Computing Resource Trading for Edge-Cloud-Assisted Internet of Things

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***Abstract*—Optimal computing resource allocation for edge-cloud-assisted Internet of things (IoT) in blockchain network is attracting increasing attention. Auction is a classical algorithm which guarantees that the computing resources are allocated to the buyers of the computing resource. However, the traditional auction algorithm only guarantees the revenue gains for the sellers of the computing resource. How to guarantee the seller and the buyer of the computing resource when both are willing to trade and moreover, bid truthfully, is still an open problem in computing resource trading for edge-cloud-assisted IoT. In this paper, we introduce a broker with sparse information to manage and adjust the trading market. We then propose an iterative double-sided auction scheme for computing resource trading, where the broker solves an allocation problem to determine how much computing resource is traded and designs a specific price rule to induce the buyers and sellers of the computing resource to submit bids in a truthful way. Thus, hidden information can be extracted gradually to obtain optimal computing resource allocation and trading prices. Hence, the proposed algorithm can achieve the maximum social welfare meanwhile protecting the privacies of the buyers and the sellers. Our theoretical analysis and simulations demonstrate that the proposed algorithm is efficient, i.e., it achieves the maximum social welfare. In addition, the proposed algorithm can provide effective trading strategies for the buyers and sellers of the computing resource, leading to the proposed algorithm satisfying incentive compatibility, individual rationality, and budget balance.**

***Index Terms*—Computing resource trading, double auction, edge-cloud computing, Internet of things (IoT).**

I. Introduction

INTERNET of things (IoT) [1], [2] is an interconnection among objects and equipped with ubiquitous intelligence.

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The traditional IoT control system is based on a centralized and trust-dependent structure, which limits the interoperability and security of the system. Very recently, blockchain, a decentralized public ledger to record transactions, has been developed [3], [4]. The blockchain-based IoT, which allows IoT to build up decentralized trust and reliance among multiple parties, is attracting increasing attention [5]–[7]. Related research of blockchain-based IoT works on both architectures (e.g., IoT data storage and protection, privacy-preserving access control in IoT, and consensus protocol for IoT [8]–[11]) and applications (e.g., energy trading, data trading, smart homes, and so on [12]–[14]). However, blockchain-based IoT faces inherent physical constraints as IoT devices have only limited computation and storage resources on board, which restricts the opportunities for more sophisticated applications, e.g., pure peer-to-peer (P2P) trading.

To enhance the computational resources and scalability of blockchain-based IoT, edge-cloud computing has been introduced for blockchain-based IoT to solve different types of tasks (e.g., real-time processing, resource-intensive applications, blockchain mining, and consensus process), where the edge provides limited computational and storage resources with low latency, and the cloud can provide power computing and storage resources but with high latency [15], [16].

In edge-cloud-assisted IoT in blockchain network, the computing resource trading problems are studied based on the traditional auction algorithms [14], [17], where the revenue gains for the seller can only be guaranteed. If the benefits for the buyers cannot be guaranteed, the buyers are not willing to trade and thus, the bids are not truthful, so that the desirable economic benefits are hard to achieve [18]. Clearly, the buyers and sellers are conflicting with each other. It is difficult to reach an agreement if they decide how much computing resource to trade, independently. Therefore, a market controller, i.e., a broker, is required to manage the computational resource trading market for IoT nodes via a smart contract. However, how to efficiently trade the computing resource to guarantee that the seller and the buyer are both willing to trade and moreover, bid truthfully, is still an open problem.

In this paper, we address the computing resource trading problem for edge-cloud-assisted IoT in blockchain network. We build a pure P2P computing resource trading system for edge-cloud-assisted IoT in blockchain network to ensure the computing resource balance among IoT devices and, moreover, to avoid problems such as privacy leakage and single-point failure. The main challenges of the computing resource trading problem for edge-cloud-assisted IoT are as follows. 1) How can

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one ensure incentive and truthful computing resource trading to achieve the desirable economic benefits meanwhile protecting private information (including the current computing resource state, capacity, welfare, etc.) of the computing resource sellers and buyers during the trading? 2) How much computing resources should each computing resource seller supply to each computing resource buyer and how much would be the reward? And, from the perspective of the computing resource buyer: How much computing resource should each computing resource buyer request from each computing resource seller and how much should they pay?

To address these challenges, we first design a computing resource trading market where a set of computing resource buyers compete to trade with a set of computing resource sellers, and a broker manages the marketplace without the actual needs of buyers and sellers. Second, we propose to employ an iterative double-sided auction scheme [19] to the computing resource trading for edge-cloud-assisted IoT in blockchain network. The broker collects the buyers' requests and the sellers' supplies and then decides how much computing resource of the seller will be provided to each buyer by solving the allocation problem. In addition, the broker designs a specific price rule to induce the buyers and sellers to submit bids in a truthful way, so that the hidden information is gradually extracted, and at the same time, the maximum social welfare can be achieved.

To our knowledge, this is the first study to tackle the computing resource trading problem for edge-cloud-assisted IoT in blockchain network based on an iterative double-sided auction scheme. Our contribution can be summarized as follows. 1) We establish a pure P2P computing resource trading system in blockchain network to achieve secure and trusted computing resource trading. 2) We introduce a broker to manage the trading market and then, propose an iterative double-sided auction-based algorithm for the computing resource trading. The proposed algorithm, while protecting the private information of computing-resource trading participants, satisfies the desirable economic properties including efficiency (i.e., maximizing the social welfare), incentive compatibility (i.e., sellers and buyers truthfully reveal their needs according to their private information), individual rationality (i.e., sellers and buyers are willing to trade), and budget balance (i.e., the broker does not lose money). 3) Numerical simulations are conducted to evaluate the performance of the proposed algorithm for the computing resource trading problem.

The remainder of this paper is structured as follows. The related work is summarized in Section II. Our system model for the computing resource trading and the proposed algorithm based on an iterative double-sided auction scheme are introduced in Section III. Performance evaluation is presented in Section IV, and our conclusions are summarized in Section V.

