electronics

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A Resource Allocation Scheme with the Best Revenue in the Computing Power Network

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Abstract: The emergence of computing power networks has improved the flexibility of resource scheduling. Considering the current trading scenario of computing power and network resources, most resources are no longer subject to change after being allocated to users until the end of the lease. However, this practice often leads to idle resources during resource usage. To optimize resource allocation, a trading mechanism is needed to encourage users to sell their idle resources. The Myerson auction mechanism precisely aims to maximize the seller's benefits. Therefore, we propose a resource allocation scheme based on the Myerson auction. In the scenario of the same user bidding distribution, we first combine the Myerson auction with Hyperledger Fabric by introducing a reserved price, which creates conditions for the application of blockchain in auction scenarios. Regarding different user bidding distributions, we propose a Myerson auction network model based on clustering algorithms, which makes the auction adaptable to more complex scenarios. The experimental findings show that the revenue generated by the auction model in both scenarios is significantly higher than that of the traditional sealed bid second-price auction, and can approach the expected revenue in the real Myerson auction scenario.

Keywords: resource allocation; auction mechanism; blockchain; deep learning; clustering algorithm

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Citation: Wang, Z.; Yu, Y.; Liu, D.; Li, W.; Xiong, A.; Song, Y. A Resource Allocation Scheme with the Best Revenue in the Computing Power Network. *Electronics* **2023**, *12*, 1990. https://doi.org/10.3390/electronics12091990

Academic Editor: Mehdi Sookhak

Received: 28 March 2023
Revised: 16 April 2023
Accepted: 21 April 2023
Published: 25 April 2023

1. Introduction

In the era of a rapidly developing digital economy, and with the rapid development of artificial intelligence technology, efficient computing power will gradually become a key factor supporting the development of intelligent society [1]. In order to achieve efficient computing power, a new "computing+network" deeply integrated network architecture is needed to achieve high throughput, and agile connectivity from data to computing power [2]. To further deepen the integration of computing power and network, the China Information and Communication Research Institute opened the research and exploration of computing power networks. The computing power network is a new type of information infrastructure that is distributed and flexibly scheduled to calculate storage resources and network resources according to actual needs [3]. Through the deep integration technology of "computing+network", using their own network service capabilities and idle resources, operators can provide cloud service users with universal artificial intelligence computing capabilities that integrate the cloud and network [4,5]. Therefore, the main research focus of this article is on how to improve the utilization rate of idle resources in the context of computing power networks, in order to further enhance their service capability.

Considering that the current common resource allocation schemes are typically completed at the beginning of user transactions, idle resources generated during user usage cannot be reused [6], thereby reducing overall resource utilization efficiency. This is particularly evident in scenarios where network resources are allocated, where natural fluctuations in traffic result in a very low average utilization rate. To address these issues, this article proposes an auction-based trading scheme that encourages users to sell their idle computing and network resources, thereby improving overall resource utilization efficiency. It should be noted that current algorithmic resource auction research aims to maximize resource utilization while increasing revenue [7,8]. However, in practical applications, users only focus on the revenue brought by the transaction, which is in line with the goal of the Myerson auction [9]. Compared to the English auction, the Myerson auction can effectively avoid malicious competition; compared to the Dutch auction, its auction cycle is shorter; the Myerson auction aims to maximize the seller's revenue, which is consistent with the auction scenario presented in this article. Therefore, this article aims to design a reasonable auction model based on the Myerson auction to maximize user revenue. Specifically, the main innovations and contributions of this article can be summarized as follows:

1. In this article, Myerson auction is introduced into the computing network resource transaction for the first time, and a set of computing network resource auction mechanism for complex bidding distribution scenarios is designed. The auction aims to maximize the expected income of the resource suppliers.
2. Under the same scenario of user bidding distribution, we combine the Myerson auction with a smart contract for the first time. Through the introduction of reserved price, the separation of the auction network model and auction transaction model is realized, creating conditions for the introduction of Hyperledger Fabric [10] in the auction mechanism.
3. Under the different scenarios of user bidding distribution, we propose an auction network model based on KL divergence classification, so that the auction mechanism can be extended to the scenario of mixed bidding distribution. Compared with the existing auction network model, this model is less affected by the number of users and the distribution of bids, and the effect of improving revenue is more obvious.

The rest of this article is organized as follows. We introduce the related work in Section 2, and present the system framework and auction process in Section 3. Section 4 describes the optimal auction design under identical bidding distribution. In Section 5, the optimal auction scheme under mixed bidding distribution is proposed, and performance evaluation is conducted in Section 6. Finally, we summarize this article in Section 7.

2. Related Work

Currently, research and application of auctions for computing power and network resources have become relatively mature. In [11], the author proposes a real auction mechanism for resource allocation in mobile edge computing to formulate resource allocation strategies with the goal of optimizing social welfare. In [12], the author proposes a bandwidth trading platform based on blockchain, and users can use an auction to sell their excess bandwidth. In [13], the author proposes an auction of cloud bandwidth resources based on the combination auction mechanism. In [14], in addition to single-resource-type auctions, cloud containers are also used to bundle various types of resources together for batch auctions, in order to ensure a flexible supply of resources and achieve the goal of maximizing social welfare. As mentioned above, the research on computing power and network resource auctions aims to maximize social welfare. However, in the computing power network transaction scenario, users who sell idle resources pay more attention to the revenue generated by the auction, rather than maximizing social welfare.

