Resource Allocation for Mobile Blockchain: A Hierarchical Combinatorial Auction Approach

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***Abstract*—As a decentralized ledger to record all transaction information, blockchain can be applied to address the security and privacy issues in mobile application system. We term the blockchain applied to mobile applications as mobile blockchain. The mining process in mobile blockchain requires high computing capacity and energy which could overwhelm that mobile devices can offer. In this case, mobile edge computing servers (MESs) can be involved to offer computation services to miners in mobile blockchain. Note that the resources of MESs are also limited, MESs could further request resources from the cloud computing server (CCS). Accordingly, in this paper, both mobile edge computing and cloud computing are considered to support the mobile blockchain applications which makes the problem a hierarchical one. Naturally, the issue of hierarchical resource allocation arises. And a hierarchical combinatorial auction model is proposed to solve this problem, based on which an efficient and truthful framework is provided. Specifically, we formulate winner determination problems (WDPs) for mobile edge computing service providers and cloud computing service provider, and computationally tractable algorithms to address both problems are proposed. Finally, numerical analysis shows the effectiveness of the proposed scheme.**

***Index Terms*—Mobile blockchain; hierarchical combinatorial auction; cloud computing; edge computing; winner determination problem.**

I. INTRODUCTION

Blockchain, as a decentralized ledger to record all transaction information, has wide application prospects in many areas (e.g., health care systems [1], Internet of things (IoT) [2] and electricity trading systems [3]). The mining process is very important in verifying and adding transaction records to blockchain. The participants joining the mining task are called miners, taking responsibility to verify the transaction and to address the proof-of-work (PoW) problem. The PoW is a complex mathematical problem which requires high computing power and energy.

With the development of mobile applications (e.g., ecommerce), mobile security problem has raised increasingly concerns [4]. Blockchain uses encryption and hash functions to store data in a chain and consensus protocol is used to ensure data consistency. Therefore, mobile blockchain has been proposed to be used in mobile applications to address the security and privacy issues [5]. Specifically, we term the blockchain applied to mobile applications as mobile blockchain. However, the mining process in mobile blockchain requires high computing capacity and energy which could overwhelm that mobile devices can offer. To solve this problem, the Mobile Edge Computing Service Provider (MESP) can be introduced into the mobile blockchain application network which allows miners to offload mining computation tasks to the mobile edge computing servers [6].

Note that the computing resources of MESPs are also limited, MESPs may be unable to meet large resource requirements of various miners. In this case, a Cloud Computing Service Provider (CCSP) can be further considered in this paper. The CCSP is the resource provider who owns a large scale of resources including computing resources. Miners can first request services from the MESPs. If the computing resources of MESPs are insufficient, MESPs could rent services from the CCSP.

Accordingly, we have a hierarchical architecture for providing computation services for mobile blockchain, which involves both MESP and CCSP. Naturally the problem of computing resource allocation becomes a hierarchical one.

To address the problem above, a hierarchical combinatorial auction model is proposed, based on which an efficient and truthful framework is provided. The hierarchical combinatorial auction model can be divided into the lower-level auction and the upper-level auction. Specifically, miners act as buyers and MESPs act as sellers in the lower-level auction, while in the upper-level auction, the CCSP is both auctioneer and seller and the MESPs act as the buyers. MESPs can be viewed as the middlemen who have no intrinsic valuations and demands and their revenues are gained from resale. MESPs' valuations depend on the demands from miners.

Specifically, for the proposed hierarchical combinatorial auction, the following three issues need to be addressed: 1) how to design the hierarchical combinatorial auction mechanism for mobile blockchain; 2) how to formulate the WDPs in both lower-level auction and upper-level auction and how to solve them in an efficient way; 3) how to design an incentive compatible pricing schemes. In this work, we will solve all the issues above. This paper's main innovations and contributions are shown as follows:

- A hierarchical combinatorial auction mechanism is proposed to address the two-level resource allocation problem for mobile blockchain.

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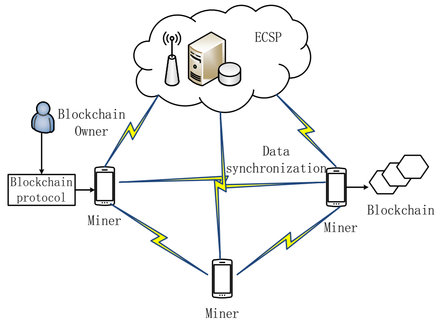

Fig. 1. The process of mining in blockchain networks.

