Coordinated Machine Learning for Energy Efficient D2D Communication

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***Abstract*—We address the problem of a coordination among machine learning tools solving different problems of radio resource management. We focus on energy efficient device-to-device (D2D) communication in a scenario with many devices communicating adhoc directly with each other. In such scenario, deep neural network (DNN) is a convenient tool to predict the channel quality among devices and to control the transmission power. However, addressing both problems by a single DNN is not suitable due to a dependency of the power control on the predicted channel quality. Similarly, a simple concatenation of two DNNs leads to a high cumulative learning error and an inevitable performance degradation. Hence, we propose a mutual coordination of the DNNs for channel quality prediction and for power control via a feedback and a knowledge transfer to mitigate the accumulation of errors in individual learned models. The proposed coordination improves the energy efficiency by 10–69% compared to state-of-the-art works and reduces the training time of DNNs more than 3.5-times compared to DNNs without coordination.**

***Index Terms*—Machine learning, device-to-device, coordination, power control, channel quality, energy efficiency**

I. INTRODUCTION

To manage device-to-device (D2D) communication in mobile networks efficiently, the quality of channels among the communicating devices (i.e., the D2D channels) should be known. The acquisition of channel quality is traditionally done via a measurement of reference signals [1]. However, the reference signals occupy radio resources from the same pool as the resources for data transmissions. Consequently, the transmission of reference signals reduces the amount of resources remaining for data transmissions. Besides, the traditional channel quality measurement leads to an additional energy consumption on the side of a transmitter (sending the reference signals and receiving reports with the measured channel quality) as well as a receiver (physical measurement and reporting) [2]. Hence, in the future networks with plenty of devices communicating adhoc with each other [3], knowledge of D2D channels for radio resource management purposes becomes a challenging issue, since not only information on direct D2D channels between the two communicating devices but also on all interfering channels should be acquired for radio resource management purposes.

To reduce the acquisition cost of a large number of D2D channels for radio resource management purposes, the channel quality between two devices can be predicted using a digital twin [4] or deep neural networks (DNN) [5]. The obtained channel quality information can be then exploited for a plethora of radio resource management processes, such as scheduling, coordinated multi-point transmission, interference mitigation/cancellation, or transmission power control.

In this letter, we focus on transmission power control and its relation to the problem of channel quality acquisition. The transmission power control can be optimally solved by water-filling [6]. However, its iterative nature and a high complexity limit practical application [6]. The power control for D2D pairs (i.e., two devices communicating directly) is a non-convex problem [7] difficult to be solved with a low complexity. Hence, the authors in [8] propose D2D power control using extreme hierarchical machine learning. In [9], the authors train the DNN to determine transmission power of individual devices. In [10]–[12], the authors adopt neural networks for power allocation. All these works rely on knowledge of all channels among all devices, making a practical implementation of these works complicated due to a huge number of channel qualities to be acquired [13].

To overcome the problem of a huge number of channels to be measured for D2D power control, the D2D channel quality prediction via DNN proposed in [5] can be adopted, and the predicted channel qualities can be fed into existing machine learning-based transmission power control approaches (e.g., [8], [9]). Unfortunately, a simple concatenation of the machine learning-based solutions for the prediction of D2D channel qualities and for the D2D transmission power control results in a high cumulative learning error. This error could be removed via an extensive training, but such training would lead to an overfitting and tuning hyperparameters of the DNNs would be complicated due to increased number of DNN features. Consequently, the network performance is degraded notably, as we show in this paper. Another option is to merge D2D channel quality prediction and D2D power control into a single DNN. Nevertheless, resulting DNN is either very large or such solution performs poorly due to a dependency among inputs and outputs of such DNN, as we also demonstrate later in this paper. The size of a single large DNN can be reduced via knowledge distillation [14]. However, the dependency among inputs on outputs of DNN still limits performance.