Only by designing a maximized auction plan can we motivate more and more users to contribute their own idle resources, thereby increasing the overall utilization rate of resources. Research has been conducted in the power and communication fields to improve the income of sellers. In [15], the author proposes an auction plan that can maximize income by learning an auction method that motivates and exhibits compatibility. In [16,17], the author proposes to build auction models through neural networks to improve wireless resources and the benefits of power resource suppliers. However, the auction network model proposed in this article is greatly affected by factors such as user bidding distribution and the number of bid users.

In addition to the appropriate trading mechanism during the distribution of computing power resources, security issues also need to be overcome [18]. Considering that blockchain technology has the characteristics of tampering and decentralization [19], there are already a large number of works combining blockchain technology with resource transactions [20].

3. Auction Systems Based on Hyperledger Fabric

3.1. Auction System Framework

We have considered a simple auction system framework based on Hyperledger Fabric, as shown in Figure 1. Organizations are created by different service providers. Each organization contains two peer nodes, and an additional order node is provided to sort transactions.

Take organization Org_1 as an example, the organization registers $Peer_1^1$ nodes, which can submit transactions to clients and help the order node to distribute transactions. In addition, Org_1 needs to register an endorsement node $Peer_1^2$ to verify the legitimacy of the transaction. During the auction process, Org_1 and Org_2 can create channel C1 for joint auction. In addition, a certificate authority (CA) is built in Org_1. The bidder needs to register through Fabric CA to obtain the identity certificate issued by the organization. The user who obtains the certificate can call the chain code through the client node to complete bidding.

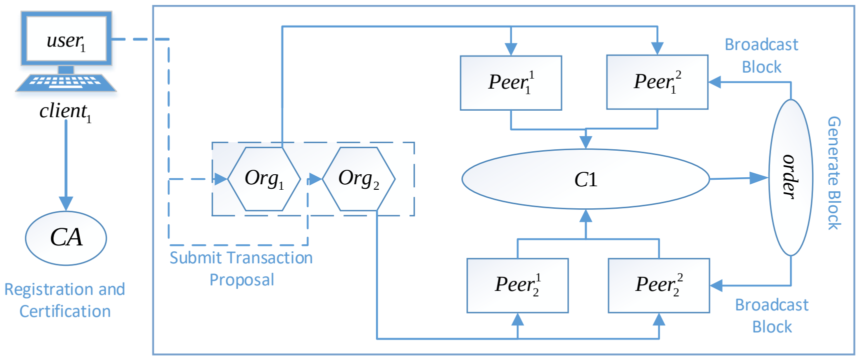

Figure 1. Model of an auction system.

3.2. Auction Process Design

3.2.1. Data Collection

As the auction mechanism is inspired by the Myerson auction, which aims to maximize the seller's revenue, the auction system needs to obtain the user's estimated value distribution for resources. The sealed-bid second-price auction (SPA) can help the system complete this task. In SPA, the highest bidder wins the auction and pays the second-highest bid price. In the single-item auction scenario, SPA and the Myerson auction are quite similar, both with Incentive Compatibility (IC) and Individual Rationality (IR) properties. They can ensure that honest bidding is the best choice for the current bidder regardless of how other bidders bid and that bidders do not pay more than their estimated value for the product in the auction. In the scenario where user bidding is independently and identically distributed, the Myerson auction can be viewed as a sealed-bid second-price auction with a transaction reserved price. Although SPA has good properties and is easy to implement, it is not aimed at increasing profit, but rather at maximizing social welfare. This is obviously unreasonable for a seller-dominated resource trading market, so SPA can only be used as an auction mechanism for data collection.

Considering that regardless of which auction method is used, user bidding is determined by the estimated value of the auction item, the change in the auction mechanism will not affect the user's actual bidding price. Therefore, the auction system can sacrifice some revenue to obtain the user's real bidding distribution. After obtaining the user's bidding distribution, the Myerson auction mechanism can be used to improve the expected revenue of resource providers.

3.2.2. Sealed Bidding

In order to ensure that user transaction information is not leaked during the auction process, we divide the bidding process into two stages: sealed bidding and transaction confirmation. In the sealed bidding stage, users submit the hash value corresponding to their actual bid value. After the bidder finds the current round of bidding information in the ledger, they enter the transaction confirmation stage. In the transaction confirmation stage, users submit their actual bidding price, and the endorsement node confirms the legality of the corresponding transaction, including whether the bidder's actual bid price hash value is equal to the sealed bid hash value and whether the bidder has the ability to pay.

3.2.3. Integrated Trading of Computing Power and Network Resources

During the formal auction stage, users with idle resources may transfer those resources to the service provider for auction. Network resources can be valued based on stability and packet loss rate, while computing power resources can be valued based on MIPS and FLOPS. To motivate users to sell their idle resources, the Myerson auction algorithm is introduced in the current auction scenario. This algorithm maximizes the expected revenue of resource suppliers when the user bidding distribution is known. The virtual valuation function is the core of the Myerson auction algorithm and is defined as follows.

$$\varphi(v_i) = v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} \tag{1}$$

where v_i represents the actual bid valuation of user i, $F_i(v_i)$ and $f_i(v_i)$ represent the distribution function and probability density function of the user valuation. It should be noted that the auction model is not fixed. As the distribution of user bids changes, the criteria for determining payment prices in the auction model will also be adjusted accordingly. In the next section, we will introduce how to design the auction model based on neural networks and the Myerson auction mechanism. After the auction is over, the final transaction results will still be recorded by the super ledger, and the corresponding fees will be deducted from the account of the winning user. The resource providers need to update the resource status based on the transaction results. Thus, the auction ends, and the process of sealed bidding is shown in Figure 2.

