The strategy space is defined to $r_i \in [\underline{r_i}, \overline{r}]$,where $\underline{r_i}$ is the average resources of mining-devices in CMN i and $\overline{r}$ is the maximum resources can be provided by ECO. So it is a nonempty, compact and convex subset of the Euclidean space $\mathbb{R}^M$, U_i^M is obviously continuous in r_i. We take the first order and second order derivatives of (7) with respect to r_i, which are given as follows.

$$\frac{\partial U_i^M}{\partial r_i} = M_i(R + rt_i)e^{-\lambda(\frac{t_i}{\gamma c} + lt_i)} \frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^2} - M_i p, \tag{29}$$

$$\frac{\partial^2 U_i^M}{\partial^2 r_i} = -2M_i^2(R + rt_i)e^{-\lambda(\frac{t_i}{\gamma c} + lt_i)} \frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^3}. \tag{30}$$

Since $\frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^2} > 0$ and $-2M_i^2 \frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^3} < 0$, the second order derivative of U_i^m with respect to r_i is always negative so that U_i^m is concave in r_i. Now we have proved the existence of the NE. □

Theorem 2. *The NE of game* Γ *is unique.*

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Proof. Let r_i^* denote the value of resource that satisfies the condition $\frac{\partial U_i^M}{\partial r_i} = 0$. From (29) we can get the best response function of CMN i as

$$r_i^* = \mathcal{F}_i(x) = \begin{cases} \underline{r_i}, & \frac{\zeta^r - \sum_{i\neq j} M_j r_j}{M_i} < \underline{r_i}, \\ \overline{r}, & \frac{\zeta^r - \sum_{i\neq j} M_j r_j}{M_i} > \overline{r}, \\ \frac{\zeta^r - \sum_{i\neq j} M_j r_j}{M_i}, otherwise, \end{cases} \tag{31}$$

where $\zeta^r = \sqrt{\frac{(R+rt_i)\sum_{i\neq j} M_j r_j}{pe^{\lambda(\frac{t_i}{\gamma c}+lt_i)}}}$.

The function $\mathcal{F}_i(x)$ is positive, monotonic and scalable, which is a standard function. Therefore, there is a unique NE for game Γ. □

Theorem 3. *The unique NE for game Γ is given as*

$$r_i^* = \frac{M-1}{M_i \sum_{j\in\mathcal{M}} \zeta_j^u} - \frac{\zeta_i^u}{M_i}\left(\frac{M-1}{\sum_{j\in\mathcal{M}} \zeta_j^u}\right)^2, \forall i \in \mathcal{M}, \tag{32}$$

where $\zeta_j^u = \frac{pe^{\lambda(\frac{t_j}{\gamma c}+lt_j)}}{(R+rt_j)}$.

Proof. Let $\frac{\partial U_i^M}{\partial r_i}$ in equation (29) be 0, we can get

$$\frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^2} = \frac{M_i p E_i}{M_i(R+rt_i)}, \tag{33}$$

where $E_i = e^{\lambda(\frac{t_i}{\gamma c}+lt_i)}$.

To make it tractable, we get

$$\sum_{j\in\mathcal{M}} M_j r_j = \sqrt{\frac{M_i(R+rt_i)\sum_{i\neq j} M_j r_j}{M_i p E_i}}. \tag{34}$$

The sum of two sides of (33) at different i is calculated as

$$(M-1)\frac{\sum_{j\in\mathcal{M}} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^2} = \sum_{i\in\mathcal{M}} \frac{M_i p E_i}{M_i(R+rt_i)}. \tag{35}$$

By simplifying (35),

$$\sum_{j\in\mathcal{M}} M_j r_j = \frac{M-1}{\sum_{i\in\mathcal{M}} \frac{M_i p E_i}{M_i(R+rt_i)}}. \tag{36}$$

Finally, by substituting equation (36) into equation (34), the NE is obtained as equation (32). □

Theorem 4. *ECO has a unique optimal price to maximize profit when $r_i \in [\underline{r_i}, \overline{r}]$.*

