Mobile Networks and Applications
https://doi.org/10.1007/s11036-018-1178-9

Deep Learning Based Cooperative Resource Allocation in 5G Wireless Networks

Dan Huang [1] · Yuan Gao [1,2,3] · Yi Li [4] · Mengshu Hou [1] · Wanbin Tang [1] · Shaochi Cheng [2] · Xiangyang Li [2] · Yunchuan Sun [5]

Abstract

Wireless personal communication has become popular with the rapid development of 5G communication systems. Critical demands on transmission speed and QoS make it difficult to upgrade current wireless personal communication systems. In this paper, we develop a novel resource allocation method using deep learning to squeeze the benefits of resource utilization. By generating the convolutional neural network using channel information, resource allocation is to be optimized. The deep learning method could help make full use of the small scale channel information instead of traditional resource optimization, especially when the channel environment is changing fast. Simulation results indicate the fact that the performance of our proposed method is close to MMSE method and better than ZF method, and the time consumption of computation is smaller than traditional method.

Keywords Deep learning · Resource allocation · Downlink · 5G · Wireless network

1 Introduction

In 5G wireless communication systems, how to make full use of precious bandwidth, power and antenna resource has become a critical topic in recent studies. The official standardization organization 3GPP has recently published the official released standard [1] and add some key features to improve system throughput and reduce the latency. The target of 5G is to spread the bandwidth and make flexible use of system resources to achieve better performance, resources in time, spectrum and spatial domain are jointly combined and optimized. Traditional studies on 5G are mainly about the proof of mathematical bound [2, 3], and then provide heuristic methods to approximate the proved bound. However, there is hardly effective operations to reach the bound considering only existing coding, modulation, antenna selection, etc.

To solve this problem, researchers tried to introduce the famous Artificial Intelligence (AI) technology. The growing discussions about deep learning in AI has brought opportunities to improve system performance in 5G related works. Relying on the study process of deep learning, benefits of resource allocation could be obtained using the dedicated neural network. So there are still quite space to approximate the theoretical bound using the resource allocation.

✉ Yuan Gao
yuangao08@tsinghua.edu.cn

1 University of Electronic Science and Technology of China (UESTC), Sichuan 610054, China

2 Academy of Military Science of PLA, Beijing 100091, China

3 State Key Laboratory on Microwave and Digital Communications, National Laboratory for Information Science and Technology, Tsinghua University, Beijing 100084, China

4 The High School Affiliated to Renmin University of China, Beijing 100081, China

5 Business School, Beijing Normal University, Beijing 100875, China

2 Related works

Resource management and allocation [4] is the popular way to improve system throughput and reduce transmission latency. To achieve the goal, the network provider are establishing plenties of network nodes [5] such as base stations, access points, etc. The increasing number of network nodes are requiring more flexible resource allocation methods, so researchers are trying to tackle this area according to recent publications.

In [6], Martin provide the content centric resource allocation method in 5G wireless network, the constraint is

Published online: 05 December 2018

the quality of experience (QoE), by concentrating the media services, the simulation provide a satisfied result. In [7], the author optimized the spectrum sensing and resource allocation in IOT scenario, but the constraint of global channel information is strong. In [8–10], the two papers are focusing on NOMA, the energy optimization and cooperation are discussed. In [11], the spectrum management method is discussed, a context aware dynamic optimization method is given, but there is still a gap to the theoretical bound. In [12], the target of this paper is to minimize the interference through resource allocation and signal processing technique and in [13], the discussion of full duplex environment is given. The above discussion are mainly about the traditional optimization methods, where the AI based method is rarely mentioned.

Considering the AI method, the author in [14] provided the reinforcement learning method in space based networks, the author discussed the cognitive spectrum sharing method but not in ground network. In [15], the scheduling using reinforcement learning is given in ground networks, but the mobility is not discussed and the channel model is simple. In [16], the state of art of deep learning in air communication is given, but there is no significant improvement. In [17, 18], Prof. Saad provide the resource allocation solution in LTE network, which is a good result to solve the dynamic arrangement using CNN. In [19], the sum assignment problem is discussed in DNN where reference [20] summarize the existing problems in this area, but the discussion is not the optimal solution but only a practical method.

