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Multi-Slot Spectrum Auction in Heterogeneous Networks Based on Deep Feedforward Network

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ABSTRACT A spectrum auction is a promising approach with respect to efficiently allocating spectrum among unlicensed users. In this paper, we study the spectrum auction based on the waveform and air-interface of wireless users, the interests of the channel for the auction, and the interference they suffered during communication as well as their economic capability. How to make the analysis and the integration of such multiple factors is a key problem for multi-slot spectrum auction. To address the problem, we adopt the deep feedforward network algorithm to perform waveform and air-interface data analysis and integration for multi-slot spectrum auction. Simulation results are presented to verify the effectiveness of the proposed algorithm in the small cell network. Our approach could be used to 5G where heterogeneous wireless networks will be applied extensively and spectrum auction decision is made based on deep learning and different user patterns.

INDEX TERMS Deep feedforward network, dynamic spectrum auction, heterogeneous networks, multi-slot, small cell, waveform and air-interface.

I. INTRODUCTION

Radio spectrum shortage are becoming increasingly serious with the development of mobile communication technology. Spectrum sharing, as an effective solution, becomes a key technology of 5G. Especially, spectrum auction is a promising spectrum sharing method which has drawn substantial attention [1]–[6]. Truthful and rationality are the premises of an effective auction. For example, a truthful spectrum auction mechanism has been proposed in [1], which considered both QoS demands and spectrum idle reuse. The truthful property makes the auction have no further benefit to be earned for bidders by cheating. The authors assumed that the bidder was rational, which made sure that the income of each bidder is more than zero, by which incentivized bidders participate in the auction voluntarily. In [2], Yi and Cai proposed a polynomial-time algorithm with multiple users. Every spectrum owner had plural idle channels to share while every unlicensed user bid for the access rights to satisfy its communication demand. In the secondary spectrum market, primary users share their spectrum channels to unlicensed users by auction. A truthful auction mechanism makes bidders have no incentive to lie. That means the unlicensed users' best strategy is to bid with their true

price. And an effective auction mechanism requires to realize the social welfare maximization [3]. In [4], a near optimal privacy-preserving mechanism was designed. In dynamic spectrum sharing networks, the way for unlicensed users to use cognitive radio spectrum is to access opportunistically and share the idle spectrum. The premise of spectrum sharing is that the interference generated by the unlicensed users are below the threshold. In [5], primary base station (PBS) divides the channels into two categories according to the service object. That is, some of the channels are used for its own communication services and the rest of them will be sold to the unlicensed users for more revenues. The paper designed a mechanism to protect the primary users. There are some channels will be recalled after auctions for the primary users to meet their communication demands. [6] designed an online auction for maximization the long-term-averaged social welfare. The goals are truthfulness and volatile traffic demands. [7] proposed a flexible spectrum auction mechanism to allocate variable bandwidth spectrum to unlicensed users. In [7], a framework was designed for truthfulness in the multiple collision domains scenarios. Reference [8] proposed a spectrum allocation mechanism with polynomial-time slots and made sure the auction truthful. In order to make the

allocation process more reasonable, a prediction for bidding as the guidance to bidders is necessary. The allocation of the spectrum is essentially a nonlinear process. To address the nonlinear problem, neural network can be adopted for its nonlinear fitting ability apart from basic properties such as self-organizing, self-adaptive, and error-tolerance. In the field of classification data, Deep Feedforward Network classification method has strong fitting ability and simple learning processing. It has a good effect especially in multi-dimensional nonlinear data processing. Reference [9] improved a genetic algorithm for scheduling the transition operations and [10] did a survey on several classical classification algorithms. Reference [11] proposed an effective training method to eliminate non-conclusive input factors. A predictive maintenance mechanism for a gradually deteriorating continuous state system was proposed in [12]. The mechanism chose the strategy to realize the balance of the utility and the cost by optimization. Back propagation neural network can easily establish the relationship between inputs and outputs without knowing the concrete expression. The learning rule is to adjust the network weights and threshold constantly by back propagation [13]. [14] proposed a nonlinear regression model and [15] built a cognitive radio enabled wireless communication system with intelligent machine learning. Neural network can describe the complex nonlinear mapping relation from inputs to outputs, and has a good generalization ability [16]–[28]. Reference [18] presented a fitting structure for the multi-layer perceptron network with back propagation algorithm. In [19], Rubaai and Kotaru proposed a new training mechanism in the neural network. In [20], an adaptive control algorithm based on neural networks was proposed. In [21] and [22], a neural network based nonlinear controller mechanism and an improved back propagation neural network with link switches were proposed. Deng *et al.* [24] proposed a task-aware back propagation through time method to cope with the gradient vanishing issue in deep training. Evolutionary algorithm is a powerful tool for optimization problem. Reference [25] proposed a neural network algorithm based on co-evolutionary computation. The proposed method shows better performance on complicated classification tasks. In [26], Rego *et al.* developed a fitting mechanism for training single-layer feedforward neural networks. Two neural networks were constructed and investigated for pattern classification in [27]. In [28], a deep neural network focused on both deep and wide structure and dismantled a complex regression problem into multiple sub-problems to be solved.