• WDPs are formulated for CCSP and MESPs, and corresponding solvable algorithms for WDP are also proposed.

• The pricing schemes of ensuring incentive compatibility are proposed.

• Simulations show that the proposed scheme can achieve high resource utilization and efficiency.

The rest of this paper is organized shown as follows: section II describes the system model and assumptions. In section III, a hierarchical combinatorial auction model is proposed and the two-level resource allocation problem for mobile blockchain users is investigated. Section IV analyzes the numerical results and the whole paper is summarized in Section V.

II. System Model and Assumptions

A. Mobile Blockchain Mining Process

The process of mining in blockchain networks is shown in Fig. 1. Blockchain owners build blockchain applications and design protocols for blockchain networks. Each mobile user applies for a block from the blockchain owner, and then she will do mining task. The mining task is actually to solve a PoW problem. After the problem is solved, the solutions must be promoted in order to reach consensus. After successfully completing all of these processes, the transactions completed by the miners are added to the blockchain. Only the miner who is the first to get the solution and reach consensus can be rewarded.

B. The Probability of Successfully Mining with Edge Computing Services

Miner i's hash power ω_i which is related to other miners' allocated resources can be formulated as follows:

$$\omega_i(c, x) = \frac{c_i x_{ij}}{\sum_{i=1}^{N} c_i x_{ij}}, \tag{1}$$

which is a fraction function and the sum of all the miners' hash power is equal to one. c_i represents computing resources required by mobile user i. x_{ij} is a binary variable and if the value of it is equal to one that dedicating mobile user i will be allocated the required resources by MESP j. Otherwise, she will get nothing.

During the mining process, the miners are competing each other to become the first to solve the PoW problem and broadcast to reach an agreement. The generation of new blocks obeys the poisson distribution which holds a constant rate $\frac{1}{\lambda}$ in mobile blockchain network [7]. Before the mining race begins, the miners keep unverified transactions information into their blocks. We use $\mathbf{t} = \{t_1, \cdots, t_N\}$ to represent the size of the transaction in each miner's block. Miners need to broadcast her blocks to mobile blockchain networks to gain consensus. The first miner to win this consensus will be rewarded. Rewards consist of fixed rewards and random rewards and can be formulated as follows:

$$R_i = (T + r \cdot t_i)\mathbb{P}_i(\omega_i(c, x), t_i), \tag{2}$$

where T is the fixed reward and $r \cdot S_i$ is the random reward which is related to the size of transaction t_i and r is always positive. Also, $\mathbb{P}(\omega_i(c, x), t_i)$ is the probability of getting a reward.

Judging from the above mining process, getting rewards successfully needs two steps. The first is successfully mining, and the second is timely propagation certification. The success rate of mining is directly proportional to the hash power. So we use the hash power to represent the probability of successfully mining which is formulated as follows:

$$P_i = \omega_i. \tag{3}$$

The time of propagation is related to the size of the transaction. Here we use $\tau_i = \varsigma \cdot t_i$ to represent the time of propagation. ς is a constant which reflects the impact of S_i on τ_i. Since the new blocks generate following the poisson distribution, the probability of miner propagation failure can be formulated as follows:

$$P_i^0 = 1 - exp(-\frac{1}{\lambda}\tau_i). \tag{4}$$

In this case, $\mathbb{P}(\omega_i(c, x), t_i)$ can be formulated as follows:

$$\mathbb{P}_i(\omega_i(c, x), t_i) = P_i(1 - P_i^0). \tag{5}$$

After substituting P_i and P_i^0, $\mathbb{P}_i$ can be formulated as follows:

$$\mathbb{P}_i(\omega_i(c, x), t_i) = \omega_i e^{-\frac{1}{\lambda}\varsigma \cdot t_i}. \tag{6}$$

C. Blockchain Management

The blockchain mining protocol is maintained by blockchain owner, which includes a fixed bonus T and transaction rate r for miners contributing to mining. In addition, the security of a blockchain depends only on the amount of computing power used to solve it in a PoW problem [8]. This has a positive network effect: as more miners take part in mining and more computing resources put into mining, rewards for miners will increase as the blockchain network becomes more secure and stable. Based on existing research [9], we use a common s-shaped utility function to define network effects:

$$\gamma(d_N) = \frac{1 - e^{-\nu d_N}}{1 + \mu e^{-\nu d_N}}, \tag{7}$$

where $d_N = \sum_{i \in N} c_i x_{ij}$ is the total amount of computing resources allocated and μ, ν are two positive parameters. The