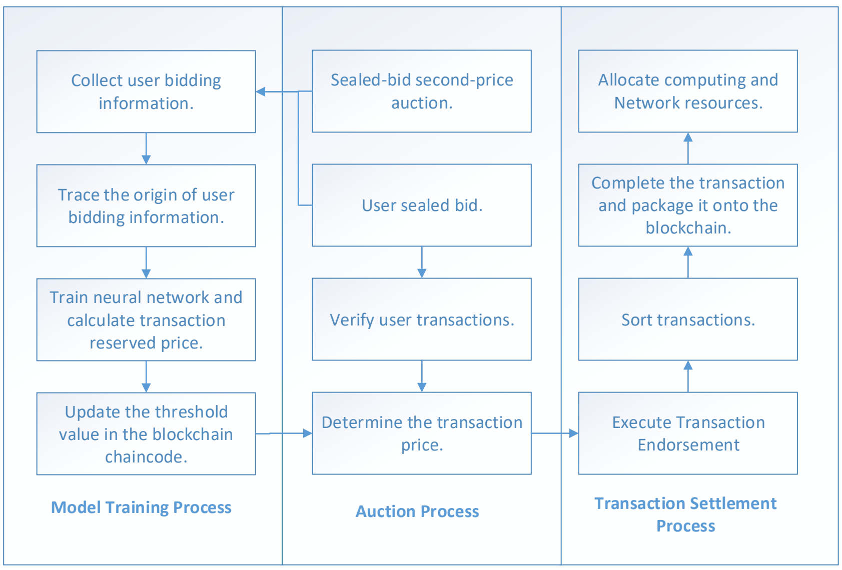

Figure 2. Auction process diagram.

4. Optimal Auction Design under Identical Bidding Distribution

4.1. Auction Mechanism Based on Reserved Price

In the same distribution scenario of user bidding, the Myerson auction can be converted into a sealed second-price auction with a transaction reserved price, which is recorded as SPA_0. The selection of transaction reserved prices directly affects the expected revenue of the seller. When the reserved price is set too high, the probability of failure will increase. When the reserved price is set too low, transactions lower than users' expectations will increase. Both cases will reduce the expected revenue of the resource supplier.

Assuming that the highest value is v_i and the auction bidder is b_i. The second-highest bid value is v_j and the auction bidder is b_j. The SPA_0 allocation rules g are the same as SPA, the resources are allocated to bidders who have the highest bid value. In the payment rules p, compared with the traditional SPA, the transaction reserved price t is introduced. When $v_i < t$, no one win. When $v_i \geq t$ and $v_j < t$, the final transaction price is $p_i = t$. When $v_j \geq t$, the final transaction price is $p_i = v_j$. In the auction scenario of single items, the benefit function can be defined as follows.

$$\mathrm{u}_i = \begin{cases} v_i - p_i & \text{if } v_i = \max(v) \text{ and } v_i > \mathrm{t}, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

Based on the payment rule and allocation rule, the algorithm SPA_0 inherits the excellent properties of SPA. Firstly, SPA_0 meets the nature of IC. The bidder can obtain the highest benefit only if it quotes truthfully. Secondly, SPA_0 meets the nature of IR. The winner's payment will not exceed its valuation. Based on the above allocation and payment rules, the expected revenue model meeting the IC and IR properties can be defined as follows.

$$\begin{aligned} &R(v,t,g,p) = \tfrac{1}{T}\textstyle\sum_{t=1}^{T}\sum_{i=1}^{n}\left[\max\left(v_j,t\right)\cdot g(v_i)\right] \\ \text{s.t. IC } &: u_i((r_i,v_{-i}),t,g,p) \geq u_i((v_i,v_{-i}),t,g,p), \quad \forall i \in N \\ \text{IR } &: u_i(v_i,t,g,p) \geq 0, \forall i \in N \end{aligned} \tag{3}$$

where T represents the number of rounds in the auction, r_i represents the bidder's valuation of the auction, v represents the bidder's true valuation, v_j represents the second highest bid value in the round t.

4.2. Auction Model Based on Reserved Price

4.2.1. Virtual Valuation Network Model

In the real auction scenario, the user's bidding distribution is more complex, and it is difficult to directly calculate the virtual valuation function. However, in scenarios where user bids are independently and identically distributed, the calculation of the virtual valuation function can be converted into the calculation of the reserved price. In addition, considering that the neural network can approach any complex nonlinear relationship through a reasonable structural design, we plan to find the optimal reserved price based on the neural network, so as to maximize the expected return. The neural network structure is shown in Figure 3.

