Stackelberg Game Based Edge Computing Resource Management for Mobile Blockchain

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ABSTRACT

Blockchain can provide a dependable environment for mobile applications. As the core of blockchain, mining consumes a large amount of computing resources, while mobile devices are too resource-limited to perform the mining. Offloading mining computation tasks to an edge computing service provider (ESP) or a cloud computing service provider (CSP) is considered as a feasible solution to mobile blockchain mining. However, the computing resources of the ESP are not unlimited. Therefore, rational edge computing resource management is critical to maximizing the utilities of the ESP and the miners. Most of the existing work assumes that the service provider is an ESP or a CSP, or both. In this paper, we construct a computing offloading model consisting of multiple miners, an ESP, and a CSP, where the ESP and the CSP are independent of each other. We formulate a Stackelberg game with the ESP as the leader and the miners as the followers for optimal pricing-based edge computing resource management. We analyze the existence and uniqueness of Stackelberg game equilibrium and derive the miners' optimal computing resource requests. We then propose an effective golden section based Stackelberg game equilibrium searching algorithm (SES) for resource pricing. We conduct the experiments through simulations. The simulation results show that the proposed computing offloading model and algorithm can achieve high unit service utilities of both the ESP and the end devices.

KEYWORDS

Edge computing, mobile blockchain mining, resource management, Stackelberg game

ACM Reference Format:
Yuqi Fan, Guangming Shen, Zhifeng Jin, Donghui Hu, Lei Shi, and Xiaohui Yuan. 2020. Stackelberg Game Based Edge Computing Resource Management for Mobile Blockchain. In *ACM Turing Celebration Conference - China (ACM TURC'20), May 22–24, 2020, Hefei, China.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3393527.3393565

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ACM TURC'20, May 22–24, 2020, Hefei, China
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ACM ISBN 978-1-4503-7534-4/20/05…$15.00
https://doi.org/10.1145/3393527.3393565

1 INTRODUCTION

Blockchain has been increasingly used in various areas such as Bitcoin, financial services, Internet of Things (IoT), smart grid power systems, etc. The annual revenue of the enterprise applications of blockchain is estimated to increase to approximately $19.9 billion by 2025 [1]. Distributed users in blockchain network record and share data blocks under the premise of following a consensus mechanism. Mining plays a vital role in blockchain. A group of users, called miners, compete to solve a compute-intensive problem. The first miner who successfully solves the computation problem and reaches an agreement with other miners is considered as the winner of the competition. The winner will receive a reward and a new block will be appended to the blockchain.

Blockchain can provide a dependable environment for mobile applications [2, 3]. However, the computing resources required to solve the compute-intensive mining problem are prohibitively high for mobile devices [4]. Edge computing is considered as a viable solution to blockchain mining in mobile environments [5], where the end devices offload the mining tasks to an edge computing service provider (ESP). The ESP makes profits by allocating the computing resources for the mining tasks offloaded by the end devices. Nevertheless, the computing resources of the ESP are not unlimited and thus competitive. Therefore, careful resource management is critical for the ESP and end devices to maximize their utilities.

Some research on resource management for mobile blockchain mining has been conducted. A game model consisting of miners for the mining process of blockchain was constructed, and each miner made the decision on which branch of the blockchain to follow [6]. The mining pool problem was investigated by proposing a cooperative game model, where the miners form an alliance to finish the computing power accumulation and share stable reward [7]. The occurrence of solving the problems of PoW is modeled as a random variable following a Poisson process, and the analytical solution to Nash equilibrium for two miners was presented [8]. A two-stage Stackelberg game was adopted to jointly maximize the profit of the ESP and the individual utilities of different miners [9]. A joint optimization framework of Fog nodes, data service operators and data service subscribers was proposed to implement the optimal resource allocation scheme in a distributed manner [10].