II. Related Work

The related research of blockchain-based IoT works will be summarized in this section. Xiong *et al.* [17] introduced edge computing for IoT blockchain for offloading mining tasks. Liu *et al.* [20] presented a mobile edge-computing-enabled wireless framework with the blockchain technology, where computation-intensive tasks could be offloaded to edge-computing nodes. Xu *et al.* [21] addressed a blockchain-enabled decentralized resource management method that could reduce the cost of the energy consumption by requesting migration and scheduling among data centers. The study [22] investigated the multilayer computation offloading framework which integrates a distributed incentive and reputation mechanism. Kang *et al.* [23] studied mobile edge computing integrated with vehicular networks based on consortium blockchain technology. Compared with the above studies, this paper addresses the computing resource trading problem for edge-cloud-assisted IoT in blockchain network and studies optimal computing resource trading based on the double auction scheme for encouraging incentive and truthful computing resource trading.

III. System Model for P2P Computing Resource Trading in Blockchain and Proposed Algorithm

In this section, we first build a blockchain network for edge-cloud-assisted IoT. Then, we build the system model of the computing resource trading and propose to use the iterative double-sided auction scheme for computing resource trading.

A. Blockchain Network for Edge-Cloud-Assisted IoT

In an edge-cloud-assisted IoT system, the computing resource trading happens in IoT nodes including the edge-cloud computing service providers (ECSPs) and IoT devices. Here ECSPs mainly play the role of selling computing resources to IoT devices and its neighboring edge server nodes. IoT devices play different roles including computing resource sellers, computing resource buyers, and idle nodes. The computing resource sellers own surplus computing resources to sell and obtain resource coins. The computing resource buyers have a computing resource demand and need to pay resource coins (the digital cryptocurrency is used as resource coins) to sellers. Idle IoT nodes neither buy computing resources from other IoT devices, nor sell computing resources to others.

We employ the blockchain technology to guarantee secure P2P computing resource trading. Blockchain is composed of a set of blocks. Every block has two parts, namely transactional data and a unique hash value. The transactional data—including pseudonyms of ECSPs and IoT devices used to protect privacy, data type, raw data, and the timestamp of transaction validation—are encrypted and signed with digital signatures for security. Then, the transactional data are packed into blocks. The hash value is used as a link pointing from the current block to the previous block. Thus, a series of blocks connected in a linear chronological order form a blockchain.

The security of a blockchain directly relies on the consensus mechanism which is carried out by the authorized ECSPs and IoT devices with the valid proof-of-work. The fastest ECSP or IoT device becomes the leader that announces its proof-of-work, block data, and the timestamp to other ECSPs and IoT devices as auditors for audit and verification. The auditors then audit the block data and announce the audit results with signatures. When receiving the audit results, every auditor compares the result with those of others, and then sends feedback information to the leader. The leader collects and analyzes the feedback information. If all the auditors reach a consensus, the block is verified. The leader then sends the block data with the signature to the ECSPs and IoT devices and will receive resource coins. The consensus mechanism can guarantee the dependability and security of blockchain systems.

B. Proposed Algorithm

We consider such a system model of P2P computing resource trading for edge-cloud-assisted IoT nodes in blockchain network where: 1) there is a broker who manages resource-trading participants and executes the trading operations. The broker is chosen with the sparse information (nodes with surplus computing resources are viewed as nonzero elements and nodes without surplus computing resources are viewed as zero elements); 2) there is a group of N_I computing resource buyers and N_J computing resource sellers. The ith buyer is indexed as B_i and a set of buyers is indexed as a vector $\mathbf{b} = \{B_i | i \in \{1, 2, \dots, N_I\}\}$. The jth seller is indexed as S_j and a set of sellers is indexed as a vector $\mathbf{s} = \{S_j | j \in \{1, 2, \dots, N_J\}\}$. Each buyer can request different demands from different sellers and each seller can serve more than one buyer. The buyer B_i is assumed to demand the computing resource amount a_{ij} from the seller S_j. The demands of B_i from different sellers are defined as a vector $\mathbf{a}_i = \{a_{ij} | j \in \{1, 2, \dots, N_J\}\}$, and all the demands of all buyers are denoted as the matrix $\mathbf{A} = \{\mathbf{a}_i | i \in \{1, 2, \dots, N_I\}\}$. Each seller is assumed to supply the computing resource amount d_{ji} to the buyer B_i. The supplies of S_j to different buyers are indexed as a vector $\mathbf{d}_j = \{d_{ji} | i \in \{1, 2, \dots, N_I\}\}$. All the supplies of all sellers are indexed as the matrix $\mathbf{D} = \{\mathbf{d}_j | j \in \{1, 2, \dots, N_J\}\}$. The buyer B_i interacts with the seller S_j and submits a bid price to the broker, which is indexed as x_{ij}. The buyer B_i interacting with each seller submits the bid prices that are indexed as a vector $\mathbf{x}_i = \{x_{ij} | j \in \{1, 2, \dots, N_J\}\}$. All bid prices of buyers to different sellers are indexed as a matrix $\mathbf{X} = \{\mathbf{x}_i | i \in \{1, 2, \dots, N_I\}\}$. Similarly, the seller S_j serving the buyer B_i submits a bid price to the broker that is indexed as y_{ji}. The seller S_j serving each buyer submits the bid prices that are denoted as a vector $\mathbf{y}_j = \{y_{ji} | i \in \{1, 2, \dots, N_I\}\}$. All bid prices of sellers to different buyers are denoted as a matrix $\mathbf{Y} = \{\mathbf{y}_j | j \in \{1, 2, \dots, N_J\}\}$. Under our consideration, we establish the system model and computing resource trading market in blockchain network, shown in Fig. 1. *Problem description*: 1) One part for the buyer: Denote $U_{ij}(a_{ij})$ as the satisfaction of the buyer B_i from satisfying its request a_{ij} through the seller S_j, and denote $U_i(\mathbf{a}_i)$ as the satisfaction of each buyer B_i interacting with different sellers. The function $U(\cdot)$ should be positive, increasing, smooth, and strictly concave, which is given as

$$U_i(\mathbf{a}_i) = \omega_i \sum_{j=1}^{N_J} \log(a_{ij} - a_{ij} * z_{ij} + 1) \tag{1}$$

where $\omega_i = \frac{\tau}{CRS}$ is the buying willingness of B_i, CRS is the computing resource state before buying and τ is a constant. z_{ij} is the distance factor between B_i and S_j.

