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Resource Competition in Blockchain Networks Under Cloud and Device Enabled Participation

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ABSTRACT Blockchain technology is a promising resource management architecture due to its ability of building trust in a decentralized transaction. Block mining participants, i.e. miners, are incentivized with reward for successfully mining blocks. Unfortunately, solving the proof-of-work puzzle consumes substantial computing powers during the mining period, which greatly challenges miners. Mobile devices also fail to participate in mining because of limited resource. To solve these issues, we are motivated to propose a mining framework of alleviating miner's computation-intensive mining burdens, as well as enabling mobile devices' participation. Depending on the proposed model, miners are capable of offloading their computation-intensive tasks to the edge cloud and mobile devices. The interactions among them formulate a muti-leader multi-follower Stackelberg game. We achieve the Subgame Perfect Equilibrium (SPE) in the game, which guarantees three types of participants to realize profit maximization. Simulation results demonstrate the effectiveness of the proposed model.

INDEX TERMS Blockchain, edge computing, Internet of Things, stackelberg game.

I. INTRODUCTION

Blockchain is a developing technology of decentralized transaction database shared by all nodes participating in a network based on a consensus protocol [11]. As indicated by the name "blockchain," blockchain store data (i.e. records of transactions) in blocks that are then chained together. The utilization of blockchain implements network data storage, verification, transmission and communication through its own distributed nodes. Moreover, data interactions are performed anonymously since the process of information exchange between nodes is not involved with their identity information. Therefore, non-trusting network participants are able to reach a consensus in a verifiable manner without resorting to any third party. Accordingly, the cost is reduced because of eliminating third-party verification. Blockchain technology has the potential to be applied for dealing with the data security and mutual trust problems, confronted by the Internet and mobile devices [25], [31], [34].

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With the development of the IoT (Internet of Things), high demands for edge computing enhance requirements for the distributed self-organizing management mode among a large number of devices. Blockchain is an underlying solution to deal with such issue due to its distributed and fault-tolerant features. Under blockchains, data is distributed and hard to tamper with. Blockchain's security depends on a proof-of-work (PoW) mechanism. The PoW of every block ensures a specific level of difficulty to create a new block, and then a decentralized consensus enforces to validate every block in the blockchain. There exist alternatives of PoW, such as "proof-of-stake" (PoS) and "Proof-of-Elapsed-Time" (POET). PoS builds on the notion that only those holding assets in the system may participate in the consensus process for growing the blockchain [25], [37]. That is to say, PoS requires strong financial strength. Moreover, PoS is vulnerable to various attacks in comparison with PoW. POET is low-cost, but it must use specific hardware [17]. Therefore, POET is not extensively suitable for public blockchain. Under such concerns, PoW is here considered for blockchain mining.

The key point in Blockchain is to utilize PoW system for validating transactions. While a fresh block is filled with new data, it requires to solve the PoW for obtaining a specific hash value that links the previous block to the fresh block [3]. The process of building blocks by PoW mechanism is generally called mining. Mining generates a lot of hashes based on a cryptographic hashing algorithm. The probability of obtaining the correct hash value is positively related with the computational power. Blockchain requires heavy computation powers for solving computation-intensive PoW, which challenges the development of blockchain in IoT mobile applications [2], [44]. Some devices, due to their hardware limitations, fail to afford the high computing resources for finding the value in mining process [5], [9], [29].

Motivated by the situation above, recent studies have proposed edge computing resource allocation schemes and blockchain mining task offloading models [4], [26], [35], [36], [40], [43]. Traditional mobile edge computing (MEC) suffers high costs of infrastructure deployment and maintenance. The complex and changeable edge computing environment also places a huge burden on the MEC servers [43]. To this end, authors in [36] proposed a resource allocation scheme based on deep reinforcement learning (DRLRA), which is able to adaptively allocate computing resources for reducing the average service time. In [16], the author proposed a multiagent DRL framework to realize long-term performance for computation offloading. In order to improve its stability, league learning is introduced for agents to explore the environment collaboratively for fast convergence and robustness. Considering the substantial resource consumption of solving the proof-of-work puzzle, the authors in [40] proposed a multi-access mobile edge computing model for resource-limited mobile devices. Such model employed a Stackelberg-based game to optimize resource allocation and pricing between mobile devices and the edge cloud.

To support the application of blockchain in mobile networks, the mining task offloading of miners is studied in our paper by considering the assistance of nearby mobile devices and edge cloud operator (ECO). Mobile devices are typically hardware-constrained mobile endpoints. Since current mobile devices are equipped with limited computation resources, the growing amount of mining tasks are able to exceed their computing powers. Therefore, the mining tasks are offloaded to mobile devices, as well as edge cloud. Edge clouds are small data centers or medium computing resources in edge computing. It is thus fit for offloading the mining tasks to edge cloud instead of traditional cloud [1]. We build a multi-leader multi-follower Stackelberg game into three stages to calculate the best resource allocation strategy and the optimal resource pricing for maximizing their profits. As matter of fact, both of edge computing and fog computing allow computing needs to be performed closer to the source of data. We here concentrate on edge computing but the proposed model is also applicable to fog computing. The salient contributions of this paper are summarized as follows:

- In order to solve the intensive computing tasks in blockchain mining, we first propose mobile device enabled block mining. Each miner is usually surrounded by mobile devices. A miner can opportunistically request mobile devices for aid of performing computation-intensive tasks. In response, the mobile devices charge the miner to compensate their energy costs, generated by mining task execution. The interactions between a miner and nearby mobile devices can be modeled as a single-leader multi-followers subgame of Stackelberg game. The miners, as leaders, have the priority to decide the market prices for their nearby mobile devices, on which mobile devices, as followers, determine mining resources for miners.
- We then consider the edge cloud for computation offloading due to massive computation of miners and limited resource of mobile devices. The interactions between the edge cloud operator (ECO) and miners can be modeled as a single-leader multi-followers subgame of Stackelberg game, The ECO, as the leader, has more market powers to determine the price per unit resource, on which the miners, as followers, decide the mining resources from ECO.
- We use a unique incentive framework for players of the ECO, miners and mobile devices to solve the utility maximization problem. Jointly considering two Stackelberg games above, we build a three-stage Stackelberg game with multiple leaders and followers. In the first stage, ECO determines its optimal resource price for miners. In the second stage, Miners decide the optimal resource demands from ECO and fix the resource price for mobile devices. In the third stage, mobile devices determine the optimal resources, allocated for miners. The aggregation of computational resources from the ECO and mobile devices reduces the uncertainty of successful mining.
- We derive the subgame perfect equilibrium (SPE), corresponding to the three-stage Stackelberg game. We show that a Nash equilibrium is achieved in every subgame of the three-stage game. Under SPE, every player determines its best strategy for profit maximization.

II. RELATED WORK

A. BLOCKCHAIN APPLICATION TECHNOLOGY

The IoT connects a large scale of 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 is a challenge because these parties often have conflicting interests [2], [28]. Therefore, blockchain technology is introduced to address such problem. The blockchain is a distributed database that does not need a central authority and eliminates the need for third party verification [24].

Despite the evident benefit of using blockchain, the privacy security is still a concern in establishing a trustable environment. In terms of privacy, authors in [7] proposed a permissioned blockchain edge model for smart grid network (PBEM-SGN) to address issues of privacy protections and energy security in smart grid. And an optimal security-aware policy is constructed through smart contracts running on the blockchain. In [6], authors presented a consortium blockchain-oriented approach to deal with the privacy leakage problem of transaction information, existing on the blockchain. This method mainly solves the privacy problem of energy transaction users in smart grid. By mining different energy transaction volumes, it detects the relationship between them and other information, such as physical location, energy use and so on. So, the distribution of seller's energy sales can be shielded. The authors in [30] proposed a secure distributed cloud framework based on blockchain technology for cost-effective and high-performance computing in IoT network. This method effectively manages the huge data storage caused by the expansion of devices in the Internet of Things.

Another concern is that in mobile edge networks, the widespread application of blockchain is challenging due to the limited computing and storage resources of mobile devices. Mobile devices with limited computation capability fail to directly participate in mining since PoW of blockchain requires huge computation powers [25], [38]. To this end, offloading tasks to MEC has been introduced for overcoming the issues of mobile blockchain application. Mobile blockchain technology has been widely applied to various networks and distributed systems [8], [12], [19], [21], [25], [32], [42]. In [8], the author proposed a blockchain-based computation scheme for edge-enabled Smart Grid. In [21]and [19], the author proposed a blockchain-based video system to build a decentralized and flexible video ecosystem. In [42], the author formulated a resource pricing and trading scheme based on blockchain technology to optimally allocate edge computing resources, and it has been successfully applied to the field of unmanned aerial vehicle.

B. MOBILE BLOCKCHAIN MINING

Edge computing provides support of blockchain deployment in mobile devices for block mining. Depending on edge computing, interactions among block miners and mobile devices can be modeled as market activities. In [22], the authors developed an optimal auction algorithm based on deep learning to realize the edge resource allocation. In [18], the authors proposed a new wireless blockchain framework, on which computation-intensive mining tasks can be offloaded to nearby edge computing nodes for addressing proof-of-work puzzle. Multiple economic incentives also focus on mining strategies in the blockchain networks [10], [13], [18], [22], [33], [38], among which Stackelberg game is a popular approach for motivating participants [10], [15], [27], [38], [41].

