Machine Learning for Power Control in D2D Communication based on Cellular Channel Gains

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***Abstract*—We consider a mobile network with users seeking to engage in a device-to-device (D2D) communication. Two D2D users (DUEs), a transmitter and a receiver, compose one D2D pair. We assume that the D2D pairs reuse a single communication channel to increase the spectral efficiency. Thus, a power control is needed to manage interference among the D2D pairs and to maximize capacity. We address the problem of D2D power control in the case when only standard cellular channel gains between the DUEs and base stations (BSs) are known while channel gains among DUEs are not available at all. We exploit supervised machine learning to determine transmission powers for individual D2D pairs. We show that the cellular channel gains can, in fact, be exploited to predict the transmission power setting for D2D pairs and, still, close-to-optimum sum capacity of the D2D pairs is reached. Moreover, even if our proposed power control requires no knowledge of the channel gains among DUEs and, thus, introduces no additional signalling, the sum capacity can be increased by 16% to 41.9% with respect to no power control, as demonstrated via simulations.**

***Index Terms*—Device-to-device; Power control; Deep neural networks; Supervised machine learning**

I. Introduction

Device-to-Device (D2D) communication is one of the promising technologies to provide higher data rates and spectral efficiency in future mobile networks [1]. In D2D communication, data is transmitted directly between two user equipment (UEs) in proximity of each other to offload the legacy cellular links relayed via a base station (BS) [2]. Each pair of D2D UEs (denoted as DUEs) is composed of a transmitter (DUE_T) and a receiver (DUE_R).

Various important problems arise when considering the use of D2D communication, including the question of resource allocation across both D2D pairs and legacy cellular links to maximize D2D capacity or to minimize negative impact to the cellular links [3]-[4]. Pursuing the goal to increase the spectral efficiency of the system, multiple D2D pairs can reuse the same channel [3]-[4]. However, mutual interference among the D2D pairs accessing the same channel occurs inevitably. The mutual interference can be, fortunately, efficiently suppressed by a power control [3].

The power control as a resource allocation problem to maximize spectral efficiency of D2D (or ad-hoc) networks has been considered extensively [5]-[14]. In general, sum capacity-oriented power control over D2D pairs is a non-convex optimization problem. Thus, various iterative methods with different levels of complexity are presented in the literature such as, binary power control [5], weighted minimum mean square error [6], or water-filling algorithm [7], to name a few. However, iterative methods can pose latency issues. As an alternative, researchers have focused recently on exploiting deep neural networks (DNN) for instantaneous power control in D2D communication [8]. The DNN highly reduces power control complexity via either supervised [9]-[10] or unsupervised [11]-[14] learning, which is based on offline training (i.e., the DNN is firstly trained offline and then exploited for power control). Crucially, power control techniques utilizing the DNN with unsupervised learning are able to outperform the existing iterative methods in terms of sum capacity. However, the unsupervised learning needs a DNN loss function that connects the input and the output of the DNN, e.g., the sum capacity as a function of channel gains among DUEs and DUEs transmission powers.

A significant drawback of all above-mentioned, both conventional and DNN-based approaches is that they typically consider full (centralized) knowledge of all the D2D channel gains (i.e., channel gains among all DUEs). In machine learning methods, the D2D channel gains are placed as an input for the neural network in order to set the transmission powers. In some cases, the full knowledge can be relaxed to limit the channel state information (CSI) requirement to a subset of distributed D2D channel gain values. Still, even partial knowledge of the D2D channel gains implies a substantial cost in terms of additional channel estimation and signaling compared with the signaling involved in classical cellular communications. In contrast, the channel gains over the cellular links (i.e., linking DUEs to BSs) are typically de-facto estimated by a default design of the network. An interesting question then arises as to whether the cellular channel gains (i.e., channel gains between DUEs and BSs) carry information that somehow relates to the D2D channel gains themselves and could be exploited as a low-cost replacement of the D2D channel gains for the D2D power control prediction. The intuition behind this idea is that, while cellular channel gains exhibit fading coefficients that are independent of those measured among the DUEs, and also constitute a far smaller dimensional object (only M cellular gains for one cell with M users, in contrast with $M(M-1)$ direct and interference D2D gains), there is actually much common information between

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these data at the statistical level. In fact, it is clear that both statistical cellular gains and statistical D2D gains could be predicted from DUEs' location information if this information would be assumed available (which is not the case here). Hence, the existence of common information between the cellular and D2D gains suggests the use of a machine learning approach so as to implicitly extract the D2D channel gains and exploit it for the power control.