The model consists of two layers of neural networks. The first layer is performed by the $M \times J$ linear mapping. The result is divided into M group and each group contains J linear functions. The mapping function can be represented as $h_{mj}(v_i) = w_{mj}^i v_i + \beta_{mj}^i$, where the weight $w_{mj}^i \in R^+, \beta_{mj}^i \in R, m = 1, 2, \ldots, M, j = 1, 2, \ldots, J$. The second layer is employed to calculate the max and min of the output of the first layer. Nonlinear factors are introduced to better fit the virtual valuation function. Based on the above network structure, the virtual valuation function can be expressed as follows.

$$\varphi_i(v_i) = \min_{m \in [M]} \max_{j \in [J]} \left(w_{mj}^i v_i + \beta_{mj}^i \right) \tag{4}$$

One of the significant advantages of this two-layer network structure is that it is easy to perform the inverse transformation, to calculate the transaction reserved price in the payment rules. The inverse transformation formula is shown as follows.

$$\varphi_i^{-1}(\bar{v}_i) = \max_{m\in[M]} \min_{j\in[J]} \left(w_{mj}^i\right)^{-1}\left(\bar{v}_i - \beta_{mj}^i\right) \tag{5}$$

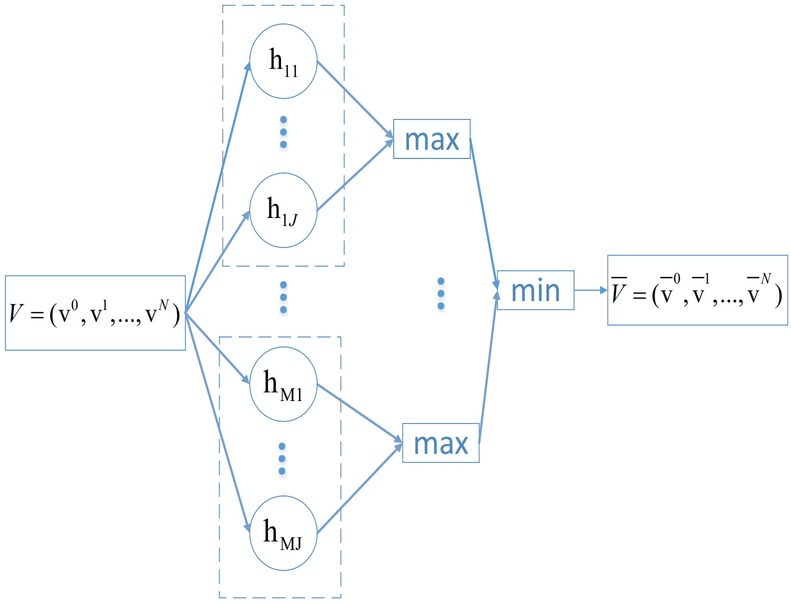

Figure 3. Virtual valuation network model.

4.2.2. Allocation and Payment Rules

Assuming the initial bids of N users are $v_i, i = 1, 2, \ldots, N$. The virtual valuation is expressed as $\overline{v_i} = \varphi(v_i), i = 1, 2, \ldots, N$. According to Myerson lemma [9], if and only if the allocation rule is monotonous, it can satisfy the nature of IC. Considering that the allocation rule is a composite function, the outer layer selects the softmax function to calculate the allocation probability. In order to ensure that the inner layer's valuation mapping function is monotonically increasing, we control the weight greater than zero in the network design process. Finally, the calculation formula of the bidder's probability of winning the auction is as follows.

$$g_i(\overline{v}) = \mathrm{softmax}(\overline{v}_1, \overline{v}_2, \ldots, \overline{v}_N) = \frac{e^{\bar{v}_i}}{\sum_{j=1}^{N} e^{\bar{v}_j}}, \forall i \in N \tag{6}$$

In the process of designing payment rules, we introduce a virtual user b_{N+1}. The output of the user b_{N+1} is fixed to 0. When the virtual user b_{N+1} wins the auction, it indicates that the auction has failed, and no one obtains resources. Finally, the auction network uses the ReLU function to determine the final payment price, and its calculation formula is as follows.

$$p_i = \begin{cases} \varphi^{-1}(\max_{j\neq i} \bar{v}_j) & \text{if } \bar{v}_i = \max(\bar{v}) \text{ and } j \neq N+1, \\ 0 & \text{else}, \end{cases} \tag{7}$$

where i represents the bidder b_i with the highest virtual valuation, and the actual payment price needs to be calculated through the inverse function φ^{-1} in (5).

4.2.3. Auction Network Model

Based on the above allocation and payment rules, we can calculate the expected revenue for users. To date, the auction network framework based on the reserved price has been designed, as shown in Figure 4.