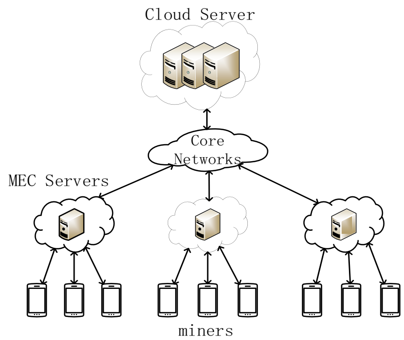

Fig. 2. System model of hierarchical resource allocation for blockchain mining.

network effect function starts slowly from 0, then accelerates, and then eventually slows down and converges to 1 asymptotically.

III. Resource allocation for mobile blockchain network

In this section, a hierarchical auction model is proposed and we will show how to apply this model for hierarchical resource allocation in mobile blockchain networks. We will elaborate on the following five aspects.

A. Hierarchical Resource Allocation Model for Blockchain Mining

In this paper, a scenario is considered where there is a CCSP, a set of $\mathbf{M} = \{1, \cdots, M\}$ MESPs and a set of $\mathbf{N} = \{1, \cdots, N\}$ mobile users as shown in Fig. 2. In this model, the CCSP provides services to MESPs and then each MESP provides services to mobile users, and naturally the problem of resource allocation is a hierarchical one. To simplify the problem, we assume that the subchannel resources of all mobile users are sufficient, and we only consider a set of $\mathbf{C} = \{1, \cdots, C\}$ computing resources. In addition, we believe that the computing resources of the mobile devices are small enough to be ignored compared to the computing resources required.

To solve the issue of two-level resource allocation jointly, a two-level auction mechanism is designed as shown in Fig. 3. Specifically, the MESPs launch a combinatorial double auction to allocate the computing resources to miners in the low-level. Meanwhile, the CCSP launches a one-side combinatorial auction to sell the computing resources to MESPs in the upper-level. Specifically, each mobile user i submits his resource demand c_i. Then, each MESP reserves computing resources C_j^{res}. Meanwhile, $\sum_{j=1}^{M} C_j^{res} \le C$, while the left $C^{up} = C - \sum_{j=1}^{M} C_j^{res}$ computing resources owned by the CCSP are to be auctioned among the MESPs. We denote $C_j > 0$ as the computing resources obtained by MESP j from the CCSP in the upper-level auction. In this case, for each MESP j in the lower-level, the available computing resources are $C_j^{low} = C_j^{res} + C_j$.

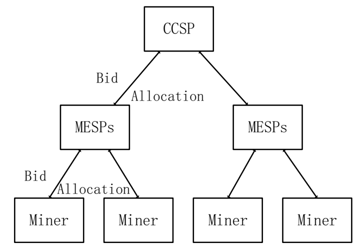

Fig. 3. The model of a single-seller multiple-buyer hierarchical auction.

B. How to Place a Bid?

Each mobile blockchain user needs to give a bid for the requested resources in the lower-level auction. Since mobile blockchain users can not know specific list of winners and total supply of computing resources until the auction is over, mobile user i's bid b_i is represented by the expected reward R_i which is equal to valuation $v_i^{'}$ called ex-ante valuation shown as follows:

$$v_i^{'} = R_i. \tag{8}$$

After substituting (1), (2) and (6), we can get the specific expression of the mobile user i's valuation:

$$v_i^{'} = (T + r \cdot t_i) \frac{c_i x_{ij}}{\sum_{i=1}^{N} c_i x_{ij}} e^{-\frac{1}{\lambda} \varsigma \cdot t_i}. \tag{9}$$

After the auction result is released, user i has an ex-post valuation $v_i^{''}$ of the edge computing service considering network effects, which is defined by

$$v_i^{''} = \gamma R_i, \tag{10}$$

where γ is the network effect mentioned in (7).