This is the core idea of this paper, where we propose a novel DNN learning-based power control scheme for the D2D communication that needs absolutely no additional knowledge of the D2D channel gains. Hence, no signaling overhead is generated at all, since the channel quality to all BSs in the user vicinity is reported during a common network operation notwithstanding [15]. First, our proposed DNN aims to find a relation between the cellular and D2D channel gains. This relation is, then, exploited for the transmission power setting of the D2D pairs to maximize the sum capacity. It is worth to mention that there is no known function that captures the relation between the cellular channel gains and the sum capacity of D2D pairs. Thus, it is difficult to propose a proper loss function for an unsupervised learning-based DNN. Due to this fact, we follow a supervised learning approach, where the targeted DUEs transmission powers maximizing the sum capacity are derived first. Subsequently, the DNN is trained to build a mapping between cellular channel gains and the targeted transmission powers with an aim to reach targeted power setting. The whole training process is done offline and the trained DNN is used for immediate power control decision in the real network without any training needed during the communication.

The rest of the paper is organized as follows. First, in Section II, system model is described and optimization problem is formulated. Then, Section III presents the principle of power control based on cellular channel gains, illustrates the architecture of the proposed DNN for power control, and gives detailed description regarding training process. In Section IV, simulated scenarios are described and results are discussed. Finally, Section V concludes the paper.

II. System model and problem formulation

In this section, the system model is described and the optimization problem is formulated.

A. System model

We consider a model with L BSs and M DUEs forming N D2D pairs (i.e., $N = M/2$ assuming M is even number) deployed within a square area. The distance between the transmitter DUE_T and the receiver DUE_R composing the D2D pair is limited by a maximum distance d_{max} to guarantee feasibility of the D2D communication similarly as in [16],[17]. The D2D pairs are assumed to share the same channel. As the channel is occupied by multiple D2D pairs, the pairs interfere mutually with each other. Thus, the capacity of the n-th D2D pair is defined as:

$$C_n = B\ log_2\left(1 + \frac{p_n g_{n,n}}{\sigma_o B + \sum_{\substack{j=1 \\ j\neq n}}^{j=N} p_j g_{j,n}}\right) \tag{1}$$

where B is the channel bandwidth, p_n is the transmission power of the n-th DUE_T, $g_{n,n}$ is the channel gain between the n-th DUE_T and the n-th DUE_R of the n-th D2D pair, σ_o is the noise power spectral density on the carrier frequency, p_j is the transmission power of the j-th DUE_T, and $g_{j,n}$ is the channel gain between the j-th DUE_T and the n-th DUE_R. Note that contrary to state-of-the-art works (e.g., [9]-[14]), a channel between any DUE_T and DUE_R ($g_{n,n}$ and $g_{j,n}$) is supposed to be unknown due to the difficulty of D2D channel gains estimation and its high cost in terms of signaling overhead.

Since the DUEs continuously monitor channels to the serving BS (for estimation, decoding, etc.) and to the neighboring BSs (for handover, interference management, etc.), the information on channel quality between each DUE and the surrounding BSs is assumed to be measured and reported periodically to the serving BS [15]. The corresponding estimated channel gain between the m-th DUE and the l-th BS is denoted as $G_{m,l}$.

