A Machine-Learning-Based Auction for Resource Trading in Fog Computing

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To achieve the full potential of fog computing, it is essential to design an incentive mechanism for fog computing service providers. Auction is a promising solution for the incentive mechanism design. However, it is challenging to design an optimal auction that maximizes the revenue for the providers while holding important properties: IR and IC.

Abstract

Fog computing is considered to be a key enabling technology for future networks. By broadening the cloud computing services to the network edge, fog computing can support various emerging applications such as IoT, big data, and blockchain with low latency and low bandwidth consumption cost. To achieve the full potential of fog computing, it is essential to design an incentive mechanism for fog computing service providers. Auction is a promising solution for the incentive mechanism design. However, it is challenging to design an optimal auction that maximizes the revenue for the providers while holding important properties: IR and IC. Therefore, this article introduces the design of an optimal auction based on deep learning for the resource allocation in fog computing. The proposed optimal auction is developed specifically to support blockchain applications. In particular, we first discuss resource management issues in fog computing. Second, we review economic and pricing models for resource management in fog computing. Third, we introduce fog computing and blockchain. Fourth, we present how to design the optimal auction by using deep learning for the fog resource allocation in the blockchain network. Simulation results demonstrate that the proposed scheme outperforms the baseline scheme (i.e., the greedy algorithm) in terms of revenue, and IC and IR violations. Thus, the proposed scheme can be used as a useful tool for the optimal resource allocation in general fog networks.

Introduction

Cloud computing is becoming a choice for a number of applications [1] due to the advantages of high computing power and flexible on-demand services. However, it has a shortcoming in supporting emerging applications that require low latency and mobility support. A new paradigm, called *fog computing* [2], has been introduced to meet the requirements. Fog computing leverages resources of *fog* nodes at the edge of the network to provide computing, storage, and offloading services. Since fog nodes are located closer to end users, fog computing is able to achieve low latency, low bandwidth cost, flexibility, and mobility. It is thus expected to support various real-time applications such as the Internet of Things (IoT), big data, and blockchain [3]. Among emerging applications, the mobile blockchain network is the most promising. Indeed, blockchain has gained enormous popularity in business, government, and academia. However, deploying blockchain in mobile environments faces critical challenges due to the mining process, that is, solving the proof-of-work (PoW) puzzle, which requires high computing power and energy. Fog computing appears to be a suitable solution that enables the mining tasks to be offloaded to fog providers.

However, resource management in fog computing has many challenges. In particular, fog computing is offered or sold by a rational service provider that aims to maximize its own revenue. Thus, one critical issue is how to incentivize the provider to sell fog resources while guaranteeing the user quality of service (QoS). Moreover, the fog computing capacity is limited, and how to efficiently allocate the limited fog resources to the users (i.e., miners in blockchain) is another important issue.

To address the above issues, forward auction is considered to be an efficient solution that guarantees a revenue gain for the provider by allocating resources to the users who value the resources most [3]. In traditional auctions, bidders compete for resource units by submitting their prices (i.e., bids) to the provider (i.e., the seller). Given the bids, the provider selects the bidders with the highest bids as the winners, and determines the prices that the winners pay. However, the existing auctions are not optimal in terms of maximizing the revenue for the provider and ensuring desired economic properties, that is, incentive compatibility (IC) and individual rationality (IR). In particular, IR guarantees that participants have a non-negative utility when participating in the auction, and IC ensures that a participant receives the highest utility by submitting its truthful bid or ask. The optimal auction is actually a constrained optimization problem that is difficult to solve with traditional algorithms.

In recent years, machine learning has gained considerable attention. Machine learning using stochastic gradient descent can successfully find globally optimal solutions for complex problems (e.g., the constrained optimization problem).