Therefore, in this letter, we propose coordinated machine

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learning for D2D channel prediction and D2D transmission power control to maximize the energy efficiency of D2D communication. We focus on the energy efficiency, as it combines aspects of a data rate maximization commonly targeted in D2D scenarios with an energy consumption minimization motivated by green communications. To determine the D2D channel qualities at a low cost even in large-scale scenarios, we adopt the D2D channel quality prediction via DNN introduced in [5]. The predicted channel quality is fed to another DNN for D2D transmission power control. The *key novelty* of our work resides in the introduction of a *mutual coordination of the two DNNs* (one for channel quality prediction and one for power control) using a feedback and a knowledge transfer in order to mitigate the accumulation of errors in individual learned models. We demonstrate that the proposed coordination improves the energy efficiency of the system and, at the same time, reduces the training time of the DNNs compared to the solution based on DNNs without coordination as well as state-of-the-art works.

II. System Model

In this section, we introduce a communication model, followed by an outline of a general architecture of the DNNs.

A. Communication model

We consider a generic urban area with buildings, L BSs, and M D2D devices creating $N = \lfloor M/2 \rfloor$ D2D pairs, as shown in Fig. 1. Since we focus on cooperation of machine learning tools, we adopt single-antenna system at all BSs and all devices for clarity of presentation and an extension towards multi-antenna system is left for future research. The bandwidth B is split arbitrarily into K communication channels. The signal-to-interference plus noise ratio (SINR) experienced by the n-th D2D pair's receiver at the k-th communication channel is:

$$\gamma_n^k = \frac{p_n^k g_{n,n}}{\sum_{i \neq n, i=1}^{i=N} p_i^k g_{i,n} + \sigma_0} \tag{1}$$

where p_n^k is the transmission power of the transmitter in the n-th D2D pair, $g_{n,n}$ is the channel quality between the transmitter and the receiver of the n-th D2D pair, p_i^k is the transmission power of the i-th device causing interference to the n-the D2D pair, $g_{i,n}$ is the quality of channel from the i-th device causing interference to the receiver of the n-th D2D pair, and σ_0 is the noise. Then, the communication data rate of the n-th D2D pair is:

$$c_n^k = B^k \log(1 + \gamma_n^k) \tag{2}$$

where B^k is the bandwidth of the k-th channel.

The energy efficiency of the n-th D2D pair is defined as:

$$E_n^k = \frac{c_n^k}{p_n^k \times \tau} \tag{3}$$

where τ indicates time interval when the metrics are observed.

B. Architecture of DNNs

In this section, general architectures of DNN for channel quality prediction (labeled as DNN-CQ) and DNN for power control (labeled as DNN-PC) are defined.

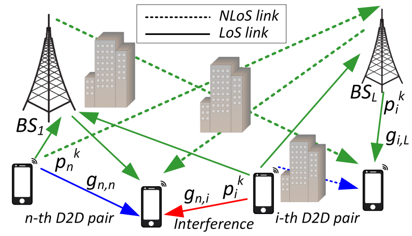

Fig. 1. System model with devices communicating directly using D2D and transmitting powers set using DNN based on predicted channel qualities.

1) DNN-CQ: The DNN-CQ, comprises an input layer, H hidden layers, and an output layer. First, cellular channel qualities, i.e., the channel qualities from the directly communicating devices to the L BSs, are inserted into the input layer [5]. Note that the channels from devices to BSs are supposed to be known, as these are required for conventional radio resource and mobility management [15].

The cellular channel qualities are then processed through H hidden layers. The h-th layer is composed of V_h neurons with weights $[w_h^1, \ldots, w_h^{V_h}]$. All the hidden layers are fully connected and are followed by the sigmoid activation function. By employing a sigmoid function, the output can be inherently confined to the desired range. By incorporating the sigmoid activation, the network can capture non-linear transformations in the data, enabling the acquisition of complex patterns and decision boundaries. This utilization enhances the network's ability to learn and represent intricate features, resulting in improved representation and discrimination capabilities. The output layer is represented by a regression that returns the predicted D2D channel quality in the form of continuous value.

