Max-min fairness energy efficiency optimization for cognitive networks based on unsupervised deep learning

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ABSTRACT

This paper aims to study the power control method for fairness energy efficiency (EE) improvement in cognitive radio networks (CRN) with interference channels, among one primary user (PU) shares the spectrum to multiple secondary users (SUs). The objective is to control the transmit power to maximize the minimum EE among all users subject to the quality of service (QoS) constraints. An extremely challenging non-convex max-min fraction optimization issue given due consideration. This work aims at developing an adaptive solving method based on deep learning (DL) techniques for the max-min EE optimization problem. To achieve such an objective, we construct a deep neural network (DNN), with the channel state information (CSI) being the input of DNN and the transmit power being the output of DNN. However, this faces two challenges. On the one hand, it is difficult to obtain label data. On the other hand, when DNNs are applied, it is very important to consider that QoS constraints should be met. These difficulties are circumvented in our work by designing an unsupervised learning strategy, in which a loss function is devised by combining the max-min EE objective and the QoS constraints via the barrier function method. The effectiveness of our proposed algorithm is ultimately demonstrated by the simulation results.

Keywords: Cognitive radio network, deep learning, energy efficiency, fairness, power control, unsupervised learning

1. INTRODUCTION

Due to the ever-growing demand for wireless data transmission, more spectrums are expected to satisfy the future need. However, the scarcity of the spectrum resource poses considerable challenges to spectrum resource allocation and government. To overcome such spectrum shortage problem, the cognitive radio (CR) was introduced to improve the spectrum efficiency by sharing the spectrum resources among multiple users[1-3]. In general, underlay, overlay and interweave are three different paradigms of CR. They can avail of accessing the spectrum of licensed users simultaneously or the unused spectrum holes opportunistically[4-6].

While CR is a promising solution for alleviating the spectrum shortage, its intrinsic characteristics raise some new challenges, the most important of which are the quality of service (QoS) provision and the energy efficiency (EE) improvement[7]. The challenge of QoS provision is originated partly from the dynamic and random nature of the available spectrum. The sharing of the spectrum of multiple users, especially in underlay mode where shared users transmit data simultaneously on the same spectrum band, will not only raise uncertainty to QoS but also deteriorate the EE. Therefore, special consideration should be given to meeting QoS objectives while maintaining high EE within the transmit power restriction. At present, the objectives of most topics on these EE maximization problems are to optimize global energy efficiency (GEE). Although a high GEE can be obtained after the optimization, the EE distribution among the users is obviously different. Some users gain a sensible lower EE performance compared with others[8].

Recently, deep learning (DL) has received great attention in the area of wireless communication[9]. Although the DL

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method used[9] can effectively improve SE and EE while reducing time complexity, it is more challenging to obtain label data because the DL methods used are all supervised learning. Unsupervised learning does not require label data, which can further improve the feasibility of the algorithm. An unsupervised learning method to maximize the rate is studied[10]. Experimental results show that it is superior to existing power control methods. Similarly, the DL method is also used in the fairness of wireless communication[11-12]. They also used unsupervised learning to obtain max-min SE and max-min EE, respectively, and finally, the proposed algorithm can reach the baseline level.

In this paper, a DL-based max-min EE unsupervised learning algorithm in cognitive radio network (CRN) was proposed by us. Expressly, we set SE QoS constraints in PU and SUs, and on this basis, max-min EE. Furthermore, the max-min EE issue under consideration is non-convex as well as challenging to solve. For this reason, a DL-based solution has been proposed by us. A new target function that adds SE constraints to the target term was constructed using our barrier function. The optimized power is output adaptively by inputting CSI. Finally, its effectiveness is verified by simulation.

2. SYSTEM MODEL, PROBLEM DESCRIPTION AND FORMULATION

2.1 System model

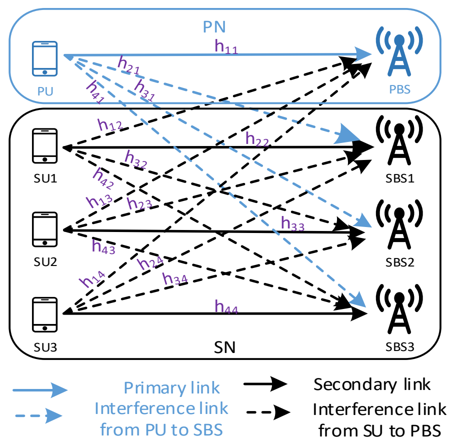

Figure 1. CRN System model.