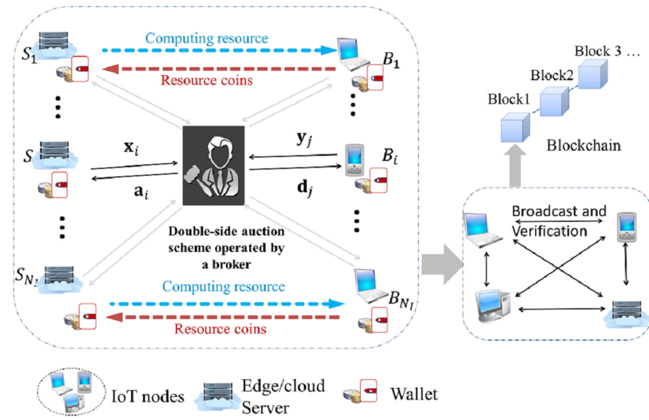

Fig. 1. System model and computing resource trading market in blockchain.

2) The other part for the seller: Let $C_{ji}(d_{ji})$ be the cost of the seller S_j when S_j supplies computing resource amount d_{ji} to the buyer B_i and let $C_j(\mathbf{d}_j)$ be the cost function of S_j serving different buyers. The function $C(\cdot)$ is also a smooth and strictly convex function, which is given as

$$C_j(\mathbf{d}_j) = n_1 \left(\sum_{i=1}^{N_I} d_{ji} \right)^2 + n_2 \sum_{i=1}^{N_I} d_{ji} \tag{2}$$

where $n_1 > 0$ and $n_2 > 0$ are cost factors.

The sum of the utility functions of all pairs is the social welfare [24]. There needs a market controller, i.e., a broker to guarantee that the market will run efficiently. The broker solves the social welfare maximization problem (SWMP) to match the buyers and the sellers as follows:

$$\begin{aligned} \text{SWMP}: \ & \max_{\mathbf{A},\mathbf{D}} \sum_{i=1}^{N_I} \sum_{j=1}^{N_J} J_{ij}(a_{ij}, d_{ji}) \\ &= \max_{\mathbf{A},\mathbf{D}} \sum_{i=1}^{N_I} U_i(\mathbf{a}_i) - \sum_{j=1}^{N_J} C_j(\mathbf{d}_j). \end{aligned} \tag{3}$$

Some constraints are imposed on the SWMP problem

$$a_i^{\min} \le \sum_{j=1}^{N_J} a_{ij} \le a_i^{\max}, \ i \in \{1, 2, \dots, N_I\} \tag{4}$$

$$\sum_{i=1}^{N_I} d_{ji} \le d_j^{\max}, \ j \in \{1, 2, \dots, N_J\} \tag{5}$$

$$\begin{aligned} a_{ij} \le d_{ji}, &\forall i \in \{1, 2, \dots, N_I\} \\ &\forall j \in \{1, 2, \dots, N_J\} \end{aligned} \tag{6}$$

$$\begin{aligned} a_{ij} \ge 0, &\forall i \in \{1, 2, \dots, N_I\} \\ &\forall j \in \{1, 2, \dots, N_J\} \end{aligned} \tag{7}$$

where $a_i^{\min}$ and $a_i^{\max}$ are the minimum and the maximum demand of B_i, respectively; and $d_j^{\max}$ is the maximum supply of S_j. The constraint (6) indicates that the amount supplied by each seller should satisfy the demand of each buyer. If $a_{ij} = d_{ji}, \forall i, j$, the market is in equilibrium. From the transaction perspective, the buyers want to maximize their satisfactions, whereas the sellers want to minimize their costs. The broker will decide the optimal allocation of computing resources to meet the buyers' demands. From the social perspective, social welfare will be maximized when all the trading is completed.

The SWMP has a unique solution, because it is strictly concave and moreover, the constraint sets are convex. Relaxing the constraints and using the Lagrangian multipliers $\alpha, \beta, \gamma, \lambda, \mu$, the Lagrangian of the SWMP can be written as

$$\begin{aligned} f_1(\mathbf{A}, \mathbf{D}, \alpha, \beta, \gamma, \lambda, \mu) &= \sum_{i=1}^{N_I} U_i(\mathbf{a}_i) - \sum_{j=1}^{N_J} C_j(\mathbf{d}_j) \\ &- \sum_{i=1}^{N_I} \alpha_i \left(a_i^{\min} - \sum_{j=1}^{N_J} a_{ij} \right) - \sum_{i=1}^{N_I} \beta_i \left(\sum_{j=1}^{N_J} a_{ij} - a_i^{\max} \right) \\ &- \sum_{j=1}^{N_J} \gamma_j \left(\sum_{i=1}^{N_I} d_{ji} - d_j^{\max} \right) - \sum_{j=1}^{N_J} \sum_{i=1}^{N_I} \lambda_{ij}(a_{ji} - d_{ji}) \\ &+ \sum_{j=1}^{N_J} \sum_{i=1}^{N_I} \mu_{ij} a_{ij} \end{aligned} \tag{8}$$

where $\alpha \geq 0, \beta \geq 0, \gamma \geq 0, \lambda \geq 0, \mu \geq 0$ for the equality and inequality constraints. According to the Karush–Kuhn–Tucker (KKT) conditions [12], the optimal solutions of $\mathbf{D}$ and $\mathbf{A}$ satisfy

$$\nabla_{a_{ij}} f_1 = 0 \tag{9}$$

$$\nabla_{d_{ji}} f_1 = 0. \tag{10}$$

Thus, obtain

$$\nabla_{a_{ij}} U_i(\mathbf{a}_i) + \alpha_i - \beta_i - \lambda_{ij} + \mu_{ij} = 0 \tag{11}$$

$$-\nabla_{d_{ji}} C_j(\mathbf{d}_j) - \gamma_j + \lambda_{ij} = 0. \tag{12}$$

The complete information of each buyer's satisfaction and each seller's cost are private. Thus, the equations (11) and (12) cannot be solved directly. We need to design a scheme to extract the hidden information from buyers and sellers.