3 Contribution and structure of this work

In this paper, we have two main contributions compared to other researchers.

First, we model and perform the resource allocation in 5G D2D networks, both space, spectrum resources are introduced and perform optimization. Compared to other modeling method, we make the optimization from discrete to continuous so a convex optimization is available under the strict constraints;

Second, we first perform the optimization using deep learning. By generating the CNN, the dynamic allocation of spectrum and antenna is given. The simulation result indicates that our proposed method is working very well.

The rest of the work is organized as follows. In part 4, we propose the theoretical modeling of the resource allocation problem; in part 5, we present the proposed method using deep learning. In part 6, simulation results are given and discussed. Conclusion and Acknowledgement are in the following paragraph.

4 Theoretical modeling

In 5G based D2D network, small cells [3] are deployed in ultra-dense. Such deployment can provide larger bandwidth and smaller interferences. In Fig. 1, we illustrate the scenario of resource allocation in 5G D2D networks. In 5G ultra dense wireless networks, macro base stations working in low

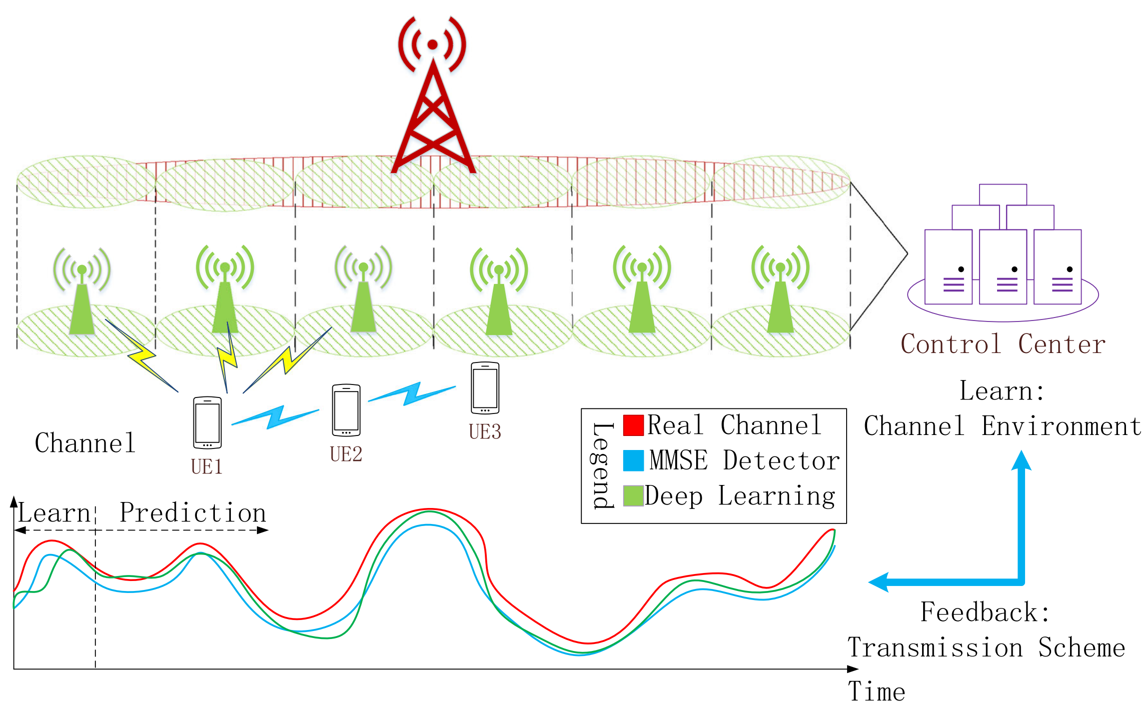

Fig. 1 Resource allocation in 5G heterogeneous D2D networks. Deep learning is the effective way to follow the change of channel

frequency (usually 800 MHz and 900 MHz), small cells are working in high frequency area, usually 2GHz and above, sometimes 15GHz above for wireless backhaul transmission. Downlink cooperation are also adopted to enhance the performance of cell edge and cancel/reduce adjacent interference.

