

# Completely Distributed Power Allocation using Deep Neural Network for Device to Device communication Underlying LTE

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**Abstract**—Device to device (D2D) communication underlying LTE can be used to distribute traffic loads of eNBs. However, a conventional D2D link is controlled by an eNB, and it still remains burdens to the eNB. We propose a completely distributed power allocation method for D2D communication underlying LTE using deep learning. In the proposed scheme, a D2D transmitter can decide the transmit power without any help from other nodes, such as an eNB or another D2D device. Also, the power set, which is delivered from each D2D node independently, can optimize the overall cell throughput. We suggest a distributed deep learning architecture in which the devices are trained as a group, but operate independently. The deep learning can optimize total cell throughput while keeping constraints such as interference to eNB. The proposed scheme, which is implemented model using Tensorflow, can provide same throughput with the conventional method even it operates completely on distributed manner.

**Index Terms**—Device to device communication, Distributed power allocation, Deep learning, Interference management.

## I. INTRODUCTION

A centralized architecture is one of the limitations of the conventional wireless communications. In the centralized architecture, most processes of wireless communications are supervised by a central node, which can be represented as an evolved node B (eNB). It controls channels, transmit powers, and schedules. For this architecture, it is required that various control signals between devices and eNB. Besides, all of user data should be transferred through the eNB. In the future, high-quality real-time video streaming services and largecapacity virtual reality services have dramatically increased mobile data traffic [1]. It is inefficient to meet the demands of the future mobile data traffic with this central architecture. Therefore, it is inevitable that the wireless communication system should evolve into a distributed architecture. Device to device (D2D) communication on cellular system is one of the significant techniques for the distributed wireless communication architecture [2]. D2D communication can be applied by directly transferring data between devices or merging data to be transmitted to an eNB. There are two types of D2D communication on LTE [3]. D2D communication overlaying LTE is conventionally considered. In the system, distinguished frequency resources are allocated for D2D links. Thus, it does

not interfere with cellular system but the throughput gain would be marginal because of the limitation on the frequency resources. The other type is D2D communication underlying LTE. It allows D2D communication to use same frequency resource with the cellular system. They interfere with each other, but it can be expected resource gains from frequency reusing. Thus, minimizing the co-channel interference is very important study topic to improve the overall performance in cells. In order to reduce the co-channel interference, studies have been conducted in three ways. Firstly, some studies have suggested efficient spectral resource allocation methods to reduce the co-channel interference [4]. Other studies have proposed efficient transmit power allocation schemes to reduce interference effects such as [3], [5]. A mode selection scheme is devised to determines devices which are in D2D communication or cellular communication [6]. These three approaches are very close to each other, and most studies have been conducted in a mixture of two categories [7]–[10].

One of the difficulties of D2D communication underlying LTE is to be distributed architecture. Although it allows D2D communication, most proposed schemes are required a central supervisor, eNB. The D2D nodes suffer from lack of information. It is difficult for D2D nodes to consider global cell environments. For that reason, the schemes as mentioned above cannot be conducted without involvements of eNB. If eNB involves the D2D process too much, the benefits of introducing D2D communication into the cellular system is lost. Therefore, we focus on the distributed architecture for D2D communication underlying LTE. Specifically, the distributed transmit power allocation scheme is the target in this paper. Other considerations, such as resource allocation, would be the next step of this paper. Each D2D node should decide their transmit power with considering both throughput of itself and interference to conventional cellular system. The processes should be conducted without involvements of eNB as possible. Thus, we propose a distributed architecture to determine transmit powers using deep learning for each D2D devices. In this proposed method, a D2D transmitter can determine the transmit power without any involvement of either eNB or other D2D devices. It uses only the location of itself to determine the transmit power. Furthermore, the powers which determined in each devices maximize the total D2D throughput. Each device learns how to decide the transmit power to get the optimal cell throughput based on locations considering the interference to the conventional cellular infrastructure like eNB. Deep

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learning is used in the learning process. We also use Lagrange function as a deep learning cost function to meet constraints such as interference to eNB. According to our study, it is the first approach to the complete distributed power allocation decision to maximize global cell throughput, and this is also the first methodology to apply deep learning to a distributed decision problem to maximize global performance in wireless communications. Additionally, the proposed scheme is not specific for the D2D power allocation problem. It can be applied other minimizing(or maximizing) problem, because it is designed to cover a customized objective function while keeping several constraints. The main contributions of this paper are as follows:

- 1) According to the proposed method, a device can decide transmit power for device to device communication without any supporting of eNB. Simultaneously, it can maximize the overall cell throughput.
- 2) It preserves the total cell throughput as previous works but it conducts in a distributed way.
- 3) The proposed method focus on how to solve a very complicated minimizing (or maximizing) problem while keeping constraints. It can be applied to solve other problems.

The rest of this paper is organized as follows. In section II, we introduce backgrounds, which are related works for D2D communications and deep learning. In section III, the proposed method is described in three aspects: distributed architecture, cost design for learning, and deep learning process. Section IV is results from actual implementation of the proposed scheme. We show various expressions of the results, including power distribution of the cells. Finally, the significance of the proposed method is summarized in the conclusion section.

## II. RELATED WORKS

### A. Power allocation schemes for D2D communication underlaying LTE

D2D communication is standardized in LTE 12 release for the first time [11]. After the standardization, many research have been conducted to allocating resources or determining transmit power in D2D-enabled underlaying LTE environments. Effective resource allocation studies are important because they minimize co-channel interference and maximize overall data rate in cell. The authors of [12] proposed a framework for D2D-enabled cellular networks. This framework is used to understand and analyze the influence of D2D communication in performance of cellular networks. The authors of [13] proposed a relaying-based D2D scheme in full duplex. The proposed idea is used to allocate transmitting power of eNB and D2D transmitter. A goal of this idea is to optimize the overall performance of D2D users while meeting minimum performance requirements of cellular users. The authors [14] proposed a power allocation mechanism to maximize the energy efficient of D2D users. They used circuit powers consumption of D2D users to maximize the energy-efficient while meeting the minimum performance of cellular users. In [15], they proposed a power allocation mechanism to avoid interference while satisfying delay constraint. In those

research, D2D devices are still dependent on the eNB. The author of [3] designed to a distributed power allocation for D2D underlaying LTE. Nevertheless, the D2D devices should be supported by eNB to recognize the information for others.

### B. Basic concepts of deep learning

In this section, we introduce the schematic operations of deep learning, and important research using deep learning in wireless communication. Deep learning is one of the most emerging technique in these days [16], and it also applied to wireless communication [17]–[20]. Deep learning can be regarded as a simple function, which is  $Y = f(X)$ . It can be assumed as a linear function, where  $Y = WX + B$ . The appropriateness of output  $Y$  must be mathematically expressible. Cost function is the mathematical expression to determine the appropriateness of output  $Y$ . Also, an optimizer is a mathematical scheme to adjust gradually the  $W$  and  $B$  according to the cost function. It tries to adjust the  $W$  and  $B$  with various  $X$  repeatedly. Consequently, the optimizer can finalize the  $W$  which can derive the appropriate  $Y$  according to the cost function. The deep neural network (DNN), which is a basic model of deep learning, can be regarded as a composite  $Y=WX+B$ . The DNN can be defined as a complex composite linear function. It may have several layers. The basic unit of the DNN is  $XW + B$ , and the outputs would be inputs for the next  $XW + B$ . Finally, for the overall  $W$  and  $B$ , they are adjusted by an optimizer such as gradient decent or Adam optimizer [21]. The optimizer changes repeatedly  $W$  and  $B$  to minimize the cost function. A big composite linear function,  $(\dots((XW_1 + B_1)W_2 + \dots)W_n + B_n)$ , with a lot of  $XW + B$  can approximate various functions. This derives a lot of impressive results in other fields, and it should be considered to solve problems on wireless communications too. There are some key concepts of deep learning as follows.