After substituting (1), (2), (6) and (7), we can get the mobile user i's specific valuation:

$$v_i^{''} = \frac{1 - e^{-\nu d_N}}{1 + \mu e^{-\nu d_N}} (T + r \cdot t_i) \frac{c_i x_{ij}}{\sum_{i=1}^{N} c_i x_{ij}} e^{-\frac{1}{\lambda} \varsigma \cdot t_i}. \tag{11}$$

For MESPs, bidding expressions differ from that of mobile users, because MESPs as the middlemen have no intrinsic demands and valuations. In the lower-level auction, each MESP j needs to submit asking bids a_j for all possible resources bundles sets. Similarly, each MESP needs to submit bid v_j for all possible resources bundles sets to CCSP in the upper-level auction.

C. How to Determine the Winning Bids?

After receiving all bids from bidders, the group of accepted bids needs to be decided by the auctioneer. For the proposed model in this paper, the WDPs for MESPs and CCSP need to be formulated. Specifically, the WDP for MESPs is shown as follows:

$$
\begin{aligned}
\text{maximize} \quad & \sum_{i=1}^{N} v_i^{''} x_{ij} + \sum_{j=1}^{M} a_j y_j \\
\text{subject to} \quad & C1 : \sum_{i=1}^{N} x_{ij} c_i \le C_j^{res} + C_j \\
& C2 : \sum_{i=1}^{M} x_{ij} \le 1, \forall i \in [1, N] \\
& C3 : x_{ij} \in \{0,1\}, \forall i \in N \\
& C4 : y_j \in \{0,1\}, \forall j \in M,
\end{aligned} \tag{12}
$$

where the objective function is to maximize the sum of both sides' valuation. Constraint C1 indicates that the amount of computing resources required should receive a maximum limit. Constraint C2 makes sure that a mobile user can get resources from only one MESP. x_{ij} in constraint C3 is a binary variable and if the value of it is equal to one that dedicating mobile user i will be allocated the required resources by MESP j. Otherwise, she will get nothing. y_j in constraint C4 is also a binary variable and if the value of it is equal to one that dedicating MESP j will allocate resources to the corresponding mobile users. Otherwise, she will be the loser.

And, the WDP for the CCSP is formulated as follows:

$$
\begin{aligned}
\text{maximize} \quad & \sum_{j=1}^{M} v_j y_j \\
\text{subject to} \quad & C1 : \sum_{j=1}^{M} y_j C_j \le C - \sum_{j=1}^{M} C_j^{res} \\
& C2 : y_j \in \{0,1\}, \forall j \in M,
\end{aligned} \tag{13}
$$

where the object is to maximize the sum of bidders' valuation. Constraint C1 indicates that the amount of computing resources required should receive a maximum limit. Constraint C2 ensures that y_j is a binary variable. y_j is a binary variable and if the value of it is equal to one that dedicating MESP j will be allocated required resources from CCSP. Otherwise, she will be the loser.

D. How to Solve the WDPs in the Hierarchical Auction?

The hierarchical problem is similar to the hierarchical game problem which is usually solved by backtracking method. In this case, to address the proposed problem, we start from the lower-level auction.

1) Solving the WDP in the Lower-Level Auction: We consider multiple mobile users and multiple MESPs in this level. The established WDP is an integer programming problem having been proved to be an NP-hard problem. Here we propose a heuristic algorithm callled Greedy-like algorithm motivated by [10] which takes "bid density" into account to get an approximate optimal solution as shown in Algorithm 1:

Algorithm 1 A Greedy-like algorithm for solving WDP for MESPs.

1: Initialization: set $x_{ij} = 0$ for each mobile user i and $y_j = 0$ for each MESP j

2: For submitted bid v_i of each mobile user i and submitted ask a_j of each MESP j, calculate "bid density". Reorder the mobile users' bid density in an descending order and the MESPs' bid density in an ascending order:

$$\frac{v_1}{\sqrt{c_1}} \ge \frac{v_2}{\sqrt{c_2}} \ge \cdots \ge \frac{v_N}{\sqrt{c_N}};$$
$$\frac{a_1}{\sqrt{C_1^{low}}} \le \frac{a_2}{\sqrt{C_2^{low}}} \le \cdots \le \frac{a_N}{\sqrt{C_N^{low}}}.$$

3: Match up one by one according to corresponding order until MESPs don't have enough resources to allocate and and set relative $x_{ij} = 1$, $y_j = 1$.

Bid density is an important concept in the proposed Greedy-like algorithm. Specifically, we define c_i as the "size" of each required bundle which is required by mobile user i, and C_i^{low} as the "size" of each MESP.