Because all the base stations and small cells are connected to the control center, the global optimization could be computed and adopted. The resource allocation operation is usually based on the channel environment, so the prediction of channel environment is very important. The pilot based channel estimation method will take up the bandwidth resource in every frame (or within some intervals), and the AI based channel prediction could study the previous channel condition and predict the upcoming channel gain according to the historical data. In Fig. 1, the red curve means the real channel response, the blue one means the MMSE detector and the green curve means the AI based prediction.

Based on the transmission scheme, we will first model and give the optimization problem of the transmission, and then use the AI based learning to perform the dynamic transmission.

4.1 System model

We assume there are $M \in N$ small cells and $N \in N$ users located in the target area. For any user $j \in N$ is served by primary small cell $i \in M$. For any small cell i, we have the following model, the received signal of small cell could be expressed using Shannon Formula. $H$is the channel matrix between user and small cell, n is the additional Gaussian noise. By using the given frequency, the transmitter and the receiver will work under the MIMO structure. Then, the users can also communicate with each other, so the signal model is still the same as given in eq. (1) and (2). The D2D is performed in the same way, the differences are the power constraint, number of antennas and bandwidth.

$$y_i = \sum_{j \in N} H_{ij} x_j + n_i \tag{1}$$

To perform cooperation, information must be exchanged between cooperative pairs, so the received signal of cooperative small cell could be expressed as:

$$\hat{y}_k = \sum_{k \in N, k \neq j} H_{kj} x_j + n_k + z \tag{2}$$

k is the index of cooperative small cell, the number of the cooperative cell is depending on the algorithm of cooperation. The received signal is recovered by target cell and the cooperative cells, which is expressed by:

$$\begin{aligned} y &= \begin{pmatrix} y_i \\ \dots \\ y_k \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} \\ \dots & \dots \\ H_{j1} & H_{ji} \end{pmatrix} \begin{pmatrix} x_1 \\ \dots \\ x_j \end{pmatrix} + \begin{pmatrix} n_j \\ \dots \\ n_k + z \end{pmatrix} \\ &= \left(H_{j1} \dots H_{ji} \right) \begin{pmatrix} x_1 \\ \dots \\ x_j \end{pmatrix} + \begin{pmatrix} n_j \\ \dots \\ n_k + z \end{pmatrix} \end{aligned} \tag{3}$$

To make the discussion simple, we consider a 2-small cell and 2-user scenario illustrated in Fig. 2. To maximize the capacity under the proper resource allocation scheme, the target is to maximize the sum capacity, which could be expressed using the following equation. $I(x_s; y_A y_B)$ is the mutual information provided by Shannon Formula,

$$\begin{aligned} & I(x_s; y_A y_B) = H(y_A y_B) - H(y_A y_B | x_s) = H(y_A y_B) - H(n_A(n_B + z)) \\ & R_{yy} = E\left(yy^H\right) = \begin{pmatrix} H_A \\ H_B \end{pmatrix} Q_s \left(H_A^H \ H_B^H\right) + \begin{pmatrix} \sigma^2 I & \\ & \sigma^2 I + \phi_B \end{pmatrix} \\ & R_{nn} = E\left(nn^H\right) = \begin{pmatrix} \sigma^2 I & \\ & \sigma^2 I + \phi_B \end{pmatrix} \end{aligned} \tag{4}$$