1) *Network size*: DNN may have various size. It can have several layers, A layer is depicted as  $XW + B$ . The number of vectors in  $W, B$  is defined as width. In addition, the number of layers can be defined as depth. Therefore, network size for DNN means the width and depth. Network size of deep learning can be larger as required to approximate a more complex function. A DNN with large network size can capture the very fine features of the input data. But this does not always derive better results. There can be a case that too minor features should be ignored to get optimal results. If too fine features are selected, the features may be too specific to the given input data. It means that the features may not represent the overall data. In this case, DNN has good performance with the given data, but it does not with other data. It is called an overfitting problem [16], [22]. In other words, the overfitting problem is caused by lack of input data. If the input data set is large enough to represent the overall data, the overfitting problem would be reduced. Fortunately, there are a lot of actual data in wireless communication. Many mobile devices are generating various data in real time. For that reason, the overfitting problem does not need to be taken seriously in deep learning of wireless communication.

2) *Xavier initiation*: Xavier initiation is a method to initiate weights of DNN [23]. Generally, weights should be initialized randomly. Gaussian or uniform random distributions are considered firstly to initiate the weights. In the xavier initiation, input size and output size are considered additionally to reduce divergence of a neural network. A neural network tends to induce divergence, because variation would increase with passing each layer. To describe it, we assume a  $Y = WX$ , which is a basic calculation unit of a neural network as follows:

$$y = w_1x_1 + w_2x_2 + w_3x_3 + \dots + w_nx_n + b \quad (1)$$

Thus, the variation of each elements,  $w_ix_i$ , can be expressed as follows:

$$\begin{aligned} var(w_ix_i) &= E(x_i)^2 var(w_i) + E(w_i)^2 var(x_i) \\ &\quad + var(w_i) var(x_i) \\ &= var(w_i) var(x_i) \end{aligned}$$

where assuming the inputs are coming from a random distribution with zero mean. Thus, the variation of Equation 1 can be described as follows:

$$\begin{aligned} var(y) &= \sum_{i=1 \dots n} var(w_i) var(x_i) \\ &= n * var(w_i) * var(x_i) \end{aligned} \quad (2)$$

where the inputs and outputs are assumed to be all identically distributed. Consequently, the variation of output,  $var(y)$  is proportional to the number of  $x$  inputs. Note that the outputs would be input for the next layer, in multi layer neural networks. The variation of  $y$  can be too large, and this situation can cause a divergence of weights,  $W$ . To reduce this divergence of variation, the Xavier initiation consider the input size,  $n$ , to initiate the weights. Additionally, backward should be considered in DNN, because the optimizer uses back propagation algorithms [16] to update the weights. Finally, the Xavier initiation can be described as follows:

$$\begin{aligned} init\_range &= \sqrt{6.0/(input\_size + output\_size)} \\ \theta &= Rand(-init\_range, init\_range) \end{aligned} \quad (3)$$

where  $Rand(min,max)$  function is continuous uniformly random distribution with the range parameters,  $[min, max]$ .

3) *Batch normalization*: Batch normalization is a method to normalize outputs of each layer in deep learning [24]. It prevents the inputs of each layer to be divergent. Firstly the weights are adopted to the input  $X$ , where  $Y=WX$ . Note that conventional bias  $b$  is not added, because shifting should be conducted later. After that,  $Y$  is normalized with mean and variance of the  $Y$ . For the normalized  $Y$ , it would be re-scaled and shifted, with  $H = S \cdot Y + b$ . The  $S$  and  $b$  are initiated with 1 and 0 respectively, and they are trained by the optimizer. Thus, the  $S$  and  $b$  can be regarded as additional weights sets. After normalization, the output  $Y$  is controlled for preventing divergence, and the  $S$  and  $b$  are adjusted to produce better results.

4) *Adam Optimization*: We use the adam optimization algorithm. The adam optimizer is one of gradient descent optimization algorithm with requiring less memory other optimization algorithm [21]. The process of adam optimizer is described follows. Firstly, the method initializes a timestamp  $t$ , 1st momentum vector ( $m_0$ ) and 2nd momentum vector ( $v_0$ ) to zero.

$$\begin{aligned} t &= 0 \\ m_0 &= 0 \\ v_0 &= 0 \end{aligned} \quad (4)$$

The goal of this algorithm is to minimize the value of stochastic objective function  $f(\theta)$  with the parameter  $\theta$ . The optimizer gets gradients from the stochastic objective function  $f(\theta)$  at time  $t$ .

$$G_t = \nabla_{\theta} f_t(\theta_{t-1}) \quad (5)$$

With the gradient  $G_t$ , the optimizer calculates the momentum vectors with two decay rates,  $\beta_1$  and  $\beta_2$ .  $\beta_1$  and  $\beta_2$  is set to a decimal number between 0 and 1.

$$\begin{aligned} m_t &= \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \\ v_t &= \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2 \end{aligned} \quad (6)$$

The calculated momentum vector is biased to zero at the beginning of the learning since the optimizer initialized the two momentum vectors to zero. Therefore, this optimizer adjusts the momentum vector values to make the momentum vectors unbiased. This process is an advantage of adam optimizer. Equations to calculate the bias-corrected momentum vectors is described follow.

$$\begin{aligned} \hat{m}_t &= \frac{m_t}{1 - \beta_1^t} \\ \hat{v}_t &= \frac{v_t}{1 - \beta_2^t} \end{aligned} \quad (7)$$

With the bias-corrected momentum vectors, the optimizer updates the  $\theta$  that is a parameter of stochastic objective function  $f(\theta)$ .

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t \quad (8)$$

5) *Tensorflow*: Tensorflow is one of the major platforms for deep learning implementation [25], which is developed by Google. It has flexible architecture to implement or customize deep learning model. Also, it has a lot of open-source models on the internet, and it is easy to apply them for other applications.

### III. PROPOSED SCHEME

In this section, we describe the distributed power allocation using DNN with interference to eNB constraint (DPADIC).

### A. System model

We focus on maximizing the total D2D throughput while keeping two constraints: maximum power of a transmitter and interference to eNB. The maximum power constraint means that a total transmit power per a user cannot be over a limit. On the other hand, the interference constraint means that interference experienced at the eNB cannot be over a threshold. It is required because we focus on D2D underlying cellular system. In the underlying system, cellular system should be mainly supported by LTE. To guarantee performances of cellular system, D2D should be allowed only if the interference is under a threshold. We assume the OFDMA interface for LTE. It has orthogonal  $N$  subcarriers, which are non-overlapped, and the spectrum are regarded as flat. Thus, we consider a set  $\mathcal{N} = \{1, \dots, N\}$  of shared OFDMA channels. Also, we consider a set of D2D devices pair,  $\mathcal{K} = \{1, \dots, K\}$ . The pair of D2D devices consists of transmitter and receiver, and we assume that they are on perfect synchronization. Likewise, we consider multi-cell environments with  $C$  cells. The set of eNB is  $\mathcal{C} = \{1, \dots, C\}$ . The signal at receiver on link  $n$  can be expressed as follows:

$$Y_{n,k,k} = H_{n,k,k}S_{n,k,k} + \sum_{i \in \mathcal{K}, i \neq k} H_{n,i,k}S_{n,i,k} + W_{n,k,k} \quad (9)$$

where  $H_{n,k,i}$  is the complex channel gain between a transmitter of  $k$  D2D pair, and a receiver of D2D pair  $i$  on channel  $n$ .  $S_{n,k,k}$  is the symbol of transmission, which is power  $p_{n,k} = E\{|S_{n,k,k}|^2\}$ .  $W_{n,k,k}$  is an additive zero-mean Gaussian disturb with variance  $(\sigma_{n,k})^2$ . Also, we assume that it includes additional noise, such as thermal noise, with the interference from the cellular networks. Therefore, the throughput  $T_k$  for a receiver of D2D pair  $k$  is expressed as follows:

$$T_k(\mathbf{p}_k) = \sum_{n \in \mathcal{N}} \log_2 \left( 1 + \frac{(H_{n,k,k})^2 p_{n,k}}{\sum_{i \in \mathcal{K}, i \neq k} (H_{n,i,k})^2 p_i^n + (\sigma_k^n)^2} \right) \quad (10)$$

where  $\mathbf{p}_k$  is a set of transmit powers for D2D pair  $k$  on each link,  $\mathbf{p}_k = \{p_1, p_2, \dots, p_N\}$ . The purpose of the proposed scheme is to maximize sum of D2D throughput, while keeping the two constraints: power constraint, and interference to eNB constraint. Therefore, the objective function and constraints can be derived as:

$$\begin{aligned} & \text{maximize} && \sum_{k \in \mathcal{K}} T_k(\mathbf{p}_k) \\ & \text{subject to} && \sum_{n \in \mathcal{N}} p_k^n \leq P_k, k \in \mathcal{K}, \\ & && \sum_{k \in \mathcal{K}} (H_{n,k,c})^2 p_k^n \leq Q_n, n \in \mathcal{N} \end{aligned} \quad (11)$$

where  $P_k$  is the power limitation of each D2D transmitter.  $Q_n$  is the interference to eNB constraint per channel.

### B. Distributed power allocation using DNN with interference constraints

We explain the DPADIC in three perspectives. The first feature of DPADIC is a distributed deep learning architecture. The devices predict their transmit power by itself, and they learn together how to maximize the overall throughput. Secondly, the objective function of the deep learning is described. It adopts the Shannon capacity equation for spectral efficiency. Also, it contains the given constraints. Finally, deep learning process of the proposed method is shown.

1) *Distributed architecture*: In Fig. 1, the architecture of the proposed method is described. Each device use the DNN to predict their power set respectively, and the overall results are merged to update the DNN. Therefore, the DNN can be described as follows:

$$\mathbf{p}_k = \text{DNN}(k, \theta) \quad (12)$$

where  $k$  is a D2D pair. The  $\theta$  is a set of weights and bias in the DNN,  $\{\mathbf{W}, \mathbf{b}\}$ , which are contents of the DNN. It determines what output DNN would derive for a given input. Also, it is shared for all  $k$  in a given D2D devices set  $\mathcal{K}$ . Deep learning is a process to find the optimal  $\theta$  with all cases of the  $\mathcal{K}$ . There are various cases of the  $\mathcal{K}$ , because the locations of  $k$  are regarded as being determined randomly. To consider the various  $\mathcal{K}$ , we define a set *batch*, as a set of  $\mathcal{K}$ , where  $\text{batch} = \{1, \dots, BN\}$ , and  $BN$  is size of *batch*. Therefore, the optimal  $\theta$  is  $\theta^*$  for the *batch*. It can be described as follows:

$$\begin{aligned} \theta^* &= \text{argmax} \sum_{\mathcal{K} \in \text{batch}} \sum_{k \in \mathcal{K}} T_k(\text{DNN}(k, \theta)) \\ &= \text{argmax} \sum_{k \in \text{batch}_k} T_k^*(\text{DNN}(k, \theta), \mathcal{K}) \end{aligned} \quad (13)$$

where the  $T_k^*$  is same as  $T_k$  but it depends on a specific  $\mathcal{K}$ . The  $\text{batch}_k$  is a set of all  $k$  in the set *batch*. The *batch* is a set of  $\mathcal{K}$ , and the  $\mathcal{K}$  is a set of  $k$ . Hence, the *batch* can be re-defined as  $\text{batch}_k$ , the set of all  $k$  in the set *batch*, where  $\text{batch}_k = \{1, \dots, BN \cdot K\}$ . Generally, deep learning process is conducted with several input data at once. The set of input data, which is processed at once, is defined as a batch. According to the design of the proposed method, *batch* should be tweaked as  $\text{batch}_k$  before learning. The process can be described as follows:

$$\text{batch} = \{k_{ij} \mid 1 \leq i \leq K, 1 \leq j \leq BN\} \quad (14)$$

$$\begin{aligned} \text{batch}_k &= \text{vec}(\text{batch}) \\ &= \{k_i \mid 1 \leq i \leq K \cdot BN\} \end{aligned} \quad (15)$$

where  $\text{vec}()$  is vectorization. It can be described as  $\text{vec}(A) = [a_{1,1}, \dots, a_{m,1}, a_{1,2}, \dots, a_{m,2}, \dots, a_{1,n}, \dots, a_{m,n}]^T$  for an  $m \times n$  matrix  $A$ . On the other hand, the  $k$  consists of the 4 values: locations of transmitter and receiver on a pair of D2D devices, where  $k = [tx\_x_k, tx\_y_k, rx\_x_k, rx\_y_k]$ . Also, the outputs of deep learning are  $N$  values: transmit power set for OFDMA with  $\mathcal{N}$ , which is the shared OFDMA channel. After training, every transmitter has the same trained DNN. They can get the

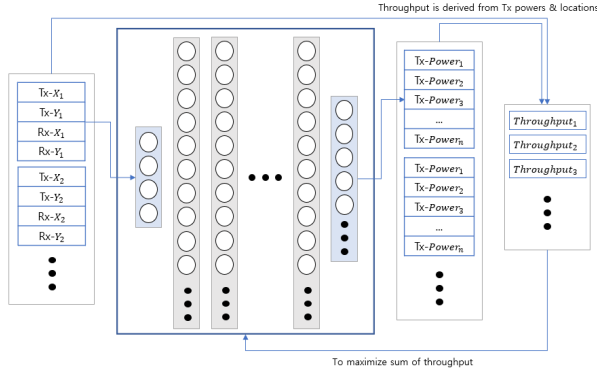


Fig. 1: Distributed DNN architecture for OFDMA

optimal transmit power on the distributed way. Of course, the results would maximize the total D2D throughput.

2) *Cost function design*: In the section, we describe the cost function design, which make possible to maximize total cell throughput while keeping the constraints. To propose a practical mechanism, we apply two constraints to the cost function: i) transmitting power constraints, ii) interferences to eNB constraints. We adopt the Lagrange function to express the two constraints in the cost function. Typically, the Lagrange function is a function that is used to minimize or maximize the target value in constrained environment [26]. Typical cost function in deep learning of regression problem is mean square error (MSE), which is an average of square of difference between predictions and pre-defined answers. It intends to give benefit or penalty to update DNN for reducing the differences. In other words, cost function can be customized if it can give benefit or penalty based on the purpose of the system. Therefore, we use throughput directly to the cost function itself in the proposed scheme, which shown in Equation 10. Thus, the answers are not required. Throughput is too complex function, but it is not a problem for deep learning. Additionally in the proposed scheme, the two constraints are adopted into the cost function. Firstly, the power constraint,  $Ct_p$  is as follows:

$$Ct_p = \sum_{k \in \mathcal{K}} \log_2 \left( 1 + \frac{\text{ReLU}(\sum_{n \in \mathcal{N}} p_k^n - P_k)}{P_k} \right) \quad (16)$$

where a rectified linear unit (ReLU) function is used.  $\text{ReLU}(x)$  function is defined as  $\text{ReLU}(x) = \max(0, x)$ . If the sum of transmit power of a D2D transmitter is under the threshold,  $P_k$ , the  $Ct_p$  would be 0. Therefore, it only delivers penalty if the transmit power of a transmitter is over the constraint. The remaining part is designed for re-scaling. The appropriate re-scaling is important to estimate the lagrange multipliers. In the proposed scheme, it is difficult to determine the lagrange multipliers,  $c_p$  and  $c_{if}$ , because the cost function is very complex. If difference scales between the objective function, which is throughput in the proposed scheme, and constraints is too large, it would be difficult to find the appropriate lagrange multipliers. Thus, the objective function and constraints are designed to be on simliar scales by having a similar forms. Note that the Shannon capacity is formed by  $\log_2(1 + \text{SINR})$ ,

and the SINR is a signal ratio, which has no quantitative unit. Therefore, the constraints are also designed as the shannon capacity as  $\log_2(1 + \text{ratio})$ , and the *ratio* has no quantitative unit too. This design is shown to work effectively in the section IV.