Proof. By substituting (32) into (10), we simplify the ECO profit maximization problem to

$$U^{ECO}(\mathbf{p},\mathbf{r}) = \sum_{i\in\mathcal{M}} \frac{p-B}{p}\frac{N(M-1)}{\sum_{j\in\mathcal{M}} \frac{Ne^{\lambda(\frac{t_j}{\gamma c}+lt_j)}}{(R+rt_j)}} - (p-B)C, \tag{37}$$

where C is $\sum_{i\in\mathcal{M}}\sum_{j\in\mathcal{N}_\rangle} c_j$. Then we calculate the first and second derivatives of profit U^{ECO} as follows.

$$\frac{\partial U^{ECO}}{\partial p} = \sum_{i\in\mathcal{M}} \frac{B}{p^2}\frac{N(M-1)}{\sum_{j\in\mathcal{M}} \frac{Ne^{\lambda(\frac{t_j}{\gamma c}+lt_j)}}{(R+rt_j)}} - C, \tag{38}$$

$$\frac{\partial^2 U^{ECO}}{\partial^2 p} = \sum_{i\in\mathcal{M}} -\frac{2B}{p^3}\frac{N(M-1)}{\sum_{j\in\mathcal{M}} \frac{Ne^{\lambda(\frac{t_j}{\gamma c}+lt_j)}}{(R+rt_j)}}. \tag{39}$$

Since the second derivative of U^{ECO} with respect to p is always negative, U^{ECO} is concave in p. Now we have proved that, with the unique optimal price, the maximum profit of ECO can be obtained. □

2) Differentiated pricing: Under the differentiated pricing scheme, ECO can charge different prices p_i for different CMNs based on their demands on resources,

Theorem 5. *There is a unique NE in $\Gamma = \langle\mathcal{M}, (r_i)_{i\in\mathcal{M}}, (u_i)_{i\in\mathcal{M}}\rangle$.*

Proof. Similar to uniform pricing, the NE exits since the second derivative (41) is always negative and U_i^m is concave in r_i.

$$\frac{\partial U_i^M}{\partial r_i} = M_i(R+rt_i)e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)}\frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^2} - M_i p_i, \tag{40}$$

$$\frac{\partial^2 U_i^M}{\partial^2 r_i} = -2M_i^2(R+rt_i)e^{-\lambda(\frac{t_i}{\gamma c}+lt_i)}\frac{\sum_{i\neq j} M_j r_j}{(\sum_{j\in\mathcal{M}} M_j r_j)^3}. \tag{41}$$

□

In addition, let r_i^* denote the value of resource that satisfies the condition $\frac{\partial U_i^M}{\partial r_i} = 0$. From (40) we can get that the best response function is standard and the NE is unique similar to uniform pricing, which is given as

$$r_i^* = \frac{M-1}{M_i \sum_{j\in\mathcal{M}} \zeta_j^d} - \frac{\zeta_i^d}{M_i}\left(\frac{M-1}{\sum_{j\in\mathcal{M}} \zeta_j^d}\right)^2, \forall i \in \mathcal{M}, \tag{42}$$

where $\zeta_j^d = \frac{p_j N e^{\lambda(\frac{t_j}{\gamma c}+lt_j)}}{(R+rt_j)}$.

Theorem 6. *ECO has a unique optimal price vector $\mathbf{p}$ to maximize profit when $r_i \in [\underline{r_i}, \overline{r}]$.*