Iterative Double-sided Auction Scheme: We introduce the concept of an iterative double-sided auction scheme for computing resource trading. The iterative double-sided auction scheme can extract the hidden information from sellers and buyers gradually, and at the same time, maximize social welfare. In our P2P computing resource trading market, the broker manages the computing resource allocations for all buyers and sellers. The buyers announce how much they are willing to pay and the sellers announce how much they are willing to sell. The broker collects the buyers' requests and the sellers' supplies and optimizes the broker allocation problem (BAP) to determine how much computing resource of the sellers will be supplied to each buyer. The buyers and sellers comply with the broker's decisions if their own interests are satisfied.

The double-sided auction scheme includes two steps in each iteration. First, the buyer B_i interacts with the seller S_j and submits a bid price x_{ij} to the broker. The seller S_j serving the buyer B_i submits a bid price y_{ji} to the broker. After submission of bid prices, the broker decides the optimal demand and supply by optimizing the BAP as follows:

$$BAP : \max_{\mathbf{A},\mathbf{D}} \left\{ \sum_{i=1}^{N_I} \sum_{j=1}^{N_J} x_{ij} \ln a_{ij} - \frac{1}{2} y_{ji} d_{ji}^2 \right\} \tag{13}$$

$$\text{s.t. } a_i^{\min} \leq \sum_{j=1}^{N_J} a_{ij} \leq a_i^{\max}, \ \forall i \in \{1, 2, \ldots, N_I\} \tag{14}$$

$$\sum_{i=1}^{N_I} d_{ji} \leq d_j^{\max}, \ \forall j \in \{1, 2, \ldots, N_J\} \tag{15}$$

$$a_{ij} \leq d_{ji}, \forall i \in \{1, 2, \ldots, N_I\} \quad \forall j \in \{1, 2, \ldots, N_J\} \tag{16}$$

$$a_{ij} \geq 0, \forall i \in \{1, 2, \ldots, N_I\} \quad \forall j \in \{1, 2, \ldots, N_J\}. \tag{17}$$

Although the BAP is different from the SWMP, it has the same constraints. Based on the submitted bid prices, the broker can allocate computing resources for each buyer and seller, leading to achieve effective market equilibrium. The BAP is also strictly concave. Similarly, the Lagrange function of the BAP can be written as

$$\begin{aligned} &f_2(\mathbf{A}, \mathbf{D}, \alpha, \beta, \gamma, \lambda, \mu) \\ &= \sum_{i=1}^{N_I} \sum_{j=1}^{N_J} x_{ij} \ln a_{ij} - \frac{1}{2} y_{ji} d_{ji}^2 + \sum_{j=1}^{N_J} \sum_{i=1}^{N_I} \mu_{ij} a_{ij}. \\ &- \sum_{i=1}^{N_I} \alpha_i \left(a_i^{\min} - \sum_{j=1}^{N_J} a_{ij} \right) - \sum_{i=1}^{N_I} \beta_i \left(\sum_{j=1}^{N_J} a_{ij} - a_i^{\max} \right) \\ &- \sum_{j=1}^{N_J} \gamma_j \left(\sum_{i=1}^{N_I} d_{ji} - d_j^{\max} \right) - \sum_{j=1}^{N_J} \sum_{i=1}^{N_I} \lambda_{ij}(a_{ij} - d_{ji}). \end{aligned} \tag{18}$$

Solving the BAP results in new optimal allocations $\mathbf{A}$ and $\mathbf{D}$ to announce to buyers and sellers for trading. The unique optimal solution can be obtained by the KKT condition. The optimal solutions of $\mathbf{A}$ and $\mathbf{D}$ for the BAP satisfy

$$\nabla_{a_{ij}} f_2 = \frac{x_{ij}}{a_{ij}} + \alpha_i - \beta_i - \lambda_{ij} + \mu_{ij} = 0 \tag{19}$$

$$\nabla_{d_{ji}} f_2 = -y_{ji} d_{ji} - \gamma_j + \lambda_{ij} = 0 \tag{20}$$

which lead to the rules of the optimal allocations as follows:

$$a_{ij} = \frac{x_{ij}}{\beta_i + \lambda_{ij} - \alpha_i - \mu_{ij}} \tag{21}$$

$$d_{ji} = \frac{\lambda_{ij} - \gamma_j}{y_{ji}}. \tag{22}$$

The broker can allocate the optimal allocations for each buyer and seller according to (21) and (22).

To ensure that the above solutions can maximize social welfare, the KKT conditions need to be matched for the SWMP and the BAP. Hence, we obtain

$$\nabla_{a_{ij}} U_i(\mathbf{a}_i) = \frac{x_{ij}}{a_{ij}} \Rightarrow x_{ij} = a_{ij} \frac{\partial}{\partial a_{ij}} U_i(\mathbf{a}_i) \tag{23}$$

$$-\nabla_{d_{ji}} C_j(\mathbf{d}_j) = -y_{ji} d_{ji} \Rightarrow y_{ji} = \frac{1}{d_{ji}} \frac{\partial}{\partial d_{ij}} C_j(\mathbf{d}_j) \tag{24}$$

which implies that the broker solving the SWMP is equivalent to solving the BAP if the buyer B_i and the seller S_j submit the bid prices based on (23) and (24).

The double-sided auction scheme needs multiple iterations. At each iteration, buyers need to solve their own buyers' utilities maximization problem (BMP) to update bids according to the new demand allocation by the broker, and sellers need to solve their own sellers' utilities maximization problem (SMP) to update their bids according to the new supply allocation by the broker. Hence, the broker has to design price rules for buyers and sellers, so that each participant will be induced to submit the bid prices based on (23) and (24).