The interference to eNB constraint is also designed in similar way to the power constraint. Before defining the constraint formula, interference to eNB should be defined. It can be described as follows:

$$eNB\_if_{(n,k,c)}(\mathbf{p}) = \sum_{k \in \mathcal{K}} (B_{(n,k,c)} p_k^n) \quad (17)$$

According to Eq. 11, the interferences to eNB constraints are set to each channel. Note that the additive zero-mean Gaussian disturb is not adopted to the formula. The purpose of this formula is to formulate the impact of each D2D transmitter on the eNB. Thus, the random noise factor should be ignored. Therefore, the interference to eNB constraints,  $Ct_{if}$ , can be formulated as follows:

$$Ct_{if} = \sum_{c \in \mathcal{C}} \sum_{n \in \mathcal{N}} \log_2 \left( 1 + \frac{\text{ReLU}(eNB\_if_{(n,k,c)} - Q_n)}{Q_n} \right) \quad (18)$$

Finally, the cost function of the proposed method can be described as follows:

$$\text{Cost} = - \sum_{k \in \mathcal{K}} T_k(\mathbf{p}_k) + Ct_{if} c_{if} + Ct_p c_p \quad (19)$$

where  $c_{if}$  and  $c_p$  are constants to control strength of  $Ct_{if}$  and  $Ct_p$  respectively. The constants can be adjusted in deep learning process, which would be described in the next section. Although the constraint formulas are designed to re-scale the constraints, the strength constant would be help more accurate approximation of the power prediction. Note that there are several parameters in deep learning, such as learning rate, network size, and batch size. They are also adjusted in training process. The strength constants of the constraints can be adjusted only a few trials. Furthermore, throughput is negative, and constraints are positive because deep learning is a process to minimize cost function. But we should maximize throughputs, while minimizing the penalty.

Parallel operation is another key point of the proposed method. Note that the deep learning process is conducted with a batch, which is a set of input data. The prediction and costs including constraints should be derived in parallel. If parallel operation is impossible, the batch size is fixed to 1. It may slow down overall operation too much. In the conventional deep learning, parallel operation is not important because the cost function has simple designs. However, it is difficult to consider interference for each device since the distance to all devices must be taken into the cost function in parallel. Therefore, we describe a detail process of the parallel operation for the cost function.

A D2D pair  $k$  has four features of locations:  $x, y$  for transmitter and receiver respectively. It can be described as follows:

$$k_{ij} = \{k_{ij(tx)-x}, k_{ij(tx)-y}, k_{ij(rx)-x}, k_{ij(rx)-y}\} \quad (20)$$

Firstly it should be separated to locations of transmitter and receiver to determine the distance between each other.

$$k_{ij}(tx) = \{k_{ij}(tx)-x, k_{ij}(tx)-y\} \quad (21)$$

$$k_{ij}(rx) = \{k_{ij}(rx)-x, k_{ij}(rx)-y\} \quad (22)$$

These input data should be processed in a batch. Thus they are regarded as batch sets as follows:

$$batch_{tx} = \{k_{ij}(tx) \mid 1 \leq i \leq K, 1 \leq j \leq BN\} \quad (23)$$

$$batch_{rx} = \{k_{ij}(rx) \mid 1 \leq i \leq K, 1 \leq j \leq BN\} \quad (24)$$

Transmit power and received power are also re-defined in the batch unit as follows:

$$\mathcal{P}_{batch} = \{\mathbf{p}_{ij} \mid 1 \leq i \leq K, 1 \leq j \leq BN\} \quad (25)$$

$$\begin{aligned} \mathcal{R}_{batch,k,k} &= \{(\mathcal{H}_{n,k,k})^2 p_{n,k} \mid n \in \mathcal{N}, k \in \mathcal{K}, \mathcal{K} \in batch\} \\ &= \mathcal{P}_{batch} - \mathcal{P}\mathcal{L}_{batch,k} \end{aligned} \quad (26)$$

where the  $\mathcal{P}\mathcal{L}$  is path loss model [27] for describing channel model according to changing distance as follows.

$$PL(k_{ij}(tx), k_{ij}(rx)) \quad (27)$$

$$\begin{aligned} &= L_1 + L_2 \log(|(k_{ij}(tx))^T k_{ij}(tx) - (k_{ij}(rx))^T k_{ij}(rx)|_2) \\ \mathcal{P}\mathcal{L}_{batch,k,k} &= \{PL(k_{ij}(tx), k_{ij}(rx)) \mid 1 \leq i \leq K, 1 \leq j \leq BN\} \end{aligned} \quad (28)$$

The path loss model considers the distance between transmitter and receiver. It is adopted to interference too. The other transmitters in same  $\mathcal{K}$  are interferers to a receiver of D2D pair  $i$ . The following process is to determine the interference from the other transmitters in the same  $\mathcal{K}$ . For that in parallel, a path loss map is required which can describe the path loss between all transmitters to all receivers in the same  $\mathcal{K}$ . First, the  $(batch_{tx})^T$ s, which is a transformed vector of transmitters, is redundantly concatenated. We define this set as  $batch_{tx(T)(ex)}$ . The number of  $(batch_{tx})^T$  in the  $batch_{tx(T)(ex)}$  is  $K$ . The  $batch_{rx(T)(ex)}$  is also defined in the same way:

$$\begin{aligned} batch_{tx(T)(ex)} &= \overbrace{(batch_{tx})^T \frown (batch_{tx})^T \cdots (batch_{tx})^T}^K \\ &= \begin{bmatrix} (batch_{tx})^T \\ (batch_{tx})^T \\ \vdots \end{bmatrix} = \begin{bmatrix} k_{1j}(tx) & \cdots & k_{Kj}(tx) \\ k_{1j}(tx) & \cdots & k_{Kj}(tx) \\ \vdots & \vdots & \vdots \end{bmatrix} \end{aligned} \quad (29)$$

$$batch_{rx(T)(ex)} = \overbrace{batch_{rx}^T \frown batch_{rx}^T \cdots batch_{rx}^T}^K \quad (30)$$

Now, the path loss map,  $\mathcal{P}\mathcal{L}_{map}$ , is defined from the Equation 29, 30.

