Against Colluding Mining with Reward Sharing in MEC Empowered Mobile Blockchain System

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***Abstract*—Mobile edge computing is considered as a promising solution to mobile blockchain system, where mobile nodes with limited computing capability may participate the mining process by offloading the computing intensive mining tasks to nearby edge service providers (ESPs). To mitigate the collusion between ESP and miners, we propose a reward sharing model in this paper, where each miner will share part of the mining rewards to ESP to build a mutual cooperation group. We model the interaction among the ESP and miner nodes as a two-stage Stackelberg game. Then, we obtain the optimal edge computing demand and the corresponding price of each miner by solving the Nash equilibrium of the game iteratively with gradient descent method. We also compare the revenues under both collusion and normal mode with the proposed reward sharing scheme. Simulation results show that the more mining rewards that miners share to ESP, the higher the computing resource demands of miners and the less of the unit price of the computing resources. In addition, if the block size of the colluding miner is much larger than other miners, the ESP can obtain higher revenues rather than colluding.**

I. Introduction

As a distributed ledger technology (DLT) with advanced cryptography, blockchain can achieve peer-to-peer transactions in a secure and tamper-proof manner in trustless environment without relying on a trusted central authority, and thus it has received extensive applications in many application areas, such as finance, supply chain, and data sharing, etc [1]–[4]. Consensus is the key to guarantee consistency and security in blockchain technology. In public blockchain, such as bitcoin system [5], the proof-of-work (PoW) [6] consensus is most commonly adopted. With PoW consensus, each participating node is required to solve a computation-intensive mathematic puzzle to find a feasible nonce that satisfies the target difficulty, and the node who finds the nonce will broadcast the results to other nodes for verification. Once most of the nodes validate the results, a new block will be generated and appended to the chain with a mining reward given to the first winner.

Even though blockchain is a promising solution for many applications, it cannot be readily applied in mobile scenarios due to the limitations of the proof like consensus. Generally, the available computing resources on mobile devices (e.g., smartphones and unmanned aerial vehicles) are very limited, and cannot support the computing intensive block mining tasks. Edge computing has been proposed as a new solution for many emerging applications, by moving the computing capability near to the end users. Thus, edge computing brings new opportunities for mobile blockchain system [7].

The combination of mobile edge computing (MEC) and blockchain network is regarded as a promising solution for mobile blockchain system [8]–[12]. To help the mobile devices in reaching consensus and storing data, an architecture of blockchain network combining with edge server was introduced in [13]. As the efficiency of the blockchain mainly depends on the network computing capability, how to make sure the acquisition of the computational resources and participation of the devices would be the driving force. The authors in [9] focused on incentive mechanism for rational miners to purchase the computation resources and formulated a two-stage Stackelberg game between the miners and edge service providers (ESPs). Many researchers have also worked on solving the security and privacy issues during the offloading of computing tasks. The optimal offloading strategy and security issues for mobile nodes were studied in [10]. The authors in [11] modeled the interaction of miners and blockchain platform as a two-stage Stackelberg game, and studied how to attract more miners to join in blochchain. Note that the work in [11] did not consider the block propagation delay in the block verification process, and a modified system utility function were considered by considering the block verification delay in [12].

The authors in [14] developed an optimal auction based on deep learning for edge computing resources allocation. An auction-based edge computing resources allocation mechanism for the edge computing service provider was proposed to maximize the social welfare in [15]. Then, the game model of multiple leaders and multiple followers was also considered in many articles. The authors in [16] developed a multi-operator multi-user Stackelberg game to analyze the interaction between multiple operators and the UE. In addition, the computation resource management in the blockchain consensus process was formulated as a two-stage Stackelberg game in [17], where the profit of the cloud/fog provider (CFP) and the utilities of the individual miners were jointly optimized. Both the uniform pricing scheme and the discriminatory pricing scheme for the CFP are considered. Considering multiple edge servers, an alternating direction method of multipliers (ADMM) based pricing algorithm was presented in [18]. The authors in [19] proposed a dynamically pricing strategy in non-orthogonal multiple access (NOMA) resource allocation.