Next, we try to derive the payment and reward functions that induce buyers and sellers to bid according to (23) and (24). Define $P_i(\mathbf{x}_i)$ as the payment of the buyer B_i given to the broker for the service. The defined $R_j(\mathbf{y}_j)$ denotes the reward of the seller S_j given by the broker. $P_i(\mathbf{x}_i)$ depends on the allocated mount $\mathbf{a}_i$ of the buyer B_i, whereas $R_j(\mathbf{y}_j)$ depends on the allocated amount $\mathbf{d}_j$ of the seller S_i.

Thus, the buyer B_i needs to solve its own BMP to determine its optimal bid price

$$\text{BMP}: \max_{\mathbf{x}_i}[U_i(\mathbf{a}_i) - P_i(\mathbf{x}_i)] \tag{25}$$

and the seller S_j needs to solve its own SMP to determine its optimal bid price

$$\text{SMP}: \max_{\mathbf{y}_j}[R_j(\mathbf{y}_j) - C_j(\mathbf{d}_j)]. \tag{26}$$

The price rules of the buyer B_i and the seller L_j are given as

$$P_i(\mathbf{x}_i) = \sum_{j=1}^{N_J} x_{ij} \tag{27}$$

$$R_j(\mathbf{y}_j) = \sum_{i=1}^{N_I} \frac{1}{y_{ji}} (\lambda_{ji} - \gamma_j)^2. \tag{28}$$

Theorem 1: The price rules (27) and (28) make the optimal bid prices for buyers and sellers satisfy (23) and (24), respectively.

Proof: The optimal bid price of the buyer B_i satisfies the function (25). Hence, we have

$$\frac{\partial U_i(\mathbf{a}_i)}{\partial x_{ij}} - \frac{\partial P_i(\mathbf{x}_i)}{\partial x_{ij}} = 0. \tag{29}$$

Based on (21), we obtain

$$\frac{\partial U_i(\mathbf{a}_i)}{\partial x_{ij}} = \frac{\partial U_i(\mathbf{a}_i)}{\partial a_{ij}} \frac{\partial a_{ij}}{\partial x_{ij}} = \frac{\partial U_i(\mathbf{a}_i)}{\partial a_{ij}} \frac{a_{ij}}{x_{ij}}. \tag{30}$$

According to the bid price (27), we have

$$\frac{\partial P_i(\mathbf{x}_i)}{\partial x_{ij}} = 1. \tag{31}$$

Hence

$$x_{ij} = a_{ij} \frac{\partial U_i(\mathbf{a}_i)}{\partial a_{ij}}. \tag{32}$$

The solution (32) is the same as (23), which means that the price rule (27) satisfies (23).

Similarly, according to (22), (26), and (28), we obtain

$$\frac{\partial R_j(\mathbf{y}_j)}{\partial y_{ji}} - \frac{\partial C_j(\mathbf{d}_i)}{\partial y_{ji}} = 0. \tag{33}$$

and

$$\frac{C_j(\mathbf{d}_j)}{\partial d_{ji}} = \lambda_{ji} - \gamma_j \Rightarrow y_{ji} = \frac{1}{d_{ji}} \frac{\partial}{\partial d_{ij}} C_j(\mathbf{d}_j). \tag{34}$$

The solution (34) is the same as (24), which means that the price rule (28) of the seller S_j satisfies (24).

Hence, the broker solving the BAP is equivalent to solve the SWMP, leading to social welfare maximization by the iterative double-sided auction for computing resource trading. ■

Proposed Algorithm: In each iteration of Algorithm 1, with the initial bids $\mathbf{X}$ and $\mathbf{Y}$ submitted by buyers and sellers, the broker solves the BAP to compute the allocated demand and the allocated supply (lines 3–4 in Algorithm 1). Meanwhile, the broker computes the price rules (27) and (28) (line 5). Based on the new allocations announced by the broker, buyers and sellers compute the optimal bid prices by solving BMP and SMP (lines 6–8), respectively. These optimal bid prices will be submitted to the broker for the next iteration. The algorithm will stop when the convergence conditions are satisfied. Thus, the new optimal allocated amounts and the new optimal bid prices can be obtained through a number of iterations. Algorithm 1 alternatively optimizes BAP, BMP, and SMP problems which are strictly concave objective functions under the convex constraints (4)–(7). The convergence of Algorithm 1 can be shown in the simulation results of Section IV.

Algorithm 1 has a relatively small communication overhead because there is a polynomial number of messages that need to be circulated in the market. In each round of Algorithm 1, there are $2N_I N_J$ bids that need to be communicated from the buyers for all their base stations. Similarly, the broker announces the $N_I N_J + N_J$ variables to the $N_I N_J$ bidders. Thereby, the complexity analysis is $O((N_I N_J)^2)$ per round.

In addition, Algorithm 1 satisfies the following properties.

1) It is efficient. The buyers and sellers submit the bids according to (23) and (24), leading to the optimal solutions of BAP being identical to the optimal solutions of SWMP. Hence, social welfare can be maximized and the efficiency of market can be guaranteed.
2) It is incentive compatible. Although the buyers and sellers do not communicate private information, they are induced to submit bid prices truthfully from (23) and (24). Thus, the hidden (private) information can be revealed gradually.
3) It is individually rational. According to (29) and (33), we have $U_i(\mathbf{a}_i) - P_i(\mathbf{x}_i) \geq 0$ and $R_j(\mathbf{y}_j) - C_j(\mathbf{d}_j) \geq 0$. The buyers and sellers obtain nonnegative utilities by participating in trading. Thus, they are willing to trade.

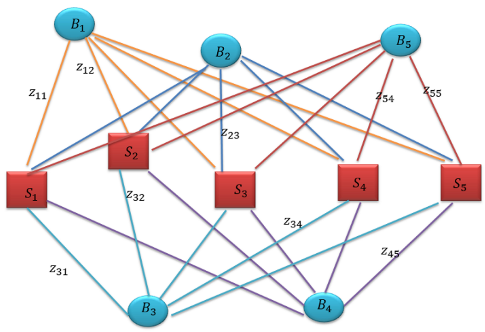

Fig. 2. Computing resource market with five buyers and five sellers.