$$\begin{aligned} \mathcal{P}\mathcal{L}_{map_{ij}} &= PL((batch_{tx(T)(ex)})_{ij}, ((batch_{rx(T)(ex)})^T)_{ij}) \\ &= PL\left( \begin{bmatrix} k_{1j}(tx) & \cdots & k_{Kj}(tx) \\ k_{1j}(tx) & \cdots & k_{Kj}(tx) \\ \vdots & \vdots & \vdots \\ k_{1j}(tx) & \cdots & k_{Kj}(tx) \end{bmatrix}, \begin{bmatrix} k_{1j}(rx) & \cdots & k_{1j}(rx) \\ k_{2j}(rx) & \cdots & k_{2j}(rx) \\ \vdots & \vdots & \vdots \\ k_{Kj}(rx) & \cdots & k_{Kj}(rx) \end{bmatrix} \right) \end{aligned} \quad (31)$$

where the number of vectors in the  $\mathcal{P}\mathcal{L}_{map}$  should be  $K$ , not the  $batch\_size$ . Note that GPU can process a vector calculation at once, e.g,  $O(\mathbf{a} + \mathbf{b}) = 1$  if the size of the vector is enough to be processed in the memory of the GPU at a time. From that, no matter how the  $batch\_size$  is, the cost is designed to be derived from only  $K$  times of calculations. After deriving the  $\mathcal{P}\mathcal{L}_{map}$ , an element vector,  $\mathcal{P}\mathcal{L}_{map}_i$  in the  $\mathcal{P}\mathcal{L}_{map}$  should be re-transformed as follows:

$$\begin{aligned} \mathcal{P}\mathcal{L}_{map}_i &= \begin{bmatrix} PL(k_{1j}(tx), k_{ij}(rx)) \\ PL(k_{2j}(tx), k_{ij}(rx)) \\ \vdots \\ PL(k_{Kj}(tx), k_{ij}(rx)) \end{bmatrix} \\ &= \begin{bmatrix} PL(k_{11}(tx), k_{i1}(rx)) & \cdots & PL(k_{1BN}(tx), k_{iBN}(rx)) \\ PL(k_{21}(tx), k_{i1}(rx)) & \cdots & PL(k_{2BN}(tx), k_{iBN}(rx)) \\ \vdots & \vdots & \vdots \\ PL(k_{K1}(tx), k_{i1}(rx)) & \cdots & PL(k_{KBN}(tx), k_{iBN}(rx)) \end{bmatrix} \end{aligned} \quad (32)$$

$$\begin{aligned} (\mathcal{P}\mathcal{L}_{map}_i)^T &= \begin{bmatrix} PL(k_{11}(tx), k_{i1}(rx)) & \cdots & PL(k_{K1}(tx), k_{i1}(rx)) \\ PL(k_{12}(tx), k_{i2}(rx)) & \cdots & PL(k_{K2}(tx), k_{i2}(rx)) \\ \vdots & \vdots & \vdots \\ PL(k_{1BN}(tx), k_{iBN}(rx)) & \cdots & PL(k_{KBN}(tx), k_{iBN}(rx)) \end{bmatrix} \end{aligned} \quad (33)$$

The  $(\mathcal{P}\mathcal{L}_{map}_i)^T$  is a table of path loss that the  $i$  th receiver receivers from all other transmitters in the same  $\mathcal{K}$ . The  $(\mathcal{P}\mathcal{L}_{map}_i)^T$  has  $BN$  vectors because  $BN$  is the number of set  $\mathcal{K}$  in a batch. Therefore, the received power  $\mathcal{R}_{batch,other,i}$  is defined as follows:

$$\begin{aligned} \mathcal{R}_{batch,other,i} &= \sum (\mathcal{P}_{batch} - (\mathcal{P}\mathcal{L}_{map}_i)^T - \mathcal{R}_{batch,i,i}) \\ \mathcal{R}_{batch,other,i(b)} &= \sum_{j=1, \dots, K} (\mathbf{p}_{jb} \\ &\quad - PL(k_{jb}(tx), k_{jb}(rx)) - \mathcal{R}_{batch,k,k(jb)}) \end{aligned} \quad (34)$$

It describes the experienced interference at the  $i$ th receiver. Note that the interference signals also reduced by path-loss. The  $\mathcal{R}_{batch,other,i(b)}$  is the sum of experienced interference at

the  $i$ th receiver in  $b$ th batch. Thus, the  $T_k(\mathbf{p}_k)$  in Equation 10 is also derived on batch from Equation 26 and 34.

$$T_{batch}(\mathcal{P}_{batch}) = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \log_2 \left( 1 + \frac{\mathcal{R}_{batch,k,k}}{\mathcal{R}_{batch,other,k(b)+(\sigma_k^n)^2}} \right) \quad (35)$$

Note that the  $T_{batch}$  has  $BN$  values. Similiary, the constraint formula 16 is re-defined. The power vectors is replaced by batches of power,  $\mathcal{P}_{batch}$ .

$$Ct_{p,batch} = \sum_{k \in \mathcal{K}} \log_2 \left( 1 + \frac{ReLU(\sum_{n \in \mathcal{N}} \mathcal{P}_{batch} - P_k)}{P_k} \right) \quad (36)$$

The interference constraint in Equation 17 is also changed on the similar way as described above. Firstly, experienced interference of a batch is described with the path loss and received power of a batch from Equation 26 and 28. The constants of the path loss,  $L_1$  and  $L_2$  could be changed if the receiver in the  $PL$  is  $c$ . Thus, the interference constraint of a batch,  $Ct_{if,batch}$  is also defined using the experienced interference of a batch.

$$eNB\_if_{batch}(\mathcal{P}_{batch}) = \sum_{k \in \mathcal{K}} (\mathcal{P}_{batch} - \mathcal{P}\mathcal{L}_{batch,k,c}) \quad (37)$$

$$Ct_{if,batch} = \sum_{c \in \mathcal{C}} \sum_{n \in \mathcal{N}} \log_2 \left( 1 + \frac{ReLU(eNB\_if_{batch}(\mathcal{P}_{batch}) - Q_n)}{Q_n} \right) \quad (38)$$

In the end,  $Cost_{batch}$  is defined from Equation 35, 36, and 38. Final cost is defined as an averaged of the batch costs as  $Cost_{final}$ . It is actually used into the optimizer to update  $\theta$ , which is the contents of the neural network.

$$Cost_{batch} = -\mathcal{T}_{batch}(\mathcal{P}_{batch}) + Ct_{p,batch}c_p + Ct_{if,batch}c_{if} \\ Cost_{final} = \frac{1}{BN} \sum_{batch=\{1,\dots,BN\}} Cost_{batch} \quad (39)$$

3) *Deep learning process*: The process is similar with a typical deep learning excepts it can include the simulation into the training process because labels are not required. It may be operated with pre-processed input data. It means that a separated simulation generates overall input data, and then the data are trained by deep learning. However, we include the simulation into training process because it is more intuitive. Thus, the simulation generates input data as much as required at every iteration. The data set for an iteration is defined as a batch. The `batch_size` is a number of input data set which is processed at an iteration. The detailed training process is described in Algorithm 1. The  $\theta$  is defined separately as  $(W, b, W_{out}, b_{out})$  to adopt drop out for the out layer. We adopt Xavier initiation [23]. The iteration means the number of training trials. The  $n\_epoch$  is the number of iterations. The simulation is designed to deliver a batch, which is a set of input data. The size of a batch is given as `batch_size`. `Train()` function is the actual training part in 1. `Get_Throughput(X,P)`

delivers the throughput as defined in Equation 10. Finally, the throughput results are included in a set `Throughput`. The throughput results are collected in order of iteration in the set `Throughput`.

The `Train()` predicts the power set  $P$  with input data  $X$  and  $\theta$ . Then, the cost function is defined as  $c$  with the input data as  $X$  and the predicted power as  $P$ . Cost function is the main part of this train function. It is implemented with Equation 19 including batch control. The  $X$  and  $P$  may have several data because batch data are trained at once. In the cost function, it delivers Equation 19 of each input data respectively, and the results are averaged. We also use Adam optimizer to adjust  $\theta$  [21]. It deals with the cost function itself, not the result of the cost function. Adam optimizer differentiates the cost function to trace the changes. Consequently,  $\theta$  is gradually changed by the optimizer to minimize the cost function. In `Predict()`, reshape function is used to change shape of the input data. The first shape of input data is `[batch_size, K, 4]`. It means that there are the number of `batch_size` input data set, and an input data has  $K$  number of d2d pairs. A pair of D2D has four figures:  $x, y$  of transmitter and receiver respectively. It should be changed to `[batch_size  $\times$  K, 4]`, because each D2D pair data should be independent to distributed learning. Thus, there are  $batch\_size \times K$  D2D pairs. After reshaping, it should be actually calculated repeatedly as mentioned above. Furthermore, we adopt batch normalization to the proposed method. The sigmoid function is used as an activation function for each layer. The sigmoid function is defined as  $\frac{1}{1+e^x}$ . It adjusts the output of the previous calculation of each layer to 0 between 1. After the iteration of calculating in the neural network, it should be reshaped again to `[batch_size, K, 8]`, to be original form. Then, it is re-scaled to between -150 to 20, because the unit of output power is dBm.