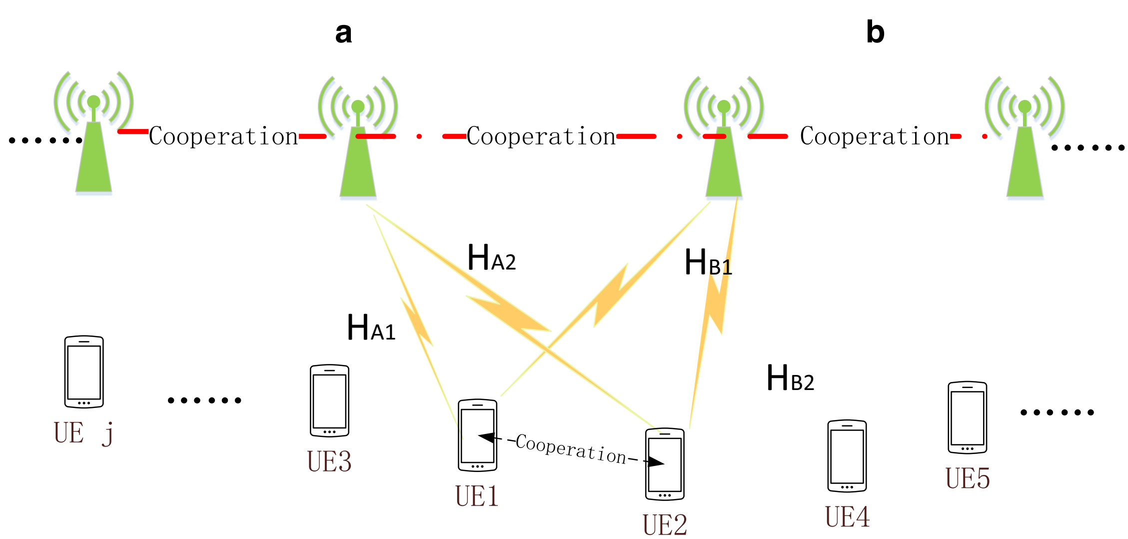

Fig. 2 System model of D2D cooperation in 5G wireless networks, cooperative links are performed in both base station side and terminal side

The mutual information from different small cell is expressed in eq. 5:

$$\begin{aligned} I(x_s;y_Ay_B) &= \mathrm{logdet}(\pi e R_{yy}) - \mathrm{logdet}(\pi e R_{nn}) = \mathrm{logdet}\left(R_{yy}R_{nn}^{-1}\right) \\ &= \mathrm{logdet}\left(I + Q_s\left(H_A^H \ \ H_B^H\right)\begin{pmatrix} \frac{1}{\sigma^2}I & \\ & \frac{1}{\sigma^2}I + \phi_B^{-1} \end{pmatrix}\begin{pmatrix} H_A \\ H_B \end{pmatrix}\right) \\ &= \mathrm{logdet}\left(I + \frac{Q_s}{\sigma^2}H_A^H H_A + Q_s H_B^H\left(\sigma^2 I + \phi_B\right)^{-1}H_B\right) \\ &= \mathrm{logdet}\left(I + \frac{Q_s}{\sigma^2}H_A^H H_A + Q_s H_B^H\left(\sigma^2 A + I\right)^{-1}AH_B\right) \end{aligned} \tag{5}$$

It is clear that the optimization is to maximize the sum capacity by changing the resource management policy. The target is concave under the constraint but the constraint is non-convex, so the optimization could not be adopted. So the optimization problem could not be tackled using CVX tool directly. A proper approximation method is in great need. In eq. 6, the objective is to maximize the sum rate of the fixed transmission and the constraint is the limitation of channel capacity and the power.

$$\begin{aligned} &\max_{A,Q_s} \quad \mathrm{logdet}\left(I + \frac{Q_s}{\sigma^2}H_A^H H_A + Q_s H_B^H\left(\sigma^2 A + I\right)^{-1}AH_B\right) \\ &s.t. \ \ \mathrm{logdet}\left(I + A\left(H_B\left(I + \frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}Q_s H_B^H + \sigma^2 I\right)\right) \\ &\qquad \le R_{BH} \ \ A \ge 0 \ \ \mathrm{tr}\left(C_1^T Q_s C_1\right) \le P_1 \ \ \mathrm{tr}\left(C_2^T Q_s C_2\right) \le P_2 \\ &\qquad Q_s = \begin{pmatrix} Q_1 & \\ & Q_2 \end{pmatrix} \ge 0 \end{aligned} \tag{6}$$

4.2 Deep learning method

To analyze the channel condition and perform proper resource allocation, it is necessary to recognize the channel environment. In this work, we introduce the deep learning method, by analyzing the historical data of channel conditions, the frequency of pilot could be significantly reduced and the accuracy of the prediction is greatly increased.