Algorithm 1: Proposed Algorithm.

Initialize bid matrices $\mathbf{X}$ and $\mathbf{Y}$, $flag \leftarrow 1, T \leftarrow 0$;
while $flag = 1$ **do**
  Buyers and sellers submit bid prices $\mathbf{X}$ and $\mathbf{Y}$ to the broker;
  The broker solves BAP to obtain the optimal allocated amounts $\mathbf{A}$ and $\mathbf{D}$;
  The broker computes $P_i(\mathbf{x}_i)$ and $R_j(\mathbf{y}_j)$ according to (27) and (28);
  The broker announces the optimal allocated amounts $\mathbf{A}$ and $\mathbf{D}$ to buyers and sellers, respectively;
  According to $\mathbf{A}$, buyers compute their optimal bid price $\mathbf{X}$ by solving BMP;
  According to $\mathbf{D}$, lenders compute their optimal bid prices $\mathbf{Y}$ by solving SMP;
  $T = T + 1$.
   Repeat until convergence, i.e., $(x_{ij}^{(T)} - x_{ij}^{(T-1)})/x_{ij}^{(T)} < \xi_1$ and $(y_{ij}^{(T)} - y_{ij}^{(T-1)})/y_{ij}^{(T)} < \xi_2$;
   $flag = 0$;
end while
Output: $\mathbf{A}$, $\mathbf{D}$, $\mathbf{X}$, $\mathbf{Y}$.

4) It is budget balanced. The rewards to the sellers should not exceed the payments from the buyers. This means that the broker will not suffer any loss with the iterative double-sided auction algorithm.

IV. Simulations

In this section, we examine the performance of the proposed algorithm based on the iterative double-sided auction scheme in terms of social welfare maximization. Then, we provide useful decision-making strategies for the ECSPs and IoT devices.

Experimental Setup: The computing resource market is a model of ten participants, where B_i $(i \in \{1, \ldots, 5\})$ is denoted as the buyer and S_j $(j \in \{1, \ldots, 5\})$ is denoted as the seller (see Fig. 2). The parameters in the proposed algorithm are presented in Table I [23]. Every connecting transmission is assumed as a unit distance. The term z_{ij} represents the distance factor between B_i and S_j, which is multiplied by a factor of 0.01, ensuring that z_{ij} is in a reasonable range. Table III presents the complete information of the distance factor. For example, the distance factor between B_1 and S_2 is $0.01 * 6$. In the utility function (1), $a_{ij} * z_{ij}$ represents the transmission loss.

TABLE I
Parameter Settings

Parameters	Values	Parameters	Values
a_i^{min}	[5,10]	a_i^{max}	[10,20]
CRS	[5,10]	d_j^{max}	[10,20]
n_1	[0.005,0.025]	n_2	(0,1]

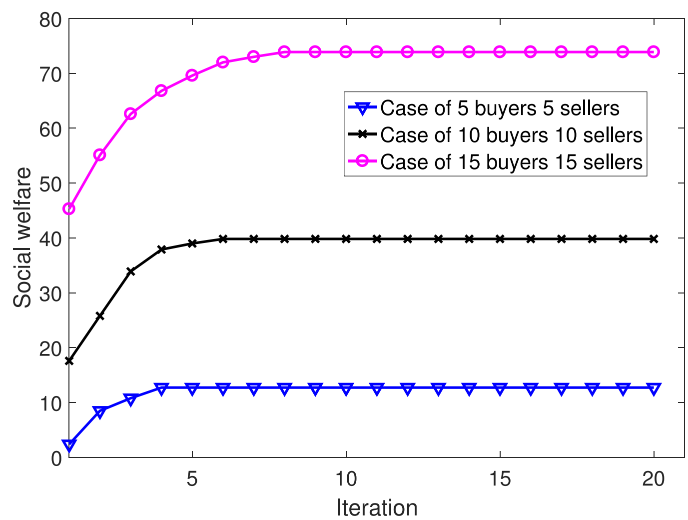

Fig. 3. Social welfare in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers.

Performance Evaluation: We evaluate the proposed algorithm considering three cases with 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers. The social welfare results achieved by the proposed algorithm in the three cases are shown versus iterations in Fig. 3. Each plot was averaged over 100 independent trials. We observe that the social welfare in the three cases increases versus the number of iterations and rapidly converges to the stable value. Furthermore, it is clear to see that higher social welfare results can be achieved with more buyers and more sellers from Fig. 3. In addition, the average iteration numbers until convergence increase slightly with more buyers and more sellers. These experimental results verify that the proposed algorithm is efficient. To evaluate the impact of the CRS before buying, we investigated the proposed algorithm in terms of the social welfare with different values of CRS. Fig. 4 shows social welfare versus CRS values, and it can be seen that social welfare decreases with increasing values of CRS. This is because the larger CRS is, the smaller is the borrowing willingness ω_i and the smaller is the social welfare.

The gap between the total allocated demands and supplies of the computing resource in the three cases is shown in Fig. 5. It is evident that the gap between the allocated demands and supplies finally converges to zero. The results verify that the market can achieve equilibrium by the proposed algorithm with different numbers of buyers and sellers. In other words, the demands of buyers can match the supplies of sellers in the market.

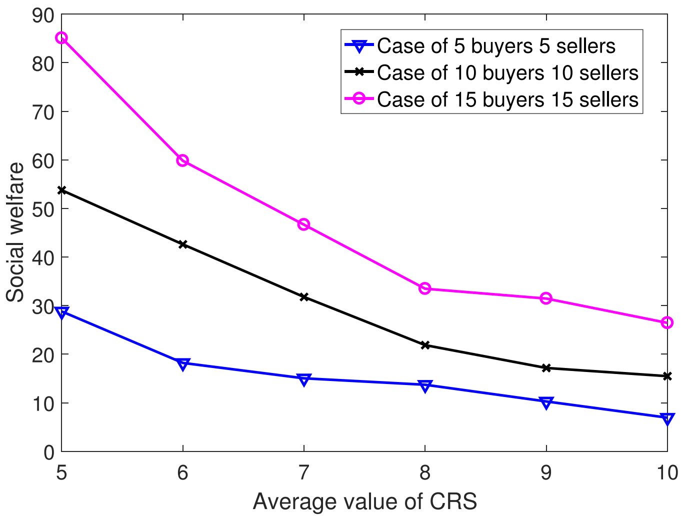

Fig. 4. Social welfare versus the value of CRS in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers.