Proof. We first take the first and second partial derivative of $U^{ECO}(\mathbf{p})$ with respect to p_i and the second mixed partial derivative with respect to p_i, p_j as

$$\frac{\partial U^{ECO}}{\partial p_i} = \frac{\sum_{j\in\mathcal{M}} B(M-1)\frac{E_j}{(R+rt_j)}}{(\sum_{j\in\mathcal{M}} \frac{p_j E_j}{(R+rt_j)})^2} - C, \tag{43}$$

$$\frac{\partial^2 U^{ECO}}{\partial^2 p_i} = \frac{-2\frac{E_i}{(R+rt_i)}\sum_{j\in\mathcal{M}} B(M-1)\frac{E_j}{(R+rt_j)}}{(\sum_{j\in\mathcal{M}} \frac{p_j E_j}{(R+rt_j)})^3}, \tag{44}$$

$$\frac{\partial^2 U^{ECO}}{\partial p_i \partial p_j} = \frac{-2\frac{E_j}{(R+rt_j)}\sum_{j\in\mathcal{M}} B(M-1)\frac{E_j}{(R+rt_j)}}{(\sum_{j\in\mathcal{M}} \frac{p_j E_j}{(R+rt_j)})^3}, \tag{45}$$

where $E_j = e^{\lambda(\frac{t_j}{\gamma c}+lt_j)}$.

Then the Hessian matrix of $U^{ECO}(\mathbf{p})$ is described as

$$H = \Delta \cdot \begin{bmatrix} \frac{E_1}{(R+rt_1)} & \frac{E_2}{(R+rt_2)} & \cdots & \frac{E_M}{(R+rt_M)} \\ \frac{E_1}{(R+rt_1)} & \frac{E_2}{(R+rt_2)} & \cdots & \frac{E_M}{(R+rt_M)} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{E_1}{(R+rt_1)} & \frac{E_2}{(R+rt_2)} & \cdots & \frac{E_M}{(R+rt_M)} \\ \frac{E_1}{(R+rt_1)} & \frac{E_2}{(R+rt_2)} & \cdots & \frac{E_M}{(R+rt_M)} \end{bmatrix}, \quad (46)$$

where $\Delta = -2B(M-1)\sum_{j\in\mathcal{M}} \frac{E_j}{(R+rt_j)} / (\sum_{j\in\mathcal{M}} \frac{p_j E_j}{(R+rt_j)})^3$.

Since the second partial derivative (44) and the second mixed partial derivative (45) are always negative, the Hessian matrix of $U^{ECO}(\mathbf{p})$ is obviously semi-negative. Therefore, $U^{ECO}(\mathbf{p})$ is concave on each p_i and there is a unique optimal price vector to get the maximum profit of ECO. □

We now finish proving the unique existence of the optimal mining resource allocation and the optimal prices under uniform pricing and differentiated pricing.

VI. Simulation Results and Evaluations

A. Simulation settings

Experimentally, the proposed system is implemented by using Hyperledger Fabric to write smart contracts on the blockchain. The Fabric network is divided into four organizations, and each organization enables sixteen peers to simulate a CMN. Each peer is installed on a x64 virtual machine with 32 vCPUs. In order to ensure the accuracy of the experimental results without being affected by device random exit or entry, we initiate 10 fabric networks and average the experimental results.

In the experiment, we first create 500 blocks based on the loadtest library of Node.js and use the peers to implement the mining process. Then we study the resource allocation and profits of ECO and CMN as the primary performance metrics for the proposed mechanism. Profits of ECO and miners are compared with the pricing-based edge computing resource management method (PECRM) in [28]. PECRM is a pricing-based method for edge resources which only considers offloading to edge cloud. Simulation results verify the superiority of the proposed mechanism. Further, we study the impact of various configurable parameters such as delay effect, transaction number, reward rate, etc. on the performance of CMN and ECO to give some suggestions on their mining strategies. The related parameters in the simulation are listed in **Table II**, which are derived from simulation on the fabric. They are applied in simulation examples unless otherwise stated.

B. Simulation results and evaluations

As described in Section IV, when the number of newly joining devices for mining reaches N_f, a new round of mining is carried out. Under the experimental parameters in Table II, we can get an average mining time of 10 minutes. In a mining interval T, we assume that 10 new devices join the CMN every 5/3 minutes. Fig. 2. shows profits of CMN under different N_f when there are 60, 80, and 100 miners in a CMN initially. We can get that, in the interval T, if a new round of mining starts when N_f is slightly less than half of the original number of miners, the maximum profit can be obtained.