The PoW protocol was formalized into a Cournot game, in which users compete to update the blockchain for rewards [11]. An optimal auction based on deep learning for the edge resource allocation was proposed to use valuations of the miners as the training data to adjust the parameters of the neural networks [12]. An auction-based market model was constructed to achieve an efficient allocation of computing resources [13]. A joint optimization problem of mining task offloading and block cryptographic hash cache was modeled, and an alternating direction multiplier method was adopted to solve the problem [14]. Two algorithms were designed to determine the amount of computing power the mobile terminal can obtain from different edge servers, with the aim to maximize the total net return of mobile terminals while maintaining the fairness between the mobile terminals [15].

Most of the existing work assumes that the service provider is an ESP or a cloud computing service provider (CSP), or both. However, the ESP and the CSP may be independent of each other. In this paper, we tackle the problem of edge computing resource management for mobile blockchain mining to maximize the utilities of ESP and end devices with the ESP and the CSP independent of each other. The main contributions of this paper are as follows:

(1) We construct a computing offloading model consisting of an ESP, a CSP, and multiple mobile miners/end devices. The mining tasks of end devices may be offloaded to the ESP which purchases computing resources from the CSP in case that the ESP has no enough capacity to accommodate the requests.
(2) We design the utility functions of ESP and miners to capture the intrinsic relationship among ESP, CSP, and miners. We formulate a Stackelberg game with the ESP as the leader and the miners as the followers for optimal pricing-based edge computing resource management. We also prove the existence and uniqueness of the Stackelberg game equilibrium and derive the optimal amount of computing resources to purchase for the miners. We then propose an efficient golden section based Stackelberg game equilibrium searching algorithm (SES) for the resource pricing.
(3) We conduct simulations to evaluate the performance of the proposed model and algorithm. Simulation results demonstrate the proposed model and algorithm can achieve high unit service utilities of the ESP and the end devices.

2 COMPUTING OFFLOADING GAME BETWEEN ESP AND MINERS

Each resource-limited end device conducts mining by offloading the mining tasks to the ESP. The ESP and the CSP are independent of each other. The CSP typically has enough processing capacity to execute the mining tasks, while the miners will experience an unpredictable Internet communication latency with the CSP. The ESP is close to the miners so that the network latency between the ESP and the end devices is low. Therefore, the efficiency of executing the tasks at the edge is better than that at the cloud; that is, the ESP achieves performance gain over the CSP. Note that the edge has a computing capacity. When overloaded, the ESP purchases computing resources from the CSP. The system model is illustrated

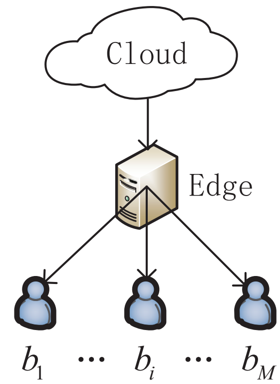

Figure 1: System Model.

in Fig. 1, and the symbols and notations used in the paper are listed in Table 1.

Table 1: Symbols and notations

B	the set of miners/end devices
M	the number of miners
b_i	the i-th miner
q_i	the amount of services/computing resources purchased miner b_i
Q_i	the maximum amount of services/computing resources that b_i will purchase
w	the unit service reward of miners
p_c	the unit service price of the CSP
p_e	the unit service price of the ESP
α	the unit service provisioning cost of the ESP
C_c	the performance of executing the mining tasks at the CSP
C_e	the performance of executing the mining tasks at the ESP
N	the ESP's computing capacity
E_i	the utility of miner b_i
E_0	the utility of the ESP

ESP's unit service price p_e has an important impact on the ESP's utility. A higher p_e leads to a higher ESP's utility for a given amount of services purchased by the miners. A low p_e will attract the miners to purchase a large amount of computing resources. Note that service provisioning also imposes cost on the ESP, where the cost includes power, equipment loss, etc. As the total amount of computing resources sold increases, the ESP's cost will also increase. If the total demand of computing resources from the miners exceed the ESP's computing capacity, the ESP has to purchase computing resources from the CSP at price p_c, which brings computing resource purchase cost to the ESP. If $p_e < p_c$, the ESP will experience a loss by providing computing resources to the miners, and hence the ESP are not willing to provide services to the end devices. Therefore, we set $p_e \leq p_c$.