B. Problem formulation

The objective of this paper is to set the transmission power p_n for each n-th D2D pair in such a way that the sum capacity of D2D pairs is maximized. In [5], it has been proven that a binary power control, in which every D2D pair transmits at either maximal or minimal transmission power level, reaches close-to-optimal performance. Therefore, we also adopt the binary power control so that $p_n \in \{p_{min}, p_{max}\}$, where p_{min} and p_{max} are the minimal and maximal transmission powers, respectively. Consequently, the problem of setting the transmission power of the D2D pairs to maximize the sum capacity of D2D pairs is written as:

$$\mathbf{P} = \text{argmax} \textstyle\sum_{n=1}^{n=N} C_n \tag{2}$$

$$\text{s.t. } p_n \in \{p_{min}, p_{max}\}, \forall n \in \{1, 2, ...N\} \quad (a)$$

where $\mathbf{P} = \{p_1, \ldots, p_N\}$ is the vector containing the transmission powers of all D2D pairs maximizing the sum capacity of D2D pairs and constraint (a) guarantees that the transmission power of each D2D pair is set either to p_{min} or p_{max}.

The optimization problem in (2) aims to maximize the sum capacity of D2D pairs. However, from (1), we see that C_n depends on D2D channel gains. Unlike existing schemes, where the authors assume full or at least partial knowledge of the D2D channel gains, we focus on the case when these gains are not known at all. Thus, in the next section we propose a power control scheme based solely on the common knowledge of the cellular channel gains while no knowledge of the D2D channels among the DUEs is required whatsoever.

III. Power control for D2D pairs based on cellular channel gains

The optimization problem in (2) relies on the fact that a mathematical relation exists between the D2D channel gains and the cellular channel gains. However, the relation between D2D channel gains and cellular channel gains is not known for mobile networks and cannot be even analytically derived from any known parameters of the mobile network. Thus, we propose to use a Deep Neural Networks (DNN) to learn this relation on its own and to set transmission power of the D2D pairs accordingly. More to the point, the DNN can be seen as a 'black box', which is able to set transmission power of the D2D pairs based simply on the knowledge of cellular channel gains from the DUEs to the BSs. The proposed DNN architecture and the learning process itself are thoroughly described in the following subsections.

A. Architecture of DNN for power control

Considering the binary power control, the optimization problem in (2) is to set the transmission power of each D2D pair either to $p_n = p_{min}$ or to $p_n = p_{max}$. Thus, setting the transmission power for N D2D pairs can be presented as N identical binary classification problems. Hence, we propose a fully-connected DNN to build up the mapping between the cellular channel gains and the proper binary transmission power setting for any n-th D2D pair maximizing the sum capacity of D2D pairs.

Fig. 1 shows the proposed fully-connected DNN for binary classification. The proposed DNN is composed of an input layer (X_0), H hidden layers (X_1,...,X_H), and an output layer (X_{H+1}). The DNN input layer contains an input vector, and thus, the cellular channel gains from the DUEs to the BSs are aligned as an input vector in the input layer of the proposed DNN (see Fig. 1). The output of the input layer $\mathbf{out_0}$ is a vector of the cellular channel gains between the DUEs and the BSs $\mathbf{out_0} = \{G_{1,1}, G_{1,2}, \ldots, G_{M,L}\}$ with a length of $M \times L$. Every hidden layer X_h has an input vector $\mathbf{in_h}$ equivalent to the output of the previous layer $\mathbf{out_{h-1}}$ (i.e., $\mathbf{in_h} = \mathbf{out_{h-1}},\ \forall h \in \{1, \ldots, H\}$). Each hidden layer X_h is composed of V_h neurons. In this respect, each i-th input element in $\mathbf{in_h}$ is fed to every neuron v in the hidden layer X_h with a weight $w_{i,v}^{h-1,h}$. Consequently, every neuron v performs dot product between the input elements in $\mathbf{in_h}$ and the corresponding weights. The result of the dot product is added to a corresponding bias $b_{0,v}^{h-1,h}$ and processed by commonly used sigmoid activation function, giving the output of the neuron. Hence, the hidden layer X_h (with V_h neurons) and its input vector $\mathbf{in_h}$ serve to determine the hidden layer output vector $\mathbf{out_h}$ of the length V_h as:

$$\begin{aligned}\mathbf{out_h} &= Sig(\mathbf{W^{h-1,h}in_h} + \mathbf{b^{h-1,h}}) \\ &= Sig(\mathbf{W^{h-1,h}out_{h-1}} + \mathbf{b^{h-1,h}})\end{aligned} \tag{3}$$

where Sig is the sigmoid function $Sig(Z) = \frac{1}{1+exp(-Z)}$, $\mathbf{W^{h-1,h}}$ is the matrix of weights of the links between every input element of X_h (i.e., equivalent to the output of X_{h-1}) and every neuron in X_h, and $\mathbf{b^{h-1,h}}$ is the vector of biases attached to the neurons in the layer X_h.