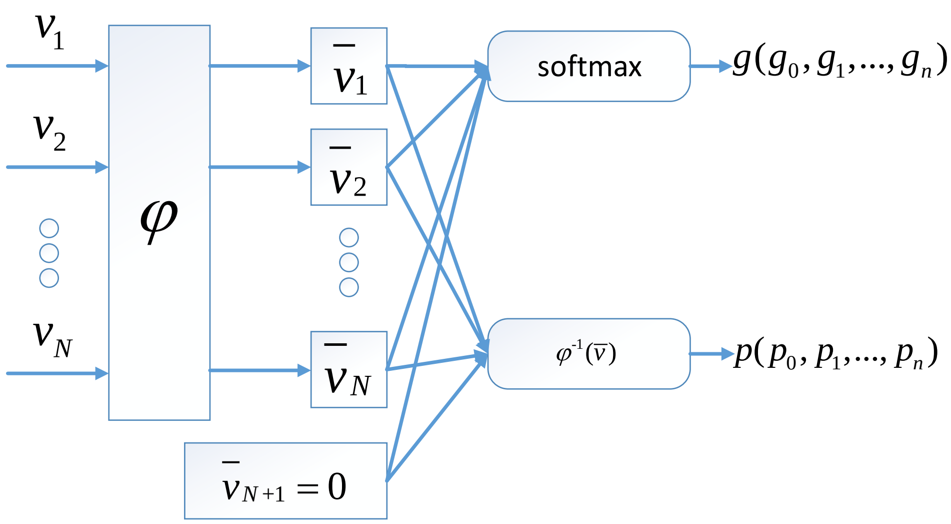

Figure 4. Network model of simple auction.

We define the loss function as the opposite of the seller's expected revenue, and the goal is to maximize the expected revenue by minimizing the loss function. The loss function is defined as follows.

$$\text{Loss}(w^+, \beta) = -\frac{1}{L}\sum_{l=1}^{L}\sum_{i=1}^{N}(g(\bar{v}_i)\cdot p_i) \tag{8}$$

where L represents the number of samples, N represents the number of bidders participating in the auction, $\bar{v}_i$ represents the virtual valuation corresponding to the bidder b_i, and p_i represents the actual amount paid by the bidder b_i. We use the random gradient descent method to optimize the parameters w^+ and β. The complete steps of the algorithm are given as follows (see Algorithm 1).

Algorithm 1 Pricing Algorithm Based on Deep Learning

Require: (1) The number of the bidder: N;
(2) The Number of training rounds: T;
(3) The number of training samples in each round: L;
(4) The number of virtual valuation network groups: M
(5) The number of linear functions in each group: J;
(6) Fixed input: $\bar{v}_{N+1}$;
(7) Data of each round of bidding: $V = \{v_0, v_1, \ldots, v_N\}$;
Ensure: (1) Allocation Rules: $\{g_0, g_1, \ldots, g_N\}$;
(2) Conditional Payment Rules: $\{p_0, p_1, \ldots, p_N\}$;
Initialize neural network weight parameters $w^i_{kj} \in R^+$,$\beta^i_{mj} \in R$,$m = 1, \ldots, M$, $j = 1, \ldots, J$
for $t = 1 \to T$ **do** //T represents the number of iterations
  $\bar{v}^l_i = \varphi(v_i) = \min_{m\in[M]}\max_{j\in[J]}\left(w^i_{mj}b_i + \beta^i_{mj}\right)$
  $g_i(\bar{v}) = \text{softmax}(\bar{v}_1, \bar{v}_2, \ldots, \bar{v}_N) = \frac{e^{\bar{v}_i}}{\sum_{j=1}^{N} e^{\bar{v}_j}}, \forall i \in N$
  if $\bar{v}_i = \max(\bar{v})$ and $i \neq N+1$ **then**
    $p_i = \varphi^{-1}(\max_{j\neq i}\bar{v}_j)$
  else
    $p_i = 0$ //This round of auction has failed
  end if
  $L(w^+, \beta) = -\frac{1}{L}\sum_{l=1}^{L}\sum_{i=1}^{N}(g_i \cdot p_i)$ //The loss function is defined as the negative value of the expected return
  Optimization of network parameters using gradient descent
end for

In order to ensure the security of the auction, the auction model based on the reserved price needs to run on the Hyperledger Fabric. Considering that the neural network is introduced into the auction model, it is difficult for smart contracts to implement the neural network model. Therefore, this article divides the auction mechanism into an offline module and an online module. The offline module needs to calculate the reserved price through the network model, while the online module needs to implement a simple sealed second-price auction. Finally, the reserved price is transferred to the chain code as a parameter, simplifying the design difficulty of the smart contract and creating conditions for the application of the blockchain structure in the auction scenario.

5. Optimal Auction Design under Mixed Bidding Distribution

In the process of computing network resource auction, there are scenarios where users have different bid distribution, different distribution corresponds to different virtual valuation functions. In this section, we will show how to design an auction network in a mixed bidding distribution scenario through deep learning.

5.1. Classification Based on KL Divergence

To reduce the difficulty of model design, we classify users with similar bidding distribution into one category. These users have the same virtual valuation function. Firstly, KL divergence is introduced to measure the difference between two users' bid distribution and calculate the distance between different users. Assuming that the bidding probability distributions of two users are p and q, respectively, the calculation formula of KL divergence is as follows.

$$\mathrm{KL}(\mathrm{p}\|\mathrm{q}) = -\int \mathrm{p}(\mathrm{x}) \ln\left(\frac{\mathrm{q}(\mathrm{x})}{\mathrm{p}(\mathrm{x})}\right) \mathrm{dx} \tag{9}$$

In the clustering algorithm, KL divergence can aggregate users with similar bid distribution. Because KL divergence is asymmetric, the calculation formula of distance is as follows.

$$\mathrm{D} = \frac{1}{2}\mathrm{KL}(\mathrm{p}\|\mathrm{q}) + \frac{1}{2}\mathrm{KL}(\mathrm{p}\|\mathrm{q}) \tag{10}$$

Finally, K cluster centers are found based on the K-means clustering algorithm to complete user classification.