#### IV. RESULTS

The results are presented in this section. We actually implement the proposed scheme in Tensorflow [25]. We consider the same environment to [3]. We assume hexagonal cells with radius  $R = 500m$ . The maximum distance between D2D pairs is  $D_{max} = 100m$ , while they are uniformly distributed in  $[0, D_{max}]$ . Also we consider multi-cell cases, which are  $C = 3$  and  $C = 7$ . The number of D2D pairs is 8 per a cell. Thus, the number of D2D pairs is  $K = 8 \times C$ . The number of OFDMA subchannels is set to  $N = 8$ , and then a spectral efficiency  $\eta$  would be derived as  $\eta = \frac{\sum T_k}{(K \times N)}$ . The maximum transmit power constraint is set to  $P_k = 0.25$  W. The channel attenuation is expressed by the path loss with distance, including shadowing and fading. The path loss exponent is  $\alpha = 4$ , with shadowing with standard deviation  $\sigma = 8dB$  on log normal distribution. The additive zero-mean Gaussian noise to cellular network from D2D is set to -130 dBW.

Table I shows default parameters of DNN. Width and depth are network size of DNN. Batch size is the number of data per a training process. We use 50 data for a batch, and the number of iterations is 100K. Thus, we use 5M cases of drops for learning, and there are no duplicated data in the 5M cases.

---

**Algorithm 1:** Training Phase

---

**Input** : input\_size=4, output\_size=8, width, depth, n\_epoch, batch\_size

**Output:** Throughputs

```

1  $\theta = (W, b)$ 
2 init_range =  $\sqrt{6.0/(input\_size + output\_size)}$ 
3  $\theta = \text{random\_uniform}(-\text{init\_range}, \text{init\_range})$ 
4 for  $i = 1, \dots, n\_epoch$  do
5    $X = \text{Simulation}(\text{batch\_size})$ 
6    $P, \theta = \text{Train}(X, \text{width}, \text{depth}, \text{batch\_size}, \theta)$ 
7    $T = \text{Get\_Throughput}(X, P)$ 
8   Throughputs.append( $T$ )
end
9 return Throughputs

```

---

**Function** Train()

**Input** :  $X$ , batch\_size, width, depth,  $\theta$

**Output:**  $P$

```

1  $P = \text{Predict}(X, \text{width}, \text{depth}, \text{batch\_size}, \theta)$ 
2  $c = \text{Cost}(X, P)$ 
3  $\theta := \text{AdamOptimizer}(c)$ 
4 return  $P, \theta$ 

```

---

**Function** Predict()

**Input** :  $X$ , width, depth, batch\_size,  $\theta$

**Output:**  $Y_{pred}$

```

1  $W, S, Z = \theta$ 
2  $X = \text{Reshape}(X, [\text{batch\_size} * K, 4])$ 
3 for  $j = 0, \dots, \text{depth}-1$  do
4    $X = X \times W[j]$ 
5    $X_m = 0$ 
6    $X_{m^2} = 0$ 
7   for  $i = 0, \dots, \text{width}-1$  do
8      $X_m = X_m + X[i]$ 
9      $X_{m^2} = X_{m^2} + X[i]^2$ 
end
10  $X_m = X_m / \text{width}$ 
11  $X_{m^2} = X_{m^2} / \text{width}$ 
12  $X_{var} = X_{m^2} - (X_m)^2$ 
13  $X_h = \frac{X - X_m}{\sqrt{X_{var} + \epsilon}}$ 
14  $X = S[j] \cdot X_h + Z[j]$ 
15  $X = \frac{1}{1 + e^{-X}}$ 
end
16  $P = \text{Reshape}(X, [\text{batch\_size}, K, 8])$ 
17 for  $p = \text{each element of } P$  do
18    $p = p \times 170 - 150$ 
end
19 return  $P$ 

```

---

Learning rate for the optimizer is 0.0001. If learning rate is increased, the DNN can attain a converged result more early with smaller iterations. But, the final converged result may be reduced.

Fig. 2a shows throughput  $\eta$  of the proposed scheme with various QMAX where  $C = 3$ . They tend to converge to a

TABLE I: Parameters of DNN

Width	1500
Depth	7
Batch size	50
The number of iterations	100K
Learning rate	0.0001

TABLE II: Deep learning model selection

	-120	-130	-140	-150
DPADIC	3.8	3.3	2.5	1.4
IADRMPIIC [3]	3.6	3.4	2.4	1.5

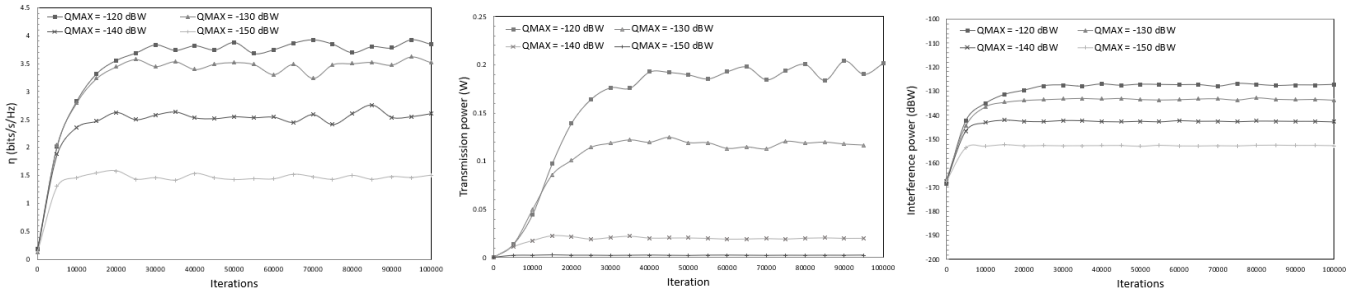
constant value after 30K iterations. Smaller QMAX cases tend to be converged earlier, because initial transmit power is near to zero in Fig. 2b. We set the range of power is between -150 to 20 dBm. The initial powers are set near the middle of the range. Because it is near to zero, the powers are growed up to find the better throughput by the optimizer. Fig. 2c shows that DNN gets the converged throughput while keeping the interference to eNB constraint. We also simulate the DPADIC on a 7-cell environment. The tendency of Fig. 3a,3b, and 3c are similar to the case of 3-cell environment. They imply that DPADIC can find the most appropriate outputs regardless of the number or shape of cells.

The table II is a comparison between the proposed scheme, DPADIC and IADRMPIIC in [3]. They have similar results of throughput on 7-cell environments. However, in the DPADIC, the D2D node can find optimal transmit power on itself if it has a pre-trained DNN. A D2D transmitter can determine transmit powers without involvement of eNB or peripheral D2D nodes, and it can approve to maximize cell throughput.