As shown in Figure 1, CRN-based uplink scenario was taken into account. In this scenario, we consider K base stations and K users sharing spectrum in underlay mode. Among them, the base stations and users are single antennae. A user only communicates with a base station, and other links are the interference link. In the CRN we are considering, the primary network is made up of a primary base station together with a PU, and the secondary network is composed of K -1 SUs with K -1 secondary base stations. We use an instantaneous CSI. y_k is defined by us as the received discrete-time baseband signal of the k -th base station, in the meanwhile, its representation can be given as

$$y_k = h_{kk}x_k + \sum_{j=1, j\neq k}^{K} h_{kj}x_j + n_k, k = 1, 2, \cdots, K, \tag{1}$$

among them, k =1 means PU or primary base station. $k = 2, \cdots, K$ represents SUs or secondary base stations. The channel gain is then defined as h_{kk} for the direct link from the k -th user to the k -th base station. Furthermore, the channel gain h_{kj} of the cross-link is expressed as the channel gain from the j -th user towards the k -th base station. The transmission signal of the k -th user is denoted as x_k, the received noise of the k -th base station is denoted as $n_k \sim \mathcal{CN}\left(0, \sigma^2\right)$. σ^2 represents the noise power. The fact that the noise of PU and SUs follows the same distribution is taken into account. The block fading channel is considered by us. The channel coefficient remains constant over a time slot. The difference, however, are that the channel coefficients will vary individually from one-time period to the next.

In the underlay model that we take into account, the SU can access the spectrum when the PU can satisfy the threshold.

2.2 Problem description and formulation

Since the application scenario of this article is a CRN, it is necessary to consider the SE constraints of the PU and the SUs to meet QoS. According to equation (1), the SE for the k -th user could by us then be denoted as

$$SE_k = log_2(1+SINR_k), k=1,2,\cdots,K, \tag{2}$$

where $SINR_k = \frac{|h_{kk}|^2 p_k}{\sum_{j=1,j\neq k}^{K} |h_{kj}|^2 p_j + \sigma^2}$,the transmitted power of the k -th user could be given as $p_k \in \{p_1, p_2, \cdots, p_K\}$.

The ratio of SE_k to power consumption Q_k is taken as the definition of the EE from the k -th user, which is given by

$$EE_k = \frac{SE_k}{Q_k} = \frac{log_2(1+SINR_k)}{\frac{1}{\zeta} p_k + P_c}, k=1,2,\cdots,K, \tag{3}$$

among them, $\zeta \in (0,1]$ represents the power amplifier factor. P_c represents static power consumption.

In this study, the issue of optimizing max-min EE in CRNs is taken into account by us. We try to find the optimal power satisfying the constraint conditions to max-min EE. The problem is defined as

$$\begin{gathered} maximize \min_{i\in K} EE_i \\ s.t. SE_k > SE_{k,min} \\ 0 \le p_k \le P_{max}, \forall k = 1,2,\cdots,K, \end{gathered} \tag{4}$$

among them, $i = argmin(EE_j)$, $j=1,2,\cdots,K$. The minimum SE constraint from the k -th user is denoted as $SE_{k,min}$. P_{max} denotes the maximum allowed transmitting power for all users.

In principle, equation (4) is a nonconvex optimization issue[13], where obtaining a globally optimal solution to equation (4) is NP-hard. Some traditional optimization algorithms are limited in their use due to their high complexity[14]. A DL-based algorithm was developed by us to overcome the shortcomings of traditional global optimization to address the max-min EE issue in CRN.

3. PROPOSED DL-BASED METHOD

3.1 Problem refactoring

In order to solve the equation (4), we rephrase it as

$$\begin{gathered} minimize\ -\min_{i\in K} EE_i, \\ s.t. SE_k > SE_{k,min}, \\ 0 \le p_k \le P_{max}, \forall k = 1,2,\cdots,K. \end{gathered} \tag{5}$$

We use the obstacle method as proposed[13], and use the SE constraint in (5) as the implicit part of the goal to solve this problem. Specifically, we redefine (5) as[15]

$$\begin{aligned} &minimize \quad -\lambda_1 \min_{i\in K} EE_i + \lambda_2 \sum_{k=1}^{K} tanh(\frac{[SE_{k,min} - SE_k]^+}{SE_{k,min}}), \\ &s.t. 0 \le p_k \le P_{max}, \forall k = 1,2,\cdots,K, \end{aligned} \tag{6}$$

among them, λ_1 and λ_2 are the positive control parameters of training. The hyperbolic tangent function is denoted by us as $tanh(\cdot)$, whose equation expression is $tanh(x) \triangleq \frac{1-e^{-2x}}{1+e^{2x}}$. The differentiable function $tanh(\cdot)$ is employed by us to construct the loss function of the DNN. $[\cdot]^+$ represent $max(\cdot,0)$.