5.2. Auction Model Based on Classification Algorithm

We need a new model to fit the virtual valuation function corresponding to different bid distributions. The auction network model in the mixed bidding distribution scenario is shown in Figure 5. The input of the network model is determined by the classification results, and the number of input nodes is the same as the number of user categories.

In the mixed bidding distribution scenario, the allocation rules and payment rules need to be adjusted. Suppose that the bid set corresponding to the k-type bid distribution has a maximum value of $V_k = \{\overline{v}_{k1}, \overline{v}_{k2}, \ldots, \overline{v}_{kS}\}$. Where S represents the number of bidders of the k-type bidding distribution. Allocation rules are defined as follows.

$$g_k(\bar{v}) = \mathrm{softmax}(\max V_1, \ldots, \max V_K) = \frac{e^{\max V_k}}{\sum_{k=1}^{K} e^{\max V_k}}, \forall k \in K \tag{11}$$

Assume that the virtual valuation corresponding to the bid of k-type user b_{ks} is the maximum value among all bids, which is recorded as $\bar{v}_{ks}$. The virtual valuation corresponding to the user b_j is second to $\bar{v}_{ks}$, which is recorded as $\bar{v}_j$. The user's actual payment price is as follows.

$$p_k = \begin{cases} \varphi_k^{-1}\left(\max\left(\bar{v}_j, 0\right)\right) & \text{if } \bar{v}_{ks} = \max(\bar{v}) \text{ and } \bar{v}_{ks} \geq 0 \\ 0 & \text{else} \end{cases} \tag{12}$$

The loss function of the neural network is defined as the opposite of the seller's expected revenue, and the goal is to maximize the expected revenue by minimizing the loss function. The loss function is defined as follows.

$$L(w^+, \beta) = -\frac{1}{L} \sum_{l=1}^{L} \sum_{k=1}^{K} g_k \cdot p_k \tag{13}$$

where L represents the number of auction rounds, and K represents the number of user categories. Finally, we use the random gradient descent method to optimize the network parameters w_+ and β until the loss function can converge to the minimum value, that is, the iteration is terminated when the expected return can reach the maximum value.

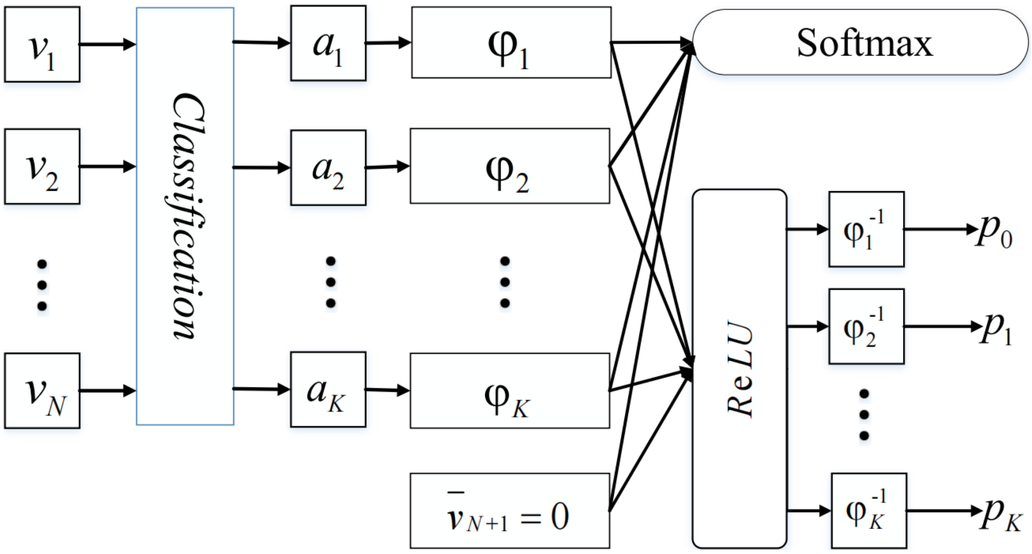

Figure 5. Network model of complicated auction.

6. Simulation Test

In this section, we will evaluate the performance of the auction model through a series of simulation experiments. First, we built an auction network of computing resources and network resources in different scenarios based on TensorFlow. The general parameters of the network model are as follows: the number of items in each auction round is 1; in the training and testing sets, the number of user bids in each auction round is 10,000; the learning rate is 0.001. Each training batch needs to use 64 rounds of complete user bidding information. The number of iterations is 5000. The total number of linear functions in the model is 100, where the number of groups is 10, and each group contains 10 linear functions.

Firstly, we analyzed the auction scenarios under identically bidding distribution. Experiment 1 tested the network's ability to accurately calculate the reserved price. Considering that the distribution of online resource auctions depends on multiple factors, including auction items, time, and participant attributes, it is highly competitive and open. In the training process, in order to highlight the superiority of the model and better validate it, this article will analyze three common and simple bidding distributions, namely uniform distribution $X \sim U(0,1)$, exponential distribution $X \sim E(3)$, and random distribution. Under the random distribution, a random number between 0 and 1 is introduced. When the random number is less than 0.75, the bidding distribution of users is $X \sim U(0,2)$; When the random number is greater than or equal to 0.75, the bid distribution of users is $X \sim U(2,5)$. These distributions can directly calculate the virtual valuation function, and obtain the calculation accuracy of the reserved price more intuitively. The experimental results are shown in Figure 6, the intersection point of the neural network's fitted mapping function and the actual virtual valuation function accurately determines the reserved price of the transaction. It should be noted that the reserved price in the bidding distribution is calculated using the virtual valuation function, which is fixed. This is also why the reserved price calculated for three different distributions is different.

