Deep Learning Based Resource Allocation for Full-Duplex-Enabled Two-Way Device-To-Device Communications

Xiaolei Tian[1], Yi Gao[1,2], and Liang Han[1,2](✉)

[1] College of Electronic and Communication Engineering, Tianjin Normal University, Tianjin 300387, China
hanliang@tjnu.edu.cn

[2] Tianjin Key Laboratory of Wireless Mobile Communications and Power Transmission, Tianjin Normal University, Tianjin 300387, China

Abstract. In recent years, device-to-device (D2D) communications and full-duplex (FD) communications, which can improve the spectrum efficiency (SE) of mobile communications, have been widely studied. FD-enabled two-way D2D communications, which integrate FD into D2D communications, can further improve the SE. Traditionally, iterative algorithms that converge to a local optimum are employed to solve the SE maximization problem of FD-enabled two-way D2D communication systems. However, its high computational complexity has stimulated the need for lower-complexity approximations at the expense of performance. Inspired by the success of deep learning in the balance between complexity and performance, we propose a novel application of the deep neural network (DNN) model for FD-enabled two-way D2D communication systems. The main idea consists of mapping a limited number of iterations of the concave-convex procedure (CCCP) algorithm into trainable neural network layers. As opposed to traditional iterative power allocation, we train the DNN to learn the nonlinear relation between the channel realizations and the corresponding power allocation schemes based on the CCCP algorithm. Extensive simulation results demonstrate that the DNN can provide a good approximation of the iterative CCCP algorithm while reducing the computational overhead significantly.

Keywords: Full-duplex · Deep learning · Two-way D2D communications · Spectrum efficiency · Concave-convex procedure algorithm

1 Introduction

In the face of the rapidly growing volume of data services, the problem of insufficient wireless resources in traditional cellular networks is becoming increasingly prominent. To improve the spectrum efficiency (SE) of cellular networks, many novel techniques are being studied, among which device-to-device (D2D) communications and full-duplex (FD) communications have been widely studied [1, 2]. In recent years, some researchers have integrated FD into D2D communications which can further improve the SE and

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reduce end-to-end latency. Existing studies have shown that an FD-enabled D2D communications have many advantages, such as increased SE [3–5] and improved network throughput [6, 7].

To improve the data transmission rate, it is important to optimize the power allocation for FD-enabled two-way D2D communication systems. In [8] the authors transformed the optimization problem into a difference of convex functions (D.C.) programming, and then proposed a concave-convex procedure (CCCP) algorithm to maximize SE. However, most of the works are mainly based on traditional methods to obtain optimal power allocation. The higher complexity of the traditional algorithms often means consuming a large amount of computational time.

Deep learning has been successfully applied to many fields, including speech recognition, automatic machine translation, and autonomous driving. Due to its characteristics, many researchers have tried to use DNN to solve wireless communication problems. Numerous studies have found that deep learning algorithms can not only achieve excellent performance in wireless communications but also significantly reduce computational complexity. Real-time power allocation using deep learning algorithms in real systems becomes a possibility. In [9], the authors use deep learning to solve critical signal processing problems, which shows that deep learning algorithms outperform traditional algorithms in terms of time reduction and computational complexity. To the best of our knowledge, there are few studies on power allocation schemes based on DNN methods. In this paper, we study deep learning algorithms for FD-enabled two-way D2D communication systems.

The rest of this paper is organized as follows. In Sect. 2, we introduce the system model including the system configuration, and formulate the SE maximization problem for the FD-enabled two-way D2D communication systems. In Sect. 3, we present the architecture of the system, the network structure, the process of data generation, and the training phase of DNN. In Sect. 4, we give the parameter selection and simulation results of the deep neural network to prove our hypotheses. Section 5 concludes the paper.

2 System Model

In this section, we consider FD-enabled two-way D2D communications with a pair of DUs (DU_1 and DU_2) sharing the uplink spectrum resource with one CU, as showed in Fig. 1. We denote the channels of the CU-BS, CU-DU_1, CU-DU_2, DU_1-BS, DU_2-BS, DU_1-DU_2 and DU_2-DU_1 links as h_{cb}, h_{c1}, h_{c2}, h_{1b}, h_{2b}, h_{12} and h_{21}, respectively.