The key is to generate the neural networks according to the previous conditions. Multilayer perceptron is the proposed way to perform deep learning that contains input layer, hidden layer and output layer [21]. The nodes located in the hidden layers and the output layers takes the sigmoid threshold function instead of the step function. Then the input layer is working only to distribute the inputs between the neurons arranged in the hidden layer.

The error of particular set of inputs, which is denoted as p, is calculated for some node j in the output layer using eq. 7, where t_{pj} represents the required output, o_{pj} is the real output and δ_{pj} is the amount of error applied to the target node. The function $f'_j(net_{pj})$ is the derivative of the threshold function, applied to the activation at node j, which is simply the weighted sum of the inputs to that node, as used for the single perceptron. Error calculation for output node is given using the following equation, where the function is not suitable for hidden nodes because the correct target output is unknown

$$\delta_{pj} = f'_j\left(net_{pj}\right)\left(t_{pj} - o_{pj}\right) \tag{7}$$

Similarly, the error calculation for hidden nodes is computed using eq. 8:

$$\delta_{pj} = f'_j\left(net_{pj}\right)\sum_k \delta_{pk}w_{jk} \tag{8}$$

Derivative of the sigmoid function with respect to $\dot{f}(net)$ is calculated by:

$$f'(net) = ko_{pj}\left(1 - o_{pj}\right) \tag{9}$$

Then the following two equations give the error calculations with the threshold-function's derivative incorporated:

$$\delta_{pj} = ko_{pj}\left(1 - o_{pj}\right)\left(t_{pj} - o_{pj}\right) \tag{10}$$

$$\delta_{pj} = ko_{pj}\left(1 - o_{pj}\right)\sum_k \delta_{pk}w_{jk} \tag{11}$$

The above functions provide the way to calculate the error function to reduce it, as it will go back through the network. It will also be confirmed that the error for the nodes in hidden layers is proportional to the error in the nodes following it, such as the output nodes. Therefore, the output nodes are calculated first, followed by the last hidden node and so on back to the first set of hidden nodes. Once we have obtained the amount of error that will be applied at each node, the weights for each connections that lead to the nodes will be adjusted using eq. 12, where η is a gain term, and w_{ij} is the weight from node $i$to node j at time t.

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_{pj}o_{pj} \tag{12}$$

5 Deep learning based resource allocation method

Considering the optimization problem in eq. 6, we provide a deep learning approach to solve this. First of all, we will simplify the optimization and reduce the dimension of this mathematical work (Table 1).

According to target function, it could be simplified using eq. 13 as follows:

Table 1 Simulation Assumptions and Parameters

Name	Value
Antenna Configuration	4 by 4
Channel Model	SCME Urban Micro
Cell Layout	7 cell, 3 sector per cell
Transmit Power	6.3 W
System Bandwidth	20 MHz
System to Link Level Mapping	MI-ESM
Inter-site Distance	50 m
Number of Users	42 total, 2 per cell
Speed of UE	0.5 m/s
Pathloss Model	L = 93.4 + 22.8log10(R)
Shadowing Std	10 dB
AMC Table	QPSK (R = {1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 2/5, 1/2, 3/5, 2/3, 3/4, 4/5})
	16QAM (R = {1/2, 3/5, 2/3, 3/4, 4/5})
MIMO Detection	MMSE
Channel Estimation	Ideal
Simulation TTIs	1000