TABLE II
SIMULATION PARAMETERS

Parameter	Description	Values
ω_i	Miner desity of CMN.	0.6
$\frac{1}{\gamma c}+l$	Delay effect.	0.01
λ	Mining complexity parameter.	0.1
R	Fixed reward.	10^5
r	Reward rate.	100
t_i	Transaction number of CMN i.	$\mathcal{N}(300,5)$
p	Price of ECO's resource.	80
c_i	Available resources of device i.	$\mathcal{U}(0,5)$
B	Cost of unit resource to ECO.	30
B_i	Cost of unit resource to CMN i.	$\mathcal{N}(30,5)$
$\bar{r}$	ECO's maximum resource number.	200

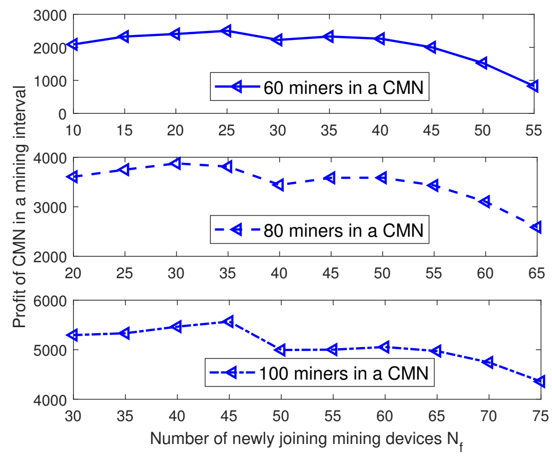

Fig. 2. Profit of CMN in a mining interval at different algorithm execution frequencies.

Next, more numerical simulations are performed to verify the superiority of the proposed mechanism. We initiate three CMNs, each with 100 devices.

We first analyze the mining success possibility of three CMNs under different parameters in Fig. 3. We can see that with the increase of delay effect, the mining success possibility decreases because the probability of generating an orphan block increases. When the delay effect is more than 0.06, the mining success possibility of CMN with miner density (number of mining-devices/total devices) 0.5 is less than 0.05. Therefore, in the case of high delay effect, it is not necessarily profitable for CMN with few mining-devices to mine. Besides, CMN with miner density 0.7 has a higher success rate under differentiated pricing than uniform pricing, while CMN with miner density 0.5 and 0.9 are opposite. This is because under differentiated pricing, ECO fixes the price flexibly in view of mining-device number. According to Fig. 5, ECO charges more for unit resource usage of CMN with more mining-devices, so that there are less resource requests in CMN with high mining-device number under differentiated pricing than uniform pricing, resulting in lower mining success rate under differentiated pricing than uniform pricing.

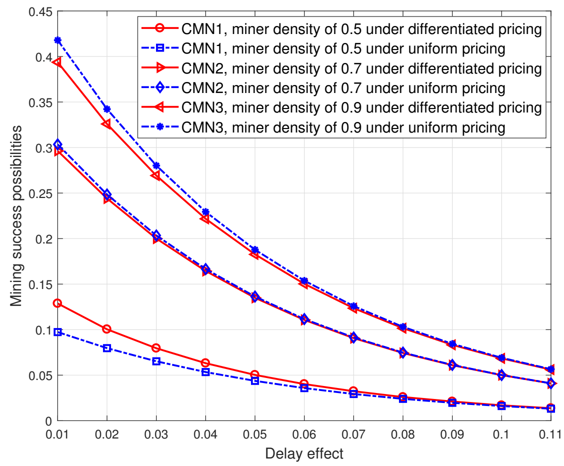

Fig. 3. Mining success possibilities under different delay effects, mining-device numbers and pricing schemes.