Stackelberg game-based mechanism frames the interactions among mining participants as leader-follower game. Through this game, computation resource allocation and price competition are studied to maximize the payoff of participants. In [38], the authors studied the interactions between the cloud/fog providers and the miners in a proof of work-based blockchain network, which formulates the computation resource management in the blockchain consensus process as a two-stage Stackelberg game. In [39],the authors considered that different unit prices are assigned to different miners, on which a two-stage Stackelberg game named ADMM algorithm is formulated to solve the PoW puzzle. Considering the competition among mining-devices, the authors in [10] adopted a double auction method to manage mining offloading for resource sharing between mobile devices in collative mining network (CMN). Besides, a two-stage Stackelberg game model is used to simulate the interactions between the edge cloud operator and different CMNs.

Most of works discussed above only considered one type of participant to assist miners. Despite the work proposed in [10] was involved in mobile devices and edge cloud, two models are built to describe the interactions between miners and them, respectively. Motivated by this situation, we propose a three-stage Stackelberg game model, which jointly takes the benefits of three types participants into consideration to stimulate their active participation in block mining.

III. SYSTEM MODEL

During blockchain mining process, a miner can be computationally powerful or resource-limited. Authors in [38] incentivize the cloud/fog providers to assist resource-limited miners. Moreover, we concentrate on building an incentive system model for considering the interactions among ECO, resource-limited miners and mobile devices. Miners offload their mining tasks to nearby non-mining devices and edge cloud when they have no insufficient resources. Fig.1 illustrates the proposed framework with one ECO, m miners and multiple mobile devices. Miners request computation offloading from the edge cloud and nearby mobile devices. However the edge cloud and mobile devices are managed by selfish owners. They unwillingly share their computation resources with the miners because of energy consumption. Therefore, the miners need to offer proper incentives for motivating their active participation. A miner should negotiate with mobile devices and ECO in an aim to maximize its own profit. Miners can offload their mining tasks to nearby non-mining devices or the edge cloud when there are insufficient resources.

Without loss of generality, we assume the system model contains a set of miners, denoted by $\mathcal{M} = \{M^1, \ldots, M^i, \ldots, M^m\}$. Miners have their local computation resources, denoted by $\boldsymbol{g} = (g_1, \ldots, g_i, \ldots, g_m)^T$. In order to solve computation-intensive PoW, a miner requests the nearby non-mining devices if they can share their unnecessary computation resource for executing computation tasks. We further assume that there are n_i mobile devices for offloading the computation workload of M^i, $i \in \mathcal{M}$, denoted by the set $\mathcal{N}_i = \{1, \ldots, n_k, \ldots, n_i\}$. Specifically, the device $k, k \in \mathcal{N}_i$ allocates its computation resource x_k^i to M^i. Hence, the vector of total resources from mobile devices is $\boldsymbol{x}^i = (x_1^i, \ldots, x_k^i, \ldots, x_{n_i}^i)^T$. The miner M^i acts as the leader and has the priority to determine the price p_k^i compensated for the

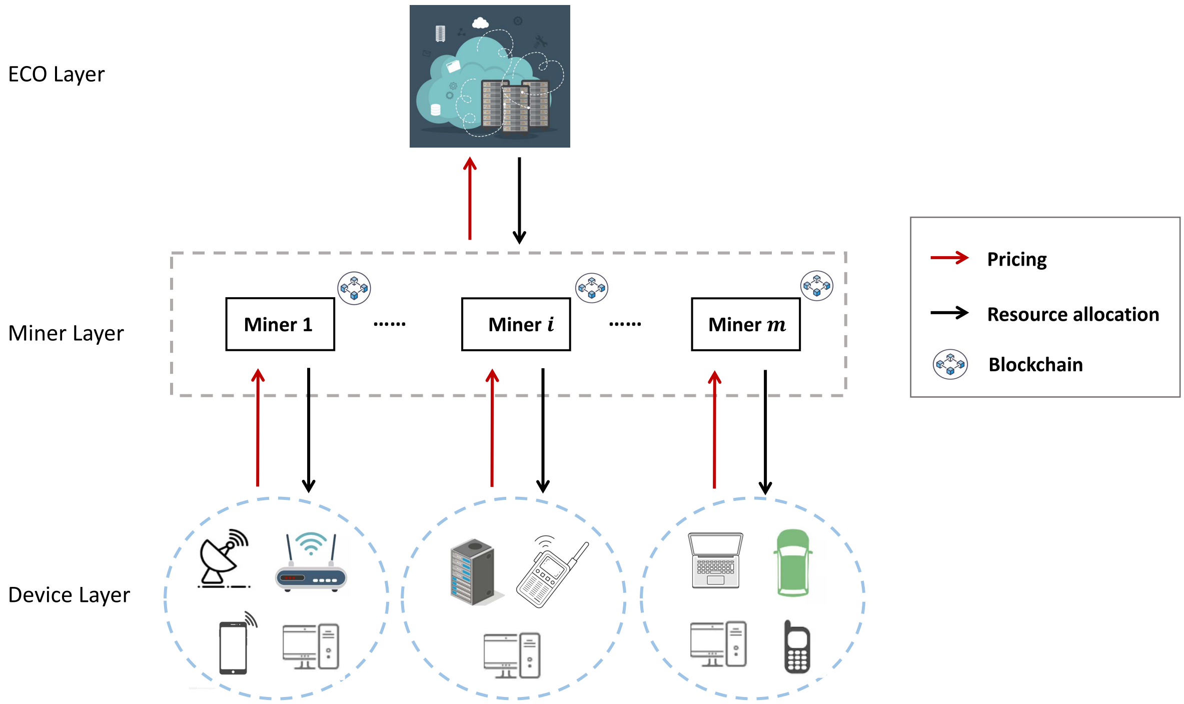


FIGURE 1. The system model with the ECO, miners and mobile devices.

mobile device k. We define $\boldsymbol{p}^i = (p_1^i, \ldots, p_k^i, \ldots, p_{n_i}^i)^T$ as the price vector of miner M^i. We also assume that y_i is the computation resource that ECO provides for miner M^i. The vector $\boldsymbol{y}$ represents the mining resources that miners obtain from ECO, where $\boldsymbol{y} = (y_1, \ldots, y_i, \ldots, y_m)^T$. Compared with miners, the ECO has significant market power to determine the resource price p paid by miners.

We formulate the interactions among miners, mobile devices and ECO as a three-stage Stackelberg game, shown in Fig.2. Through the game, three participants achieves maximal profits by deciding their strategies. The definition of profit relies on the traditional "gain minus cost."

In the first stage, ECO acts as the leader of miners to determine the resource price for maximizing its own revenue. The gain of ECO is generated from all of the miners' compensation for its resource consumption. The cost of ECO is incurred by allocating its computation resource to miners for task execution. Therefore, the profit of ECO is defined as:

$$U^{ECO}(p, \boldsymbol{y}) = p \sum_{i=1}^{m} y_i - c \sum_{i=1}^{m} y_i, \tag{1}$$

where p is the ECO's price per unit resource and c is the cost for performing unit computation on edge cloud.

In the second stage, the miners act as followers of ECO to decide the computation resource $\boldsymbol{y}$, requested from ECO. In the meantime, miners act as leaders of mobile devices to decide the resource price $\boldsymbol{p}^i$, paid for mobile devices. Obviously, the cost of miner M^i is $\sum_{k\in\mathcal{N}_i} x_k^i \cdot p_k^i + \sum_{k\in\mathcal{N}_i} y_i \cdot p$, since the miner M^i is charged for utilizing computation resources of the ECO and mobile devices in $\mathcal{N}_i$, $i \in \mathcal{M}$. The gain of miner M^i is the reward of successfully mining a valid block.

To be valid, a block needs to go through two consecutive procedures: mining and propagation. In the mining procedure, miners compete to generate a new block. The probability of mining the new block for a miner is positively related with its computing/hash power. A miner M^i, $i \in \mathcal{M}$ has computing resources $g_i + y_i + \sum_{k\in\mathcal{N}_i} x_k^i$, shared from ECO and mobile devices, g_i is the local resource, and different miner may have deffrent resource capacity. Accordingly, the total computation resources of miners in the system are $\sum_{j=1}^{m} (g_j + y_j + \sum_{l\in\mathcal{N}_j} x_l^j)$. Referring to the total computing/hash power, we calculate the relative computing/hash power

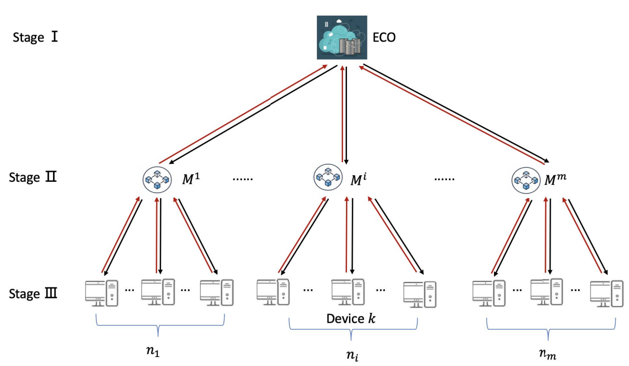


FIGURE 2. Interactions among miners, mobile devices and ECO.

h_i of the miner M^i

$$h_i = \frac{g_i + y_i + \sum_{k\in\mathcal{N}_i} x_k^i}{\sum_{j=1}^{m}(g_j + y_j + \sum_{l\in\mathcal{N}_j} x_l^j)}, \quad h_i > 0, \tag{2}$$

such that $\sum_{i\in\mathcal{M}} h_i = 1$.