2) DNN-PC: Similar to DNN-CQ, DNN-PC is structured with an input layer, H hidden layers, and an output layer [9]. Different from DNN-CQ, the input of DNN-PC is represented by the predicted D2D channel qualities. The predicted D2D channel qualities are processed through the hidden layers. All hidden layers are fully connected and accompanied with the sigmoid activation function. The output regression layer of DNN-PC determines the transmission power p_n^k.

III. Problem formulation

To demonstrate benefits of the proposed coordination of the two DNNs, DNN-CQ for the D2D channel quality prediction and DNN-PC for the power control, we define a common problem targeting maximization of the energy efficiency for D2D communication via controlling the transmission power of the D2D transmitters. The problem is expressed as:

$$\begin{aligned} &\max_{p_n^k} \sum_k E_n^k \\ &\quad a)\ c_n^k > c_{n,req}, \forall n \\ &\quad b)\ 0 < p_n^k < p_{max}, \forall n \end{aligned} \tag{4}$$

where 4a) ensures the minimum data rate $c_{n,req}$ required by the n-th D2D pair while 4b) limits the transmission power of the transmitter in the n-th D2D pair to p_{max}.

Since measurement of the quality of all channels among all devices in a traditional way via reference signals is not feasible in real-world applications with a high number of devices, we exploit the channel quality prediction via DNN proposed in [5]. Besides, as the transmission power control for D2D devices is a non-convex problem [7], we adopt DNN-based power control proposed in [9]. Of course, an application of these two DNNs itself would be of limited novelty. However, our main *novelty and contribution* consist in development and demonstration of the fruitful *mutual coordination between both DNNs*. Note that such coordination between DNNs or other machine learning tools is required in any scenario, where the channel prediction via DNNs coordinates with any other radio resource management techniques. Thus, the problem of power control defined in this section is considered as a tool for the demonstration of the DNNs coordination, but the formulated problem itself is not the major innovation in our paper.

IV. Proposed coordination of DNNs

This section first gives a motivation and a high-level overview of the proposed DNN coordination. Then, details of the coordination for training and exploitation are elaborated.

A. Motivation and high-level overview of proposed concept

To control the transmission power of D2D pairs, the channels among D2D pairs should be known. In the state-of-the-art works, both sub-problems, i.e., the D2D channel quality prediction from the channels to neighboring BSs and the power control for D2D, are solved separately via two independent DNNs, see e.g., [5] and [8], [9], respectively. These two DNNs can be simply concatenated so that the first DNN predicts the D2D channel qualities from the known channel qualities to BSs [5] and feeds these learned D2D channels to the second DNN, which predicts the D2D transmission power [8], [9]. Then, both DNNs can be trained jointly. Unfortunately, joint training would lead to relatively long learning with plenty of required samples and to a performance degradation due to relatively small but accumulated and propagated errors in both DNNs, as we demonstrate later in this paper.

Motivated by the above-mentioned limitations of the related works, we suggest a mutual coordination of both DNNs. In our concept, both originally independent DNNs are interconnected and accompanied by a feedback and a knowledge transfer, as shown in Fig. 2. The objective of such interconnection is to minimize the total error accumulated in and propagated via both DNNs and, consequently, to improve performance (in our case, the energy efficiency of D2D communication).

The interaction between both DNNs is related to the training phase and to the phase of exploitation of the trained DNNs. We discuss details of these aspects in the following subsections.

B. Coordination of DNNs in training

In the training, the coordination between DNN-CQ and DNN-PC is implemented by transferring the learned knowledge. In particular, the DNN-CQ trained on one task (D2D channel prediction) is reused as a starting point for the training of the DNN-PC to perform another task (power control).