The above researchers proposed a two-stage Stackelberg game and an auction-based edge computing resources allocation mechanism, in the same time, which has reference significance for us to further study the optimal computing resource allocation strategy. But it is worth noting that most works above have investigated resource allocation of MEC servers in a mobile blockchain system with the assumption that ESPs are trusted. However, under current revenue model, ESP is much likely to collude with some miners to obtain more revenues. The collusion of the ESP and miners will cause severe security threats to the blockchain system. Considering the collusion issue in computing offloading, the authors in [20] proposed a nonce ordering mechanism to provide fair computation resource allocation. The ESP maps the nonce sequence submitted by all users into a merged nonce sequence, and provides hash computing services for the merged sequence. However, the calculation task is conducted serially, which reduces the computational efficiency as compared with the parallel processing mode.

In this paper, we propose a revenue sharing strategy and distribute part of the mining rewards to the ESP, so that no matter which miner joins the blockchain, the ESP can obtain mining rewards. The model proposed in this paper not only mitigates the collusion between ESP and miners, but also avoids the problem of reducing computational efficiency. In particular, we use the two-stage Stackelberg game theory of single leader and multiple followers to model the interaction among the ESP and miners. Then, we solve the Nash equilibrium of the game iteratively using gradient descent method. Moreover, we study the revenues under both collusion and normal model under different conditions. The simulation results show that the more mining rewards that miners share to ESP, the higher the computing resource demands of miners and the less of the unit price of the computing resources. In addition, if the block size of the colluding miner is much larger than other miners, the ESP can obtain higher revenues under the reward sharing model.

The remainder of this paper is organized as follows. The system model is described in Section II. In Section III, we analyze the game among the ESP and miners, and derive the Nash equilibriums. The simulations and discussions are given in Section IV, and conclusions are drawn in Section V.

II. System Model and Problem Formulation

A. System Model

As shown in Fig. 1, we consider a MEC aided mobile blockchain network, where miners perform block mining tasks to earn rewards. Due to the limitation of computing capability, miners need to offload the computing intensive tasks to the nearby ESPs. We consider a scenario with one ESP and multiple miners. Denote the set of miners as $\mathcal{M} = \{m_1, m_2, \ldots, m_M\}$. The ESP dynamically changes the unit price of computing resource for each miner, and then broadcasts the prices to miners, so that miners can determine their optimal computing demands to maximize their own revenues. Different from existing computation offloading and resource allocation strategies, we consider a reward sharing model where the successful miner will distribute part of the mining rewards to the ESP to facilitate cooperation and mitigate potential collusion between the ESP and miners. Note that, to facilitate the theoretical analysis, we ignore the communication overhead and the synchronization issues.

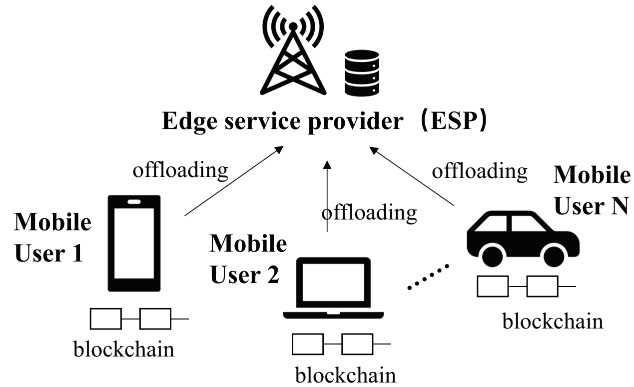

Fig. 1: Edge computing in the mobile blockchain network.

B. Problem Formulation

Since both the ESP and miners aim to maximize their own revenues, the interactions among ESP and miners can be modeled with game theory. Hence, we adopt a two-stage multi-followers Stackelberg game, where the ESP and miners act as leader and followers, respectively. In the upper stage, the ESP dynamically adjusts the unit computing resource price to maximize its revenue. In the lower stage, according to the price given by the ESP, each miner decides the optimal computing resource demands to maximize its own revenue.