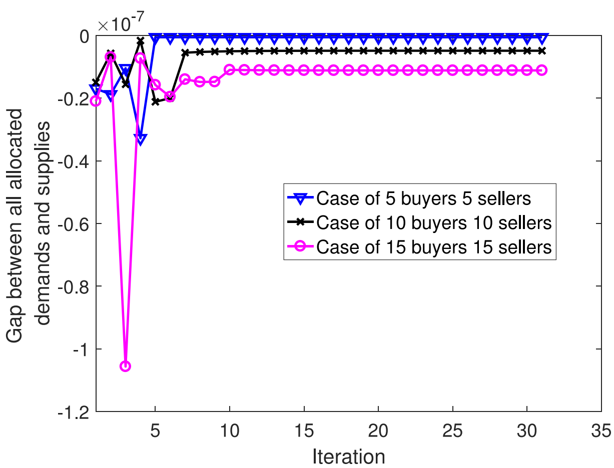

Fig. 5. Gap between the allocated demands and the allocated supplies in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers.

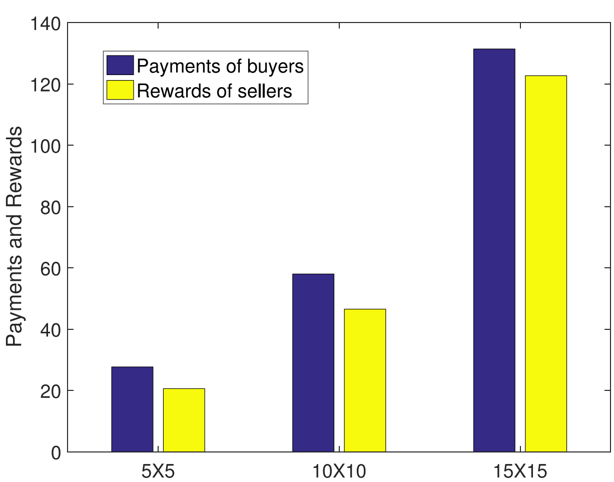

Fig. 6. Payments of all buyers and rewards of all sellers in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers.

TABLE II
COMPARISONS

	SW	Payment	Reward	BM	SM
5×5	12.7321	27.67	20.5895	2.0280	3.6714
10×10	39.8264	57.99	46.5344	10.6078	17.7601
15×15	73.8881	131.40	122.67	17.7765	46.3875

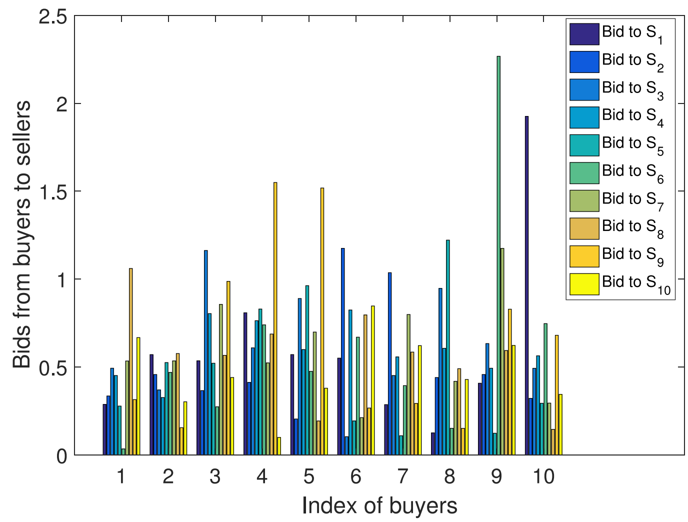

Fig. 7. Bids from ten buyers to ten sellers.

The payments of all buyers and the rewards of all sellers in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers are shown in Fig. 6. Clearly, the payments of all buyers are larger than the rewards of all sellers in each case. The results demonstrate that the broker does not suffer any loss, and moreover, could gain benefit. In other words, the proposed algorithm is budget balanced.

In Table II, we summarized all indexes in the cases of 5 buyers/5 sellers, 10 buyers/10 sellers, and 15 buyers/15 sellers, including the social welfare (SW), the payments, the rewards of all buyers and sellers, the buyers' utilities maximization (BM) and the seller's utilities maximization (SM). According to (3), (25), and (26), we had $\text{BM} + \text{SM} = \text{SW} + \text{Reward} - \text{Payment}$, which also can be verified from the results of Table II.

According to the above Figs. 3–6 and Table II, it can be seen that the proposed algorithm based on the iterative double-sided auction scheme can reveal the private information gradually and obtain optimal solutions, resulting in achieving social welfare maximization. Hence, the proposed algorithm satisfies the property of incentive compatibility.