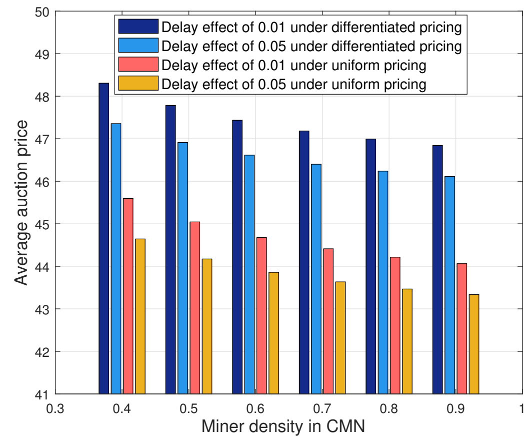

Fig. 4. Average auction price under different mining-device numbers, delay effects and pricing schemes.

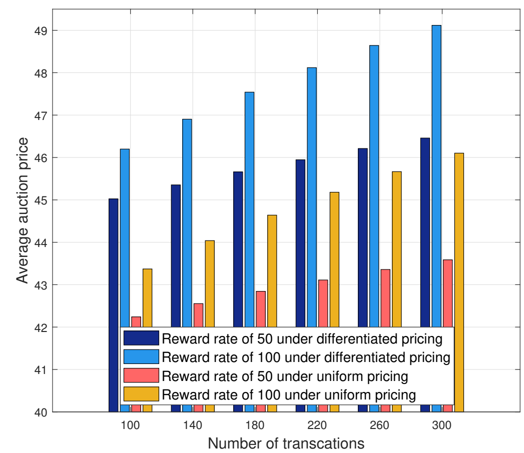

Fig. 5. Average auction price under different transaction numbers, reward rates and pricing schemes.

Fig. 4 and Fig. 5 depict the auction price of resources within the CMN with respect to transcation number, reward rate, and delay effect.

According to Fig. 4, the average auction price of resources is between 40 and 50. This range is reasonable due to higher than computational cost and lower than ECO's price. In terms of mining-device number, the auction price within the CMN decreases as the mining-device number increases, as mining-devices give bids based on their expected profits, which decrease as the number of mining-devices increases. The figure also compares the auction price under differentiated pricing and uniform pricing. Since the optimal price under differentiated pricing is lower than uniform pricing, the expected profit under differentiated pricing is higher, generating higher auction price. Meanwhile, the possibility of successful mining drops when delay effect increases, so the auction price steps down.

In Fig. 5, the increase in transaction number brings an increase in the auction price. Similar to Fig. 4, the auction price is determined by the expected profit and the computing cost. When the number of transactions is not overloaded, the commission remuneration is proportional to transaction number. And since the cost is fixed and the expected profit rises as transaction number rises, the expected profit increases too. Similarly, the auction price is higher under high reward rate.

In Fig. 6, CMNs with price limits of 70, 80 and 90 are compared to obtain the pricing strategy of ECO. CMN with a price limit under uniform pricing always sets the optimal price to the highest price within the limit. But the optimal price under differentiated pricing is slightly lower than uniform pricing and approaches the limit gradually as the mining-device number increases. Due to differentiated pricing, the optimal price can be dynamically adjusted according to different resource demands. It is expected that competition with more miners forces up the optimal price.

The analysis of resource demand is presented in Fig. 7 and Fig. 8. In Fig. 7, we find that under uniform pricing, as the mining-device number increases, the optimal average resource demand increases. However, under differentiated pricing, as the increase in mining-device number leads to a rise in resource prices, the average resource demand decreases after reaching a certain level due to high price. Besides, when the mining-device number is fixed, the lower the delay effect, the higher the average resource demand. This is because miners have higher enthusiasm to mine when the possibility of success is high. Fig. 8 shows that a higher reward rate motivates miners to request more resources. It also shows that with the increase of transaction number, average resource demand increases. That's because more transactions introduces higher profitability, thus motivating miners to compete for more resources to improve the possibility of successful mining.