$$
\begin{aligned}
&\mathrm{logdet}\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A+Q_s H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\right)\\
&=\mathrm{logdet}\left(\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)\left(I+Q_s H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}\right)\right)\\
&=\mathrm{logdet}\left(\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)+\mathrm{logdet}\left(I+Q_s H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}\right)\right.\\
&=\mathrm{logdet}\left(\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)+\mathrm{logdet}\left(I+\left(\sigma^2 A+I\right)^{-1}AH_B\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}Q_s H_B^H\right)\right.\\
&=\mathrm{logdet}\left(\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)+\mathrm{logdet}\left(I+\left(\sigma^2 A+I\right)^{-1}A\left(R_{y_B|y_A}-\sigma^2 I\right)\right)\right.\\
&=\mathrm{logdet}\left(\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)+\mathrm{logdet}\left(I+AR_{y_B|y_A}\right)-\mathrm{logdet}\left(I+\sigma^2 A\right)\right.
\end{aligned}
\tag{13}
$$

So the optimization problem could be simplified as the following format:

$$
\begin{aligned}
\max_{A}\quad & \mathrm{logdet}\left(I+AR_{y_B|y_A}\right)-\mathrm{logdet}\left(I+\sigma^2 A\right)\\
s.t.\quad & \mathrm{logdet}\left(I+AR_{y_B|y_A}\right)\le R_{BH}\\
& A\ge 0
\end{aligned}
\tag{14}
$$

Where $R_{y_B|y_A}=H_B\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}Q_s H_B^H+\sigma^2 I$. By simplify the correlation matrix at the transmitter side, the optimization problem could be further reformed as:

$$
\begin{aligned}
\max_{Q_s}\quad & \mathrm{logdet}\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A+Q_s H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\right)\\
s.t.\quad & \mathrm{logdet}\left(I+A\left(H_B\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A\right)^{-1}Q_s H_B^H+\sigma^2 I\right)\right)\\
& \le R_{BH}\quad \mathrm{tr}\left(C_1^T Q_s C_1\right)\le P_1\quad \mathrm{tr}\left(C_2^T Q_s C_2\right)\le P_2\\
& Q_s=\begin{pmatrix} Q_1 & \\ & Q_2\end{pmatrix}\ge 0
\end{aligned}
\tag{15}
$$

Then the target function could also be simplified through basic matrix computation theory:

$$\begin{aligned}&\operatorname{logdet}\left(I+\frac{Q_s}{\sigma^2}H_A^H H_A+Q_s H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\right)\\&=\operatorname{logdet}\left(I+Q_s\left(\frac{H_A^H H_A}{\sigma^2}+H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B\right)\right)\\&=\operatorname{logdet}(I+Q_s(M+N))\end{aligned} \tag{16}$$

Thus, we have finally get the presentation of the optimization problem with $M=\frac{H_A^H H_A}{\sigma^2}$,: and $N=H_B^H\left(\sigma^2 A+I\right)^{-1}AH_B$

$$\begin{aligned}&\max_{Q_s}\quad \operatorname{logdet}(I+Q_s(M+N))\\&s.t.\quad \operatorname{logdet}(I+Q_s(M+N))-\operatorname{logdet}(I+Q_sM)\\&+\operatorname{logdet}\left(I+\sigma^2 A\right)\leq R_{BH}\ \ \operatorname{tr}\left(\mathrm{C}_1^T Q_s \mathrm{C}_1\right)\leq P_1\ \ \operatorname{tr}\left(\mathrm{C}_2^T Q_s \mathrm{C}_2\right)\leq P_2\\&\qquad Q_s=\begin{pmatrix}Q_1 & \\ & Q_2\end{pmatrix}\geq 0\end{aligned} \tag{17}$$