To mitigate the collusion between ESP and the miners, we consider a reward sharing model where the successful miner will share part of the mining reward, $(1-\alpha)R_i$, to the ESP, where α is a reward sharing factor, R_i is the total mining reward of the i-th miner. Thus, the total revenue of the miner is composed by the remaining mining reward minus the cost of purchasing computing resources. Denote the set of computing resource purchased by each miner and the corresponding prices as $\boldsymbol{\mu} = \{\mu_1, \mu_2, ...\mu_M\}$ and $\mathbf{p} = \{p_1, p_2, ...p_M\}$, respectively. Then, the i-th miner's cost on purchasing computing resources is given by $p_i\mu_i$. The successful mining rewards from the blockchain platform include both fixed reward R and transaction dependent variable rewards rs_i, where r is transaction fee rate and s_i is the block size of the i-th miner. In addition, we consider the impact of block verification delay, which is related to the block size. The delay of block verification is given by $\exp(-\xi s_i)$ [21], where ξ is the delay factor. Then, the probability of successful mining is given by [12]

$$q_i = \frac{\mu_i}{\sum\limits_{m_j \in \mathcal{M}} \mu_j}. \tag{1}$$

Considering the propagation delay of block verification, the mining reward is given by [12]

$$R_i = (R + rs_i)e^{-\xi s_i} \,. \tag{2}$$

Thus, the revenue of the i-th miner is given by

$$U_i = \alpha R_i \frac{\mu_i}{\sum\limits_{m_j \in \mathcal{M}} \mu_j} - p_i \mu_i \,. \tag{3}$$

For the ESP, the revenue can be defined as the income by providing computation services to miners plus the shared rewards from all miners. Therefore, the revenue function of the ESP can be defined as follows:

$$U_s = \sum_{m_i \in \mathcal{M}} \frac{(1-\alpha)\mu_i}{\sum\limits_{m_j \in \mathcal{M}} \mu_j} R_i + \sum_{m_i \in \mathcal{M}} p_i \mu_i \,. \tag{4}$$

Then, the utility maximization problem of the two sides can be modeled as the following problems.

Problem 1. *For each miner in the lower stage, the optimization problem can be formulated as:*

$$\max_{\mu_i} \, U_i(\mu_i | \boldsymbol{\mu_{-i}}, p_i) \,, \tag{5}$$

where μ_i is the computing capability of the i-th miner.

Problem 2. *The problem in the upper stage (ESP side):*

$$\max_{p_i} \, U_s(p_i, \boldsymbol{\mu}) \,, \tag{6}$$

where p_i is the unit price of computing resources for the i-th miner.

III. Stackelberg Game Analysis

In this section, we analyze the Stackelberg game, and derive the optimal strategies of the ESP and each miner, respectively.

The equilibrium point of Stackelberg game (SE) is a Nash equilibrium (NE) between the leader (ESP) and followers (miners). At the equilibrium point of the game, participants can not unilaterally change their strategies to gain a larger utility without damaging the utility of other participants. In this paper, the SE point (μ_i^*, p_i^*) is defined as follows:

Definition 1. *Let μ_i^* and p_i^* be the optimal computing resources purchased by the i-th miner and the corresponding price, respectively, where $\boldsymbol{p^*} = \{p_1^*, p_2^*, ...p_M^*\}$. The point (μ_i^*, p_i^*) is the Stackelberg equilibrium point if it satisfies the following conditions:*

$$U_s(p_i^*, \boldsymbol{\mu^*}) \geq U_s(p_i, \boldsymbol{\mu^*}) \,, \tag{7}$$

$$U_i({\mu_i}^* | \boldsymbol{\mu^*_{-i}}, {p_i}^*) \geq U_i(\mu_i | \boldsymbol{\mu^*_{-i}}, {p_i}^*) \,, \tag{8}$$

where $\boldsymbol{\mu^*_{-i}} = \boldsymbol{\mu^*} \setminus \{\mu_i^*\}$.

Next, we use the method described above to sovle the equilibrium point of the game. First, given the computing resource prices profile $\boldsymbol{p} = \{p_1, p_2, ...p_M\}$, we solve the optimal computing resource demands of miners in the lower stage. Subsequently, we deduce the optimal computing resource prices of ESP in the upper stage.

A. Lower stage (miners side) analysis

Before solving the equilibrium point, we first prove its existence and uniqueness in the miners' sub-game through the following proposition.