The ESP's utility, E_0, is defined as follows:

$$\begin{aligned} E_0 = \quad & p_e \Sigma_{i=1}^{M} q_i + \gamma \frac{C_e - C_c}{C_c} \min\{n, \Sigma_{i=1}^{M} q_i\} \\ & - \alpha \Sigma_{i=1}^{M} q_i - p_c \max\{0, \Sigma_{i=1}^{M} q_i - N\}, \end{aligned} \tag{1}$$

where γ is the weight of task execution efficiency.

The objective of the ESP is

$$\begin{aligned}\max E_0 = \quad & p_e\Sigma_{i=1}^{M} q_i + \gamma \frac{C_e - C_c}{C_c}\min\{n, \Sigma_{i=1}^{M} q_i\} \\ & -\alpha\Sigma_{i=1}^{M} q_i - p_c \max\{0, \Sigma_{i=1}^{M} q_i - N\},\end{aligned} \tag{2}$$

subject to:

$$0 \le p_e \le p_c.$$

Running the offloaded tasks at the cloud increases the latency of executing mining tasks and degrades the performance of task execution. The utility of miner b_i, E_i, is defined as follows:

$$E_i = wq_i - p_e q_i - \frac{\beta_i q_i^2}{N}, \tag{3}$$

where β_i is the weight of task response time for miner b_i.

The objective of each miner b_i is

$$\max E_i = wq_i - p_e q_i - \frac{\beta_i q_i^2}{N}, \tag{4}$$

subject to:

$$0 \le q_i \le Q_i.$$

During the interaction between the ESP and the miners, the ESP acts first to set unit service price p_e, and then the miners respond to the price by deciding the amount of computing resources to purchase. Therefore, the interaction between the ESP and the users can be formalized as a Stackelberg game with a single leader and multiple followers, where the leader is the ESP and the each follower is a miner.

3 RESOURCE MANAGEMENT BASED ON GOLDEN SECTION SEARCH

In this section, we first prove the existence and uniqueness of equilibrium of the Stackelberg game between the ESP and the miners and derive the miners' optimal amount of computing resources to purchase. We then propose a Stackelberg game equilibrium search algorithm based on the golden section search (SES) for resource pricing.

3.1 Analysis of the Stackelberg game

LEMMA 1. *There is a unique equilibrium in miner sub-game.*

Proof: During miner sub-game, i.e. the second phase of the Stackelberg game, each miner b_i determines q_i, the amount of computing resources to purchase, with the goal of maximizing the utility at given resource price p_e. The miner's utility function defined in Equation (3) is continuous, and the second derivative of the function is calculated as follows:

$$\frac{\partial^2 E_i}{\partial q_i^2} = -\frac{2\beta_i}{N}. \tag{5}$$

We can get $\frac{\partial^2 E_i}{\partial q_i^2} \le 0$, since $\beta_i \ge 0$ and $N > 0$. Therefore, miner's utility E_i is a strict concave function of variable q_i, and there exists a unique equilibrium in miner sub-game. □

LEMMA 2. *At given computing resource price p_e, the optimal amount of computing resources purchased by miner b_i is calculated as*

$$q_i^* = \min\left(\frac{(w - p_e)N}{2\beta_i}, Q_i\right). \tag{6}$$

Proof: At given p_e, miner b_i decides q_i by making the first derivative of Equation (3) equal to zero as Equation (7).

$$\frac{\partial E_i}{\partial q_i} = w - p_e - \frac{2\beta_i}{N} q_i = 0. \tag{7}$$

Note that $q_i \le Q_i$. Therefore, the lemma is proven. □

THEOREM 1. *The unique equilibrium exists in the Stackelberg game between the ESP and the miners.*