To solve this problem through deep learning, we model the deep learning architecture to follow the status of channel and help the flexible and precise allocation scheme. Deep learning refers to a group of algorithms that can compute optimal policies given a perfect model of the environment. Generally, Deep learning algorithms represent the solution what the channel condition is to approximate, just with less computation and without assuming a perfect model. The dynamics are given by the transition probabilities $P_{ss'}^a=\Pr\left\{s_{t+1}=s'|s_t=s,a_t=a\right\}$, and the expected immediate rewards$R_{ss'}^a=E\left\{r_{t+1}|a_t=a,s_t=s,s_{t+1}=s'\right\},\forall$ $s\in S$, $a\in A(s)$, and$s\in S+$, where $S+$ is a terminal state of S if the problem is episodic. An optimal policy is a simple ordering of policies based on their optimal value functions, denoted by V^* or Q^*,which is expressed using eq. 18:

$$\begin{aligned}&V^*(s)=\max_a\sum_{s'}P_{ss'}^a\left[R_{ss'}^a+\gamma V^*\left(s'\right)\right],\quad or\\&Q^*(s,a)=\sum_{s'}P_{ss'}^a\left[R_{ss'}^a+\gamma\max_{a'}Q^*\left(s',a'\right)\right],\\&\qquad\forall\ \ s\in S,a\in A(s),\text{and }s'\in S^+.\end{aligned} \tag{18}$$

Then we have the following deep learning method to tackle the problem expressed in eq. 17.

6 Simulation and performance analysis

In the simulation part, we present the simulation to evaluate the performance of our proposed method compared to MMSE optimization. Simulation assumptions and parameters are given in the following table.

The simulation platform is provided by Matlab 2018a and neural time series. To make the simulation simple, we use the dense urban channel provided by 3GPP. In Fig. 3, we present the training result of channel and the error. In this figure, the black line indicates the channel response generated from the channel model, the blue dot means the target of the optimization and the blue cross indicates the proposed output. The green dot means the target result of MMSE and the green cross means the real output adopted by the system. From this figure, we can infer that: for each inflection point, the deep learning method can follow most of the changing of the channel condition, so that the resource allocation is nearly approximated to the bound. However, some of the channel information is mission in our proposed deep learning method, where we circle them in the following figure. Compared to MMSE [22], there is about 1.04% loss (average value, depending on the scenario of channel), but we have the advantages of flexibility and computing speed. From the brown error diagram, we can see clearly that the errors is controlled within 10^{-6} orders of magnitude, which is satisfied in 5G systems.

In Fig. 4, the result of MSE [23] is given between deep learning and MMSE. The x-axis means the number of iterations and the y-axis means the mean square error (MSE). The red curve reflect the performance of MMSE method and the blue one reflect the deep learning method. From the figure, we can infer that, both the two methods can satisfy the demand of 5G wireless transmission, even when the number of iteration is small, the performance can reach the bound of 10^{-6}. When the number of iteration increase, especially about 450 times, there exists a deep decent and both two methods reach the bound of 10^{-11}, it is because the iteration slows down the speed of computing and more details of the channel is obtained, but it is not quite necessary for us to strive such small benefits [24, 25].

7 Conclusion

In this work, we present the cooperative resource allocation using deep learning in 5G based wireless networks. The contribution and the novelty of this work are summarized as follows:

First of all, we prove the modeling simplification of the optimization problem using the fixed resource allocation and convex optimization method, which helps reduce the complexity of the optimization;

Second, we perform the deep learning based optimization to approximate the bound of the allocation according to the channel condition, simulation result indicates that our proposed method can effectively reduce the complexity and achieve satisfied performance.