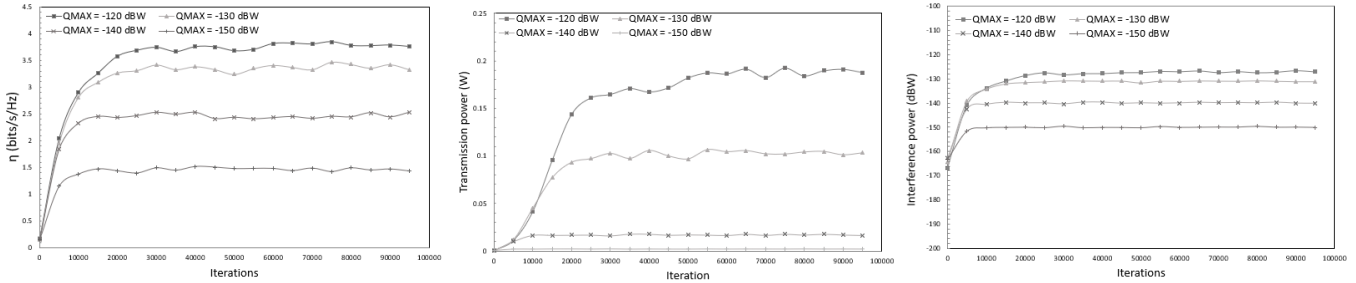
In the proposed scheme, there are two significant parameters for adopting constraints,  $c_{if}$  and  $c_p$ . They should be determined manually, but it is not difficult. The valid range of the parameters is wide enough. Fig. 4 and 5 show the effects of the interference to eNB constraint factor,  $c_{if}$ . If too small  $c_{if}$  is used, the interference to eNB constraints may be ignored. In that case, it is more profitable to ignore  $C_{if}c_{if}$  in minimizing the cost, though DNN takes the penalty from  $C_{if}c_{if}$ . Thus, the spectral efficiency,  $\eta$ , is high but it is not valid because the interference to eNB are over the limit, QMAX. If the  $c_{if}$  is high enough, DNN cannot ignore the constraint. Then, DNN should keep the constraints with reducing transmit powers. If it uses too high  $c_{if}$ , the  $\eta$  can be reduced, but the falling is not meaningful. Note that  $C_{if}$  includes ReLU function. It turns off the constraint if it is not over the threshold. Because of this, an effect of the high  $c_{if}$  is limited. However, D2D transmitters are dropped randomly, and it may be very close to the eNB. Thus, there can be a few cases of being over QMAX though it has very small transmit power. The cases affect the results. Consequently,  $\eta$  can be reduced slightly with larger  $c_{if}$ .

Fig. 6 describes effects of the transmit power constraint factor,  $c_p$ . The  $c_p$  is less sensitive than  $c_{if}$ , because  $PMAX = 0.25 W$ . Similar to the case of  $c_{if}$ , DNN may ignore the power constraint if  $c_p$  is not enough. With very small  $c_p$ , the  $\eta$  can be increased but it cannot keep the constraint. The DNN adopts the transmit power constraints appropriately where  $c_p$  is over 10. Unlike the  $c_{if}$ , larger  $c_p$  does not has a problem. Even





(a) Spectral efficiency for the proposed scheme, where  $C = 3$ . (b) Transmit power of each D2D transmitter for the proposed scheme, where  $C = 3$ . (c) Interference experienced at the eNB, where  $C = 3$ .



(a) Spectral efficiency for the proposed scheme, where  $C = 7$ . (b) Transmit power of each D2D transmitter for the proposed scheme, where  $C = 7$ . (c) Interference experienced at the eNB, where  $C = 7$ .

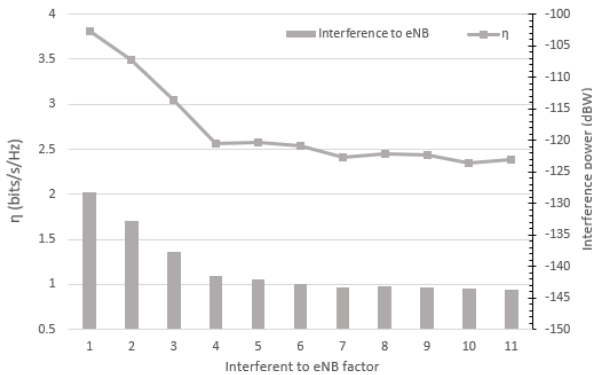


Fig. 4: Spectral efficiency with the interference to eNB constraint factor, where  $C = 3$  and  $QMAX = -140$  dBW.

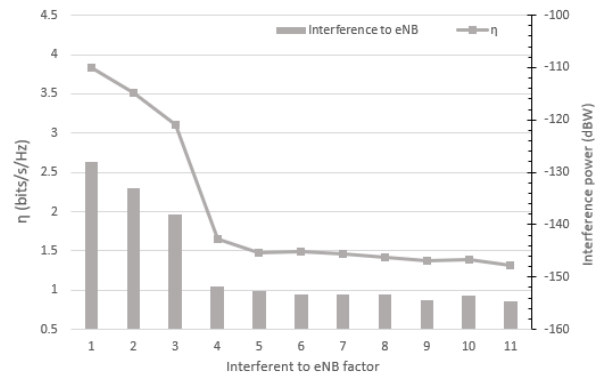


Fig. 5: Spectral efficiency with the interference to eNB constraint factor, where  $C = 3$  and  $QMAX = -150$  dBW.

when the  $c_p$  is 200, the performance of spectral efficiency is not changed. It is because there is no D2D transmitter which is over the PMAX after enough training.

We adopt batch normalization into the implementation of the proposed method. Fig. 7 shows comparisons with non adopted batch normalization cases where  $B=7$ . The  $\eta$  is not optimized enough where batch normalization is not adopted. Likewise, the learning process can be regarded to unstable. This means that applying batch normalization has a significant impact on learning performance. The reason is variation of the input data. We use  $(x,y)$  coordinate as input data. The variation of inputs is too wide to adopt the sigmoid function, which is in the range 0 to 1. In the sigmoid function, too large or small data lose their meaning. But, the large numbers can be regarded to close by the sigmoid function. It reduces

effects of difference between large numbers. Inevitably, the sigmoid function has information loss with large numbers. It makes difficult to learn differences between large numbers. On the other hand, batch normalization moves distribution of the data, including scales. It would be more appropriate for learning. Intuitively, batch normalization is expected to show performance improvement in deep learning for wireless communication when it treats wide coordinate values as input data.

Fig. 8 show that time to derive the cost function is not affected from the batch size, BN. The time to generate data is implemented regardless parallelism, so it is increased lineary. The  $\mathcal{O}(\text{Simulation}())$  is BN. On the other hand, the cost function is not affected from the batch size. It means that the  $\mathcal{O}(\text{Cost})$  is not related with BN. Because of the parallel

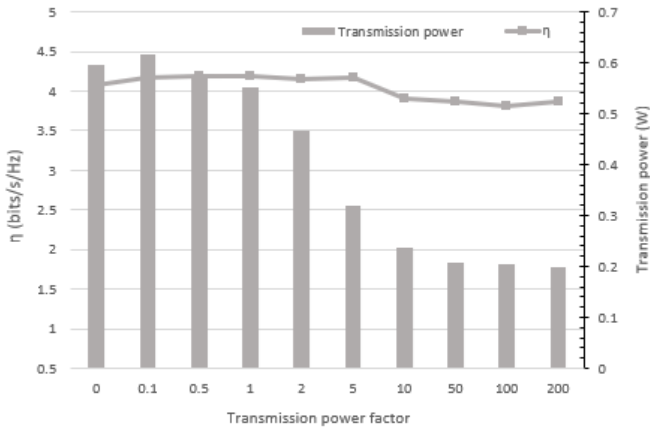


Fig. 6: Spectral efficiency with the transmit power factor, where  $C = 3$  and  $QMAX = -110$  dBW.