Proposition 1. *The NE point in the miners' sub-game exists and is unique.*

Proof. The first and second order derivatives of the miners' revenue function (3) can be written as follows:

$$\frac{\partial U_i}{\partial \mu_i} = \alpha R_i \frac{\sum\limits_{m_j \in \mathcal{M} \setminus \{m_i\}} \mu_j}{\left(\sum\limits_{m_j \in \mathcal{M}} \mu_j \right)^2} - p_i \,, \tag{9}$$

$$\frac{\partial^2 U_i}{\partial {\mu_i}^2} = (-2)\alpha R_i \frac{\sum\limits_{m_j \in \mathcal{M} \setminus \{m_i\}} \mu_j}{\left(\sum\limits_{m_j \in \mathcal{M}} \mu_j \right)^3} \leq 0 \,. \tag{10}$$

Therefore, the miners' revenue function is strictly concave, and there must exist a unique μ_i^* which is the Nash equilibrium point in the miners' sub-problem. To ensure the positivity of the utility function U_i, we have $\alpha R_i / \sum_{m_j \in M} \mu_j > p_i$. Let the equation in (9) be zero, we can get the optimal computing resource demand as

$$\mu_i^* = \begin{cases} 0, & if \; \frac{\alpha R_i}{\sum\limits_{m_j \in \mathcal{M}} \mu_j} < p_i, \\ \sqrt{\frac{\alpha R_i \sum\limits_{m_j \in \mathcal{M} \setminus \{m_i\}} \mu_j}{p_i}} - \sum\limits_{m_j \in \mathcal{M} \setminus \{m_i\}} \mu_j, & else. \end{cases} \tag{11}$$

Theorem 1. *The unique Nash equilibrium for the i-th miner is given by*

$$\mu_i^* = \frac{(M-1)}{\sum\limits_{m_j \in \mathcal{M}} \frac{p_j}{\alpha R_j}} - \left(\frac{(M-1)}{\sum\limits_{m_j \in \mathcal{M}} \frac{p_j}{\alpha R_j}} \right)^2 \frac{p_i}{\alpha R_i} \,, \forall i \,. \tag{12}$$

Proof. According to (9), for each miner i, we have

$$\frac{\sum\limits_{m_j \in \mathcal{M} \setminus \{m_i\}} \mu_j}{\left(\sum\limits_{m_j \in \mathcal{M}} \mu_j \right)^2} = \frac{p_i}{\alpha R_i} \,. \tag{13}$$

Then, we take the summation of (13) for all miners yields, we have

$$\sum_{m_j \in \mathcal{M}} \mu_j = \frac{(M-1)}{\sum\limits_{m_j \in \mathcal{M}} \frac{p_j}{\alpha R_j}} \,. \tag{14}$$

According to (9), we have

$$\sum_{m_j \in M} \mu_j = \sqrt{\frac{\alpha R_i}{p_i} \sum_{m_j \in M \setminus \{m_i\}} \mu_j} \,. \tag{15}$$

By substituting (14) into (15), with simple transformations, we can obtain the Nash equilibrium for the i-th miner as shown in (12).

Because of (13) ,we have

$$\frac{\sum\limits_{m_j \in M \setminus \{m_i\}} \mu_j}{\left(\sum\limits_{m_j \in M} \mu_j\right)^2} < \frac{1}{\sum\limits_{m_j \in M} \mu_j} = \frac{p_i}{\alpha R_i}, \tag{16}$$

substituting (14) into (16), we can get

$$\frac{(M-1)p_i}{\alpha R_i} < \sum_{m_j \in \mathcal{M}} \frac{p_j}{\alpha R_j}, \tag{17}$$

which can guarantee $\mu_i^* > 0$.

B. Upper stage (ESP side) analysis

For any price given by the ESP, each miner has a unique Nash equilibrium point, so the ESP's revenue can be maximized by setting a reasonable price.