Once a block is mined by a miner, the propagation procedure is then implemented across the blockchain network. The miner propagates the new block to other miners for verification to reach consensus. However, this block is likely to be invalid due to slow propagation. We call such phenomenon as orphaning and the block as orphaned block. The orphaned block will be abandoned eventually. The propagation latency of a block depends on the transactions it contains. Considering the fact that block mining process follows the Poisson distribution, the orphaning probability can be approximated as

$$P_o(t_i) = 1 - e^{-\lambda\tau(t_i)}, \tag{3}$$

where λ is the mean value of Poission distribution and t_i is the number of transactions in the block [20]. The function $\tau(t_i)$ denotes the block propagation time, which is a directly proportional function of number of transactions. We therefore let $\tau(t_i) = zt_i$, where z is a fixed latency factor. The block with a large number of transactions leads to long latency while propagating the block to the whole network [14]. Thus, the probability of M^i successfully mining to generate a valid block is

$$P_i(y_i, t_i) = h_i \times (1 - P_o(t_i)) = \frac{(g_i + y_i + \sum_{k\in\mathcal{N}_i} x_k^i)e^{-\lambda z t_i}}{\sum_{j=1}^{m}(g_j + y_j + \sum_{l\in\mathcal{N}_j} x_l^j)}, \tag{4}$$

The miner earns the corresponding reward by itself while successfully mining a valid block. The reward consists of a fixed reward R, paid by the system and a variable reward rt_i, paid by blockchain users. The parameter r is the average reward from blockchain users for each transaction. So, the profit of M^i is formulated,

$$U_i(\boldsymbol{x}^i, \boldsymbol{p}^i, y_i, \boldsymbol{y}_{-i}, p) = (R + rt_i)\frac{(g_i + y_i + \sum_{k\in\mathcal{N}_i} x_k^i)e^{-\lambda z t_i}}{\sum_{j=1}^{m}(g_j + y_j + \sum_{l\in\mathcal{N}_j} x_l^j)} - \sum_{k\in\mathcal{N}_i} x_k^i \cdot p_k^i - y_i \cdot p, \tag{5}$$

Numerous mobile devices are able to gather their computation resources and share their hashing power in order to smooth out their mining rewards effectively. Then they split the reward in proportion for their contribution to solve a block [10]. In the third stage, mobile devices in $\mathcal{N}_i$ act as followers to decide the computation resource x^i, allocated for M^i, $i \in \mathcal{M}$. The profit of mobile device k is quantified,

$$U_k^i(x_k^i, x_{-k}^i, p_k^i) = p_k^i \cdot x_k^i - s_k^i \cdot \left(x_k^i\right)^2 - c_k^i \cdot x_k^i. \tag{6}$$

The first two terms represent the gain obtained by mobile device k, which captures the intrinsic value of the shared resources to miner M^i. The first term is the compensation paid by miner M^i and the second term is the mobile devices k's sensibility to the satisfaction of shared resources. The elasticity factor s_k^i measures the sensitivity of the device satisfaction to change in shared computation resources. A simple example is used for illustration. Assume that device 1 and device 2 can share unnecessary resources with size of 8 for a miner. However, the miner only requests computation resources with size of 5 to each of them. As a result, device 2 is more satisfied with the shared resources than device 1. So, we see that device 1 is more sensitive to the satisfaction of shared resources than device 2 [27]. The third term is the cost of mobile device k, in which c_k^i represents the cost per unit resource, allocated for miner i in M^i.

TABLE 1. Symbol summary.

Symbol	Definition
U^{ECO}	Profit of ECO
U_i	Profit of M^i
U_k^i	Profit of sharing-device $k, k \in \mathcal{N}_i$
M^i	Miner i
p	Price of ECO's unit resource to M^i
p_k^i	Price of device k's unit resource to M^i
t_i	Transaction number of M^i
λ	Complexity of mining a block
R	Fixed reward for mining
r	Reward for unit transaction(reward rate)
c	Cost of using unit resource on ECO
c_k^i	Cost of using unit resource on device k
s_k^i	Sensibility of M^i to resource
x_k^i	Computation offloading of device k to M^i
y_i	Computation offloading of ECO to M^i
g_i	Local resources of miner M^i
z	Latency factor

IV. STACKELBERG GAME FORMULATION FOR SYSTEM MODEL

In game theory, a Stackelberg game is an approach of modeling the layers of action between two types of users: one is a leader and the other is a follower. The leader first initiates a strategy, on which the followers decide their optimal response strategies and then submit them to the leader. After obtaining followers' response, the leader updates its strategy. This process continues until the strategies of the leader and followers constitute Nash equilibrium. Under Nash equilibrium, there is no motivation for the leader and followers to violate unilaterally [10], [15], [27], [45].

In this section, we formulate the interactions among ECO, miners and mobile devices as a three-stage Stackelberg game with multiple leaders and followers. In each stage, one type of participants decides its strategy for maximizing its own profit. The optimal strategies of the ECO, miners and mobile devices jointly constitute the Subgame Perfect Equilibrium (SPE).

Under such SPE, there is no motivation for the ECO, miners and mobile devices to unilaterally modify their strategies.

A. MINING GAME FORMULATION

In stage one, the ECO, acting as miners' leader, prices the computation resources allocated for miners. The goal of ECO is to maximize its profit by allocating computation resources to miners. In stage two, miners, acting as the ECO's followers, decide the computation resources requested from ECO. In the meantime, miners, acting as the mobile devices' leaders, price computation resources allocated from mobile devices. Utilizing the resources from ECO and mobile devices, miners improve the possibility of mining valid blocks for profit maximization. In stage three, mobile devices act as miners' followers to decide computation resources allocated for miners. The goal of mobile devices is to maximize their profits by sharing computation resources to miners. The three-stage Stackelberg game is defined in a mathematical way as follows.

Stage one: The leader ECO determines the unit price p^* of computation resources allocated for miners to maximize its total profit. So, the ECO's optimization problem is defined,

$$p^* = arg \max_{(p \geq 0)} U^{ECO}(p, \boldsymbol{y}) \tag{7a}$$

$$\text{subject to } \underline{y} \leq y_i \leq \overline{y} \tag{7b}$$

where $\underline{y}$ and $\overline{y}$ denote minimal and maximum resources provided by ECO, respectively.

Stage two: Given the unit price p, the follower M^i chooses the amount of computation resources y_i^*, allocated from ECO. Meantime, M^i acts as the leader to decide a unit resource price $p_k^{i\,*}$ for mobile devices to maximize the profit function U_i. The M^i's optimization problem is defined as:

$$(\boldsymbol{p}^{i^*}, \boldsymbol{y}^*) = arg \max_{\boldsymbol{p}^i, \boldsymbol{y}} U_i(\boldsymbol{x}^i, \boldsymbol{p}^i, y_i, \boldsymbol{y}_{-i}, p) \tag{8a}$$

$$\text{subject to } \underline{x} \leq x_k^i \leq \overline{x}, \tag{8b}$$

$$\underline{y} \leq y_i \leq \overline{y}, \tag{8c}$$

where $\boldsymbol{y}_{-i}$ denotes mining resource of other miners expect M^i in $\mathcal{M}$, obtained from ECO. $\underline{x}$ and $\overline{x}$ correspond to the minimum and maximum resources that mobile device share with miners.

Stage three: The mobile device k in $\mathcal{N}_i$ chooses the optimal resource strategy given the unit price p_k^i to maximize its profit function. Therefore, mobile device k's optimization problem is defined as:

$$x_k^{i^*} = arg \max_{x_k^i} U_k^i(x_k^i, x_{-k}^i, p_k^i) \tag{9a}$$

$$\text{subject to } \underline{x} \leq x_k^i \leq \overline{x}, \tag{9b}$$

where x_{-k}^i denotes the resources of other mobile devices expect device k in $\mathcal{N}_i$.

Problem (7), Problem (8) and Problem (9) compose the Stackelberg game together. Our aim is to achieve the Subgame Perfect Equilibrium (SPE) of such game. SPE is a stable point of the Stackelberg game that the three types of players interact through self-optimization to reach. At such a point, none of the players have any incentive to deviate. The SPE is defined in the proposed game as follows.

Definition 1: Subgame Perfect Equilibrium (SPE) [23]: The strategy profile is a subgame perfect equilibrium if it constitutes a Nash equilibrium in every subgame of the three-stage multi-leader multi-follower game.

$$\begin{cases} \text{Stage one: } p^* = arg \max U^{ECO}(p, \boldsymbol{y}), i \in \mathcal{M}, \\ \text{Stage two: } (\boldsymbol{p}^{i^*}, y_i^*) = arg \max_{(\boldsymbol{p}^i, \boldsymbol{y})} U_i(\boldsymbol{x}^i, \boldsymbol{p}^i, y_i, \boldsymbol{y}_{-i}, p), \\ \text{Stage three: } x_k^{i^*} = arg \max_{x_k^i} U_k^i(x_k^i, x_{-k}^i, p_k^i), \end{cases} \tag{10}$$

with $k \in \mathcal{N}_i, i \in \mathcal{M}$.