Proof:

According to Lemma 1, there is a unique equilibrium in the second phase of the Stackelberg game. Next, we consider the first phase of the Stackelberg game during which p_e is determined by the ESP. We can recalculate ESP utility E_0 based on q_i^* obtained by Lemma 2 as Equation (8).

$$\begin{aligned}& E_0 = p_e\Sigma_{i=1}^{M} \min\{\tfrac{(w-p_e)N}{2\beta_i}, Q_i\} + \gamma\tfrac{C_e - C_c}{C_c} \times \min(N, \\ & \min\{\tfrac{(w-p_e)N}{2\beta_i}, Q_i\}) - \alpha\Sigma_{i=1}^{M} \min(\tfrac{(w-p_e)N}{2\beta_i}, Q_i) \\ & -p_c \times \max\{0, \Sigma_{i=1}^{M} \min \tfrac{(w-p_e)n}{2\beta_i}, Q_i - N\}.\end{aligned} \tag{8}$$

The second derivative of the function is calculated via Equation (9).

$$\frac{\partial^2 E_0}{\partial p_e^2} = \sum_{i=1}^{M} \begin{cases} 0, & \frac{(w-p_e)N}{2\beta_i} \ge Q_i; \\ -\frac{N}{\beta_i}, & \frac{(w-p_e)N}{2\beta_i} < Q_i. \end{cases} \tag{9}$$

Since $w > 0$, $\beta_i \ge 0$, and $N > 0$, we can get $\frac{\delta^2 E_0}{\delta P_e^2} \le 0$, and hence E_0 is a strict concave function of p_e ($0 < p_e < p_c$). That is, the ESP can find the optimal p_e to maximize the ESP's utility. Therefore, the Stackelberg game has a unique equilibrium. □

3.2 Stackelberg game equilibrium search algorithm

Algorithm 1 *SES*

Input: $B, M, N, w, p_e, p_c, Q_i, \alpha, \beta_i, \gamma, \epsilon$.
Output: Optimal computing resource price p_e^*.

```
Initialize t_0 = 0, t_3 = p_c;
while t_3 − t_0 ≥ ϵ do
    t_1 = t_0 + 0.382(t_3 − t_0), t_2 = t_0 + 0.618(t_3 − t_0);
    Calculate q_i^* (∀b_i ∈ B) at price t_1;
    Calculate ESP's utility E_0' with q_i^*;
    Calculate q_i^* (∀b_i ∈ B) at price t_2;
    Calculate ESP's utility E_0'' with q_i^*;
    if E_0' > E_0'' then
        t_3 = t_2;
    else if then
        t_0 = t_1;
    end if
end while
return p_e = (t_0 + t_3)/2.
```

The miners can calculate the optimal amount of computing resources to purchase with Equation (6) when the ESP determines computing resource price p_e, so we need to find the optimal p_e to maximize the ESP's utility. The equilibrium point prediction of the Stackelberg game in this paper is a one-dimensional single-peak concave function extreme value searching problem, since the range of p_e is $[0, p_c]$.

We propose an efficient golden section based Stackelberg game equilibrium searching algorithm as shown in Algorithm 1. Two points t_1 and t_2 are inserted in the searching interval of $[t_0, t_3]$ based on the ratio of 0.618, where t_0 and t_3 are initialized as 0 and p_c, respectively. For points t_1 and t_2, we calculate the optimal amount of computing resources to purchase via Equation (6). We then obtain the ESP's utility function values at the two inserted points, i.e. $E_0^{'}$ and $E_0^{''}$. The searching interval is divided into three segments by the inserted points. We compare the values of $E_0^{'}$ and $E_0^{''}$ according to the nature of the single-peak function, and one of the segments, either $[t_0, t_1]$ or $[t_2, t_3]$, is deleted to reduce the original searching interval. The algorithm proceeds iteratively following the process of narrowing the searching interval until the size of searching interval $[t_0, t_3]$ is less than the predefined precision threshold ϵ. The middle value of the final searching interval is returned as the approximate maximum value of ESP's computing resource price.