Let $\beta = (2\alpha - 1)/\alpha$, $H_i = p_i/\alpha R_i$, $J = \sum_{m_j \in \mathcal{M}} H_j$ and $X = (M-1)/J$, by substituting (12) into (4), we have the ESP's revenue fuction as follow:

$$U_s = \sum_{m_j \in M} \left((1-\alpha) R_i + p_i X \right) (1 - X H_i). \tag{18}$$

Then we caculate the first order and second order derivatives of (18), which are given as follows:

$$\frac{\partial U_s}{\partial p_i} = \sum_{m_i \in \mathcal{M}} \left(X \frac{J - H_i}{J} \right) (\beta - 2XH_i), \tag{19}$$

$$\frac{\partial^2 U_s}{\partial {p_i}^2} = \sum_{m_i \in \mathcal{M}} \frac{-2X(J - H_i)}{\alpha R_i J^2} (\beta - 3XH_i + XJ). \tag{20}$$

Substituting (17) into (20), we have two cases as follows:

case 1: When $M - 2 < 1/\alpha$, we have $\partial^2 U_s / \partial {p_i}^2 > 0$. Because the feasible region of p_i in (11) is $0 < p_i < \alpha R_i / \sum_{m_j \in M} \mu_j$, then the optimal unit price of computing resources is $p_i = \alpha R_i / \sum_{m_j \in M} \mu_j$.

case 2: When $M - 2 > 1/\alpha$, we have $\partial^2 U_s / \partial {p_i}^2 < 0$, which indicates that the revenue function (18) is concave on each p_i. Thus we know that the optimal value of $U_s^*(\boldsymbol{p})$ is achieved in the concave parts.

Then we use gradient descent method to iteratively solve the optimal unit price. Through constant iterations until $\frac{\|\mathbf{p}(t+1) - \mathbf{p}(t)\|_1}{\|\mathbf{p}(t)\|_1} < \varepsilon$, with the precision threshold ε. Since the revenue function $U_s(\mathbf{p})$ is concave on each p_i, thus $\mathbf{p}^*$ exists and is unique. The optimal price is the NE solution, $\mathbf{p}^* = \mathbf{p}(t)$. In summary, $\boldsymbol{p}^*$ is the unique NE solution. The distributed algorithm to find the NE points of miners and ESP is summarized in Algorithm 1.

Algorithm 1: Nash equilibrium calculation algorithm for miners and ESP.

1: **Initialization:**
Select initial input $\mathbf{p} = \{p_1, p_2, ...p_M\}$, $t \leftarrow 1$, precision threshold ε;
2: **repeat**
3: Each miner i decides its computing demands μ_i^* as shown in (12) ;
4: ESP uses a gradient assisted searching algorithm to update the prices, i.e.,

$$\mathbf{p}(t+1) = \mathbf{p}(t) + \lambda \nabla U_s(\mathbf{p}(t)),$$

where λ is the step size of the price update and $\nabla U_s(\mathbf{p}(t))$ is the gradient with $\frac{\partial U_s(\mathbf{p}(t))}{\partial \mathbf{p}(t)}$. The price information is sent to all miners;
5: $t \leftarrow t + 1$;
6: **until** $\frac{\|\mathbf{p}(t+1) - \mathbf{p}(t)\|_1}{\|\mathbf{p}(t)\|_1} < \varepsilon$
7: **Output:** optimal demand $\boldsymbol{\mu}^*$ and optimal price $\boldsymbol{p}^*$.

IV. Simulation Results and Discussions

In this section, we conduct simulations to verify the performance of the proposed scheme. Specifically, we consider an ESP and 50 miner nodes ($M = 50$) in this scenario. The simulation process is done using MATLAB. The simulation parameter values are in the TABLE I.

The impact of the reward sharing factor on the unit price of the computing resources, the miners' average computing resource demands, the revenue of the ESP, and the average revenue of the miners are evaluated in Figures. 2-5, respectively. In Fig. 2, we can observe that the unit price of ESP gradually increases with the reward sharing factor, α. When α becomes larger, because the reward shared by miners to ESP decreases, the ESP needs to increase the computing resource prices to obtain higher revenue. In addition, for a fixed α, as the number of miners increases, the price will be decreased to encourage miners to offload more computing tasks. When the block size of miners increases, the block verification delay also increases, and the probability of becoming an orphan block increases, which promotes ESP to offer higher prices to increase its own revenues.