Under SPE in (10), every player optimizes its strategy to maximize its profit. We employ the backward induction to determine the optimal strategies of all players. The mobile devices first act as followers of miners to achieve their optimal resources allocation strategies $\boldsymbol{x}^{i*}, i \in \mathcal{M}$. The miners then take action to derive their optimal price strategies $\boldsymbol{p}^{i*}$ on those of the mobile devices. Meantime, the miners act as followers of ECO to achieve their optimal allocation resource strategies $y_i{}^*$. Finally, ECO derives its optimal price strategy p^* based on the NE of miners' strategies. The optimal strategies of all players are derived in the following work.

B. GAME IN STAGE THREE

Given the price vector $\boldsymbol{p}^{i*}$ determined by miner M^i, mobile devices in $\mathcal{N}_i$ are entitled to decide how much mining resource they can offer. The purpose of Stage three is to achieve profit maximization of M^i's followers, defined in (9). The interaction between leader M^i and its followers formulates the subgame $\Gamma_i = \{\mathcal{N}_i, \{x_k^i\}_{k \in \mathcal{N}_i}, \{p_k^i\}_{k \in \mathcal{N}_i}\}$. The optimal strategies, decided by the M^i's followers, $\boldsymbol{x}^{i*}$ achieve a unique Nash Equilibrium. Obviously, there exist m Nash Equilibrium in Stage three since m miners participate in mining. Given Miner M^i, the NE of game Γ_i is defined as follows.

Definition 2: Given the price vector set by M^i, $\boldsymbol{p}^{i^*} = (p_1^{i^*}, \ldots, p_k^{i^*}, \ldots, p_{n_i}^{i^*})^T$, a computation resource vector $\boldsymbol{x}^i = (x_1^i, \ldots, x_k^i, \ldots, x_{n_i}^i)^T$ is the Nash equilibrium of the subgame $\Gamma_i = \{\mathcal{N}_i, \{x_k^i\}_{k \in \mathcal{N}_i}, \{p_k^i\}_{k \in \mathcal{N}_i}\}$, if, for device $k \in \mathcal{N}_i$,

$$U_k^i(x_k^{i^*}, \boldsymbol{x}_{-k}^{i^*}, \boldsymbol{p}^{i*}) > U_k^i(x_k^i, \boldsymbol{x}_{-k}^{i^*}, \boldsymbol{p}^{i*}), \tag{11}$$

for all $x_k^i = [\underline{x}, \overline{x}]$.

According to Definition 2, no followers of M^i can increase its profit by altering its resource strategy $\boldsymbol{x}_k^{i\,*}$. Based on the NE of the mining resources in the game Γ_i, M^i optimizes the pricing strategy to maximize its profit.

Definition 3: Given the NE of the strategies of miner M^i's followers, a strategy profile $\boldsymbol{p}^{i*}$ is the optimal price, if at $\boldsymbol{p}^{i*}$, M^i can't further increase its profit by unilaterally changing its strategy,

$$U_i(\boldsymbol{x}_i^*, \boldsymbol{p}_i^*, y_i^*, \boldsymbol{y}_{-i}^*, p^*) > U_i(\boldsymbol{x}_i^*, \boldsymbol{p}_i, y_i^*, \boldsymbol{y}_{-i}^*, p^*), \quad \forall \boldsymbol{p}_i > 0, \tag{12}$$

The Nash equilibrium among followers of M^i achieves when each follower $k \in \mathcal{N}_i$ select its optimal mining resource strategy, defined in the following Theorem 1.

Theorem 1: The optimal mining resource of mobile device k is

$$x_k^{i*} = \mathcal{F}_k(\boldsymbol{x}^i) = \begin{cases} \underline{x} & \text{if } \dfrac{p_k^i - c_k^i}{2s_k^i} < \underline{x}, \\ \overline{x} & \text{if } \dfrac{p_k^i - c_k^i}{2s_k^i} > \overline{x}, \\ \dfrac{p_k^i - c_k^i}{2s_k^i} & \text{otherwise.} \end{cases} \tag{13}$$

Proof: The problem (9) is solved by Karushi-Kuhn-Tucker (KKT) analysis. The KKT conditions of problem (9) are written:

$$\nabla U_k^i(x_k^i, x_{-k}^i, p_k^i) - \alpha_k^i + \beta_k^i = 0, \tag{14a}$$
$$\alpha_k^i(x_k^i - \overline{x}) = 0, \tag{14b}$$
$$\beta_k^i(\underline{x} - x_k^i) = 0, \tag{14c}$$
$$\underline{x} \le x_k^i \le \overline{x}, \tag{14d}$$
$$\alpha_k^i, \beta_k^i \ge 0, \tag{14e}$$

where $\alpha_k^i, \beta_k^i \ge 0$ are the optional Lagrange multipliers. While $\alpha_k^i = 0$ and $\beta_k^i = 0$, x_k^{i*} can be obtained by solving (14a),

$$\nabla U_k^i(x_k^i, x_{-k}^i, p_k^i) = \frac{\partial U_k^i(x_k^i, x_{-k}^i, p_k^i)}{\partial x_k^i} = 0. \tag{15}$$

In such case, the best strategy x_k^{i*} is calculated as

$$x_k^{i*} = \frac{p_k^i - c_k^i}{2s_k^i}. \tag{16}$$

While $\alpha_k^i > 0$, the best strategy is $x_k^{i*} = \overline{x}$ based on (14b) and thus $\beta_k^i = 0$ based on (14c). While $\beta_k^i > 0$, the best strategy is $x_k^{i*} = \underline{x}$ based on (14c) and thus $\alpha_k^i = 0$ based on (14b).

To guarantee the optimal strategies of leader M^i and its followers, we next prove the existence and uniqueness of NE in the game Γ_i. Theorem 2 illustrates the existence of NE in game Γ_i. Moreover, the uniqueness of NE in game Γ_i is proved in Theorem 3.

Theorem 2: The NE of game Γ_i exists.

Proof: The strategy space for each mobile device is $[\underline{x}, \overline{x}]$, which is obviously non-empty, convex, and compact. It is easily observed that U_k^i is continuously differentiable with respect to x_k^i. We calculate its first and second derivatives in x_k^i,

$$\frac{\partial U_k^i}{\partial x_k^i} = p_k^i - 2s_k^i x_k^i - c_k^i, \tag{17}$$

$$\frac{\partial^2 U_k^i}{\partial^2 x_k^i} = -2s_k^i. \tag{18}$$

Since $-2s_k^i < 0$, the second order derivative of U_k^i in x_k^i is negative. So, U_k^i is concave with respect to x_k^i. Therefore, Γ_i is a concave game of admitting a NE.

Theorem 3: The NE of game Γ_i is unique.

Proof: It is obviously seen from (13) that the best response function $\mathcal{F}_k(\boldsymbol{x}^i) > 0$. Let $\boldsymbol{x}^{i''} > \boldsymbol{x}^i$. We see that $\mathcal{F}_k(\boldsymbol{x}^{i''}) - \mathcal{F}_k(\boldsymbol{x}^i) = 0$, demonstrating the monotonicity of $\mathcal{F}_k(\boldsymbol{x}^i)$. For all $\Phi > 1$, $\Phi\mathcal{F}_k(\boldsymbol{x}^i) - \mathcal{F}_k(\Phi\boldsymbol{x}^i) > 0$, which exhibits the scalability of $\mathcal{F}_k(\boldsymbol{x}^i)$. So, $\mathcal{F}_k(\boldsymbol{x}^i)$ is a standard function that guarantees the unique NE of game Γ_i.

C. GAME IN STAGE TWO

We investigate the behavior of miners to achieve their profit maximization, defined in (8). A miner acts two roles: leader of mobile devices and follower of ECO. We have discussed the noncooperative game between a miner and mobile devices in Stage one. The main work here is to analyze the interaction between miners and ECO, which forms miners' mining subgame $\Gamma_{m+1} = \{\mathcal{M}, \{y_i\}_{i\in\mathcal{M}}, p\}$. Given the ECO's pricing strategy, miners, followers of ECO, optimize their mining resource strategies to achieve a Nash Equilibrium.

Definition 4: Given the price strategy p^*, a mining resource vector $\boldsymbol{y}^* = (y_1^*, \ldots, y_i^*, \ldots, y_m^*)^T$ is the Nash equilibrium of the subgame $\Gamma_{m+1} = \{\mathcal{M}, \{y_i\}_{i\in\mathcal{M}}, p\}$, if, for miner i,

$$U_i(\boldsymbol{x}^{i*}, \boldsymbol{p}^{i*}, \boldsymbol{y}_i^*, \boldsymbol{y}_{-i}^*, p^*) > U_i(\boldsymbol{x}^{i*}, \boldsymbol{p}^{i*}, \boldsymbol{y}_i, \boldsymbol{y}_{-i}^*, p^*), \tag{19}$$

for all $y_i = [\underline{y}, \overline{y}]$, where $\boldsymbol{y}_{-i}^*$ is other miners' optimal resource strategy except miner i in $\mathcal{M}$. While the NE of subgame Γ_{m+1} reaches, no miners increase its profit overhead by unilaterally altering its strategy. Moreover, ECO can optimize its pricing strategy to maximize its profit defined in (7).