Digital Object Identifier:
10.1109/MCOM.001.1900136

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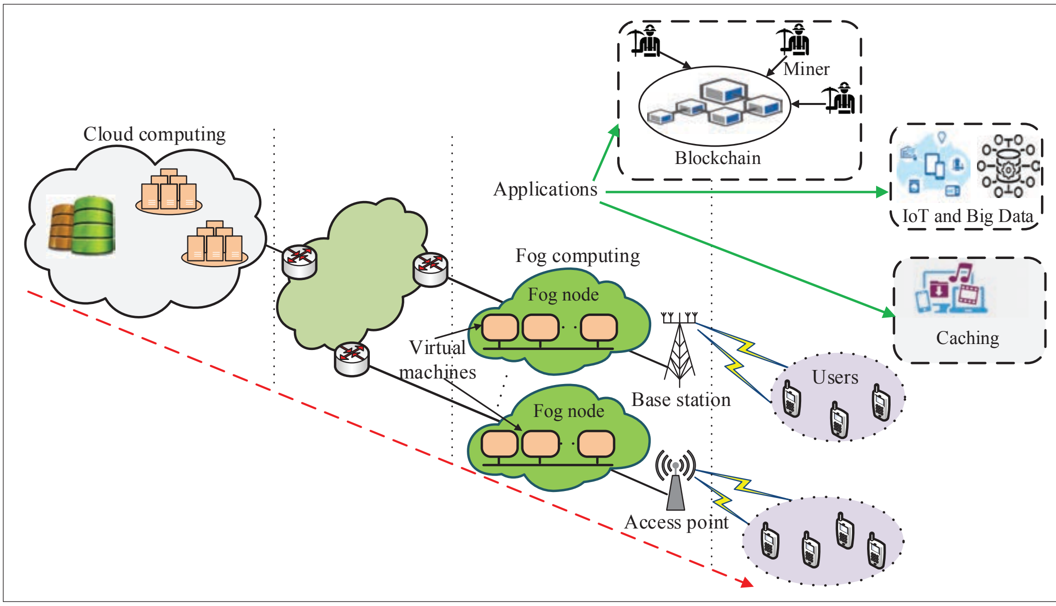

Figure 1. Fog computing environment. The dashed arrow indicates layers closer to users.

Due to being located at the edge of network, fog computing changes the way that we deliver services to users and inspires new business models. For the service delivery, fog computing reduces the service latency due to the use of local fog nodes. Also, without consuming the backbone bandwidth, offloading to the fog nodes is much cheaper than that to the cloud.

Therefore, machine learning is employed to derive the optimal auction, as proposed in [4].

In this article, we thus use the machine learning approach in [4] for the fog resource allocation. We first overview fog computing and review the literature on fog resource management with a special focus on economic approaches. Then we present a brief background of blockchain. Next, we propose an auction-based mechanism for fog resource allocation. We also incorporate specific requirements of blockchain applications in the auction mechanism design in which the solution can be obtained from a deep learning model. The performance evaluation clearly shows the merit of the auction and its applicability to fog resource allocation with blockchain applications.

Economic and Pricing Models in Fog Computing

In this section, we first introduce fog computing. Then we discuss its resource management issues, and review economic and pricing models for the resource management.

Fog Computing and Applications

Fog computing is an extension of cloud computing that broadens the scope of cloud computing services to the edge of networks by deploying fog nodes between the cloud and users (Fig. 1). A fog node is a small to medium-sized computing unit (e.g., an embedded server), which includes computing, storage, and networking elements. Fog nodes are located close to users and can be connected to a central cloud. When resources at the fog layer are not enough for a redundancy deployment, redundancy offloading to the cloud is used to enhance service reliability. Fog computing keeps computing resource at the edge of the network to support latency-sensitive applications and services. It also supports edge analytics and stream mining by processing data volume at a very early stage, which reduces delay and saves bandwidth significantly. Furthermore, fog computing supports mobility well since the geo-distributed fog node is able to infer its own location and track end users. To provide computing services, fog resources are deployed on top of fog nodes and accessed by users over networks. Fog computing can support emerging applications:

- *Big data analytics:* Fog computing provides an effective solution to real-time data analytics.
- *Content delivery and caching:* Fog nodes cache web and video contents from the cloud and then deliver replicas of the contents to users with shorter response time.
- *Blockchain networks:* Fog nodes can offload computing tasks from low-computation devices in blockchain networks and guarantee lower delay in the communication between the devices and fog nodes.

Resource Management in Fog Computing

Due to being located at the edge of the network, fog computing changes the way we deliver services to users and inspires new business models. For service delivery, fog computing reduces the service latency due to the use of local fog nodes. Also, without consuming the backbone bandwidth, offloading to fog nodes is much cheaper than that to the cloud. Moreover, fog computing enhances data security for users since data does not go out of local networks. For business models, fog computing liberates the cloud market by introducing more providers. However, this makes the resource management in fog computing challenging. As fog providers are rational, the critical issue is how to incentivize them to contribute fog resources and cooperate with each other to guarantee the users' quality of service (QoS). Traditional approaches (e.g.,, optimization methods [5]) can be used. However, they are not suitable for fog computing with multiple stakeholders in the networks. Incentive mechanisms using economic and pricing models should be adopted to guarantee a stable scale of participants and the users' QoS.