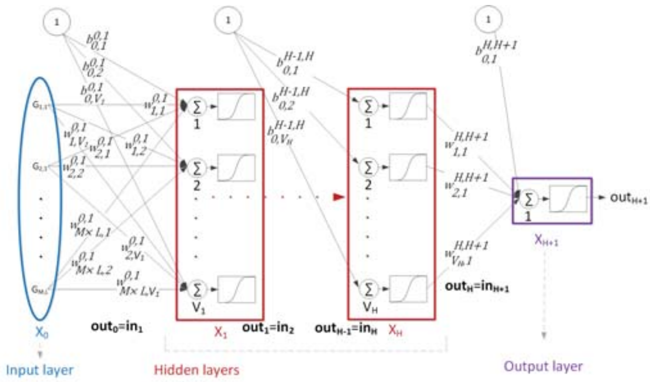

Fig. 1: Proposed architecture of DNN for binary classification corresponding to the transmission power of a single D2D pair.

The output of the last hidden layer $\mathbf{out_H}$ is followed by the output layer. The output layer in a DNN for binary classification is composed of one neuron. The single neuron of the output layer performs the dot product between $\mathbf{out_H}$ and the corresponding weights $\mathbf{W^{H,H+1}}$ (i.e., the vector of weights related to the links between the outputs of the last hidden layer X_H and the single neuron in the output layer X_{H+1}). Then, the output layer neuron also sums its attached bias scalar $b^{H,H+1}$ and implements the sigmoid function defining the output of the DNN as:

$$out_{H+1} = Sig(\mathbf{W^{H,H+1}out_h} + b^{H,H+1}) \tag{4}$$

Note that the sigmoid function value is between 0 and 1, and thus, the output of our DNN is $out_{H+1} \in [0,1]$ which presents the probability of $p_n = p_{max}$. Hence, the transmission power of the n-th D2D pair is set as:

$$p_n = \begin{cases} p_{max} & \text{if } out_{H+1} > 0.5 \\ p_{min} & \text{otherwise} \end{cases} \tag{5}$$

B. Offline learning and exploitation of the proposed DNN

There is no direct analytical function connecting the cellular channel gains and the sum capacity of D2D pairs in order to set the transmission power of the D2D pairs. Therefore, we propose an offline supervised learning-based solution in which the optimal binary transmission powers are derived by an exhaustive search to maximize the sum capacity of D2D pairs. Then, the transmission power of the n-th D2D pair is fed to the proposed DNN as a targeted class attached to the set of the cellular channel gains as features. The features (i.e., cellular channel gains) and the targeted class (i.e., the transmission power of the n-th D2D pair) compose together a single learning sample. The learning samples are collected and, then, split into a training set and a test set. While the former is used to train the DNN the latter is run over the trained DNN to show the accuracy on a set of cellular channel gains samples that are not used for training.

During training process of the proposed DNN, a loss function is defined to evaluate the misclassifications between the targeted transmission powers and the predicted transmission powers (from (5)) after every training iteration. Our DNN considers binary cross-entropy loss function written as:

$$\begin{aligned} \iota = &-[\![p_T == p_{max}]\!] log\,(out_{H+1}) \\ &- [\![p_T == p_{min}]\!] log\,(1 - out_{H+1}) \end{aligned} \tag{6}$$

where p_T is the targeted transmission power for the corresponding sample.

The binary cross-entropy loss function is averaged out over all training samples at the end of each iteration. Then, the weights and biases of the proposed DNN are updated using scaled-conjugate gradient backpropagation [18].

It is worth to mention that the whole learning phase (i.e., including collecting samples, training, and testing the proposed DNN) is done offline, i.e., before its application to the real network (or before its testing by means of simulations). Therefore, the cellular channel gains derived from the simulations can be used for the offline training and testing of the DNN, and then, the trained DNN is exploited directly in the real network. The proposed DNN is able to predict the transmission power of a single D2D pair in order to maximize the sum capacity of D2D pairs. Thus, for N D2D pairs, the trained and tested DNN is utilized to predict the transmission power for each D2D pair independently maximizing the sum capacity of D2D pairs.