Definition 5: Given the NE of game Γ_{m+1}, a strategy profile p^* is the optimal price, if at p^*, ECO can't improve its profit by unilaterally deviate,

$$U^{ECO}(p^*, \boldsymbol{y}^*) > U^{ECO}(p, \boldsymbol{y}^*), \quad \forall p > 0 \tag{20}$$

The following Theorem 4 defines miners' optimal resource strategies, allocated by ECO. Such optimal strategies admit the Nash equilibrium among miners. We also calculate the optimal pricing strategy $\boldsymbol{p}^{i*}$ while the miners act as leaders of mobile devices.

Theorem 4: The optimal resource of miner i, allocated from ECO, is calculated in (21), as shown at the bottom of the next page. And the unique optimal price of miner i for mobile device k in $\mathcal{N}_i$ is, with $B = \frac{m-1}{\sum_{i=1}^{m} \frac{e^{\lambda z t_i}}{(R+rt_i)}}$.

$$p_k^i = \frac{p + c_k^i}{2}. \tag{22}$$

Proof: The problem (8) is solved by Karushi-Kuhn-Tucker (KKT) analysis. The KKT conditions of problem (8) are written:

$$\nabla U_i(x^i, p^i, y_i.y_{-i}, p) - \mu_i + \nu_i = 0, \tag{23a}$$
$$\mu_i(y_i - \overline{y}) = 0, \tag{23b}$$
$$\nu_i(\underline{y} - y_i) = 0, \tag{23c}$$
$$\underline{y} \le y_i \le \overline{y}, \tag{23d}$$
$$\mu_i, \nu_i \ge 0, \tag{23e}$$

where $\mu_i, \nu_i \geq 0$ are the optional Lagrange multipliers. While $\mu_i = 0$ and $\nu_i = 0$, we obtain y_i^* based on (23a). Solving $\nabla U_i(x^i, p^i, y_i.y_{-i}, p) = \frac{\partial U_i}{\partial y_i} = 0$, we get,

$$(R + rt_i)\frac{\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{[\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})]^2}e^{-\lambda z t_i} - p = 0. \tag{24}$$

For easy use, we rewrite (24),

$$\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j}) = \sqrt{\frac{(R + rt_i)\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{p}e^{-\lambda z t_i}}. \tag{25}$$

Summarizing two sides of (24) at different i, we get,

$$\frac{(m-1)\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{[\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})]^2} = p\sum_{i=1}^m \frac{e^{\lambda z t_i}}{(R + rt_i)}. \tag{26}$$

We simplify (26),

$$\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j}) = \frac{m-1}{p\sum_{i=1}^m \frac{e^{\lambda z t_i}}{(R+rt_i)}}. \tag{27}$$

Combining (25) and (27) together, we obtain,

$$\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j}) = \frac{e^{\lambda z t_i}}{p(R + rt_i)}(\frac{m-1}{\sum_{i=1}^m \frac{e^{\lambda z t_i}}{(R+rt_i)}})^2 \tag{28}$$

We compare (27) with (28) to realize,

$$y_i = \frac{m-1}{p\sum_{i=1}^m \frac{e^{\lambda z t_i}}{(R+rt_i)}} - \frac{e^{\lambda z t_i}}{p(R + rt_i)}(\frac{m-1}{\sum_{i=1}^m \frac{e^{\lambda z t_i}}{(R+rt_i)}})^2 - \sum_{k\in\mathcal{N}_i}\frac{p_k^i - c_k^i}{2s_k^i} - g_i. \tag{29}$$

Considering the case that $\mu_i > 0$, the best strategy is $y_i{}^* = \overline{y}$ according to (23b). In such case $\nu_i > 0$, the best strategy is $y_i{}^* = \underline{y}$ according to (23c). So, the optimal resource strategy that miner i gain from ECO is calculated in (21).

We then calculate the first and second derivatives of U_i with respect to p_k^i in (30) and (31), as shown at the bottom of the next page. It is easily seen from (31) that $\frac{\partial^2 U_i}{\partial^2 p_k^i} < 0$. So, U_i is concave on p_k^i. It demonstrates the unique optimal pricing of M^i to mobile devices. By substituting (27) and (28) into (30), we rewrite $\frac{\partial U_i}{\partial p_k^i}$,

$$\frac{\partial U_i}{\partial p_k^i} = \frac{p - 2p_k^i + c_k^i}{2s_k^i}. \tag{32}$$

We thus calculate the unique optimal pricing in (22) by letting $\frac{\partial U_i}{\partial p_k^i} = 0$. To guarantee the optimal strategies of leader ECO and miners, we prove the existence and uniqueness of Nash equilibrium in game Γ_{m+1} in the following work.

Theorem 5: The NE of the game Γ_{m+1} exists.

Proof: We see $y_i \in [\underline{y}, \overline{y}]$ based on (7). According to (13), we also have $p_k^i \in [2\underline{x}s_k^i + c_k^i, 2\overline{x}s_k^i + c_k^i]$. So, the strategy space of game Γ_{m+1} on y_i and $p_k^i, k \in \mathcal{N}_i$ is obviously nonempty, compact and convex. For easy illustration, we denote the utility function U_i into $U_i = \varphi_i + \omega_i$, where $\varphi_i = (R + rt_i)\frac{g_i + y_i + \sum_{k\in\mathcal{N}_i} x_k^i}{\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j} x_l^j)}e^{-\lambda z t_i}$ and $\omega_i = -\sum_{k\in\mathcal{N}_i} x_k^i \cdot p_k^i - y_i \cdot p$.

Substituting (13) into φ_i, it is easily observed that the second derivate of φ_i is the same with that of U_i in (31). we then calculate the first and second derivatives of φ_i with respect to y_i,

$$\frac{\partial \varphi_i}{\partial y_i} = (R + rt_i)\frac{\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{[\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})]^2}e^{-\lambda z t_i}, \tag{33}$$

and

$$\frac{\partial^2 \varphi_i}{\partial^2 y_i} = (R + rt_i)\frac{-2\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{[\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})]^3}e^{-\lambda z t_i}. \tag{34}$$

The mixed partial derivative of φ_i on p_k^i and p_t^i is calculated,

$$\frac{\partial^2 \varphi_i}{\partial p_k^i \partial p_t^i} = (R + rt_i)\frac{-\frac{1}{2s_k^i s_t^i}\sum_{j\neq i}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})}{[\sum_{j=1}^m (g_j + y_j + \sum_{l\in\mathcal{N}_j}\frac{p_l^j - c_l^j}{2s_l^j})]^3} \times e^{-\lambda z t_i}. \tag{35}$$

$$y_i{}^* = F_i(\mathbf{y}) = \begin{cases} \underline{y} & \text{if } \frac{B}{p} - \frac{e^{\lambda z t_i}}{p(R + rt_i)}B^2 - \sum_{k\in\mathcal{N}_i}\frac{p_k^i - c_k^i}{2s_k^i} - g_i < \underline{y} \\ \overline{y} & \text{if } \frac{B}{p} - \frac{e^{\lambda z t_i}}{p(R + rt_i)}B^2 - \sum_{k\in\mathcal{N}_i}\frac{p_k^i - c_k^i}{2s_k^i} - g_i > \underline{y} \\ \frac{B}{p} - \frac{e^{\lambda z t_i}}{p(R + rt_i)}B^2 - \sum_{k\in\mathcal{N}_i}\frac{p_k^i - c_k^i}{2s_k^i} - g_i & \text{otherwise} \end{cases} \tag{21}$$

The mixed partial derivative of φ_i on p_k^i and y_i is also calculated,

$$\frac{\partial^2 \varphi_i}{\partial p_k^i \partial y_i} = (R+rt_i)\frac{-\frac{1}{s_k^i}\sum_{j\neq i}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})}{[\sum_{j=1}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})]^3} \times e^{-\lambda z t_i}. \quad (36)$$

The Hessian matrix of φ_i with respect to y_i and p_k^i is described,

$$H^{\varphi} = \begin{bmatrix} -2\alpha & -\frac{\alpha}{s_1^i} & -\frac{\alpha}{s_2^i} & -\frac{\alpha}{s_3^i} & \cdots & -\frac{\alpha}{s_{n_i}^i} \\ -\frac{\alpha}{s_1^i} & -\frac{\alpha}{2{s_1^i}^2} & -\frac{\alpha}{2s_1^i s_2^i} & -\frac{\alpha}{2s_1^i s_3^i} & \cdots & -\frac{\alpha}{2s_1^i s_{n_i}^i} \\ -\frac{\alpha}{s_2^i} & -\frac{\alpha}{2s_1^i s_2^i} & -\frac{\alpha}{2{s_2^i}^2} & -\frac{\alpha}{2s_2^i s_3^i} & \cdots & -\frac{\alpha}{2s_2^i s_{n_i}^i} \\ -\frac{\alpha}{s_3^i} & -\frac{\alpha}{2s_1^i s_3^i} & -\frac{\alpha}{2s_2^i s_3^i} & -\frac{\alpha}{2{s_3^i}^2} & \cdots & -\frac{\alpha}{2s_3^i s_{n_i}^i} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\frac{\alpha}{s_{n_i}^i} & -\frac{\alpha}{2s_1^i s_{n_i}^i} & -\frac{\alpha}{2s_2^i s_{n_i}^i} & -\frac{\alpha}{2s_3^i s_{n_i}^i} & \cdots & -\frac{\alpha}{2{s_n^i}^2} \end{bmatrix}, \quad (37)$$

where $\alpha = \sum_{j\neq i}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})$. We then substituting (13) into ω_i to calculate the Hessian matrix of ω_i with respect to y_i and p_k^i, where $\omega_i = -\sum_{k\in\mathcal{N}_i}\frac{p_k^i-c_k^i}{2s_k^i}\cdot p_k^i - y_i \cdot p$. It is easily seen that the Hessian matrix of ω_i with respect to y_i and p_k^i is denoted,

$$H^{\omega} = \begin{bmatrix} 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & -\frac{1}{s_1^i} & 0 & 0 & \cdots & 0 \\ 0 & 0 & -\frac{1}{s_2^i} & 0 & \cdots & 0 \\ 0 & 0 & 0 & -\frac{1}{s_3^i} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & -\frac{1}{s_n^i} \end{bmatrix}. \quad (38)$$

The two Hessian matrices above are obviously semi-negative, therefore, the Hessian matrix of U_i with respect to y_i and p_k^i is semi-negative. It indicates that U_i is concave on y_i and p_k^i, $i \in \mathcal{N}_i$ to reach an optimal solution.