The optimization problem for the agent is formulated to determine renting prices paid to the providers and service prices offered to the users to maximize the agent's profit. The profit is defined based on probability distributions of service price acceptance by the users and those of renting price acceptance by the providers. The problem is then solved by a sequential optimization algorithm.

Economic and Pricing Models for Resource Management in Fog Computing

Profit Maximization: This approach aims at determining resource prices that lead to the greatest profit for sellers. It can be used to motivate providers and intermediate agents (i.e., brokers [1]) to participate in the fog resource market. Such an approach is found in [6], where the agent rents fog resources from the providers to serve computing service requests from the users (i.e., the buyers). The optimization problem for the agent is formulated to determine renting prices paid to the providers and service prices offered to the users to maximize the agent's profit. The profit is defined based on probability distributions of service price acceptance by users and those of renting price acceptance by providers. The problem is then solved by a sequential optimization algorithm.

Combinatorial Auction: The approach proposed in [6] aims to maximize the profit of the agent, but it does not guarantee IR, which may discourage users from participating in the market. To guarantee IR, the authors in [7] introduced the use of the combinatorial auction for the fog resource trading. The model consists of one provider (ie., the auctioneer) and multiple mobile users (bidders) as the miners in a blockchain mobile network. The provider provides fog resource units to the miners to offload their mining tasks. The miners submit their bids to the provider. The problem is to determine the winners of the fog resources and the prices that the winners need to pay the provider. The objective is to maximize social welfare while guaranteeing IR and IC. The social welfare is defined as the sum of utilities of the users. The definition aims to motivate users to participate in the market. The greedy algorithm and the payment policy of the Vicrkey-Clarke-Goves (VCG) mechanism are adopted to solve the problem. However, improving the revenue of the provider is not considered in the proposed approach.

Optimal Auction: To maximize the revenue of the provider while guaranteeing IR and IC, the authors in [3] designed an optimal auction based on deep learning. The model in [3] is similar to that in [7], but there is only a single fog resource unit. The miners submit bids to the provider. The provider determines the winning probabilities of the miners and the payments for the miners. The allocation and payment rules are implemented by using neural networks. The neural networks are constructed based on an analytical solution of the optimal auction [4]. Therefore, the proposed auction is optimal in terms of maximizing the revenue while ensuring IR and IC. However, the proposed auction is constrained to a single fog unit. Moreover, the characterization results of the analytical solution are required to construct the neural networks.

The approaches proposed in [3, 4] motivate us to investigate an optimal auction by using deep learning for trading multiple fog resource units in the mobile blockchain network. The deep learning is constructed without using any characterization results.

Fog Computing for Blockchain

Decentralized applications (DApps) based on the blockchain network have emerged explosively in recent years [8]. Some examples are seen in crowdfunding and sharing economy. The success of DApps contributes to the distinct advantages of blockchain:

- *Decentralization:* Without a trusted third party or intermediary, blockchain ensures the validity of recorded transactions. This also largely reduces overhead and cost.
- *Immutability:* By using sophisticated cryptographical methods, it is almost impossible or too costly to tamper with the transactional data in blockchain.
- *Transparency and trust:* Public blockchains can offer full transparency of transactions while guaranteeing each user node's privacy through pseudonymity.

In the form of a chain of blocks, blockchain is actually a tamper-proof, distributed database or ledger that records transactional data in a decentralized peer-to-peer (P2P) network. The above advantages stem from a consensus process, which is the core part of the blockchain technology. We discuss a blockchain network that operates with the PoW protocol [8]. There are two types of member nodes that jointly use and maintain the distributed database according to the PoW protocol: consensus nodes or miners, and user nodes. The miners are required to complete the transaction validation and the block mining task. Specifically, each miner first collects new transactions received from user nodes and broadcasts the transactions to the other miners. Each miner aggregates a set of transactions into a block. Then the miners find a nonce value and add it into the block such that the hash value of the block is below a preset threshold. The process is known as *mining*. Once the nonce value is found, the corresponding miner broadcasts its successfully mined block to the whole network. The miners that receive the block verify the block. If the majority of the miners agree that all transactions in the block are valid, the block is linked to their chains. Every miner must have the same chain. The consistency of the transactions and the chains among the miners is guaranteed by using *data synchronization protocols*, for example, Bitcoin Developer application programming interfaces (APIs). The miner that finds the block obtains a reward including a fixed bonus and a transaction fee. When the difficulty of mining increases, the miners can pool their resources to find the block. The mining in this case is considered to be *parallel processing* in which each miner in the pool uses its computing resources to find the nonce.