IV. Performance Evaluation

In this section we describe simulation scenarios and parameters. Then, simulation results are discussed including offline learning results and performance analysis related to D2D communication with the proposed power control scheme.

A. Simulation scenarios

We consider six DUEs composing three D2D pairs (like in [10]) deployed uniformly within an area of 250×250 m^2. Although the DUEs are uniformly distributed, the maximum distance between the DUE_T and the DUE_R of the same D2D pair is upper-bounded by a maximal distance of $d_{max} = 50$ m as in [16],[17]. Nevertheless, we also show the effect of different values of d_{max} on the performance of our proposal. Without loss of generality, we set the bandwidth of the channel reused by the D2D pairs to 1 Hz [10] as the capacity scales with the bandwidth (see (1)). Moreover, for any D2D transmitter, the maximal transmission power p_{max} is considered to be 24 dBm like in [3]; while the minimal transmission power p_{min} is set to 1 dBm to guarantee existence of data transmission.

We consider two different scenarios according to the signal propagation between the DUEs and the BSs and among all DUEs. The first scenario assumes an open rural area with full availability of line-of-sight (LOS) for all channels (D2D channels and channels to BSs). The second scenario, shown

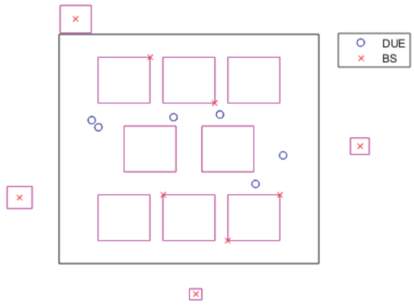

Fig. 2: Example of simulation deployment with buildings (pink rectangles) for urban area. Note that no buildings are present in rural area.

in Fig. 2, presents an urban area (such as scenario C2 in [19]) with building blocks forming a regular Manhattan-like grid (see the pink rectangular building blocks in Fig. 2). The BSs are deployed on the roof tops serving outdoor DUEs at the street level. In the second scenario, the buildings lead to a non-line-of-sight (NLOS) D2D and cellular channels. In both rural and urban areas, the LOS path loss is generated in line with 3GPP recommendations [20]. However, in the urban scenario, we assume that the communication channel intercepted by a single or more building walls is exposed to an additional loss [21]. We set the value of the signal attenuation induced by a single wall to 10 dB. Note that Fig. 2 presents a 2D projection of the simulated urban area, while in our simulations, building heights range uniformly from 20 to 30 m and, thus, affect NLOS and LOS probabilities.

For the training of DNN, 500 000 samples are collected and 70% of these samples are used for training (i.e., the training set), while the remaining 30% are left for testing (i.e., the test set). The proposed DNN exploits six hidden layers composed of 24, 20, 18, 15, 12, and 8 neurons, respectively. Note that the number of hidden layers and number of neurons in each layer are set by trial and error approach.

For the evaluation of D2D communication with the proposed power control scheme, the sum capacity of D2D pairs (i.e., $C = \sum_{n=1}^{n=N} C_n$) is averaged out over 1 000 drops. Simulation parameters are summarized in Table I.

TABLE I: Simulation parameters.

Parameter		Value
Carrier frequency	f_c	2 GHz
Bandwidth	B	1 Hz [10]
Noise power spectral density	σ_o	-174 dBm/Hz
Number of D2D pairs	N	3 [10]
Number of BSs	L	$3-9$
Maximal transmission power	p_{max}	24 dBm[3]
Minimal transmission power	p_{min}	1 dBm

B. Simulation results

In this subsection, we present first the offline learning results, i.e., the accuracy of the learning process. Then, we show the impact of the proposed power control scheme on the performance of D2D communication.