In this paper, we propose an auction mechanism with multiple time slots as a technique for the spectrum sharing. In the communication scenarios, the licensed macro cell will share the spectrum with the unlicensed small cells through the way of auction. To optimize the auction, the neural network is adopted as a guidance of allocation. The simulation results indicate that the proposed auction algorithm can improve the communication quality effectively and efficiently. This paper makes the following main contributions.

1) A dynamic multi-time slots spectrum auction mechanism is proposed. Bidders set access to the channel through the auction allocation. The payment is related to the price they quoted and their experience from the history information.

2) We adopt the deep feedforward network as the guidance of auctions to improve the rationalization of allocation. Bidder's economic capability, the interests of the channel for the auction, and the interference they suffer during communication are all taken into consideration by deep learning, which is a pattern recognition approach.

The architecture of this paper is as follows. Section II introduces the system model and the transmission model of the signals. The auction mechanism is presented in Section III. The model and the algorithm of deep feedforward network are described in Section IV. Finally, simulation results are shown in Sections V.

II. SYSTEM MODEL

We propose a two layers of heterogeneous network as our communication system model. There are several unlicensed small cells covered by the macro cell base station (MBS). As a low-powered radio access node, many operators are starting to use the small cells to offload the data traffic of the macro cell. In addition, small cells can provide a larger coverage area. All unlicensed users covered by small cells access to the small cell base stations (SBSs) during the communication. Fig.1 shows the system model and Fig.2 shows the signal transmission model.

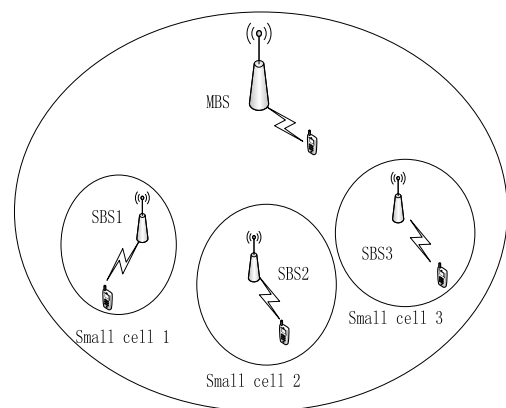


FIGURE 1. System model.

We define the licensed users who access to the MBS as MUs. In the same way, the unlicensed users who access to the SBS are denoted as SUs. Under the assumption that the channel state information is known, the analysis for the signal transmission process in a time slot has been made.

The m -th MU receives signals in the form of (1)

$$y_m = \sqrt{P_T} g_m z_m + \sum_{j=1, j \neq m}^M \sqrt{P_T} g_j z_j + \sum_{i=1}^K \sqrt{P_i} h_{pi} x_i + n_p. \quad (1)$$

In this equation, z_m is the signal transmitted from the MBS to the m -th MU. z_j is the signal transmitted from the MBS to the

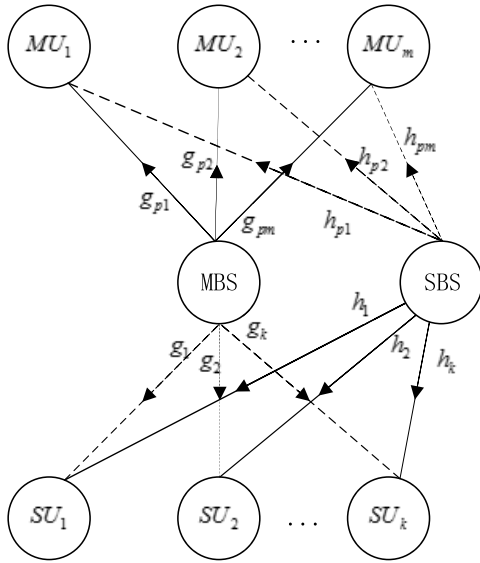


FIGURE 2. Signal transmission model in heterogeneous networks.