Theorem 6: The NE of game Γ_{m+1} is unique.

Proof: It is observed that the best response function $F_i(\mathbf{y}) > 0$ based on (21). Assuming $\mathbf{y}^{i''} > \mathbf{y}^i$, we thus get $F_i(\mathbf{y}^{i''}) - F_i(\mathbf{y}^i) = 0$. It demonstrates the monotonicity of $F_i(\mathbf{y})$. For all $\psi > 1$, $\psi F_i(\mathbf{y}) - F_i(\psi\mathbf{y}) > 0$, which exhibits the scalability of $F_i(\mathbf{y})$. So, $F_i(\mathbf{y})$ is a standard function that guarantees the unique NE of game Γ_{m+1}.

D. GAME THEORY IN STAGE ONE

Theorem 7: ECO achieves the unique optimal price p^* for profit maximization while $y_i \in [\underline{y}, \overline{y}]$, $i \in \mathcal{M}$.

Proof: Substituting (21) and (22) into (1), we get the objective function of problem (7),

$$U^{ECO} = (p-c)[\frac{m-1}{p\sum_{i=1}^{m}\frac{e^{\lambda z t_i}}{(R+rt_i)}} - \sum_{i=1}^{m}\sum_{k\in\mathcal{N}_i}\frac{p-c_k^i}{4s_k^i} - \sum_{i=1}^{m} g_i]. \quad (39)$$

We then calculate the first and second derivatives of U^{ECO} with respect to p in (40) and (41), as shown at the bottom of the next page. It is obviously seen from (41) that the second order derivative of U^{ECO} on p is always negative. So, U^{ECO} is concave on p. It concludes that the unique optimal price can be achieved for maximizing ECO's profit.

The optimal price of ECO can be acquired by solving the problem (40). However, the non-linearity of the objective function in (40) prevents us to obtain the optimal solution by directly solving the first-order derivative equation $\frac{\partial U^{ECO}}{\partial p} = 0$. Instead, we propose the use of gradient ascent method to approximate the optimal solution iteratively. It follows that,

$$p^{(l+1)} = p^{(l)} + \delta^{(l)} \cdot \frac{\partial U^{ECO}}{\partial p}\Big|_{p^{(l)}}, \quad (42)$$

where $\delta^{(l)}$ is the step size at iteration l and $\frac{\partial U^{ECO}}{\partial p}$ is shown in (40). Correspondingly, the following Algorithm 1 is designed to solve p.

V. PERFORMANCE EVALUATION

In this section, the performance of our proposed model is measured by extensive experiments. To begin with, we initialize the simulation setup. Then, we conduct numerical simulations for illustration.

$$\frac{\partial U_i}{\partial p_k^i} = (R+rt_i)\frac{\frac{1}{2s_k^i}\sum_{j\neq i}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})}{[\sum_{j=1}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})]^2}e^{-\lambda z t_i} - \frac{2p_k^i-c_k^i}{2s_k^i} \quad (30)$$

$$\frac{\partial^2 U_i}{\partial^2 p_k^i} = (R+rt_i)\frac{-\frac{1}{2{s_k^i}^2}\sum_{j\neq i}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})}{[\sum_{j=1}^{m}(g_j+y_j+\sum_{l\in\mathcal{N}_j}\frac{p_l^j-c_l^j}{2s_l^j})]^3}e^{-\lambda z t_i} - \frac{1}{s_k^i} \quad (31)$$

Algorithm 1 Algorithm of Gradient Ascent to Solve for p

Input: precision threshold ϵ and $p^{(l)}$
Output: $p^{(l)}$
initialization: $l \leftarrow 0, p^{(0)}$;
do
  $p^{(l+1)} = p^{(l)} + \delta^{(l)} \cdot \frac{\partial U^{ECO}}{\partial p}\Big|_{p^{(l)}}$ as in (42);
  $l = l + 1$;
while $|p^{(l)} - p^{(l-1)}| > \epsilon$;
return $p^{(l)}$;

TABLE 2. Simulation parameter initialization.

Parameter	Description	Values
z	Latency factor	0.01
R	Fixed reward	10^5
r	Reward rate	100
c	Cost of unit resource to ECO	10
λ	Mining complexity parameter	0.1
μ_d, σ_d	Mean and variance of n_i	10, 1
μ_b, σ_b	Mean and variance of t_i	300, 5
μ_c, σ_c	Mean and variance of c_k^i	0.2, 0.1
μ_s, σ_s	Mean and variance of s_k^i	10, 2
μ_g, σ_g	Mean and variance of g_i	5, 1

A. SIMULATION SETUP

We here consider the scenario that m miners participate in mining tasks with $m = 10$. Because of massive computation powers for mining, each miner is motivated to offload computation. In our model, each miner has the opportunity of offloading computation to the ECO and its nearby mobile devices. We assume that n_i mobile devices shares their computation resource to miner $M^i, i \in \mathcal{M}$, where n_i follows a normal distribution $N(\mu_d, \sigma_d)$. The miner M^i owns its local computation resource, which follows a normal distribution, $N(\mu_g, \sigma_g)$. The size of block mined by miner i considers a normal distribution $N(\mu_b, \sigma_b)$. The mobile device k's mining cost c_k^i and sensibility s_k^i are assumed to follow the normal distributions, such as $N(\mu_c, \sigma_c)$ and $N(\mu_s, \sigma_s)$, $k \in \mathcal{N}_i, i \in \mathcal{M}$. We refer to system parameter initialization of the ming tasks, stated in [10], [15], [27], [38]. The default system parameters are set in Table 2, unless otherwise described.

B. SIMULATION RESULT

To validate the efficiency of the proposed algorithm for mobile blockchain, we compare it with the outcome of cloud/fog computing resource management and pricing algorithm proposed in [38], which only considers the cloud to admit computation offloading. We investigate the computing resource allocated to miners and resource pricing, on which evaluate profits of different participants. To further evaluate how miners' computation resources affect the model performance, we extend the baseline algorithm for comparison. Miners also have their local computation resources in the extended baseline algorithm, which follow a normal distribution, $N(\mu_g, \sigma_g)$.

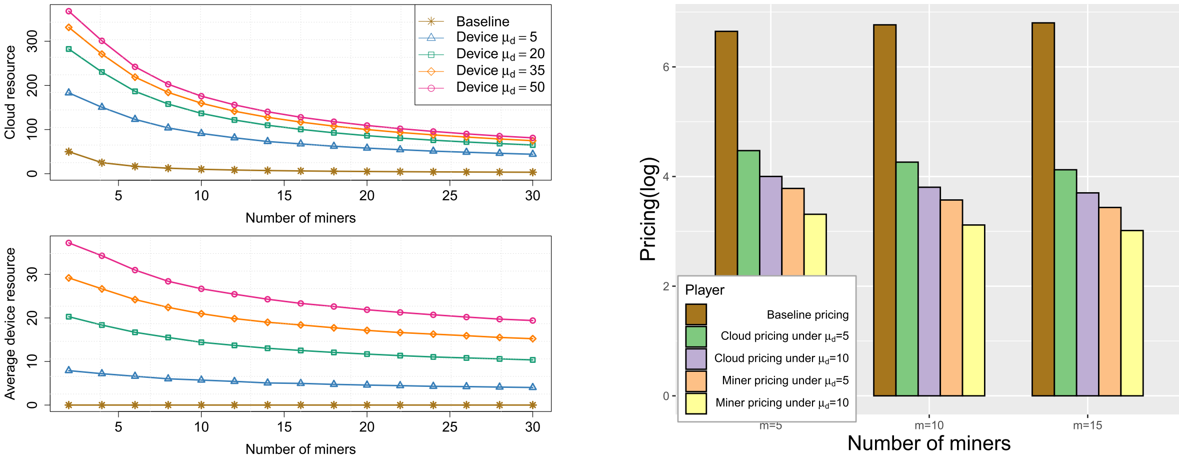
We first observe the comparison by changing the number of participants. To do this, we assume that miners' local resources are zero for the proposed algorithm. Fig.3 shows different strategies of participants with respect to miner number and device number. The increase of miner number incurs the increasingly fierce competition among miners, which forces them to decrease the pricing for mobile devices in Fig.3b, as well as the computation resources requested from the edge cloud in Fig.3a. Accordingly, mobile devices decrease computation resources for executing miners' tasks in Fig.3a. By a drop on resource pricing in Fig. 3b, the cloud inspires miners to request more resources for profit maximization. For the baseline algorithm, with the increase of miners, miners reduce the resources requested from the cloud due to the increasing price. It can be easily found that the pricing in the baseline algorithm is higher than that in the proposed algorithm.