2) Solving the WDP in the Upper-Level Auction: After formulating the WDP problem which can be seen as set-packing problem (SSP) [11], we should determine the winning buyers in the next step. The established WDP is also an integer programming problem. We consider two possible ways to address the aforementioned WDP problem.

Firstly, a dynamic programming-like algorithm motivated by [12] is proposed to obtain the exact solution. Specifically, we decompose the original WDP into similar subproblems that can be solved in a recursive way. To be specific, the service allocation is divided into K phases, which is denoted by the subproblem considering the service allocation to k users who have required resources $e(k) = [e_{c_k}]^{\top}$, where e_{c_k} denotes the required computing resources. In each phase k, the service provider with resources can be denoted by $u(k) = [u_{c_k}]^{\top}$. Therefore, the state transition can be formulated as:

$$e(k+1) = e(k) - u(k). \tag{14}$$

Accordingly ,we can have $f(k, e(k)) = \max\{f(k-1, e(k)), f(k-1, e(k) - u(k)) + v_k\}$. The details are shown in Algorithm 2:

Algorithm 2 A dynamic programming-like algorithm .

1: Collect bids $B_k(S_k)$ from each user k, and initial the condition $f(1, e(1))$.

2: Calculate the optimal value function $f(k, e(k))$ for each state.

3: Output: using $x_k^* = arg\max_{x_k} f(k, e(k))$ to get the optimal allocation in each state.

However, the dynamic programming algorithm is only suitable for the case of small number of users. When the number of users is relatively large, the Greedy-like algorithm is more applicable. Because the time complexity of the dynamic programming-like algorithm is exponentially increasing, and that of Greedy-like algorithm increases linearly. Considering the efficiency requirements in real-world applications, the Greedy-like algorithm will be used in the case of large number of users as shown in Algorithm 3:

Algorithm 3 A Greedy-like algorithm for solving the WDP for CCSP.

1: Initialization: set $y_j = 0$ for each MESP j
2: For submitted bid v_j of each MESP j, calculate "bid density". Reorder the MESPs' bid density in an descending order:

$$\frac{v_1}{\sqrt{C_1}} \geq \frac{v_2}{\sqrt{C_2}} \geq \cdots \geq \frac{v_N}{\sqrt{C_N}}.$$

3: Allocate computing resources to corresponding MESPs until the CCSP don't have enough resources and set relative $y_j = 1$.

E. How to Price the Winning Bidders?

1) Pricing Scheme for Lower-level Auction: How to design a pricing scheme is the key to achieve incentive compatibility while each bidder always bids truthfully. The incentive compatibility of the VCG scheme is realized, which proves that the scheme is only compatible with the exact algorithm [13].

In this case, we design a VCG-like scheme which can suit approximate algorithms, in which we introduce a base price. To be specific, each type of resources has a base price, and a user who is the winner will pay the larger one between the base price and the VCG price. The charged price can be formulated as follows:

$$P_k(i) = \max\left\{P_k^{base}(i), P_k^{vcg}(i)\right\}, \tag{15}$$

where

$$P_k^{base}(i) = b_i, \tag{16}$$

$$P_k^{vcg}(i) = \frac{v_k}{\sqrt{c_k}}\sqrt{c_i}, \tag{17}$$

where $P_k^{base}(i)$ represents the base price of user i, and $P_k^{vcg}(i)$ is the VCG price. We will choose $P_k^{base}(i)$ as the final payment price in the case that the VCG price is smaller. Otherwise, the VCG price will be chosen.

2) Pricing Scheme for Upper-level Auction: For solving WDP for CCSP, we propose two algorithms which are an exact algorithm based on dynamic programming algorithm and an approximate algorithm based on greedy algorithm, and the pricing scheme for them should be distinctive. To be specific, for dynamic programming-based algorithm, we use VCG pricing. The VCG price of bidder i can be formulated as:

$$P_k(i) = \sum_{j \neq i} v_j(B^*) - \sum_{j \neq i} v_j(B), \tag{18}$$

B^* and B denote the resources obtained by bidder j without bidder i and with bidder i, respectively.

The pricing scheme in the Greedy-like algorithm is similar to that in lower-level auction.