For training phase, the inputs of DNN-CQ are represented by $M \times L$ channel qualities from M devices to L BSs

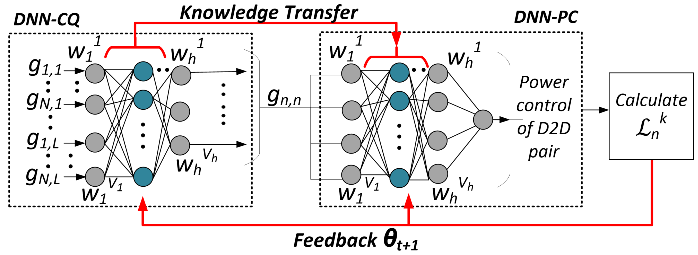

Fig. 2. Architecture of the proposed coordination among DNNs for D2D channel quality prediction (DNN-CQ) and DNN for power control (DNN-PC) interconnected for training and exploitation purposes.

(representing features), and N true D2D channel qualities for N D2D pair are the outputs (targets). These features and targets constitute a learning sample for the DNN-CQ. The DNN-PC in our proposed work processes the training samples composed of N predicted D2D channel gains (features) and generates output in the form of N predicted D2D transmission powers (targets). The input and output of both DNNs are aligned with the information commonly available and used in existing mobile networks, see, e.g. [5], [17].

The trained layers of DNN-CQ are used as an initialization for the training of DNN-PC. Also, the weights are transferred from the DNN-CQ to the DNN-PC for the initiation. However, the weights are adjusted and fine-tuned on a new dataset with different features and targets using DNN-CQ as a teacher network guiding the learning of DNN-PC acting as a student network. As a result, DNN-PC benefits from the features and representations previously learned by DNN-CQ and learns the task faster and more accurately.

C. Coordination of DNNs during exploitation of trained DNNs

The coordination of DNNs during exploitation for D2D communication is motivated by a need to satisfy the constraints of the targeted problem. To this end, the coordination facilitates a relation of the predicted channel qualities and powers to the environment, where the performance is optimized. We implement the coordination via a loss function that provides a feedback to both DNN-CQ and DNN-PC to update their internal weights. The feedback indicates to both DNNs that there is a potential error in predictions and both DNNs acquire information from the environment enabling them to take an appropriate action. In the loss function, we consider a logarithmic component that continuously encourages high energy efficiency and penalizes low energy efficiency. We also incorporate a penalty if the differences $c_{n,req} - c_n^k$ and $p_n^k - p_{max}$ are positive. Unlike the traditional representation of typical loss functions based on energy entropy or mean square error, in our case, the penalties are added to satisfy the constraints in (4). Hence, the loss function is defined as:

$$\begin{aligned}\mathcal{L}_n^k &= \mathbb{E}[-\log(E_n^k) + \max(0, [c_{n,req} - c_n^k]) \\ &\quad + \max(0, [p_n^k - p_{max}])\end{aligned} \tag{5}$$

The loss function $\mathcal{L}_n^k$ is calculated every iteration and is continuously fed back to both DNN-CQ and DNN-PC to update their respective weights. The weights are updated based on the objective function' gradients during the training as:

$$\theta_{t+1} = \theta_t + \epsilon \nabla_\theta \mathcal{L}_n^k(\theta_t) \quad (6)$$

where t is iteration of the update, $0 < \epsilon \ll 1$ is the initial learning rate of both DNNs (note that both DNNs are initialized with the same initial learning rate to maintain synchronization and a similar learning pace of both), $\nabla_\theta \mathcal{L}_n^k(\theta_t)$ is the gradient of the loss function $\mathcal{L}_n^k$ with respect to the parameters θ at the iteration t, and ∇_θ is the gradient element, which is computed with respect to the loss function and is used to adjust the parameters to minimize the loss. The value of the gradient is determined by the partial derivatives of the loss function $\nabla_\theta \mathcal{L}_n^k = (\frac{\partial \mathcal{L}_n^k}{\partial \theta^1}, \frac{\partial \mathcal{L}_n^k}{\partial \theta^2}, ..., \frac{\partial \mathcal{L}_n^k}{\partial \theta^\eta})$ concerning each layer's parameters, where η represents the number of parameters.