The individual bids of buyers and sellers for the case of 10 buyers/10 sellers are shown in Figs. 7 and 8. The vertical scale represents the bids and the horizontal scale represents the buyer's index. The color bars in Fig. 7 show the bids from the ten buyers to the ten sellers, while the color bars in Fig. 8 show the bids from the ten sellers to the ten buyers. We note that if a certain seller gives a high bid to a certain buyer, the latter will try to force down the price and give a low bid to that seller. It can be seen that the bid from the seller S_6 to the buyer B_1 is

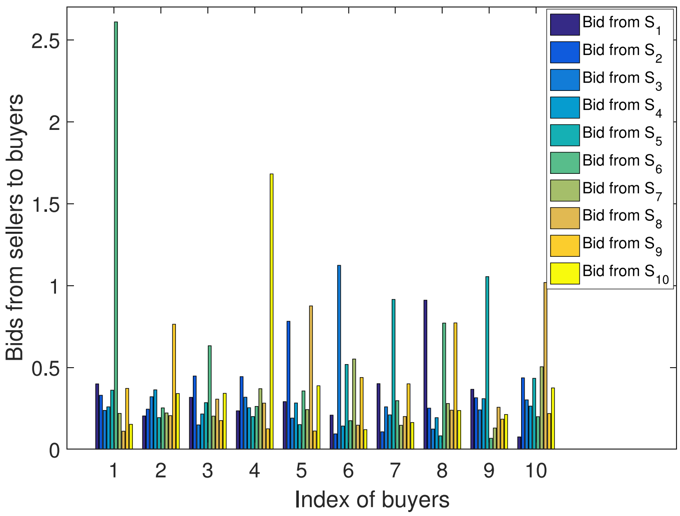

Fig. 8. Bids from ten sellers to ten buyers.

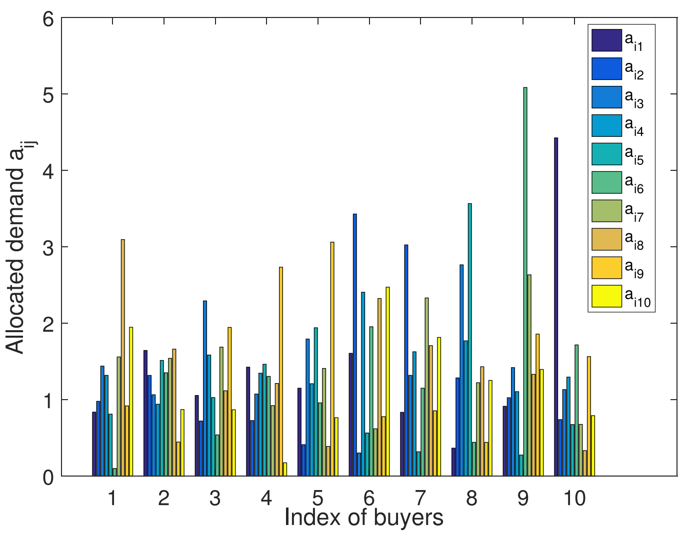

Fig. 9. Allocated demand a_{ij}.

the maximal bid among all bids from other sellers to the buyer B_1 in Fig. 8. Therefore, the buyer B_1 submits the minimum bid to the seller S_6 (see Fig. 7). In turn, if a certain seller submits a low bid to a certain buyer, the latter will try to raise the price and win the trade from this seller. For example, the bid from the seller S_6 to the buyer B_9 is the minimum among all bids to other buyers. Hence, the buyer B_9 submits the maximum bid to the seller S_6 among all bids from other buyers to the seller S_6, so that the buyer B_9 wins the trade with the seller S_6. These results demonstrate that our approach matches the market discipline.

In addition, we studied the relationship between the distance factor and the allocated demands of buyers. Fig. 9 shows the allocated demands of buyers, and Table III presents the distance factor z_{ij} for the case of 10 buyers/10 sellers. We see that the distance factor is larger, and the transmission loss is larger, so the computing resource trading should be decreased and the bids will be decreased. Table III indicates that the distance factor for B_1 to S_6 is longer than that to other sellers, i.e., $z_{16} = 0.09$. The buyer B_1 wants to buy a smaller amount of the computing resource from S_6 than from other sellers, i.e., $a_{16} = 0.1023$ (see Fig. 9), so the corresponding transmission loss is decreased. Furthermore, the bid of the buyer B_1 to S_6 (see Fig. 7) is smaller than that to other sellers, which is submitted based on the buyer's distance factor. In turn, the distance factor for B_9 to S_6 is shorter than that to other sellers, i.e., $z_{96} = 0.01$. The buyer B_9 wants to buy a higher amount of the computing resource from S_6 than from other sellers, i.e., $a_{96} = 5.0871$, and the bid of the buyer B_9 to S_6 is the maximum compared with other sellers. These results match the market discipline well.

TABLE III
DISTANCE FACTOR z_{ij} FOR THE CASE OF 10 BUYERS/10 SELLERS

z_{ij}	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
B_1	0.05	0.06	0.03	0.05	0.05	0.09	0.06	0.02	0.07	0.05
B_2	0.04	0.06	0.07	0.08	0.07	0.05	0.07	0.02	0.08	0.06
B_3	0.06	0.08	0.02	0.07	0.05	0.08	0.04	0.05	0.03	0.04
B_4	0.05	0.07	0.03	0.02	0.07	0.04	0.05	0.03	0.02	0.08
B_5	0.02	0.09	0.08	0.04	0.03	0.03	0.04	0.08	0.02	0.07
B_6	0.04	0.01	0.09	0.02	0.05	0.04	0.08	0.05	0.06	0.03
B_7	0.03	0.02	0.05	0.04	0.08	0.02	0.05	0.03	0.02	0.05
B_8	0.09	0.07	0.03	0.04	0.02	0.03	0.05	0.06	0.08	0.07
B_9	0.08	0.07	0.04	0.03	0.09	0.01	0.03	0.07	0.02	0.04
B_{10}	0.02	0.07	0.08	0.07	0.06	0.08	0.06	0.09	0.07	0.06

V. CONCLUSION

In this paper, we have developed an optimal computing resource allocation based on the iterative double-sided auction scheme for edge-cloud-assisted IoT in blockchain network, where the broker solves the computing resource allocation problem and designs the price rules to extract hidden information from the computing resource sellers and buyers, leading them to be willing to trade and moreover, submitting the bids in a truthful way. Thus, the proposed algorithm can achieve the social welfare maximization meanwhile protecting the private information of the sellers and buyers. From both theoretical analysis and experimental results, we have shown that the proposed algorithm based on an iterative double-sided auction scheme is efficient, has individual rationality, incentive compatibility, and is budget balanced. For future work, we will consider the optimal computing resource allocations for edge-cloud-assisted IoT in blockchain networks based on machine learning, e.g. sparse neural network and deep learning.

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