3.2 Model design

We use a DNN to solve the equation (6). As shown in Figure 2, we employ multilayer fully connected layers for building the DNN.

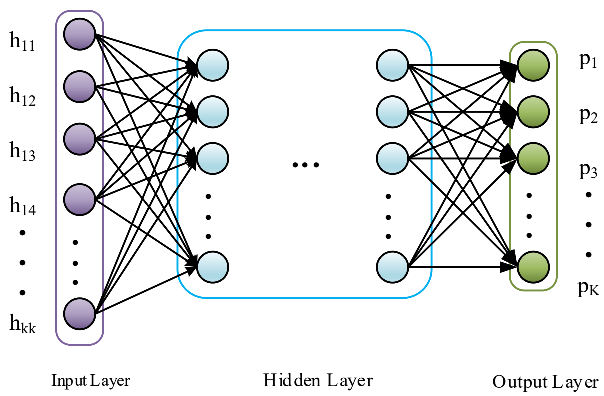

Figure 2. DNN model.

The input layer of the DNN is $K*K$ dimension H, and the output layer output is a K dimensional P. In addition to the input and output layers, there is an L layers hidden layer, which is located between the input as well as the output layers. We use $x_{\ell-1}$ to represent the input of ℓ, where $\ell = 1,2,\cdots,L$. Output layer with output node number defined as N_{L+1}. x_ℓ can be defined as

$$x_\ell = f_\ell(\omega_\ell x_{\ell-1} + b_\ell), \tag{7}$$

among them, the weight term, as well as the bias term for the ℓ-th layer from the DNN, are denoted as $\omega_\ell \in \mathbb{R}^{N_{\ell-1}\times N_\ell}$ and $b_\ell \in \mathbb{R}^{N_\ell \times 1}$ respectively. The ℓ-th layer of non-linear activation functions is given as f_ℓ. The output layer uses the Sigmoid function to control the output of the DNN from 0 to 1. The output x_{L+1} of DNN is given as follows

$$x_{L+1} = \mathrm{Sig}(\omega_{L+1} x_L + b_{L+1}) \tag{8}$$

among them, $\mathrm{Sig}(x) = \frac{1}{1+\exp(-x)}$. Equation (6) contains a transmission power constraint, and the transmit power must be limited to [0, P_{max}]. Finally, the transmission power P_i of user i is $P_i = P_{max} \cdot x_{L+1}$.

3.3 Model training

In addition, the parameters in the DNN need to be adjusted in such a way that the DNN could learn the relationship between the input and output, and Keras could be employed to automate the gradient descent of the DNN as well as to automatically adjust the parameters.

Due to the high complexity of label data acquisition, we use unsupervised learning to build DNN. We redefine the equation (4) to be solved as equation (6), and use a DNN to obtain a sub-optimal solution with less time complexity than traditional methods. In this method, the input CSI of the DNN is $H \in \mathbb{R}^{K*K}$, and the output is the power control vector $P \in \mathbb{R}^{K*1}$.

According to equation (6), we define the loss function $\mathcal{L}(\boldsymbol{p})$ of the DNN as

$$\mathcal{L}(\boldsymbol{p}) = -\lambda_1 \min_{i \in K} EE_i + \lambda_2 \sum_{k=1}^{K} tanh(\frac{[SE_{k,min} - SE_k]^+}{SE_{k,min}}) \tag{9}$$

We hope max-min EE because the loss value of DNN needs to be constantly reduced and finally converges, so the negative value of max-min EE is adopted. For the QoS constraint, we use the barrier function. When it meets the QoS constraint, the value of this part is 0. When the QoS constraint is not met, this part will produce a more significant positive value. λ_1 and λ_2 determine which is more important to max-min EE or satisfy the SE constraint. However, when the value of λ_1 is much larger than λ_2, it may result in the DNN failing to satisfy the SE constraint. Adam was employed by us as a method of gradient descent for DNN.