4 PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithm (SES) through simulations. We also investigate the impact of important parameters on the proposed algorithm.

4.1 Unit service utility of ESP

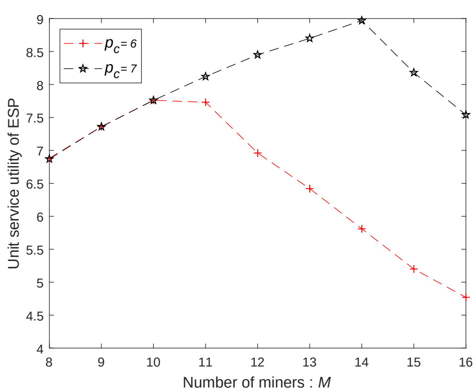

Figure 2: Impact of the number of miners on unit service utility of ESP.

Fig. 2 shows the unit service utility of ESP $\frac{E_0}{\sum_{i=1}^{N} q_i}$ versus different numbers of miners, assuming $N = 100$, $w = 10$, $\frac{C_e - C_c}{C_c} = 1$, $\alpha = 1$, $\gamma = 3$, $\beta_i \in [15, 25]$, and $Q_i \in [40, 50]$ $(\forall b_i \in B)$. The unit service utility of ESP initially increases and then decreases with the increasing number of miners. A large number of miners leads to a large number of computing resource requests, and hence the ESP increases computing resource price p_e to earn more income and control the total amount of services sold. As a result, the unit service utility of ESP initially shows an increasing trend. When the total number of services purchased by miners exceeds the ESP's computing capacity, high p_e makes the miners unwilling to buy computing resources, resulting in a decreasing trend in the unit service utility of ESP. A high cloud service price p_c makes the ESP take a large increase of p_e to control the total number of services purchased by the miners. Therefore, the unit service utility of ESP starts to decline with a higher p_c later than that with a lower p_c.

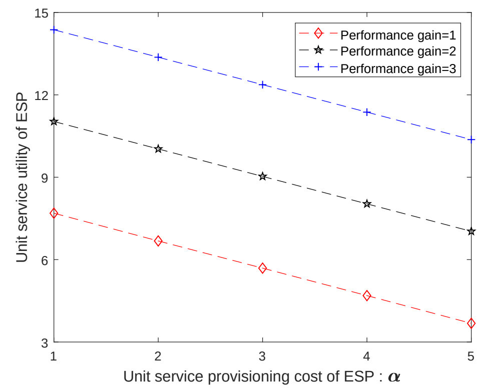

Figure 3: Impact of unit service provisioning cost on unit service utility of ESP.

Fig. 3 illustrates the unit service utility of ESP with different α, the unit service provisioning cost imposed on the ESP, assuming $M = 10$, $N = 300$, $w = 12$, $p_c = 8$, $\gamma = 5$, $\beta_i \in [10, 13]$, and $Q_i \in [40, 50]$ $(\forall b_i \in B)$. The unit service utility of ESP decreases as α increases. The increase of α indicates that the ESP takes an increasing cost to provide services to the miners, which leads to a decrease in the unit service utility of ESP. With the same α, the increase in performance gain of ESP over CSP means that the ESP performs increasingly better than the CSP, which increases the unit service utility of ESP.

In general, Figs. 2 and 3 demonstrate that the unit service utility of ESP increases with the increase of (1) w which is the unit service reward obtained by the miners, (2) cloud service price p_c, and (3) ESP's computing capacity N. With the increase of the number of miners, the unit service utility of ESP initially increases and then decreases.