With the increasing number of mobile devices in the proposed algorithm, cloud hostilely compete with mobile devices to interest miners at the cost of price. We observe the declining price of cloud in Fig.3b, on which more resources are requested by miners in Fig.3a. The miners correspond to decrease device resources in Fig.3a, by declining the pricing for mobile devices in Fig.3b. Compared with the baseline algorithm, the proposed algorithm significantly assists miners to obtain more computation resources, allocated by the cloud, with a relatively low price in Fig.3b.

Base on the analysis above, we explore the profits of the edge cloud, miners, and mobile devices in Fig.4. It is observed from Fig.3 that the increase number of miners incurs cloud's lower pricing for miners. The total of requested resources by miners accordingly improves, which leads to a temporal rise of cloud profit. However, with the continuingly increasing number of miners, the benefit from requested resources of

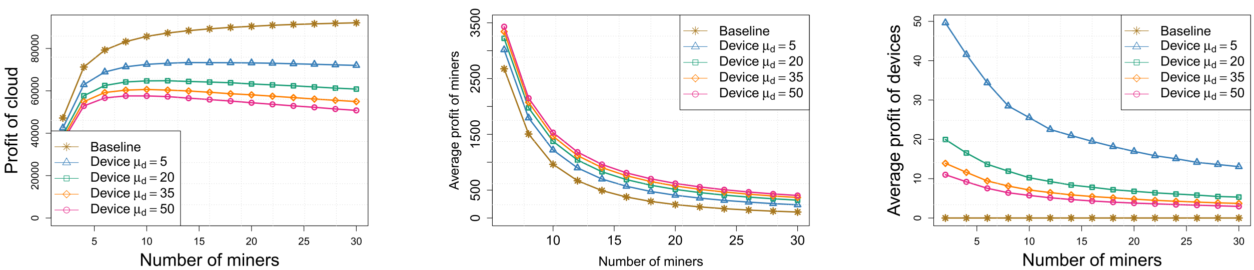
$$\frac{\partial U^{ECO}}{\partial p} = \frac{c(m-1)}{p^2 \sum_{i=1}^{m} \frac{e^{\lambda z t_i}}{(R+rt_i)}} - \sum_{i=1}^{m} \sum_{k \in \mathcal{N}_i} \frac{p - c_k^i}{4 s_k^i} - (p-c) \sum_{i=1}^{m} \sum_{k \in \mathcal{N}_i} \frac{1}{4 s_k^i} - \sum_{i=1}^{m} g_i \tag{40}$$

$$\frac{\partial^2 U^{ECO}}{\partial^2 p} = \frac{-2c(m-1)}{p^3 \sum_{i=1}^{m} \frac{e^{\lambda z t_i}}{(R+rt_i)}} - 2 \sum_{i=1}^{m} \sum_{k \in \mathcal{N}_i} \frac{1}{4 s_k^i} \tag{41}$$



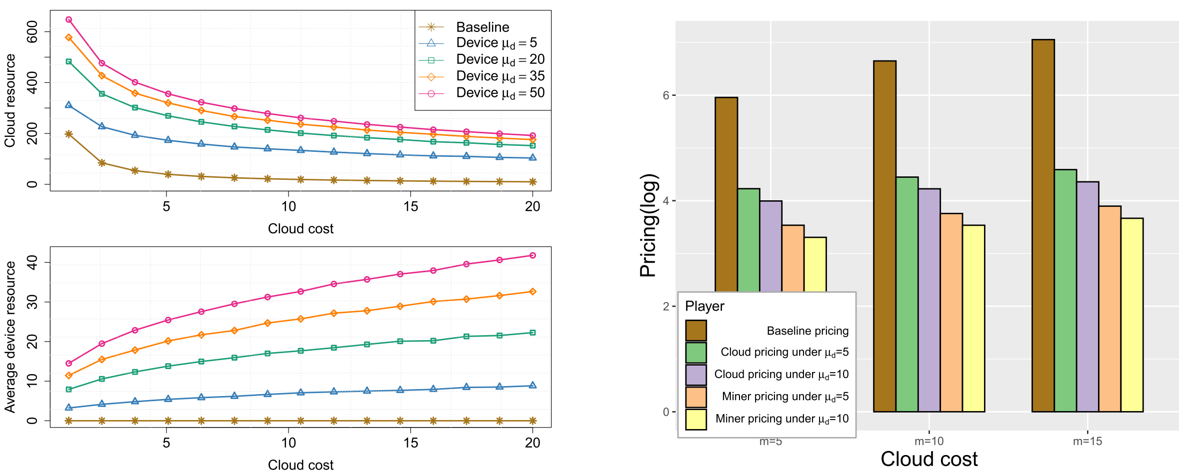
(a) (b)

FIGURE 3. Effect of number of miners and devices on resource allocation and pricing.



(a) (b) (c)

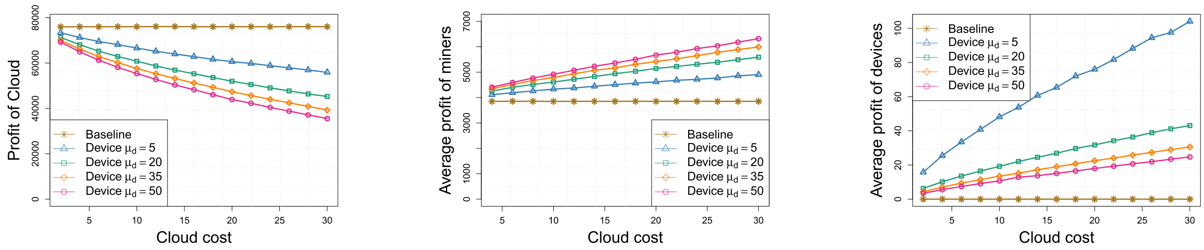
FIGURE 4. Effect of number of miners and devices on profits of cloud, miners and devices.



(a) (b)

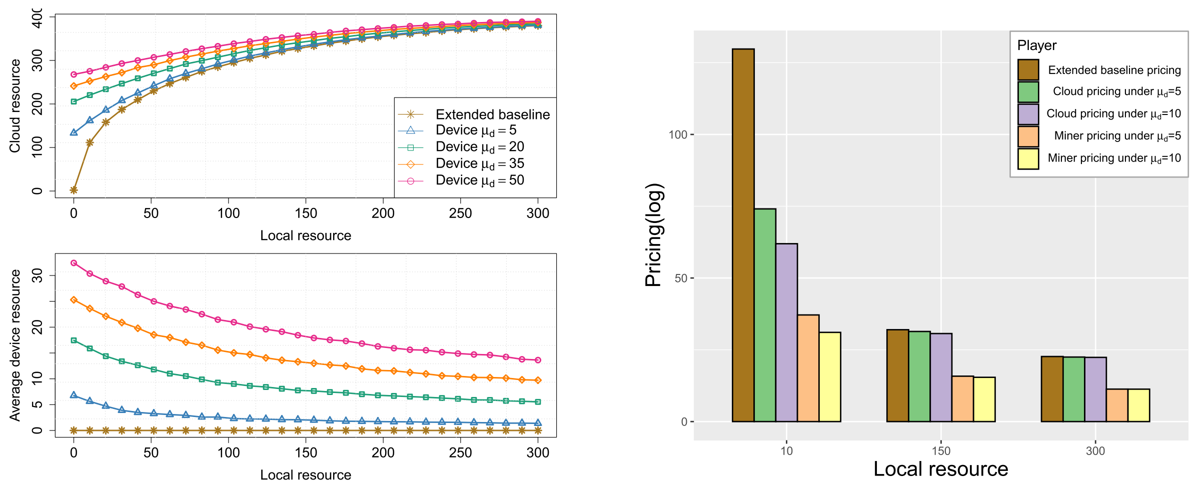
FIGURE 5. Effect of cloud cost on resource allocation and and pricing.

miners fails to compensate the loss, generated by the lower pricing. Therefore, the cloud profit temporally improves and finally diminishes in Fig.4a. The increasing number of miners incurs the fierce competition among miners, which reduces the profits of miners and mobile devices in Fig.4b and Fig.4c. Without loss of generality, the increase of number of miners has a negative effect on profits of three types of participants. Fig.4 also shows that the increase of mobile devices



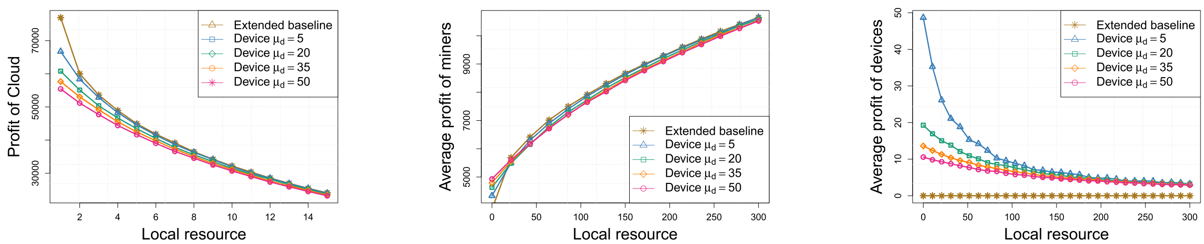
(a) (b) (c)