We assume all the channels are frequency-flat and quasi-static, and all the channel state information is perfectly known at the base station (BS). There has been a lot of work on self-interference cancellation techniques, but in practice self-interference cannot be eliminated. We assume the residual self-interference is subject to the complex Gaussian distribution, which can be considered the worst-case assumption about the interference. The problem of maximizing SE for the uplink FD-enabled two-way D2D communication system can be modeled as [8]:

$$\begin{aligned}
&\max SE = \frac{1}{W}(R_c + R_1 + R_2)\\
&s.t. R_c \geq W\log_2(1 + \frac{P_c|h_{cb}|^2}{P_1|h_{1b}|^2 + P_2|h_{2b}|^2 + WN_0}) \geq R_c^{\min}\\
&R_1 \geq W\log_2(1 + \frac{P_2|h_{21}|^2}{P_c|h_{c1}|^2 + \beta P_1 + WN_0}) \geq R_1^{\min}\\
&R_2 \geq W\log_2(1 + \frac{P_1|h_{12}|^2}{P_c|h_{c1}|^2 + \beta P_2 + WN_0}) \geq R_2^{\min}\\
&0 < P_c \leq P_c^{\max}, 0 < P_1, P_2 \leq P_d^{\max}
\end{aligned} \tag{1}$$

where P_c, P_1 and P_2 denote the transmit power of the CU, DU_1, and DU_2, respectively, $R_c^{\min}$, $R_1^{\min}$ and $R_2^{\min}$ denote the minimum rate requirement for CU, DU_1 and DU_2, respectively, β is a constant that reflects the self-interference cancellation ability [8], and N_0 denotes the one-sided power spectral density of the additive white Gaussian noise (AWGN). We assume the maximum transmit power of the CU and DUs are $P_c^{\max}$ and $P_d^{\max}$, respectively, and the channels consist of small-scale and large-scale fading [4].

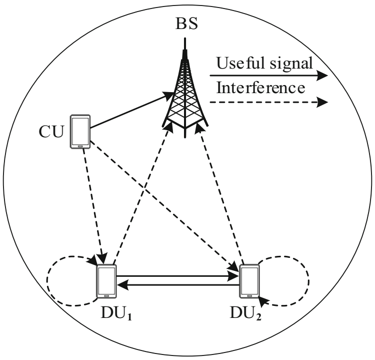

Fig. 1. System model

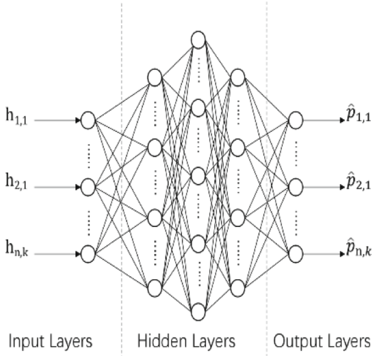

Fig. 2. The architecture of DNN

3 Proposed Deep Neural Network Approach

In this section, we present deep learning algorithms for the SE maximization problem. From the traditional algorithmic point of view, the CCCP algorithm can be treated as an unknown relationship between the channel realization and the corresponding power allocation. Deep neural networks can learn this unknown relationship very well. Although the ability of DNNs to learn this unknown relationship cannot be given a concrete explanation at the moment, people like to use DNNs, which are considered 'black boxes', to solve practical problems.

3.1 Making the Dataset

This paper aims to demonstrate that the DNN algorithm can be applied to FD-enabled two-way D2D communication systems with different maximum transmit power. Later we will verify the results by comparing the performance of the DNN algorithm with that of the conventional CCCP algorithm for different maximum transmit powers. The different maximum transmission powers can be expressed as $P_{\max 1}, P_{\max 2}, \ldots, P_{\max i}$. To ensure the rigor of the comparison, we pass in the traditional CCCP algorithm and the DNN algorithm in which the channel implementation is the same.

Because deep learning requires a large dataset of different instances to train a DNN, we need to prepare a large amount of training data and the corresponding labels. In the first step, a bulk channel matrix $H^{(t)}$ is generated, where t is the index of the training samples. The second step is to use the conventional CCCP algorithm to obtain the optimal power allocation matrices $P^{(t)}_{\max 1}, P^{(t)}_{\max 2}, \ldots, P^{(t)}_{\max i}$, which are the labels of the corresponding $H^{(t)}$, respectively. For convenience, we use $P^{(t)}$ to denote the label at different maximum transmitting powers. Thus, $[H^{(t)}, P^{(t)}]$ denotes the t-th sample.

3.2 The Architecture of Neural Network

Once the dataset is produced, from an artificial intelligence perspective, we need to design a supervised learning method to approximate the CCCP algorithm to maximize the SE in the FD-enabled two-way D2D communication system. As shown in Fig. 2, we propose a fully connected neural network that consists of an input layer, multiple hidden layers and an output layer. The channel gains in the model diagram are the input to the DNN and the optimal power allocation schemes are the output of the DNN. It is worth noting that since this is a regression problem in machine learning, the output of the DNN should be a continuous value. To increase the learning capability of the DNN, we apply rectified linear units (ReLU) as the activation function of the hidden layer.