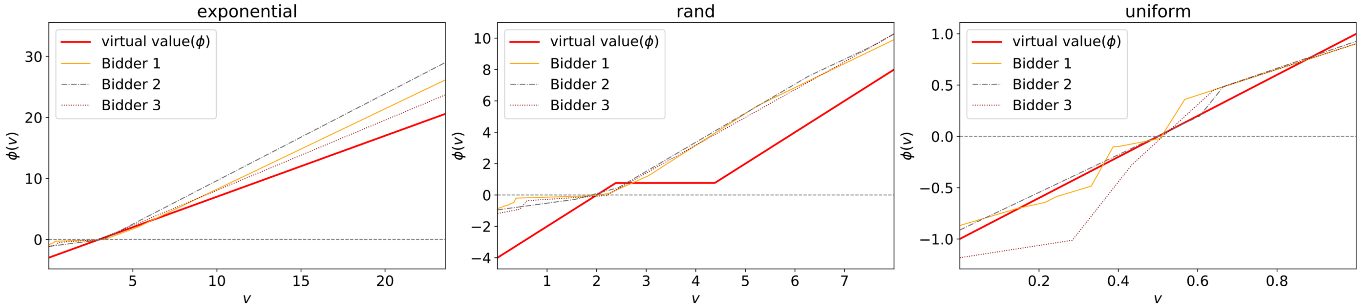

Figure 6. Solution to the reserved price of different distributions.

In the second experiment, we used sealed second-price and Myerson auctions as the control group to determine whether the auction revenue generated by the model closely approximates the expected revenue of the Myerson auction. The experiment is divided into four scenarios. The first and second scenarios correspond to two conventional distributions, namely uniform distribution $X \sim U(0,2)$ and exponential distribution $X \sim E(3)$. To test the extensibility of the model, we also choose two more special distributions, namely random distribution and quadratic distribution. The random distribution configuration is the same as that in Experiment 1, and the distribution function for the quadratic function distribution is defined as follows.

$$F(x) = x^2 - 2x + 1 \quad x \in [1,2] \tag{14}$$

Figure 7 shows the expected revenue obtained by the seller under different bidding distributions. It can be seen that after a certain number of training rounds, the seller's revenue corresponding to all distributions will tend to be stable, and the revenue is close to the real Myerson auction. Therefore, the auction mechanism based on the neural network can improve the seller's revenue and has good extensibility.

All of the above experiments are conducted under identical bidding distributions. However, in real auction scenarios, there can be various scenarios of user bid distribution. In Experiment 3, we analyzed an auction scenario with a mixed bid distribution, which includes three types of user bid distribution: uniform distribution $X \sim U(0,1)$, uniform distribution $X \sim U(0,2)$, and exponential distribution $X \sim E(3)$.

In the mixed bidding distribution scenario, we generate 10 samples for each distribution. For these samples, we first classify users by clustering algorithm based on KL divergence. The number of clusters is 3. The number of model input nodes is equal to the number of clusters. Users of the same type are input by the same node. In contrast, we introduce the auction model designed in [17]. This model does not classify users and directly employs all users' bids as input to train the Myerson auction model. The expected auction revenue generated by the two models is shown in Figure 8. The expected revenue of the auction model proposed in this article is higher than the existing Myerson auction model and closer to the expected revenue under the real Myerson auction.