4.2 Unit service utility of miners

Fig. 4 shows the unit service utility of miners $\frac{\sum_{i=1}^{M} E_i}{\sum_{i=1}^{M} q_i}$ versus different ESP's computing capacity N, assuming $M = 10$, $w = 12$, $p_c = 7$, $\frac{C_e - C_c}{C_c} = 1$, $\alpha = 1$, $\gamma = 3$, and $Q_i \in [40, 50]$ $(\forall b_i \in B)$. The unit service utility of miners increases with the increase of N. A large ESP's computing capacity enables a big number of tasks to be executed by the edge, which increases the miners' utilities. It can be observed that a large β, the weight range of task response time, results in a low unit service utility of miners, since the negative impact of executing the tasks at the cloud increases with the increase of β.

Fig. 5 depicts the unit service utility of miners by varying w, the unit service reward of the miners, assuming $M = 10$, $p_c = 7$,

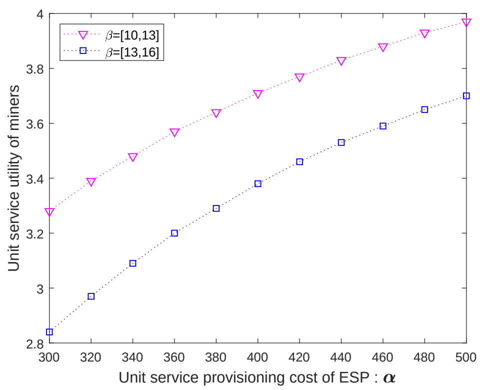

Figure 4: Impact of ESP's computing capacity on unit service utility of miners.

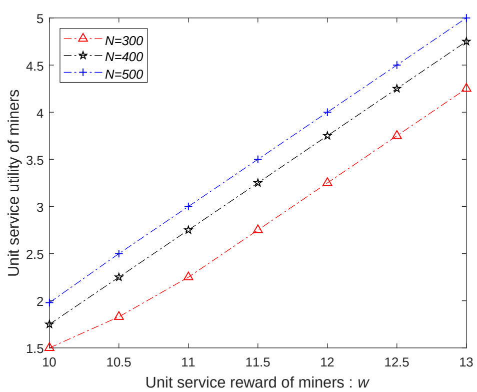

Figure 5: Impact of unit service reward w on unit service utility of miners.

$\frac{C_e - C_c}{C_c} = 1$, $\alpha = 1$, $\gamma = 3$, $\beta_i \in [10, 13]$, and $Q_i \in [40, 50]$ ($\forall b_i \in B$). The service utility of miners increases as w increases. The increase of w leads to more rewards of the miners, such that the miners are willing to purchase more computing resources. With a small ESP's computing capacity, the miners' competition for edge resources is intense so that a big number of tasks are executed by the CSP, which decreases the miners' utilities.

In general, Figs. 4 and 5 demonstrate that the unit service utility of miners increases with the increase of (1) α which is the weight of ESP's unit service provisioning cost, (2) β_i which is the weight of task response time for each miner b_i, (3) w which is the unit service reward obtained by the miners, and (4) ESP's computing capacity N.

5 CONCLUSIONS

Offloading mining computation tasks to an edge computing service provider (ESP) or a cloud computing service provider (CSP) is considered as a feasible solution for end devices to conduct blockchain mining in mobile environments. The ESP makes profit by allocating computing resources for the mining tasks of end devices. The computing resources of the edge server are limited, and hence rational management of computing resources at the edge is critical to maximizing the utilities of the ESP and the miners. In this paper, we constructed a computing offloading model which includes multiple miners, an ESP, and a CSP, where the ESP and the CSP are independent of each other. We formulated a Stackelberg game between the ESP and the miners for optimal pricing-based edge computing resource management. We proved the existence and uniqueness of Stackelberg game equilibrium and derived the miners' optimal amount of computing resources to purchase. We then proposed an effective golden section based Stackelberg game equilibrium searching algorithm (SES) for resource pricing. The simulation results demonstrated that the proposed model and algorithm could achieve high unit service utilities of both the ESP and the end devices.

6 ACKNOWLEDGMENTS

This work was partly supported by the National Natural Science Foundation of China under Grant U1836102.

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