3.3 Training and Testing the DNN

We train the DNN using a normalized training dataset and normalized labels. The process mainly consists of forwarding propagation and back-propagation. The purpose of forwarding propagation is to calculate the error value of the DNN. In addition, back-propagation updates the weights of the DNN by reducing the error values so that the target power allocation results obtained from the CCCP algorithm and the current DNN output are similar. The training process can be briefly described as shown in Fig. 3. We call the function consisting of all error values a loss function. The hidden loss function is represented as

$$
\begin{aligned}
loss &= E[loss_{mse} + loss_{const}] \\
&= E[\lambda_1(\sum(\hat{P}_c - P_c)^2 + \sum(\hat{P}_1 - P_1)^2 + \sum(\hat{P}_2 - P_2)^2) + \lambda_2 \sum \mathrm{ReLU}(\hat{P}_c - P_c^{\max}) \\
&+ \lambda_3 \sum \mathrm{ReLU}(\hat{P}_1 - P_d^{\max}) + \lambda_3 \sum \mathrm{ReLU}(\hat{P}_2 - P_d^{\max})]
\end{aligned}
\tag{2}
$$

where $\hat{P}_c$, $\hat{P}_1$, and $\hat{P}_2$ represents the output of the DNN.

The loss function consists of two parts, the first part is the mean square error $loss_{mse}$ between the DNN and the labeled output, and the second part is the constraint error $loss_{const}$.

The binding factors λ_1, λ_2 and λ_3 are used to balance the $loss_{mse}$ and $loss_{const}$ to ensure that the DNN can be trained well enough. Unlike other papers where only DNN and label errors are estimated, we think about the effect of constraints on the neural network in the loss function.

We experimented extensively to select suitable training parameters for the DNN. Furthermore, the training process was different when different learning rates were used. By testing different learning rates and batches, appropriate learning rates and batch sizes were selected based on the validation error of the previous 300 times DNN training sessions, as shown in Figs. 4 and 5 respectively.

Once we have optimized the weights of the DNN, we will obtain a neural network with good performance, and next we need to verify the performance of the DNN algorithm using a test dataset. To reduce the impact of chance on the performance evaluation, we average over multiple optimal power allocation schemes.

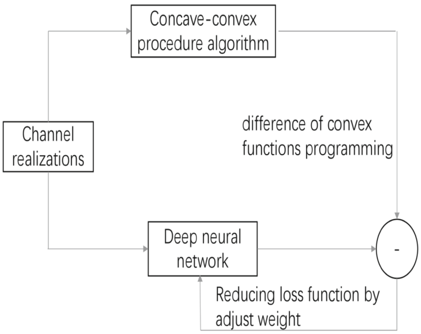

Fig. 3. The training flowchart

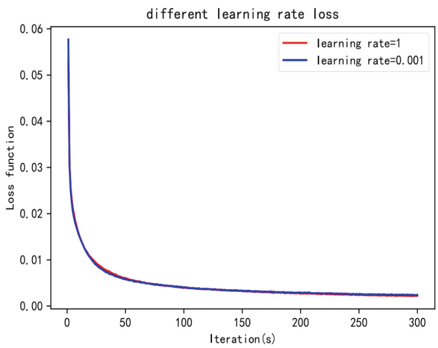

Fig. 4. Learning rate selection

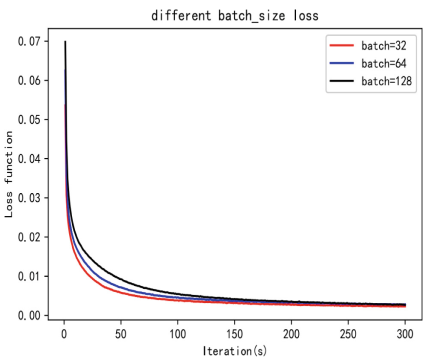

Fig. 5. Learning rate selection

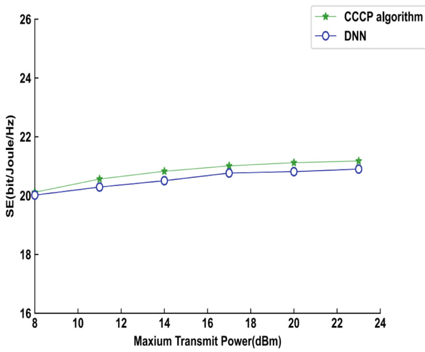

Fig. 6. Performance comparison

4 Numerical Results

In this section, we use the above channel modality to generate a 60000 samples dataset, with 50000 samples as the training dataset and 10000 as the test dataset. As the neural network is trained by reading the datasets sequentially, we randomly disrupt the order of the training datasets during training to reduce the impact of the fixed position information of the datasets on the neural network.

We consider the scenario of a single base station, a cellular user and a pair of D2D users. A new fully connected deep neural network algorithm has been developed. This network structure contains the following parts, an input layer with 7 nodes, three hidden layers with 64, 128 and 64 nodes, and an output layer with 3 nodes.