The profit of miners under our mechanism is compared with PECRM in [28] in Fig. 9. We consider the impact of delay effect and reward rate under differentiated pricing respectively. On average, the total profit of miners in a CMN under our mechanism is 6.86% higher than PECRM. This is because we support mining offloading to neighbor mobile devices to take advantage of the idle computing resources in the network,

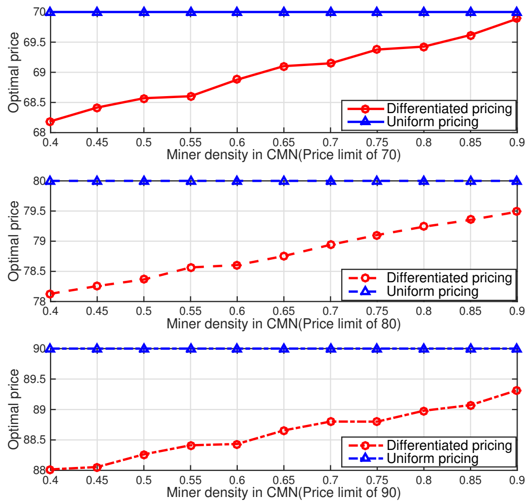

Fig. 6. Optimal price of ECO under different mining-device numbers, price limits and pricing schemes.

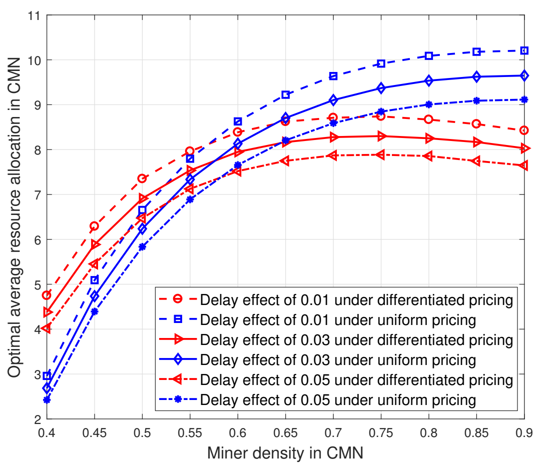

Fig. 7. Optimal average resource allocation under different mining-device numbers, delay effects and pricing schemes.

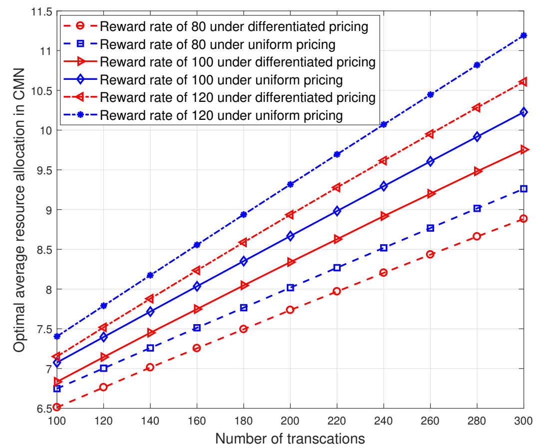

Fig. 8. Optimal average resource allocation under different mining-device numbers, transaction numbers and pricing schemes.

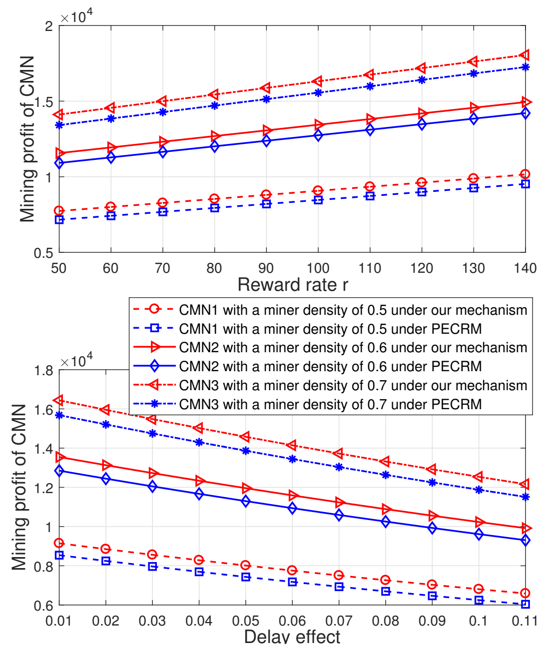

Fig. 9. Comparison of CMNs' profit under PECRM and our mechanism.