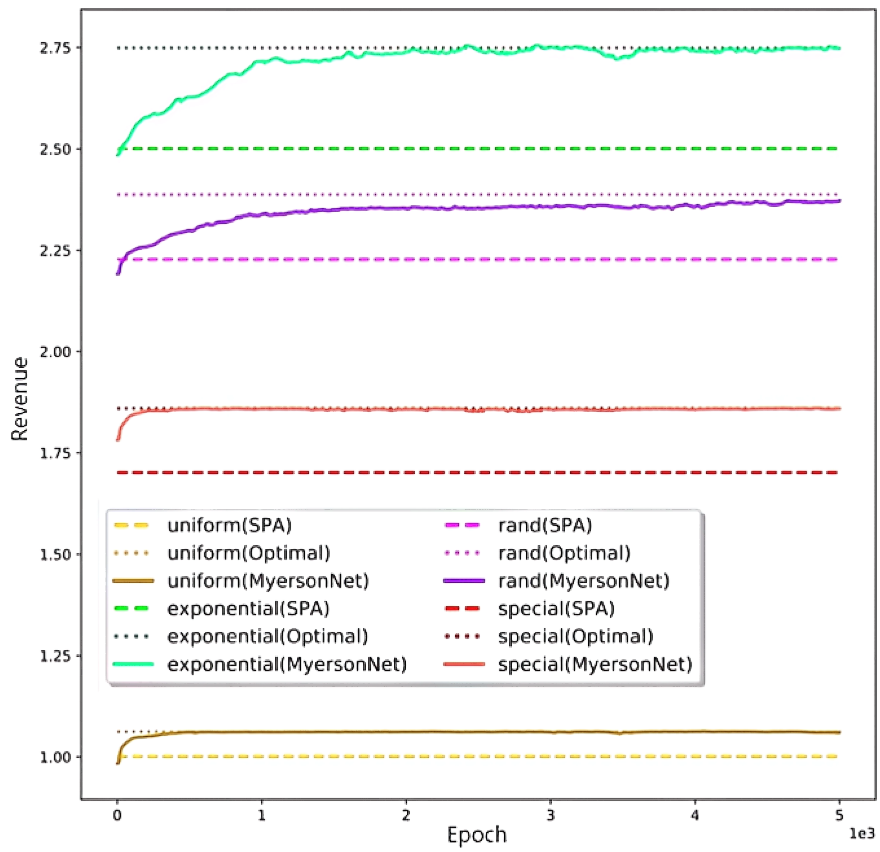

Figure 7. Expected revenue analysis.

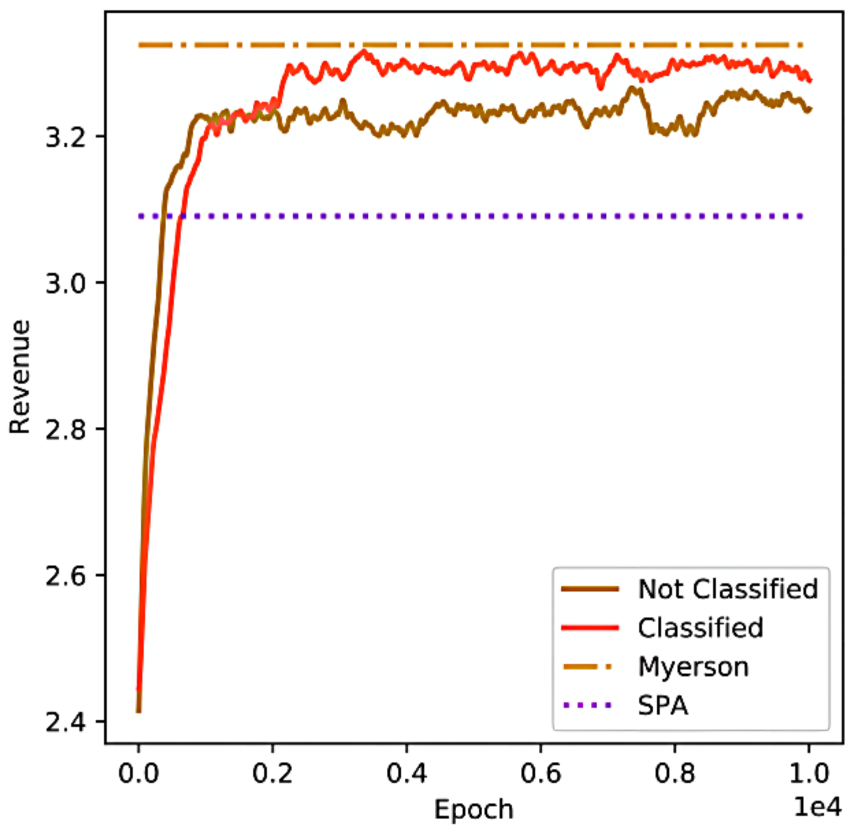

Figure 8. Mixed distribution benefit analysis.

7. Summary

In the transaction scenario of the computing power network, we propose a resource allocation scheme based on the Myerson auction, in which service providers are responsible for auctioning users' idle resources. Based on satisfying IC and IR properties, the Myerson auction can maximize the expected revenue of resource providers and prevent malicious competition, encouraging users to sell idle computing resources and network resources, leading to improved overall resource utilization.

Under the same scenario of user bidding distribution, this article combines the Myerson auction with a smart contract and designs an auction scheme based on reserved price. The scheme calculates the reserved price through the offline network model and transfers it to the chain code of the actual transaction application in the form of parameters. The chain code only needs to implement a simple sealed second-price auction based on the reserved price. This scheme facilitates the use of Hyperledger Fabric in the auction scenario. Under a mixed bidding distribution scenario, to reduce the difficulty of model design and the impact of the number of users and bidding distribution on the model, we propose an auction model based on KL divergence classification, which produces better training results than the existing Myerson auction model, leading to higher revenue.

For computing power network scenarios, this paper studies optimization schemes for single resource auctions. In the computing power network, different types of computing power and network resources emerge endlessly. Therefore, our research focus is on how to package such resources into a container for auction when the bidding distribution is known. In future research, we will continue to explore this issue.

Author Contributions: Conceptualization, Z.W. and Y.Y.; methodology, Z.W. and Y.Y.; software, W.L. and Y.S.; validation, A.X. and Z.W.; formal analysis, A.X. and Z.W.; investigation, Y.Y. and D.L.; resources, Y.Y. and D.L.; data curation, Z.W. and A.X.; writing—original draft preparation, Z.W., Y.Y. and A.X.; writing—review and editing, Z.W., Y.Y., D.L., W.L., A.X., Y.S.; supervision, Z.W., Y.Y., D.L., W.L., A.X., Y.S.; funding acquisition, D.L. and W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research and Development Program of China: Research and Application Demonstration of Intelligent IoT and Control Technology for Urban Integrated Energy (2020YFB2104500).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

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