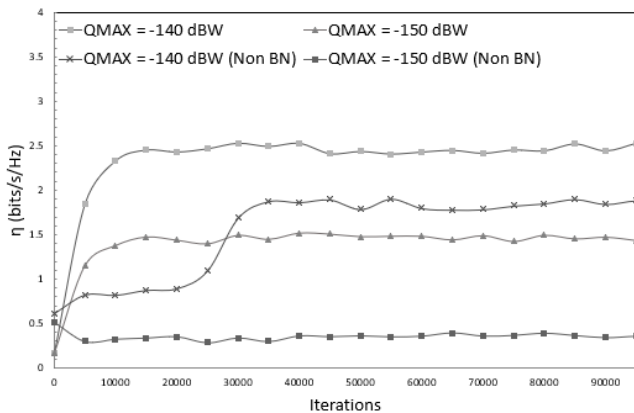


Fig. 7: Spectral efficiency on non batch normalization mode, where  $C = 7$ .

operations, the batch size can be freely adjusted according to the amount of given data or given learning time.

Fig. 9 and 10 show visualized training results for each cell environments respectively. Because of the interference constraints to eNB, the D2D power allocations are more distributed in a cell edge area. With 100K iterations, it can get the almost converged results. These results can be regarded as that DNN divides the compartments for power allocation to maximize throughput. It allocates fractionally transmit power by very slight subdividing. In particular, it is remarkable that the transmit power increases as the edge area of the cell. It implies that D2D links with the proposed method can be helpful to enhance the poor performances of cell edge users. The signals of cell edge users can be combined or multi-hopped by D2D communication. Furthermore, The DPADIC can be derived in a distributed way. It means that the performance enhancements of the cell edge users can be conducted without the involvement of the eNB.

### V. FUTURE WORK

In the future, we would develop an independent deep learning system for distributed D2D wireless communication.

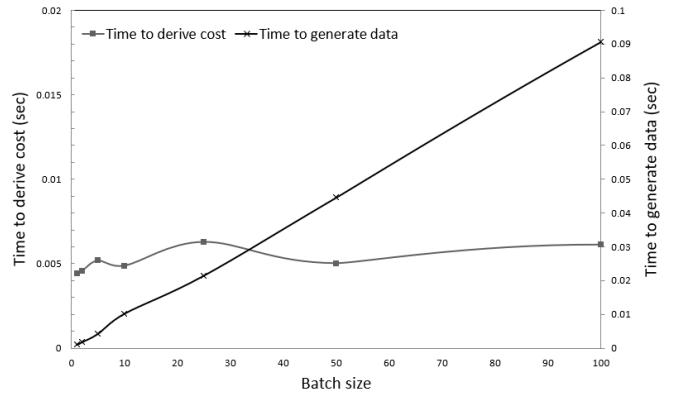


Fig. 8: Comparison time to derive cost and generate data in the actual implementation, where  $C = 7$ ,  $QMAX = -140$  dBW.  $O(Cost)$  is not affected from the batch size.

To adopt deep learning in wireless communication, a lot of data are essential, and it should be preserved before learning. It implies that a new scheme is difficult to be adopted without a conventional well-operated scheme. Thus, most deep learning based schemes for wireless communication have dependency on simulations. However, it is also difficult for the simulation to fully represent the actual field. To adopt deep learning into wireless communication more freely, it should be operated when a simulation cannot represent the actual field. It means that a deep learning method which is not based on a specific simulation. This work would be the future work of this paper.

### VI. CONCLUSION

We propose perfectly distributed power allocation for D2D link underlying LTE. One of the major purpose of D2D communication underlying LTE is to relieve the dense burden of eNB. Thus, it is important that the D2D nodes are operated in distributed way. According to our study, this is the first method that a D2D transmitter can decide the transmit power without any helps of either eNB or other nodes to meet the global optimum. With the deep learning module, each D2D node can memorize the transmit power according to locations for global optimum. Also, it maintains the performance with previous works. As shown in Fig.9 and 10, furthermore, the results of the proposed method show that D2D underlying LTE is appropriate to cover the edge users. Poor performance for edge users is one of the major concerns to cellular networks. Multi-hop communication using D2D link is a main candidate to solve the cell edge user problems. Finally, the method which we proposed can be used generally. There are two features which can be adopted for not only wireless communication, but also other optimization problems. First feature is that it supports to solve general minimizing(or maximizing) problems while keeping constraints using deep learning. Deep learning is a best tool to solve optimize problems, and we show that it can be operated to optimize a problem while keeping several constraints. Another feature is the distributed architecture. We solve the distributed power allocation problem for D2D links with this distributed learning architecture. It can be applied to develop a centralized system into a distributed system.

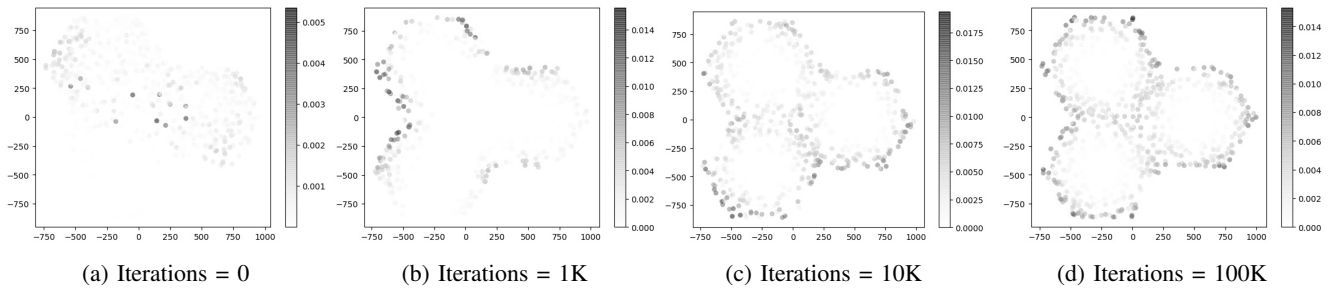


Fig. 9: Cell power distribution during the learning process, where QMAX=-150 dBW and B=3.

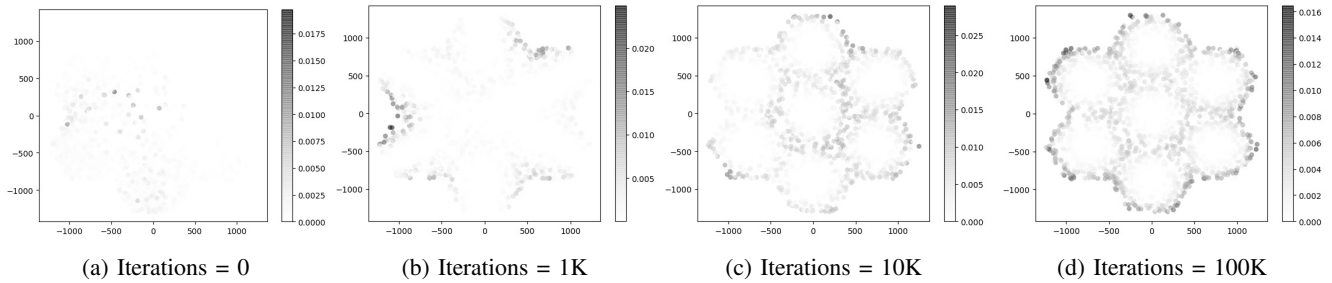


Fig. 10: Cell power distribution during the learning process, where QMAX=-150 dBW and B=7.

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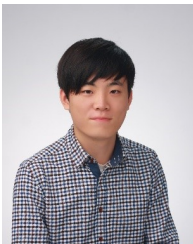


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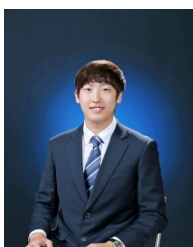
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