j -th MU, for which $j \neq m$. x_i is the signal transmitted from the SBS to the i -th SU. P_T and P_i are the transmission powers of the MBS and the SBS's antenna i , respectively. g_m, g_j and h_{pi} are the channel coefficients. n_p is an additive white Gaussian noise.

The k -th SU receives signals in the form of (2)

$$y_k = \sqrt{P_k} h_k x_k + \sum_{i=1, i \neq k}^K \sqrt{P_i} h_i x_i + \sum_{m=1}^M \sqrt{P_T} g_k z_m + n_k. \quad (2)$$

According to (1) and (2), we can elicit the signal to-interference-plus-noise ratio (SINR) of the SU and the MU.

The k -th SU's SINR is shown in the form of (3)

$$SINR_k = \frac{P_k |h_k|^2}{\sum_{i=1, i \neq k}^K P_i |h_i|^2 + P_T |g_k|^2 + \sigma_k^2}. \quad (3)$$

And the m -th MU's SINR is shown in the form of (4)

$$SINR_m = \frac{P_T |g_{pm}|^2}{\sum_{j=1, j \neq m}^M P_T \cdot |g_j|^2 + \sum_{m=1}^M \sum_{i=1}^K P_i |h_{pmi}|^2 + \sigma_m^2}. \quad (4)$$

III. AUCTION MODEL

Due to the scariness of the spectrum resources and the evolution of the mobile communication, spectrum auction is proposed as an effective technology. For the sake of improving the channel capacity, the MBS will share its unused channels with small cells, in which spectrum auction is introduced as a reliable method to improve the spectrum efficiency. We introduce the model of multiple time slots auction in the following. Under this communication scenario, the licensed users are allowed to sell their idle continuous spectrum to the unlicensed users in multiple time slots. There are more than one unlicensed small cells covered by a macro cell. During

the process of an auction, the MBS plays the role as both the auctioneer and the seller, which requires the MBS to be trust worthy. Idle channels in different time slots will be leased to the SUs in small cells with a price.

Auctioneering is an economic concept of studying human behaviors during the auction. The principles of openness, fairness and honesty have already become a common law in many country. In our model, bidders always comply with this law and with individual rational.

Specifically, the bidder's revenue need to be positive. An efficient auction mechanism requires bidders' sum utility is maximized with the demands and indications of interest known. Once some bidders attempt to cheat, a large number of uncertain factors need to be considered for all bidders.

A truthful mechanism enforces bidders to behave truthfully by offering them incentives. An effective mechanism will fit (5)

$$u_i(\omega_i, b_{-i}) \geq u_i(b_i, b_{-i}). \quad (5)$$

u_i is the revenue of the bidder i , and b is denoted as the bid of the agent i . The final sale price is b_i with one strategy that is adopted by the bidder i . And there's a ω_i with $\omega_i \neq b_{-i}$ that can reach the maximum of utility.

In the traditional auction mechanism, bidders select strategies and forecast by collecting other bidders' information. And a common way to describe bidders' interference and other information is the conflict graph. Usually, the idle spectrum would be shared to the bidder whose interlayer interference is below the threshold. The traditional spectrum auction x_i describe the situation who of spectrum allocation. When the interference of unlicensed users to the licensed users are below the threshold, the value of x_i equals one.

$$x_i = \begin{cases} 1, & \text{interference} \leq \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

The influence factor of the traditional sharing mode is too unitary and unreasonable, which can rarely embody the competition and other influential factors of auctions. In our study, more influence factors are considered such as the weighted interlayer interference, the utility of small cell users as well as the economic capacity. We denote these three factors as the interference, experience, and economic ability. These factors will be classified as the inputs of Deep Forward Network.