FIGURE 6. **Effect of cloud cost on profits of cloud, miners and devices.**



(a) (b)

FIGURE 7. **Effect of miners' local resources on resource allocation and pricing.**



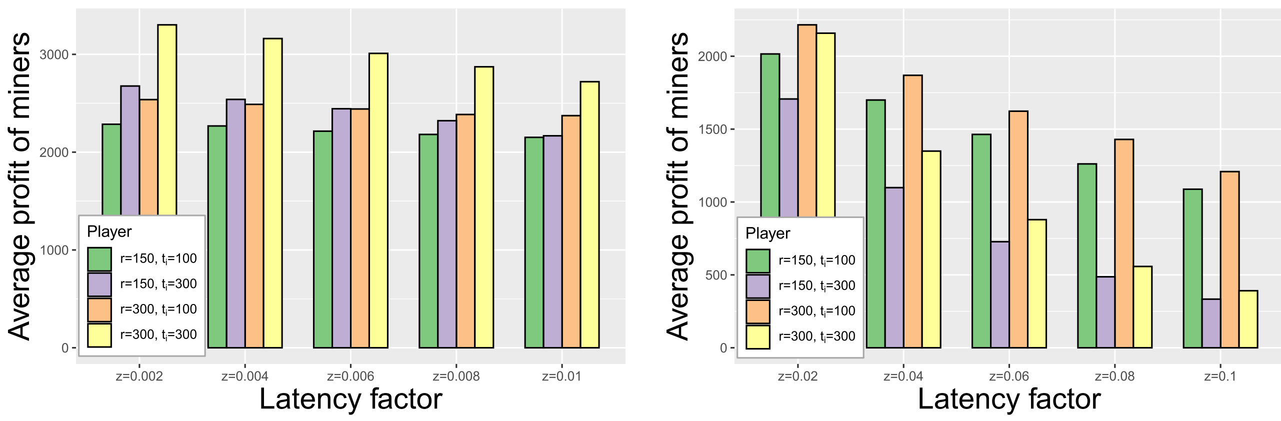
(a) (b) (c)

FIGURE 8. **Effect of miners' local resources on profits of cloud, miners and devices.**

improves the miner profits while reducing the profits of cloud and mobile devices. Compared with the baseline algorithm, the utilization of the proposed algorithm enables miners to improve their profits by offloading mining tasks to devices in Fig.4b.

We next consider the variation of cloud cost if it determines the performance of different models. With the increasing cloud cost, cloud improves the resource pricing in Fig.5b, on which miners reduce computation resources requested from the cloud. Moreover, for the proposed algorithm, miners raise the price to increase computation resources from mobile devices. Such resource allocation and pricing incurs the increase of profits of miners and devices in Fig.6b and Fig.6c, as well as the drop of cloud profit in Fig.6a. In comparison with the baseline algorithm, the use of the proposed algorithm improves miner profits by offloading mining tasks to devices, shown in Fig.6b.

We are also interested in evaluating miners' local computation resources on model performance. Fig.7 shows the computing resources, allocated by cloud and devices, and resource pricing. The larger local resource incurs cloud's lower pricing in order to increase the resource requested by miners for profit maximization. So, the pricing by cloud shows a declining trend in Fig.7b while the resources,



(a) (b)

FIGURE 9. Associations among latency factor, number of transactions and reward rate.

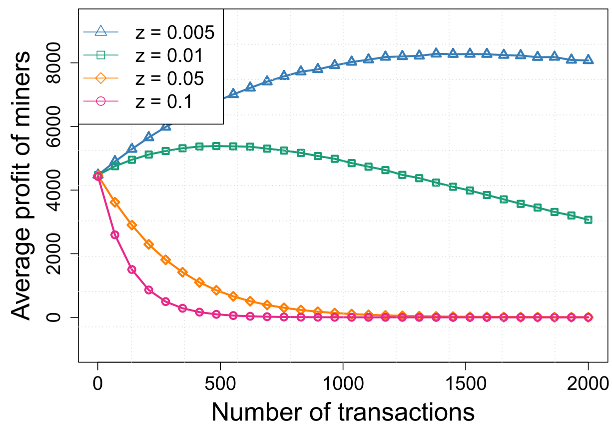


FIGURE 10. Effect of number of transactions and latency factor on miner profits.

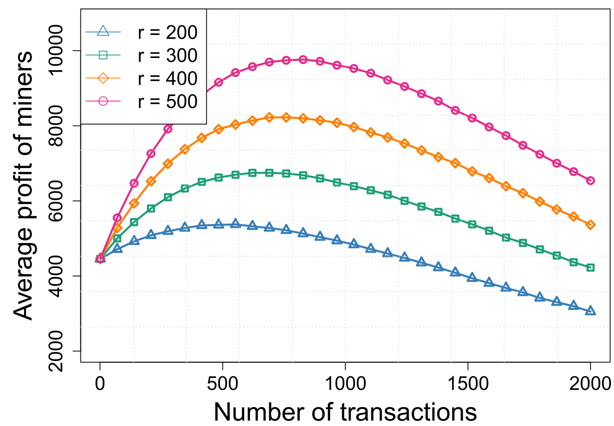


FIGURE 11. Effect of number of transactions and reward rate on miner profits.

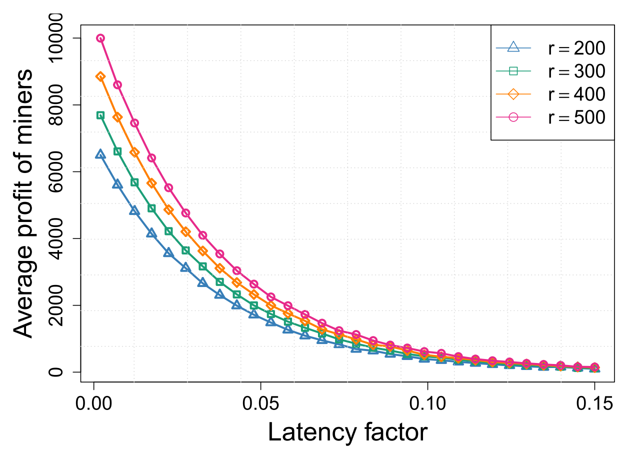


FIGURE 12. Effect of latency factor and reward rate on miner profits.

allocated by cloud, improve with incremental local resources in Fig.7a. Under such case, a miner reduces the pricing for devices in Fig.7b, on which mobile devices decrease the resources, allocated for miners, in Fig.7a. The increase of miners' local resources reduces the economic payment for cloud and mobile devices. Therefore, Fig.8b shows that miners' average profit tends to swell. Profits of ECO and mobile devices tend to dwindle in Fig.8a and Fig.8c. We also see from Fig.8b that the increasing number of devices improve miner profits while miners are equipped with limited local resources. Device number has no obvious effect on miner profits while miners have large local computation resources.

Our model here takes the latency factor, reward rate and number of transactions into account since the profit of each miner is jointly affected by these parameters. We therefore investigate the associations among them, displayed in Fig.9. We see from Fig.9a that, given a latency factor, average profit of miners improves with the increasing number of transactions. However, Fig.9b shows a descending trend of average profit of miners. So, it should be particularly noteworthy of number of transactions on block mining. To this end, we further investigate the effects of such parameters on the performance of the proposed model for mobile blockchain. We see from Fig.10 and Fig.11 that miner profits start with increasing and then decrease with incremental number of transactions. It indicates that relatively large number of transactions has a negative effect on miner profits. We also see from Fig.10 that latency factor is negatively related with number of transactions. Large latency factor reduces the possibility of successful mining a valid block, which discourage participants to participant in block mining. Miner profits finally accord with reduction. It is also observed that the reward rate has a positive correlation with number of transactions in Fig.11 and Fig.12.

In summary, the comparative experiments demonstrate that the superiority of the proposed algorithm. Miners obtains more profits while offloading to ECO and mobile devices than only to ECO. We imitate how our proposed algorithm adapts to blockchain mining in different scenarios. The simulation results conclude the practicality and applicability of the proposed algorithm, which indicates that it can work well in practical scenarios.

VI. CONCLUSION

In this paper, we utilize edge computing for mobile blockchain application. Due to the computation-intensive mining tasks, it is difficult for single mobile device to participate in block mining. We therefore consider the assistance of mobile devices for miners in mining process. The edge cloud is also considered for computation offloading due to its powerful computation capability. The miners, mobile devices and cloud jointly cooperate for mining. To maximize their profits, we model the interactions among them as a three-stage Stackelberg game. Moreover, we derive the subgame Stackelberg game, which guarantees the uniqueness of three types of participants' optimal decisions. The performance of the proposed model is verified by numerical simulations. The utilization of PoW in the proposed model consumes powerful computation resources. Therefore, our future work focuses on studying how to reduce computing resource demands for application of blockchain in mobile networks.

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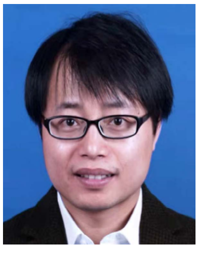

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