The proposed coordination during the exploitation of the trained DNNs is summarized in following steps: *i)* the channel quality $g_{n,n}$ is predicted via DNN-CQ; *ii)* $g_{n,n}$ for all devices is fed into DNN-PC to predict the transmission power p_n^k for the n-th D2D pair at the k-th channel; *iii)* the predicted values of p_n^k for all devices at all channels are adopted in the network and c_n^k, and E_n^k of the system are observed; *iv)* $\mathcal{L}_n^k$ is determined using (5) to maximize the energy efficiency and to reflect constraints in (4); *v)* the weights of both DNN-CQ and DNN-PC are updated via feedback using (6).

The proposed solution is of a low computational complexity proportional to the number of math operations in each DNN ($\approx$ 4820 operations per DNN for $M = 10$ and $L = 4$) and an enumeration of (5). Hence, we can claim that the required computational resources are marginal and do not limit real-time processing assuming commuting power in the existing networks. Thus, both DNNs can be implemented directly at the BS, which commonly handles the power control of devices. Similarly, also the proposed coordination can be managed by the BS. Hence, there is no obstacle in implementation of the proposal into mobile networks.

V. Performance Evaluation

This section describes a simulation scenario, competitive algorithms, and provides a discussion of the simulation results.

A. Simulation scenario, models and competitive algorithms

We consider four BSs and 16–48 D2D devices (composing 8–24 D2D pairs) randomly distributed so that the maximum distance between the D2D transmitter and the D2D receiver is 50 meters [16], [18]. The minimum and maximum transmission power for D2D transmitters is 1 dBm and 23 dBm, respectively [9]. The carrier frequency is set to 2 GHz and bandwidth is 20 MHz. A common level of thermal noise of –110 dBm is assumed. We consider a mixed LoS/NLoS scenario. In case of LoS, path loss is modeled in line with the 3GPP outdoor-to-outdoor environment [1]. The communication channel interrupted by one or more buildings in NLoS is subject to additional attenuation of 10 dB per wall [5], [19].

Both DNN-CQ and DNN-PQ are composed of three hidden layers with 60, 30, and 20 neurons in respective layers. The batch size is set to 32, and the learning rate is 0.01. These settings are determined by trial and error approach. For a fair comparison of all evaluated approaches based on DNNs, DNN setting is the same and even their training and inference are performed over the same dataset with 100.000 samples.

We compare performance of our proposed concept of the DNNs with coordination to the following competitive works:

- *Upper bound – Measured Channel and Power Control (MCPC):* The actual channel qualities among D2D pairs are assumed to be known and the power control is performed using a water-filling algorithm [20]. Hence, MCPC represents an upper bound that is not feasible in practice due to very high complexity.
- *DNNs w/o coordination:* The state-of-the-art solutions for D2D channel qualities prediction [2] [5] and transmission power control [9] based on DNN are implemented in a cascade/sequential way without any coordination.
- *Single DNN:* One DNN with two outputs (channel quality prediction and power control) with same setting and hyperparameters as DNNs in our proposal.
- *DNN-CQ + water-filling:* DNN-based channel quality prediction [5] with water-filling power control acc. to [6].
- *Unfolded weighted minimum mean squared error (UWMMSE):* The state-of-the-art work [21] leveraging graph neural networks with multiple layers to efficiently solve the transmission power optimization problem.

B. Simulation results

First, in Fig. 3, we analyze the convergence of the proposed coordinated DNNs and compare it to the convergence of the traditional non-coordinated DNNs (DNNs w/o coordination). The DNNs with coordination converge significantly faster (after about 270 episodes) than the non-coordinated (after about 960 episodes). This is because of utilizing the experience and insights gained from DNN-CQ transferred to DNN-PC. Additionally, the proposed coordinated DNNs converge to a higher energy efficiency (an improvement of 10%–19%).