Finding the PoW solution to complete the consensus process is critical to guarantee the security and trustworthiness of the blockchain network (i.e., to prevent Sybil attacks). In general, the mining task is computing-ntensive, and computationally lightweight nodes (e.g., IoT devices) cannot directly participate in the consensus process. However, the nodes can share the mining task with fog nodes in fog computing. As such, more nodes can easily join the consensus process as miners, which significantly improves the robustness of the blockchain network. To a great extent,

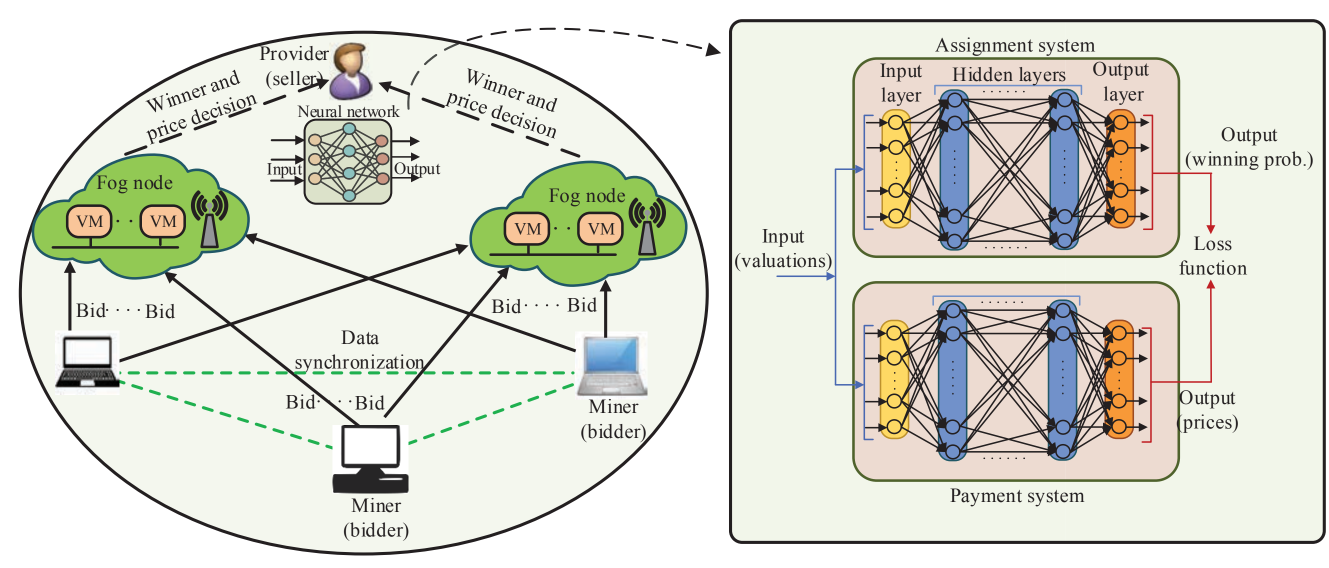

Figure 2. Fog computing for blockchain networks.

fog computing popularizes blockchain and widens the scope of blockchain-based applications.

Optimal Auction Using Deep Learning for Fog Resource Market

Auction, that is, a centralized approach, can be applied since we only consider a local fog network that guarantees a low delay of the consensus process in the blockchain network (Fig. 2) to support proximity-based mobile services. The objective is to guarantee that the auction can optimize the revenue for the provider while guaranteeing IR and IC [4]. First, we introduce the fog resource market and auction. Second, we present two neural networks used for the assignment and payment decisions. Third, we discuss the training of these neural networks. Finally, we present the numerical results.