4. SIMULATION AND EXPERIMENTAL RESULTS

The independent identically distributed complex Gaussian distribution was taken into account as the distribution to which the CSI was generated, i.e. $h_{kj} \sim \mathcal{CN}(0,1)$, $\forall k, j = 1, 2, \cdots, K$. Noise power normalized $\sigma^2 = 1$. $K = 4$. Both the user side and the base station side are single antenna which is taken into account. Transmission circuit power consumption $P_c = 33dBm$, maximum transmit power $P_{max} = 30dBm$. Power amplifier efficiency $\zeta = 0.35$. SE threshold $SE_{min} = [0.3, 0.1, 0.1, 0.1]$ bit/s/Hz. The Adam gradient descent method we employ has the default values of Keras for the parameters β_1=0.9, β_2=0.999 and ϵ =1e-7, except for the learning rate, which is set to 0.000002. An instantaneous CSI is repeated 10^4 times to construct a training set, the batch size is set to 50, and it goes through 1000 iterations. λ_1 and λ_2 are set to 1.0 and 1.1 respectively. The number from hidden layers is given as L =5. $50*K$ is defined as the number of nodes in each layer of the hidden layer in the DNN. All layers except the output layer employ $Relu$ as the activation function. The output layer applies $Sig(\cdot)$ as the activation function employed to control the output power at [0,1], the value of the output layer output multiplied by P_{max} yields the final user transmit power.

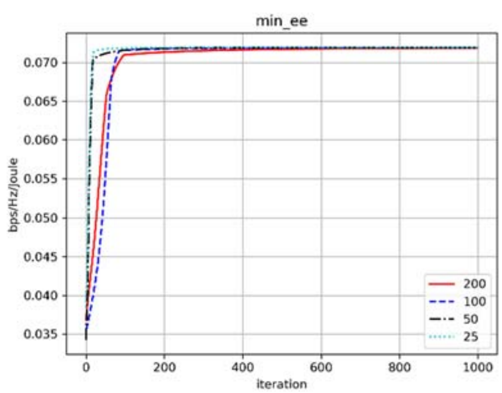

Figure 3. Convergence curves of min-EE under different batch size.

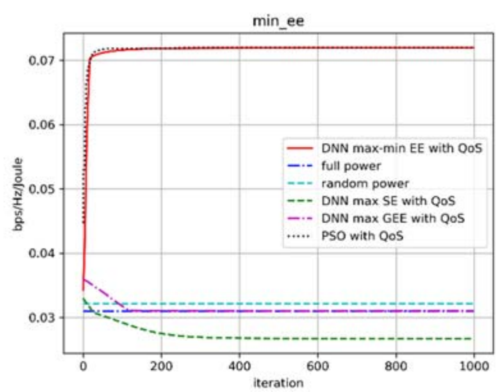

Figure 4. Min-EE comparison of different algorithms when K=4.

After 1000 iterations, the DNN finally converged. Figure 3 represents the min-EE change curve of DNN under different batch sizes. As seen in Figure 3, the min-EE converges fastest when the batch size is 25, and the slowest when the batch size is 200. Figure 4 shows the min-EE performance of the comparative experiment of different algorithms. As seen in Figure 4, there is not much difference between the min-EE obtained from full power and random power. The min-EE obtained by the algorithm aiming at maximizing the SE and maximizing GEE is not as good as other algorithms, and the min-EE is declining. The min-EE of the DNN algorithm we proposed can finally converge to the same level as PSO[16]. The min-EE converges to around 0.0719 bps/Hz/Joule. The SE of our proposed algorithm when it finally converges is [0.3015 0.1535 0.3490 0.1994] bit/s/Hz. The SE constraint of our proposed algorithm is finally satisfied.

5. CONCLUSION

This paper studied the power control method to improve the fairness of EE in the CR interference channel networks, where one PU and multiple SUs share spectrum resources in the underlying model. We propose a fair EE optimization problem that maximizes the minimum EE among all users while satisfying the QoS constraints of the SE. To overcome the difficulty in obtaining the labeled data, we relied on the unsupervised learning strategy when designing the deep learning networks. To train the constructed neural network, we transformed the QoS constraint into a fraction for the loss function through the employment for barrier function approach. The efficiency for the presented algorithm was validated through simulation, indicating that our presented deep learning-based approach achieved similar performance to traditional algorithms.

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