There are two types of users covered by the MBS. Users who are not covered by SBSs directly access to the MBS during the communication. Others unlicensed communicate via the SBSs. The heterogeneous network can not only offload wireless traffic but also improve the communication system throughput capacity and ensure the quality of communication. It is worth noting that the unlicensed users need to bid for spectrum resources.

All unlicensed users are required to provide their information to the MBS. In the traditional spectrum auction, SUs only bid for idle spectrum in a time slot and it is just a simple superposition when considering the multi-slot fact.

In practice, the utility of bidders will be changed over time. We set the discount factor to represent the changes. In order to connect the utility of users with the real earnings, we define the social welfare of user i as

$$S(c_i, SINR_t) = \max E[\sum_{t=t'}^{\infty} \sum_i^N \delta^{t-t'} q_{i,t'} U(c_i, SINR_{i,t})]. \quad (6)$$

δ is the discount factor, and the value of $\delta (\delta \in (0, 1))$ is a balance weight of intending depreciating in the future. Based on the Game Theory, the discount factor should be the degree of patience. The more patient the users are, the lower the degree of the urgency to communicate requirements for the subsequent time and the discount factor becomes higher. We define the utility of SUs as

$$U(c_i, SINR_{i,t}) = c_i B \log(1 + SINR_{i,t}). \quad (7)$$

The weighted value c_i represents the benefit that SU i receives when using the band. In order to measure the performance of proposed algorithm, we assume that each user satisfies $c_i = c$. We denote $m_{i,t}$ as the SU i 's marginal contribution to the social welfare at time t :

$$m_{i,t} = S(c, SINR_t) - S_{-i}(c, SINR_t) - \delta E[S(c, SINR_{t+1}) - S_{-i}(c, SINR_{t+1})]. \quad (8)$$

When SU i acquires the channel at time slot t , we can get

$$S(c, SINR_t) = U(c, SINR_{i,t}) + \delta E[S(c, SINR_{t+1})] \quad (9)$$

SU's SINR would not change during the auction process because the user has not got the channel yet. So we have $SINR_{i,t} = SINR_{i,t+1}$, and then we can rewrite (9) as

$$S(c, SINR_t) = U(c, SINR_{i,t}) + \delta E[S(c, SINR_t)] \quad (10)$$

Then substituting the (10) into (8), we can find

$$m_{i,t} = U(c_i, SINR_{i,t}) - (1 - \delta) S_{-i}(c, SINR_t) \quad (11)$$

It is well known that the social welfare can also be written as the difference value between utility and the payment of SU i :

$$m_{i,t} = U(c_i, SINR_{i,t}) - p_{i,t}. \quad (12)$$

As a result we can get the payment function as

$$p_{i,t} = (1 - \delta) S_{-i}(c_i, SINR_t). \quad (13)$$

The social welfare without SU i in (13) is

$$S_{-i}(c, SINR_t) = \max_{Q \in \mathbb{Q}-i} E[\sum_{t=t'}^T \sum_{j,j \neq i}^N \delta^{t-t'} q_{j,t} U(c_j, SINR_{j,t})]. \quad (14)$$

Here \mathbb{Q} is a matrix which represent the output of the spectrum allocation.

IV. DEEP FEEDFORWARD NEURAL NETWORK

The established spectrum auction allocation mechanism network can be considered as a deep feedforward neural network (DFNN), which is composed of input layer, hidden layer and output layer. Determining the structure of DFFN model is of crucial importance to the prediction model.

The number of the nodes in the input layer of DFNN is normally determined by dimension of the eigenvector. Representative indicators are selected during the auction, which respectively reflects these three aspects of the information, such as the bidders' interference, experience, as well as economic ability, so there are three input nodes.

Through continuous data testing, we may get a relatively close estimation of the actual value. Therefore we can choose the trial and error method, a commonly used method based on the user's experience, to determine the number of neurons in the hidden layer. Through setting some number of neurons in the hidden layer of the training network, and gradually increasing or decreasing the number and use the same samples for training, we can determine the number of neurons is four within the least deviation.

The dimension number of the output vector is generally determined by the type of output information.

The number of the hidden layer decides the ability of fitting. To describe a complex relationship, a certain number of the hidden layers are necessary. However, the training time and the time complexity will increase with the increasing number of the hidden layer.

According to the output value, general judgment of evaluation indexes can be realized. The model of DFNN is constructed as shown in Fig. 3.