TABLE I: Default Parameter Values

Parameters	**Values**
Mining reward, R	20
Step size, λ	0.1
Transaction fee rate, r	0.01
Delay factor, ξ	0.001
Reward sharing factor, α	$(0, 1]$

In Fig. 3, for fixed s_i and M, the reduction of the reward sharing factor α leads miners to purchase less computing resources, this is because miners have to reduce the cost of

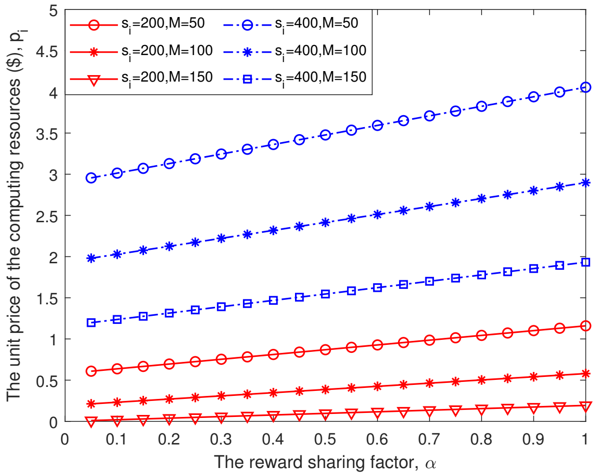

Fig. 2: The unit price of ESP vs. the reward sharing factor.

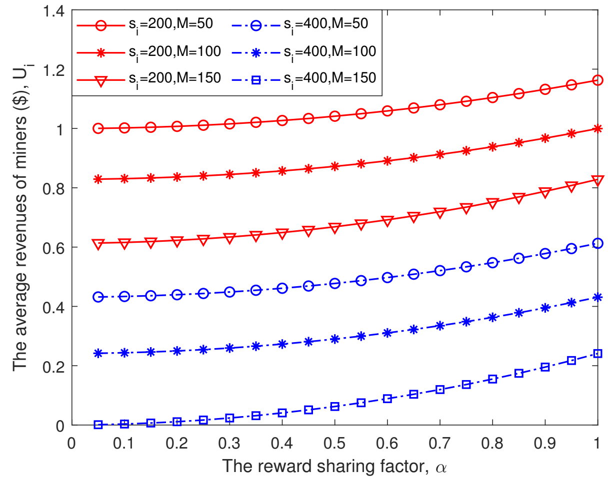

Fig. 4: The average revenues of miners vs. the reward sharing factor.

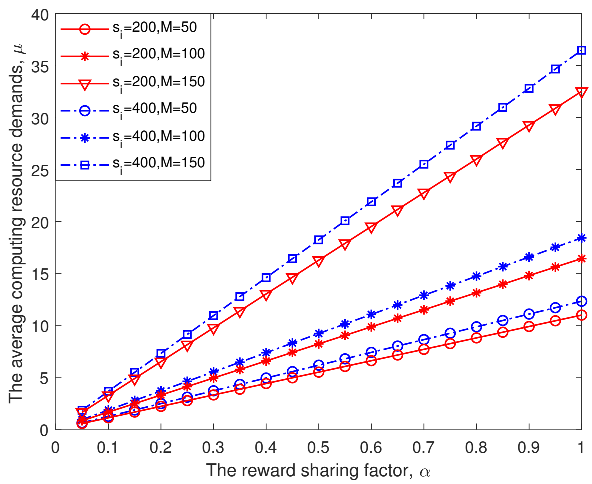

Fig. 3: The average computing resource demands of miners vs. the reward sharing factor.

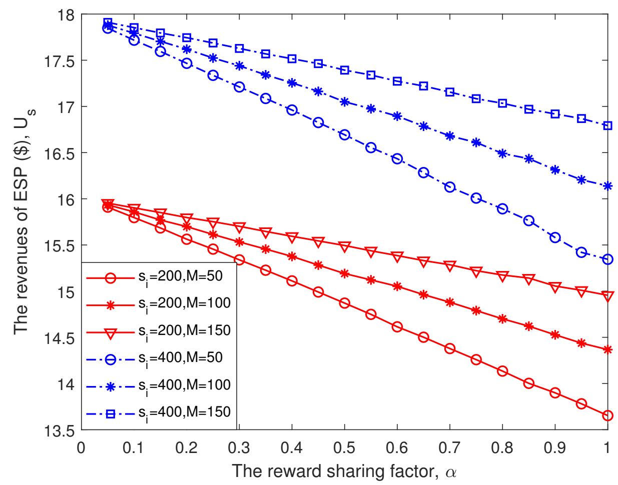

Fig. 5: The revenue of ESP vs. the reward sharing factor.