Fog Computing Resource Market

The fog resource market consists of one provider and multiple miners. The miners are assumed to be lightweight devices, and the provider deploys fog nodes across the blockchain network to provide nearby computing resource units to the miners. Each miner purchases one or multiple computing resource units at the fog nodes to support solving PoW puzzles. Here, solving the PoW has to calculate a value that makes the header hash value lower than a given "difficulty target." Note that each fog node has a limited number of computing resource units. In the case where the resource demand exceeds the resource availability, the fog node can share its mining task to the cloud to offload the PoW puzzle. Optimal links are used between the fog computing and the cloud to minimize the offloading service latency. The provider conducts a multi-item forward auction for trading resource units. The auction model is illustrated in Fig. 2 in which the provider is the auctioneer, and the miners are the bidders. Each miner submits bids, that is, the prices that the miner is willing to pay the provider for the resource units. The provider chooses a fog node to maintain the blockchain if the fog node has sufficient computing resource units and is located close to the winner. Without exact knowledge about miners, the provider resorts to deep learning to determine the winners and prices to maximize the revenue and guarantee the IR and IC. For this purpose, the deep learning system is trained based on training data that is constructed from valuations of fog resource units to the miners. The provider estimates the valuation of a fog unit to each miner by using [7, Eq. 1]. The valuation is proportional to the fixed reward for mining a new block, the transaction fee, the size of the block, and the factor that reflects the impact of the size of block on the miner's block propagation time, and inversely proportional to the average time of mining a block. Note that the size of the block is privately chosen by the miners, but the provider can know its probability distribution, for example, by observation. Other parameters are public on the network.

Neural Networks for Auction

This section discusses the use of feed-forward neural networks (FFNs) to derive the optimal auction. The FFN fits for our setting since it is able to map in only one direction from the input (the miners' valuations) to the output (the assignment and price decisions) [4]. As shown in Fig. 2, the NN includes one input layer, multiple hidden layers, and one output layer. Each layer consists of a number of neural nodes that use activation functions (e.g., sigmoid) to capture the potential relations among input variables. The neural nodes are connected with each other through *weights*, which are interpreted as the strength of connections among the neural nodes. The weights imply how much the output changes as the input varies. Since the output in our setting is either the assignment probabilities or price decisions, there are two corresponding deep learning systems: the assignment and payment systems.

The assignment system uses an FFN to select the winners for fog resource units. In Fig. 2, the input layer receives valuations of the miners. The hidden layers use sigmoid activation functions that transform the valuations of the input to the

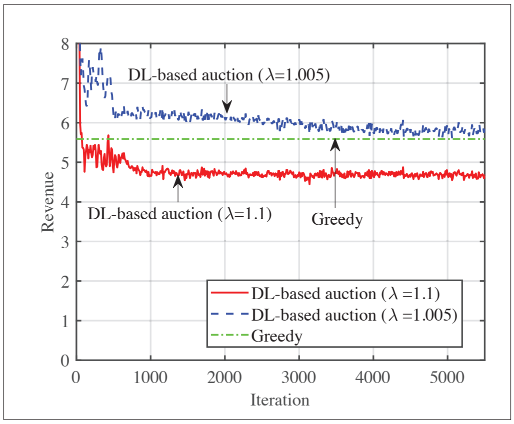

Figure 3. Revenue comparison.

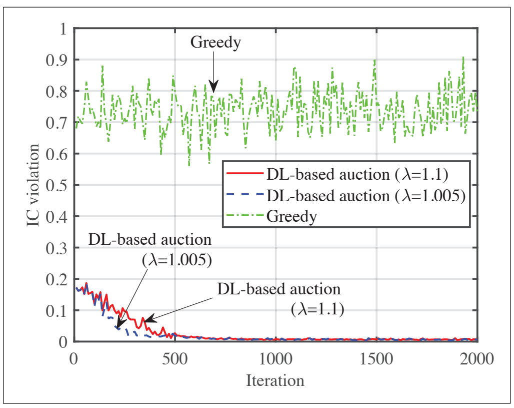

Figure 4. IC violation comparison.

output layer. There may be multiple miners competing for each resource unit. Thus, the output layer uses softmax functions to produce the winning probabilities of the miners. The output of the assignment system is a vector in which each element refers to the probability that a miner wins a resource unit. Note that each miner can win more than one computing resource unit.