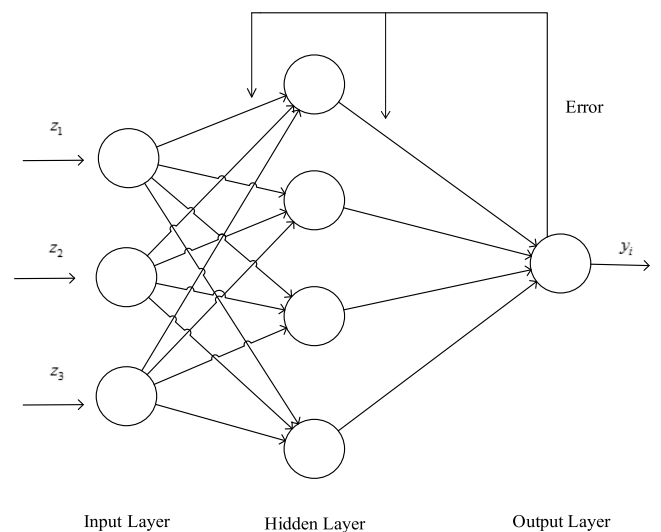


FIGURE 3. Deep feedforward neural network model.

DFNN includes two processes: positive propagation and error back propagation. The features will enter as the input to the output layer through multiple hidden layers in the positive propagation process. The error will be feedback from the output layer and hidden layers to the last layer during the error

back propagation. In case that we cannot obtain the expected output in the output layer, in the back propagation process, the network's weights are adjusted by the error feedback, so that the actual output is more close to the expected value. The results will be compared with the label of the data. With the iteration of the training, the deviation will be reduced. The learning rule of DFNN is the gradient descent algorithm. By using back propagation algorithm to adjust the network weights and threshold, we can get the minimized sum of the squared error.

For the j -th neuron in the l -th layer, we denote the weighted input as z_j^l , since the value Δz_j^l has been changed, the output will be influenced layer by layer. Thereby the cost function $\frac{\partial C}{\partial z_j^l} \Delta z_j^l$ will be changed. In this algorithm $\frac{\partial C}{\partial z_j^l}$ is defined as the error of the neural neurons.

We denote the error as $\delta_j^l = \frac{\partial C}{\partial z_j^l}$. Then the output layer's error of the j -th neuron in the L -th layer is

$$\delta_j^L = \frac{\partial C}{\partial z_j^L} = \frac{\partial C}{\partial a_j^L} \frac{\partial a_j^L}{\partial z_j^L} = \frac{\partial C}{\partial a_j^L} f'(z_j^L). \quad (15)$$

In (15), $a_j^L = f(z_j^L)$, $f(x)$ is the active function and $\frac{\partial C}{\partial a_j^L} = a_j - y_j$.

Similarly, the hidden layer's error of the j -th neuron in the l -th layer is

$$\begin{aligned} \delta_j^l &= \frac{\partial C}{\partial z_j^l} = \sum_k \frac{\partial C}{\partial z_j^{l+1}} \frac{\partial z_j^{l+1}}{\partial z_j^l} \\ &= \sum_k \frac{\partial C}{\partial z_j^{l+1}} \frac{\partial z_j^{l+1}}{\partial a_j^l} \frac{\partial a_j^l}{\partial z_j^l} = \sum_k \delta_j^{l+1} \omega_{kj}^{l+1} f'(z_j^l). \end{aligned} \quad (16)$$

Then we denote the connection of the error between the layer l and the layer $l + 1$ as

$$\delta^l = \delta^{l+1} w^{l+1} f'(z^l) \quad (17)$$

δ^{l+1} and w^{l+1} are the error and the weight of the next layer.

Based on the theories mentioned above, we can established the neural network and the computational processes as follows:

In the stage of initialization, we enter the training set and generate the weight initial value $\omega_0 \in [-1, 1]$. We set the activation function as the sigmoid function. The sigmoid function is the standard Bernoulli margin in the exponential function group, which is the optimal class in the linear generation model. Intuitively, the model with larger entropy is more robust than the model with small entropy, and the impact from the data noise is small and the function $sigmoid(x) = \frac{1}{1+e^{-x}}$.

In the stage of error calculation, we denote the output of the DFNN as: $f(x) = sigmoid(input, \omega) = \frac{1}{1+e^{-input*\omega}}$, and the input and output of the training set are denoted as $inputT$ and $outputT$.