Through extensive experiments, we have come up with the most suitable batch size and learning rate of 32 and 0.001 respectively. We also found that by setting the balance factors λ_1, λ_2 and λ_3 to 1, 0.001 and 0.001 respectively, the DNN could achieve better performance. We give some numerical parameters for simulation, as shown in Table 1.

We measured the performance of the power allocation scheme of the newly proposed DNN algorithm and the power allocation scheme of the conventional CCCP algorithm as shown in Fig. 6. It is well known that the dataset for the DNN method is derived from the traditional CCCP algorithm, so the DNN scheme results cannot exceed the CCCP scheme. It is easy to observe from Fig. 6 that the performance of the proposed new DNN algorithm scheme is very close to that of the traditional CCCP algorithm.

In order to show the performance of the two algorithm allocation schemes more intuitively, we have drawn a comparison table of the accuracy of the two schemes, as shown in Table 2. From Table 2 we can see that when the target problem is SE maximization, the DNN algorithm can achieve more than 98% of the performance of the traditional CCCP algorithm and can be applied in practical scenarios.

Although the graphics processing unit (GPU) has a speed-up effect when processing neural networks, for the sake of comparative rigor, we use the central processing unit (CPU) to calculate the complexity of the DNN algorithm and the traditional CCCP algorithm separately. Their computation times are shown in Table 3.

Table 1. Simulation parameters

Parameters	Value
The cellular radius	1000 m
System bandwidth	1.8 MHz
Noise spectrum density	−174 dBm/Hz
The minimum rate requirement of CU	5 Mbps
The minimum rate requirement of D2Ds	10 Mbps
The maximum communication range of D2Ds	50 m
Path loss exponent	4

Table 2. The accuracy of DNN

The maximum transmit power	Accuracy
8 dBm	99.51%
11 dBm	98.67%
14 dBm	98.45%
17 dBm	98.83%
20 dBm	98.55%
23 dBm	98.7%

Table 3. Computational times for the two methods

The maximum transmit power	Total CPU Time(s)	
	DNN	CCCP (MATLAB)
8 dBm	0.000127	16.501179
11 dBm	0.000100	14.093196
14 dBm	0.000103	13.159920
17 dBm	0.000123	17.190953
20 dBm	0.000125	8.748877
23 dBm	0.000157	8.039851

5 Conclusion

Our research indicated that it is possible to learn a well-defined algorithm very well by using finite-sized deep neural networks. Our empirical results show that, for maximizing the SE problem of FD-enabled two-way D2D communications, deep neural networks can be trained to well-approximate the behavior of the state-of-the-art algorithm CCCP. However, this paper still exists some limitations. There are several interesting issues to investigate in the future, e.g., we will consider developing an unsupervised learning based power allocation scheme for FD-enabled two-way D2D communications, without using an optimization algorithm to provide training labels.

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References

1. Gupta, A., Jha, R.K.: A survey of 5G network: Architecture and emerging technologies. IEEE Access **3**, 1206–1232 (2015)

2. Ansari, R.I., et al.: 5G D2D networks: techniques, challenges, and future prospects. IEEE Syst. J. **12**(4), 3970–3984 (2018)
3. Wang, L., Tian, F., Svensson, T., Feng, D., Song, M., Li, S.: Exploiting full duplex for device-to-device communications in heterogeneous networks. IEEE Commun. Mag. **53**(5), 146–152 (2015)
4. Li, S., Ni, Q., Sun, Y., Min, G.: Resource allocation for weighted sum rate maximization in multi-user full-duplex device-to-device communications: approaches for perfect and statistical CSIs. IEEE Access **5**, 27229–27241 (2017)
5. Vu, H.V., Tran, N.H., Le-Ngoc, T.: Full-duplex device-to-device cellular networks: power control and performance analysis. IEEE Trans. Veh. Technol. **68**(4), 3952–3966 (2019)
6. Chai, X., Liu, T., Xing, C., Xiao, H., Zhang, Z.: Throughput improvement in cellular networks via full-duplex based device-to-device communications. IEEE Access **4**, 7645–7657 (2016)
7. Liu, F., Hou, X., Liu, Y.: Capacity improvement for full duplex device-to-device communications underlaying cellular networks. IEEE Access **6**, 68373–68383 (2018)
8. Han, L., Zhang, Y., Li, Y., Zhang, X.: Spectrum-efficient transmission mode selection for full-duplex-enabled two-way D2D communications. IEEE Access **8**, 115982–115991 (2020). https://doi.org/10.1109/ACCESS.2020.3004487
9. Sun, H., Chen, X., Shi, Q., Hong, M., Fu, X., Sidiropoulos, N.D.: Learning to optimize: training deep neural networks for interference management. IEEE Trans. Signal Process. **66**(20), 5438–5453 (2018)