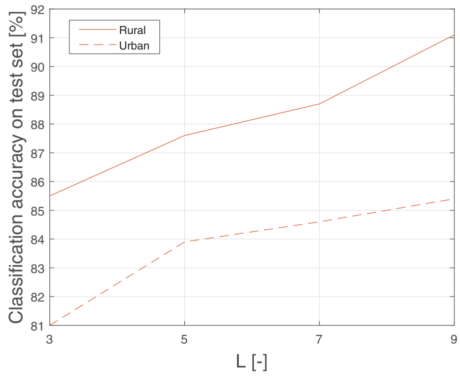

Fig. 3: Classification accuracy on the test set over number of BSs L for $d_{max} = 50m$.

Rural			Urban		
p_{min}	p_{max}	p_T \ p_n	p_{min}	p_{max}	p_T \ p_n
46.7%	5.4%	p_{min}	44.4%	8.8%	p_{min}
3.6%	44.3%	p_{max}	5.8%	41.0%	p_{max}
Acc. on p_{min} 92.9%	Acc. on p_{max} 89.2%	**Total accuracy 91.1%**	Acc. on p_{min} 88.4%	Acc. on p_{max} 82.4%	**Total accuracy 85.4%**

TABLE II: Confusion matrices for rural and urban areas for 9 BSs and $d_{max} = 50m$, showing learning accuracy.

1) Learning results: The proposed DNN is trained via samples of cellular channel gains from the training set and their corresponding targeted transmission powers. Then, the trained DNN is tested on the test set to show the classification accuracy on the set of samples with cellular channel gains that are not used for the training to prevent overfitting.

Fig. 3 shows the total accuracy of the transmission power prediction on the test set for the rural and urban areas over different numbers of BSs L. As expected, the prediction accuracy increases with the number of BSs. This accuracy improvement with more BSs is a result of knowing more information about each DUE (i.e., knowing cellular channel gains to more BSs). Furthermore, we can see that the prediction accuracy on the test set for the rural area is higher than for the urban area. This can be explained by the fact that the cellular channel gains to the BSs are less random in the rural area with LOS comparing to the urban area where the probability of NLOS is high. Therefore, in the rural area, our proposed DNN is able to build a better-performing mapping between the cellular channel gains of the DUEs and the proper transmission power.

Table. II shows the confusion matrices for rural and urban areas with $L = 9$ BSs. Considering that p_T is the targeted transmission power and p_n is the transmission power predicted by the proposed DNN, there are four possible outcomes of prediction result as the binary power control is applied. Each confusion matrix in Table. II shows the probability of each of the four possible cases. For rural area, the accuracy of the correct prediction on p_{min} and p_{max} is 92.9% and 89.2%, respectively. For urban area, the accuracy of correct prediction is 88.4% and 82.4% for p_{min} and p_{max}, respectively. We can also see that the total accuracy on both p_{min} and p_{max} is 91.1% and 85.4% for the rural and urban areas, respectively.

It is worth to remember that the proposed DNN predicts the transmission power of a single D2D pair as explained in Section III-A, and based on this predicted transmission power, the shown accuracy is calculated. However, in the next subsection, the trained DNN is exploited to predict the transmission power of multiple D2D pairs (three D2D pairs in this paper), each independently, aiming to maximize the sum capacity of D2D pairs as clarified in Section III-B. Note that as the DNN is trained to predict p_n of the n-th D2D pair, every D2D pair is considered to be the n-th D2D pair to predict its transmission power, and the cellular channel gains at the input of the DNN are sorted accordingly.

2) Evaluation of the proposed power control scheme: In this subsection, we analyze the performance of D2D communication when the proposed DNN predicts the transmission power of each D2D pair. Up to our best knowledge, there is no work in the literature exploiting the cellular channel gains of the DUEs for D2D power control. Thus, the proposed power control scheme (denoted as proposal) is compared with two other existing schemes. The first one is the optimal binary power control derived by the exhaustive search. The optimal binary power control (denoted as Target) corresponds to the targeted transmission powers, which are used as the proposed DNN benchmark and which the DNN tries to reach (see Section III-B). The second scheme assumes that each D2D pair transmits with the full power without power control (denoted as No-PC). The perfect estimation of the cellular channel gains is considered for the rural area. In the urban area, an error in the estimation of the cellular channel gains might occur in the real network. Thus, for any channel gain between the m-th DUE and the l-th BS $G_{m,l}$, we add an estimation error $e_{m,l}$ as a percentage of the real channel gain in the urban area. The error percentage for cellular channel gain estimation is generated via the Gaussian distribution with a mean of 0% and a standard deviation of 5%.