The error of layer2 is $error2 = outputT - output2$ and the weight modifier is $\Delta\beta_2 = error2 \cdot f'(output2)$. The error of layer1 is $error1 = \Delta\omega_2 \cdot \omega_2$ and the weight modifier is

$\Delta\beta_1 = error1 \cdot f'(output1)$. So the adjustment value of weight $\Delta\omega_2 = (output1) \cdot \Delta\beta_2$ and the adjustment value of weight $\Delta\omega_1 = (inputT) \cdot \Delta\beta_1$.

Update the weight through the function $\omega_i = \omega_i + \Delta\omega_i$. The algorithm asks the users to limit the accuracy and maximum training time of the neural network. When training Deep Feedforward Network reaches one of these two conditions, the training will be terminated.

We can use a trained neural network as a guide for the distribution of spectrum auctions. The output is a number closed to zero or one which represents whether the channel is allocated. We denote these three input factors as the interference, experience, and economic ability in Section III. For the convenience of computing, we preprocess the inputs by fuzzy recognition.

V. SIMULATION RESULTS

In this section, the performance of the proposed algorithm is evaluated through simulations. In the simulations, we consider a heterogeneous network which consists of several small cells and a macro cell. The simulation parameters settings are listed in Table 1.

TABLE 1. Parameters used in simulation.

Symbol	Parameters	Value
B	Total Bandwidth	100MHz
σ^2	Noise Power	-110dBm
P_p	MBS Transmission Power	10W
P_s	SBS Transmission Power	5W
δ	Discount Factor	0.7
λ	Price Index	0.1
	Number of MUs	1
	Number of SUs	3~10

The results of the proposed spectrum auction algorithm are compared with the traditional spectrum auction algorithm. The traditional spectrum auction algorithm allocates the channel by a myopic policy and irrespective of the attenuation of the price. The social welfare of the two algorithms with different number of SUs are shown in Fig. 4.

From Fig.4, we can see that the traditional auction algorithm's social welfare with different users is tend to be stable while the proposed auction algorithm's social welfare increase as the number of SUs grows.

The social welfare with 3 SUs and 5 SUs in different time slots are shown in Fig. 5. The social welfare has attenuated over time and their social welfare has decreased significantly from the fifth time slot. This performance matches the bidder's demand for communication over time.

From Fig. 6, we can observe that in the traditional auction algorithm the average payment is tends to be stable while

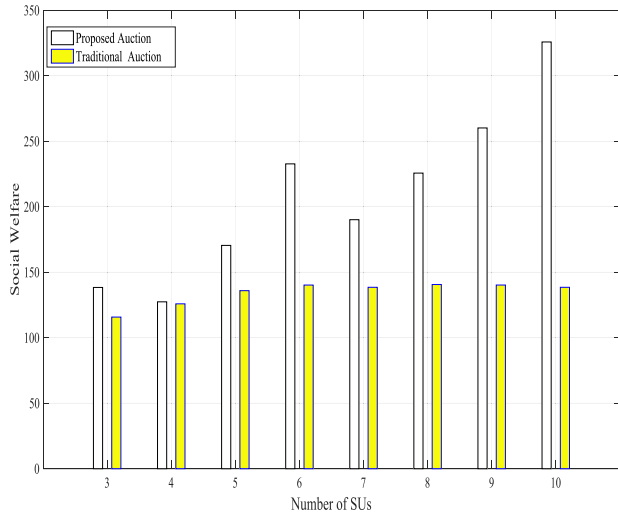


FIGURE 4. Social welfare with different number of SUs.

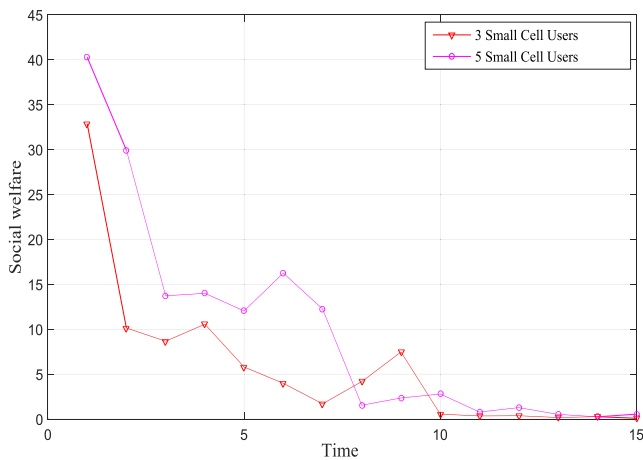


FIGURE 5. Social welfare in different time slots.