Similar to the assignment system, the payment system also uses an FFN. However, the output layer includes the prices that each miner pays the provider if it wins resource units. The prices must be non-negative, that is, zero or positive, real numbers, and thus the output layer uses rectifier activation functions.

Note that two FNNs in the assignment and payment systems use the common input, that is, the valuations of the miners. The outputs of the FNNs are used to calculate a common loss function. The loss function is constructed with the following components [4]:

- *Expected revenue:* The expected revenue is the sum of prices that the miners pay the provider.
- *IR violation:* An IR violation happens if the auction results in negative utility for any miner (i.e., the end user). The utility of each miner is proportional to probabilities that the miner wins fog units and the valuations of the fog units, and inversely proportional to the total price that the miner pays the provider. We want to design the auction with the smallest, preferably zero, IR violation.
- *IC violation:* IC of the auction guarantees that every bidder achieves the highest utility just by submitting its truthful bid. Then the IC violation is defined as the maximum gain in utility that the miner can receive if the miner submits an untruthful bid knowing the bids of others [4]. Thus, the IC violation is expected to be zero such that the miner has no incentive to submit a non-truthful bid.

Neural Network Training

Loss Function: We need to define a common loss function for the assignment and payment systems. In the optimal auction design, the revenue function is the objective function, and the IR and IC violations are the constraints. The augmented Lagrangian method [9] is used to formulate the common loss function since it allows the constraints to be enforced through weighted terms in the objective. Since the training process aims to maximize the revenue and minimize the IR and IC violations, the common loss function is proportional to the IR and IC violations and inversely proportional to the expected revenue. Denote $\hat{J}(v, w^g, w^p)$ as the common loss function, where v is the vector including valuations of the miners, and w^g and w^p are the matrices that contain all weights of the NN in the assignment system and the payment system, respectively. Also, let λ_i and λ'_i denote the Lagrange multipliers associated with the corresponding constraints. Note that the loss function is defined as a function of the input (i.e., the valuations of the miners) without the learning target. Thus, the learning algorithm is unsupervised learning.

Training Phase: The training phase uses a dataset to find weights (w^g, w^p) that minimize loss function $\hat{J}(v, w^g, w^p)$. The dataset of both NNs includes bidder valuation profiles of the miners. Each profile is a vector of valuations of fog resource units to the miners. Given each valuation profile, the assignment system and payment system calculate the winning probabilities and corresponding prices of the miners, respectively. Then the training algorithm determines the expected revenue, the IR and IC violations, and the loss function. The training algorithm adjusts the weights of the systems until the loss function converges.

Numerical Examples

In this section, we provide experimental results to demonstrate that deep learning can be used for the optimal auction in fog computing to support blockchain networks. For convenience, the proposed scheme is named deep learning (DL)-based auction. The baseline scheme is the greedy algorithm [10] in which the provider lists the miners in descending order of their bids, and iteratively selects the miners with the highest bids as the winners. The greedy algorithm is used since it aims to improve the provider's revenue. It is especially suitable to the scenario with multiple fog resource units, while well-known auctions such as the first-price sealed-bid auction is not.

The DL-based auction is implemented by using the TensorFlow library [3]. The DL model has 2 hidden layers, and the number of neural nodes in each hidden layer is 20 [4]. To ensure that the training phase does not miss local minima, the learning rate is set low: 0.001. However, this may slow down the training progress. To achieve fast and smooth convergence, we use the Adam optimizer in the training. The training data consists of 5000 valuation profiles of the miners. For ease of presenting the findings, we consider a blockchain network with five miners and three resource units in the fog computing system. The valuations of fog resource units to each miner are determined depending on the blockchain parameters, which are set as follows. The average time of mining the block is 600 s, and the fixed reward for mining the block is 2. The transaction fee is 0.007. The size of the block is assumed to follow a uniform distribution between 0 and 500. The factor that reflects the impact of the size of block on the miner's block propagation time is set to 1. Note that the Lagrange multipliers, λ_i and λ'_i, are considered to be trade-off parameters in the loss function. To enable the fairness between the IR and IC constraints, we set $\lambda_i = \lambda'_i = \lambda$.

We compare the performance between the DL-based auction and the greedy scheme in terms of expected revenue, and IR and IC violations. The simulation results for the revenue vs. iterations are shown in Fig. 3, and those for the IC and IR violations vs. iterations are illustrated in Figs. 4 and 5, respectively.