Fig. 4 shows the sum capacity of D2D pairs over the number of BSs L for the rural and urban areas. Comparing to the No-PC, our proposed DNN-based solution achieves a gain ranging from 18.7% to 21.4% and from 16% to 18.7% for the rural and urban areas, respectively. Moreover, we observe that the sum capacity of D2D pairs of the proposal reaches close-to-optimal sum capacity (i.e., close to Target) even for a low number of BSs. The small loss of our proposal with respect to the Target further decreases with the availability of the cellular channel information to more BSs. To be more specific, increasing the number of BSs from 3 to 9 decreases the loss comparing to the Target from 3.5% to 1.6% and from 5.4% to 3.2% for rural and urban areas, respectively.

In Fig. 5, the effect of different values of d_{max} on the sum capacity of D2D pairs is illustrated for $L = 9$ BSs. The sum capacity of D2D pairs for all schemes decreases with increasing d_{max} due to the corresponding increment in the attenuation of signal between $\mathrm{DUE_T}$ and $\mathrm{DUE_R}$. Fig. 5 shows that when compared to No-PC, our proposal introduces

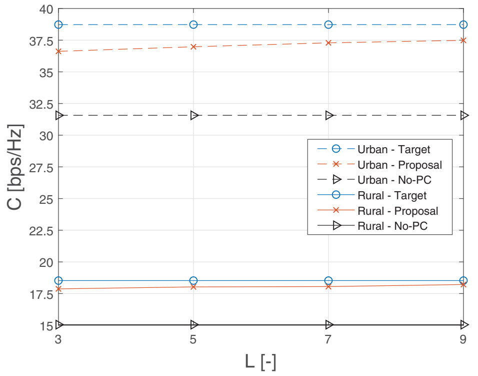

Fig. 4: Sum capacity over number of BSs L for $d_{max} = 50m$.

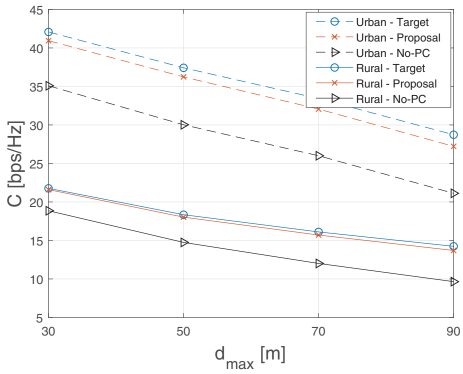

Fig. 5: Sum capacity over d_{max} for $L = 9$.

a gain up to 41.9% and 28.8% for rural and urban areas, respectively. In addition, comparing to the Target, the loss in the performance of the proposal ranges from 2.7% to 5.2% for the urban area. Nevertheless, for the rural area, our proposal loses only between 0.7% and 3.7%, depending on d_{max}, in terms of the sum capacity.

It is worth to remind that with respect to existing schemes that rely on the knowledge of the D2D channel gains, our proposed scheme requires no additional signaling to set the transmission power of the D2D pairs except the signaling that is anyway available for classical communication via BS.

V. Conclusion

In this paper, we have proposed a new power control scheme for D2D communication requiring absolutely no knowledge of the D2D channel gains. The proposed scheme relies on a deep neural network that exploits solely the cellular channel gains between DUEs and neighboring BSs to set the transmission power of each D2D pair. The key benefit of the proposed scheme, comparing to existing works, is that there is no additional signaling overhead to the network. Only the cellular channel gains, reported anyway periodically for multiple purposes related to conventional communication and handover, are needed to be known. The proposed scheme reaches close-to-optimal sum capacity of D2D pairs and outperforms the case with no power control by 16% to 41.9%.

The future work should focus on generalization of the proposed solution towards prediction of the D2D channel gains that can be, then, exploited for any radio resource management problem (e.g., power control, channel allocation, D2D relay selection, etc.).

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