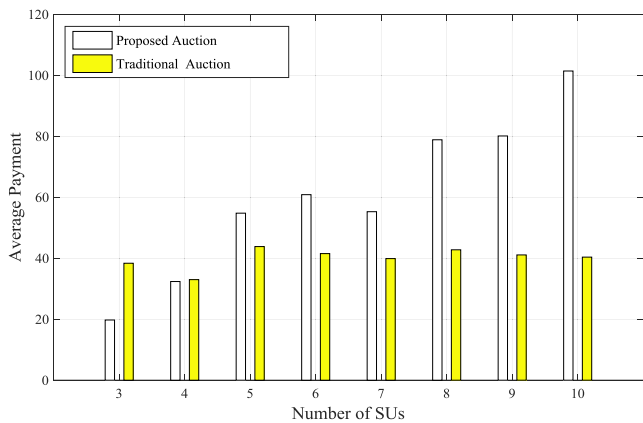


FIGURE 6. Average payment with different number of SUs.

in the proposed auction algorithm the average payment keep increasing as the number of SUs grows.

The revenue of MBS under both auction algorithms increases with increasing number of SUs. It can be observed

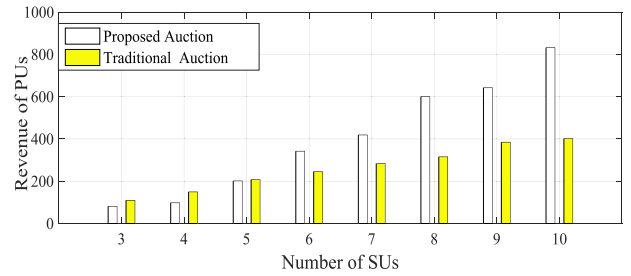


FIGURE 7. Revenue of MBS with different number of SUs.

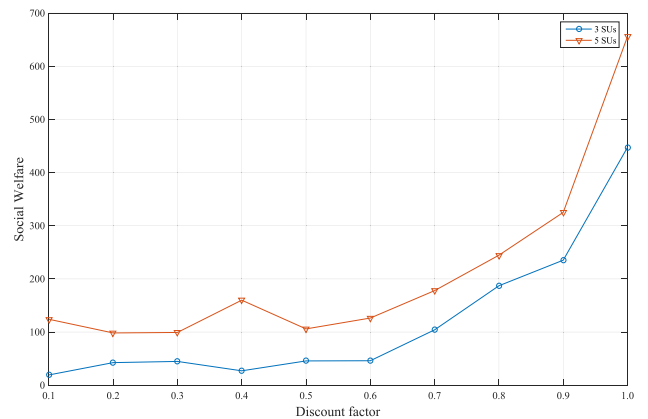


FIGURE 8. Social welfare with different discount factors.

from Fig. 7 that the proposed auction algorithm’s revenue of MBS is close to the traditional auction algorithm when the number of SUs is less than five and the performance is much better than the traditional auction algorithm when the number of SUs is greater than six.

All diagrams above are simulated with a fixed discount factor 0.7. To discuss the influence of discount factor on the social welfare, we fix three SUs and five SUs and observe the performance with different discount factors in Fig. 8. When the discount factor increases, the social welfare grows and the growth tends to be flat when the discount factor is between 0.1 and 0.7.

VI. CONCLUSION

In this paper, we proposed a multi-slot spectrum mechanism with deep neural network algorithm in heterogeneous networks. In the proposed auction mechanism, much more realistic factors are considered than the traditional auction mechanism. In addition, with the support of the deep neural network, the proposed auction mechanism can both raise the revenue of the PUs via spectrum auction and the social welfare. From Fig.4, the simulation results showed that the proposed auction mechanism can achieve more and more social welfare with increasing number of SUs. The results in Fig.7 showed that the revenue of MBS obtained by the proposed scheme is much more than that obtained by the traditional auction when the number of SUs exceeds a certain value.

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