The energy efficiency of the proposed and related works is investigated in Fig. 4 over the number of devices. With more devices, there are more opportunities for data transmission and reception; hence, the total energy efficiency. The energy efficiency of the proposal compared to DNNs w/o coordination, Single DNN, DNN+CQ + water-filling, and UWMMSE is increased by up to 44.3%, 59.5%, 56.5%, and 69.5%, respectively, since the coordination among DNNs allows to suppress the negative effect of learning errors in each DNN and enables an adjustment of DNNs' weights to improve performance. The efficiency of the DNNs w/o coordination is affected by the accumulation of the learning errors in both DNNs. Then, single DNN suffers from an impossibility to properly reflect a dependency of the power control on the predicted channel qualities. The combined DNN-CQ + water-filling is impaired by the sensitivity of the optimal water-filling to the errors in the channel quality prediction and the imperfect channel quality prediction is emphasized by the water-filling, which is trying to reach the optimum, but with inaccurate inputs (channel qualities).

We also demonstrate the upper bound energy efficiency reached by MCPC assuming accurately known all channel

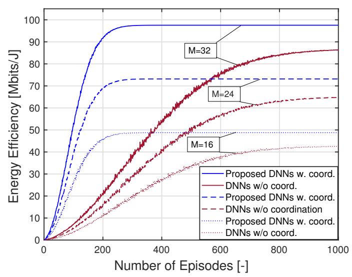

Fig. 3. Convergence of proposed coordinated learning and of learning without coordination for 16, 24, and 32 devices.

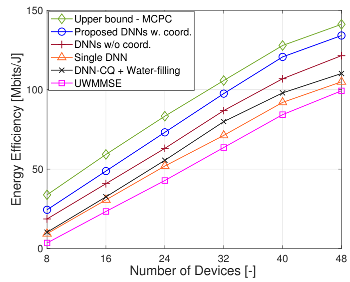

Fig. 4. Impact of the number of devices on the energy efficiency of all investigated algorithms for $c_{n,req} = 2$ Mbps

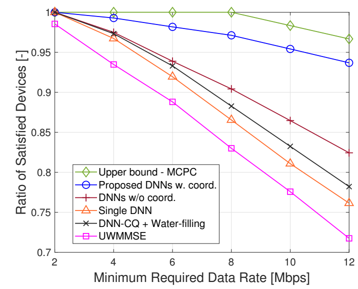

Fig. 5. Ratio of devices satisfied with the received required rate (i.e., $c_n^k > c_{n,req}$) for 24 devices.

qualities and optimally determined transmission power control. The upper bound energy efficiency derived via MCPC is only a few percent (up to 8%) above the proposed coordinated learning, even if the MCPC is not feasible in practice due to unrealistic assumptions and huge complexity. Moreover, the relative gap between the upper bound and the proposal decreases with increasing number of D2D devices and such behavior demonstrates a robustness of the proposal for future scenarios with a high number of devices.

Figure 5 illustrates the impact of $c_{n,req}$ on the ratio of satisfied devices, i.e., the devices experiencing data rate equal or higher than $c_{n,req}$. An increase in the minimum required rate results in a decrease in the ratio of satisfied devices for all algorithms. The lower satisfaction for higher requirements is caused by limited communication resources available in the system. The proposal outperforms the DNNs w/o coordination, Single DNN, DNN+CQ + water-filling, and UWMMSE by up to 13.6%, 23.7%, 20.5%, and 29.7%, respectively. The proposal also reaches the ratio of satisfied devices close to the upper bound (MCPC) with a degradation below 3%.

VI. Conclusion

In this paper, we have proposed a novel concept of coordinated DNNs to predict the transmitting power for the D2D devices in scenario, where measurement of all channel qualities among all devices is not feasible. The novel mutual coordination among the DNNs through transfer learning and a feedback are incorporated to suppress the learning error of individual DNNs. Simulation results show the effectiveness of the proposed scheme in terms of improved energy efficiency by at least 14%, ratio of devices satisfied with received data rate increased by up to 13%, and about 3.5-times faster training compared to approach with DNNs without coordination.

In the future, the proposal should be extended towards general coordination of multiple machine learning tools solving jointly various radio and mobility management techniques in a scalable way.

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