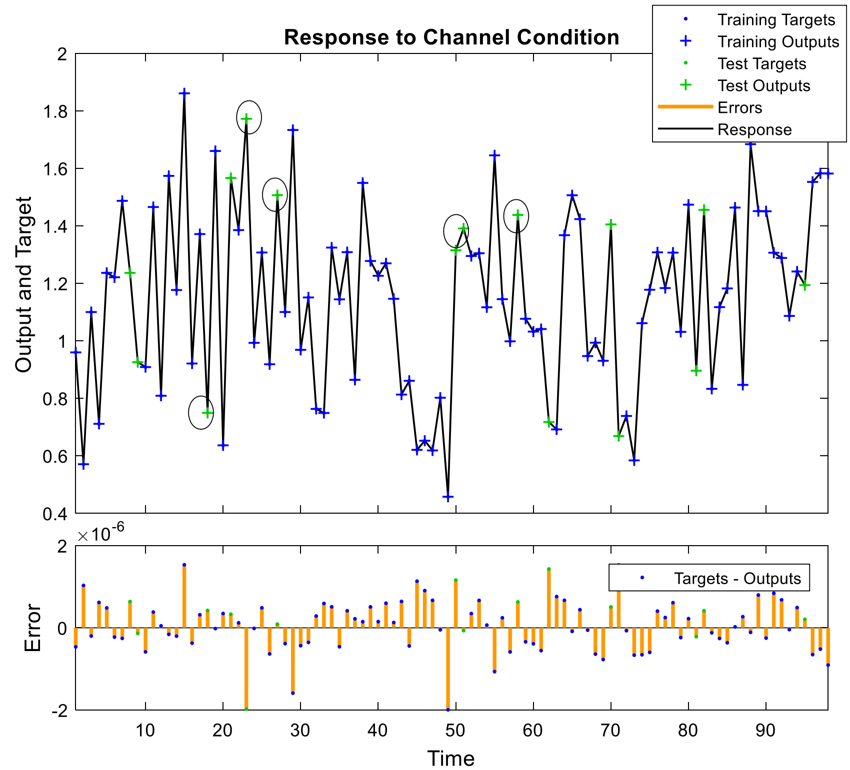

Fig. 3 Comparison of Deep Learning and MMSE

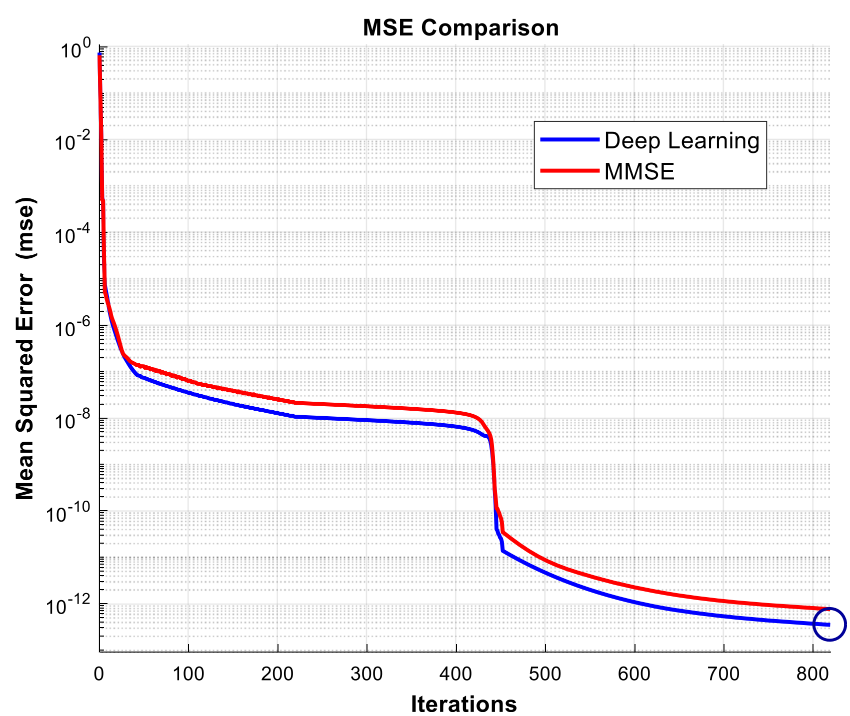

Fig. 4 Iteration versus MSE between Deep Learning and MMSE

Acknowledgments This work is funded by National Nature Science Foundation of China under grant of 61701503. The author would also like to thank all the reviewers, their suggestions help improve my work a lot.

Compliance with ethical standards

Conflict of interests The authors declare that there is no conflict of interests regarding the publication of this paper.

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