As shown in Fig 3, the DL-based auction is able to converge quickly to the revenue value which is higher than that obtained by the greedy scheme. In particular, for $\lambda = 1.005$, the revenue obtained by the DL-based auction is 5.75, while that obtained by the greedy scheme is 5.58. Note that as the value of λ is set to be higher, $\lambda = 1.1$, the revenue obtained by the DL-based auction decreases. The reason is that the value of λ reflects the trade-off between the revenue objective and the IC and IR violations. By increasing λ, minimizing the IC and IR violations is prioritized over improving the revenue.

Next, we evaluate the performance in terms of IC violation. As shown in Fig. 4, the IC violation of the greedy scheme is around 0.77, while those of the DL-based auction are close to zero regardless of the values of λ. Clearly, the IC violation of the DL-based auction is much lower than that of the greedy scheme. Recall that the IC violation close to zero means that the truthfulness is guaranteed. Therefore, the DL-based auction outperforms the greedy scheme in terms of guaranteeing the truthfulness.

Finally, we evaluate the performance in terms of IR violation. As shown in Fig. 5, the IR violation of the greedy scheme is around 3.2, while those of the DL-based auction reach 0.09 and 0.3 for $\lambda = 1.1$ and $\lambda = 1.005$, respectively. Apparently, the IR violation of our proposed scheme is much lower than that of the greedy scheme. Note that the small value of IR violation means that the utilities of the miners have a lower chance of being negative, and thus the miners have more incentive to participate in the auction (i.e., the IR is guaranteed).

From Figs. 4 and 5, it is also worth noting that the IR violation of the DL-based auction is more sensitive to the change of trade-off parameter λ compared to the IC violation. The reason is the definitions of the revenue and the IR violation. Both revenue and IR violation are proportional to the prices that the provider receives from the

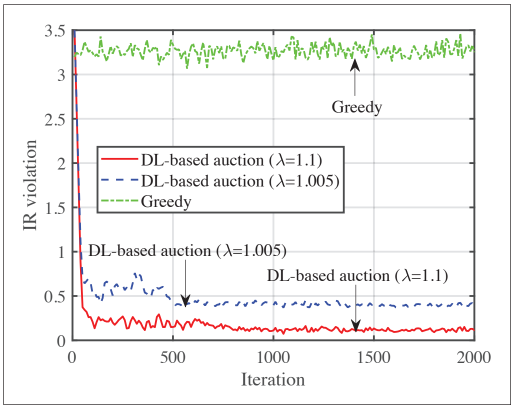

Figure 5. IR violation comparison.

miners. While we change the trade-off parameter to increase the prices (improving the revenue), the IR violation also increases. This may offer the miners less incentive to participate in the auction. Therefore, choosing the trade-off parameter to guarantee an acceptable IR violation is important.

Conclusion and Future Directions

In this article, we have developed an optimal auction using deep learning for fog resource allocation in blockchain networks. We have constructed assignment and payment systems for the auction using neural networks. The assignment system outputs assignment probabilities of miners, and the payment system outputs corresponding prices. We have presented how to formulate the loss function for the neural networks and to train the neural networks. The simulation results demonstrate the effectiveness of our proposal, which clearly outperforms the baseline approach. The proposal is scalable when the number of miners increases. One future research direction can be designing the optimal auction in terms of maximizing social welfare and guaranteeing the IR, IC, and fairness. Also, the general scenario of multiple providers needs to be investigated. Moreover, the dynamics of the fog system, that is, the arrival and departure of the devices as well as the appearance and disappearance of resources, should be studied.

Acknowledgments

This work was supported in part by Singapore NRF National Satellite of Excellence, Design Science and Technology for Secure Critical Infrastructure NSoE DeST-SCI2019-0007, A*STAR-NTU-SUTD Joint Research Grant Call on Artificial Intelligence for the Future of Manufacturing RGANS1906, WASP/NTU M4082187 (4080), Singapore MOE Tier 1 2017-T1-002-007 RG122/17, MOE Tier 2 MOE2014-T2-2-015 ARC4/15, Singapore NRF2015-NRF-ISF001-2277, Singapore EMA Energy Resilience NRF2017EWT-EP003-041, and in part by a National Research Foundation of Korea Grant funded by the Korean Government (MSIT) under Grant 2014R1A5A1011478.

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