purchasing computing resource. For a fixed α, to reduce the delay of block verification, a larger block size will encourage miners to purchase more computing resources to increase the success probability of mining. In Fig. 4, with fixed M and s_i, we can observe that the increase of the reward sharing factor will increase the miners' revenue. In addition, the increase in s_i will decrease the mining rewards, which further decreases miners' revenues. Moreover, the larger the number of miners, the lower the success probability of mining, which leads to the decrease in the average revenues of miners. Figure. 5 shows that by increasing the reward sharing factor the ESP's revenue will be lowered. This is because the reward shared by miners to ESP decreases. Moreover, because the increase of the block size s_i will increase the unit price and the computing resources demands, ESP's revenue will gradually increase. In addition, the increase of the number of miners will make ESP get more mining rewards distributed by miners, so the ESP's revenue will be increased.

To evaluate the performance of the proposed reward sharing scheme on the mitigation to colluding miners, we assume that ESP colludes with the k-th miner, with $k = 2$ in the simulations. In the case of collusion, ESP provides computing services according to the strategy proposed in this paper, but it actually uses all computing resources for the second miner. In this way, the revenues of ESP are the payments of all miners purchasing computing resources plus the mining rewards for the second miner. Then we can sum the revenues of the second miner and ESP, and consider the total revenues in the normal and collusion model. In particular, because under the collusion situation and the revenue sharing model, the income on computing resources $p_i\mu_i$ is the same, we only consider the revenue from the mining reward, $(1-\alpha)\mu_i R_i / \sum_{m_j \in M} \mu_j$. In Fig. 6, we can observe the impact of the block size of miners on the sum revenues under different cases, respectively. With a fixed block size of the second miner, $s_2 = 2500$, we change other miners' block size s_i. As shown in Fig. 6, when $\alpha = 1$, the total revenue is always higher than that of the normal case. Under the parameters we set, the mining reward R_i decreases with the increase of s_i. Therefore, when $0 < \alpha < 1$, if the block size of the second miner is much larger than other miners, that is, the mining reward is much smaller than other miners, the revenue of reward sharing model proposed in this paper can be higher than that of collusion.

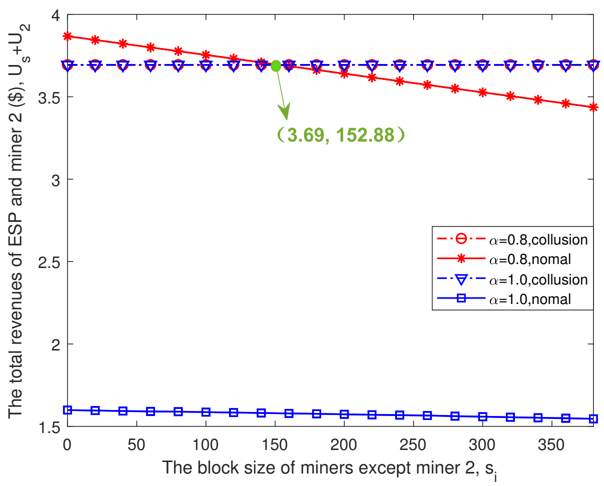

Fig. 6: Comparison of the total revenues under different cases, with $M = 20$ and $s_2 = 2500$.

V. Conclusion

In this paper, we have proposed a reward sharing scheme to mitigate potential colluding miners in the mobile blockchain system. We have presented a pricing strategy and resource allocation for MEC aided blockchain system under the game model, and the Nash equilibrium of the game has been solved and simulation results have proved the convergence of the algorithm. We have also compared the revenues under collusion and normal conditions. The simulation results have shown that the more mining rewards that miners share to ESP, the higher the computing resource demands of miners and the less of the unit price of the computing resources. In addition, if the block size of the colluding miner is much larger than other miners, the ESP can obtain higher revenues under the normal case with the proposed reward sharing model as compared with the collusion case, which shows its potential to mitigate colluding in MEC enabled blockchain mining.

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