thus reducing the amount of resources requested from ECO. The top picture shows that the higher the reward rate, the higher the CMN's profit. It's expected that high returns inspire miners requesting more resources to mine, which in turn improves the profit of CMN. And as more miners contribute more hashing power in the CMN, the possibility of successful mining increases, so the CMN with more mining-devices get higher profits. The picture below shows that under different delay effect, the profit under our mechanism is still higher than PECRM. Moreover, with the increase of the delay effect, the expected profit of CMN decreases. The reason is that longer propagation delays reduce the probability of block generation, thus reducing the expected profit.

We also observe the changing trend of ECO's profit with respect to delay effect and reward rate under our mechanism and PECRM. According to Fig. 10, the profit of ECO increases as reward rate increases due to that higher reward rate inspires more resource demand. On the contrary, the profit of ECO decreases when the delay effect increases. Recall from Fig. 6, average resource demand in CMN decreases as the delay effect increases, which in turn brings down the profit of ECO. We also compare the profit of ECO under our mechanism with PECRM. By reason of more resource sharing within the CMN to reduce mining costs, the resource demand from ECO under our mechanism is less, thus the profit of ECO under our mechanism is lower than PECRM. This is reasonable because we are more focused on determining the optimal resource allocation and obtaining the maximum profit of CMN based on ECO's optimal price.

In summary, we come to the conclusion that miners request more resources and benefit more with lower delay effect, larger transaction volumes, and higher reward rate. And there are more resource requests under the differentiated pricing scheme, so that ECO profits more. What's more, miners obtain more profits on average when offloading to both CMNs and

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ECO than only to ECO.

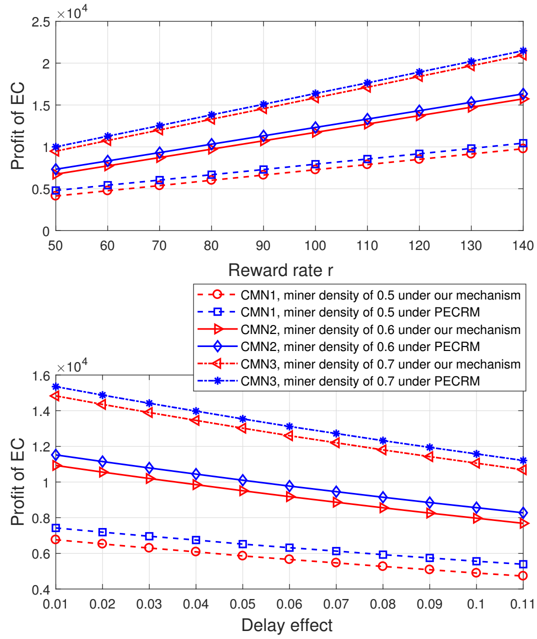

Fig. 10. Comparison of ECOs' profit under PECRM and our mechanism.

VII. Conclusion

Aiming at applying blockchain in IoT mobile devices, this paper proposes that the free resource displayed on non-mining-devices and edge cloud can be selected to construct collaborative mining network (CMN) to execute mining tasks for mobile blockchain. In the CMN, mobile users decide whether to offload mining tasks to sharing-devices in the CMN or edge cloud. Further, offloading within the CMN is managed by a double auction mechanism, in which the BNE is calculated to figure out the optimal auction price. Then, we model the interactions between ECO and CMNs as a Stackelberg game and analyze the NE of the game to obtain the optimal price and resource allocation method. In the simulation, we study the impact of various configurable parameters on the performance of CMNs and ECO. Moreover, the performance of our mechanism is compared with the PECRM method, simulation results show that under our proposed mechanism, CMNs obtain 6.86% more profits on average.

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