IV. PERFORMANCE EVALUATION

For numerical analysis, we consider a CCSP with 10000 Million Instructions Per Seconds (MIPSs) computing capacity. There are two MESPs each of which reserves 3000 MIPS computing capacity, and the leftover 4000 MIPS computing capacity are available for the upper level. There are 20 miners who want to be miners to solve the PoW problem considered in this paper. Each mobile user i requests c_i computing capacity. c_i is a uniformly distributed integer random variable within the interval $[100, 1000]$. The bandwidth is set as 200 kHz. The mining bonus T is varied from 0 to 6, and the transaction fee rate r is varied from 0.002 to 0.01. We set ς = 0.6, λ = 0.006 and τ = 1. In addition, μ, ν is set as 1 and 0.5. The transaction size t of each miner is within the interval $[100, 1000]$.

For comparison, a fixed sharing scheme is considered, where each MESP reserves 4000 MIPS computing capacity in the upper level. Besides, a rand allocation scheme is considered in upper-level auction in which each MESP reserves computing capacity ranging from 3000 to 4000 MIPS. For the hierarchical combination auction problem, the upper level auction adopts algorithm 2, algorithm 3, fixed sharing and rand scheme, and the lower level auction adopts algorithm 1.

In order to investigate the results, Fig. 4 shows the average social welfare of these four algorithms. It can be seen that the average social welfare by using DP-Algorithm can obtain the best social welfare. This indicates that the exact solutions can perform better than the approximate solutions do. We can also see that greedy-like algorithm can obtain better social welfare than both fixed and rand algorithms. This because that the fixed algorithm and rand algorithm can not consider the requirements of buyers, both of which lose the significance of the auction. In addition, the effects of different number of miners on the average utilization are studied in Fig. 5. According to the picture, we can see that the resource utilization obtained by DP-Algorithm can do the best as the increasing number of miners.

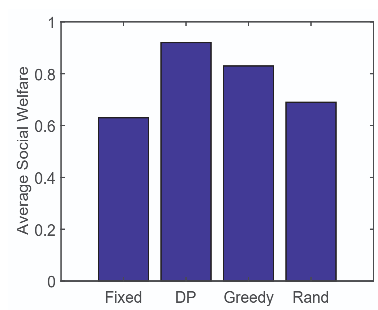

Fig. 4. The average social welfare achieved by different algorithms.

Moreover, we compare the scheme which only considers edge computing named "Uniform" with our proposed scheme which jointly considers edge computing and cloud computing named "Joint" in satisfaction ratio with increasing number of mobile users as shown in Fig. 6. It can be seen that the satisfaction ratio is becoming lower with the increasing number of mobile users. This may be due to that as the number of mobile users grows, and competition among them becomes intense. In this case, the possibility of users gaining requested resources decreases, and naturally the satisfaction ratio becomes lower. We also can observe that jointly consideration can achieve better satisfaction ratio than uniform one. This is due to the fact that our proposed scheme which jointly considers edge computing can provide much more resources than the scheme which only considers edge computing.

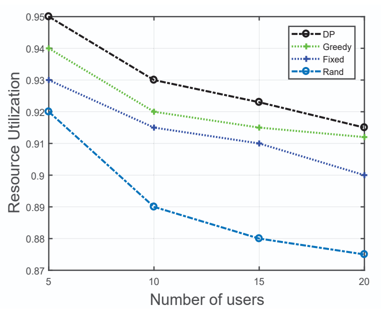

Fig. 5. Average resource utilization achieved by different algorithms with different number of miners.

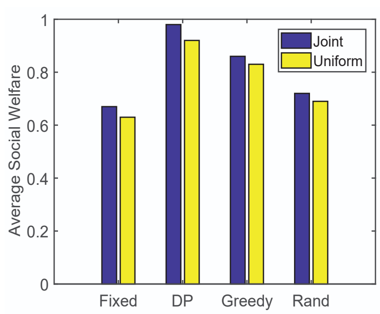

Fig. 6. The comparison in satisfaction ratio with increasing number of mobile users.

V. Conclusion

In this paper, we propose a hierarchical architecture for providing computation services for mobile blockchain, which involves both MESP and CCSP. Also, a hierarchical combinatorial auction model has been proposed to solve the problem of resource allocation for mobile blockchain. Specifically, we have formulated winner determination problems (WDPs) for mobile edge computing providers and the cloud computing provider, and relevant computationally tractable algorithms to solve these problems have also been proposed. Besides, different pricing schemes have been designed to determine the final prices. The properties of the proposed schemes have also been proved theoretically. Finally, the effectiveness of the scheme is verified by simulation and comparison.

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