Power Control in Device-to-Device Communication using Multilayer Perceptron based Neural Network

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***Abstract*– Device-to-Device (D2D) communication has sparked attention as a possible technology for next-generation wireless networks since it enables the use of point-to-point communications between User Equipment (UE) without passing via base stations (BS). Device-to-device (D2D) communication has been proposed as a supplemental paradigm in cellular networks to primarily boost network connectivity. This study considers a cellular network where users attempt device-to-device (D2D) connections. A D2D pair is made up of two DUEs, a transmitter, and a receiver. To increase spectral efficiency, we assume that D2D pairings only use one communication channel. A power control is necessary to reduce interference between D2D pairs and boost capacity. We address the issue of D2D power regulation in the case where only typical cellular channel gains between base stations and DUEs are available and channel gains among DUEs are entirely unreachable. We determine the transmission power for each individual D2D pair using an artificial neural network (ANN). We show that employing cellular channel gains, the maximum aggregate capacity for D2D pairs may be obtained while anticipating the transmission power setting for D2D pairs.**

***Keywords*– ANN, BS, CUE, D2D, DUE, MLP, UE, etc.**

I. INTRODUCTION

The emergence of new applications including the distribution of large-scale content and advertising based on the position of users has introduced, in recent years, new use cases for cellular communications, highlighting the need of a new communication technology that is Device-to-Device (D2D).

Beyond the very interesting application aspect, D2D has many advantages: this type of communication can considerably increase the spectral efficiency of networks - the frequency reuse factor is in fact considerably increased [1] and network capacity, and reduce communication latency, in the case of close communications.

D2D communications are defined as direct communications between two mobiles that do not pass through the base station (BS) or the core network. These communications can use either the cellular spectrum [2] (in this case, we speak of Inband communication), or another spectrum, without license. In the latter case, we speak of Outband communication [3].

Nowadays, mobile users are in increasing demand for services with high data rates, whether for video sharing [4], online games, social networking, etc. D2D is a concrete response to the various technical issues linked to this growing demand, in particular for use within a very short range. In such applications, D2D can dramatically increase the spectral efficiency of the entire network. In addition, the use of D2D makes it possible to glimpse promising results in terms of throughput, latency, quality of service, but also, and above all, in terms of energy efficiency.

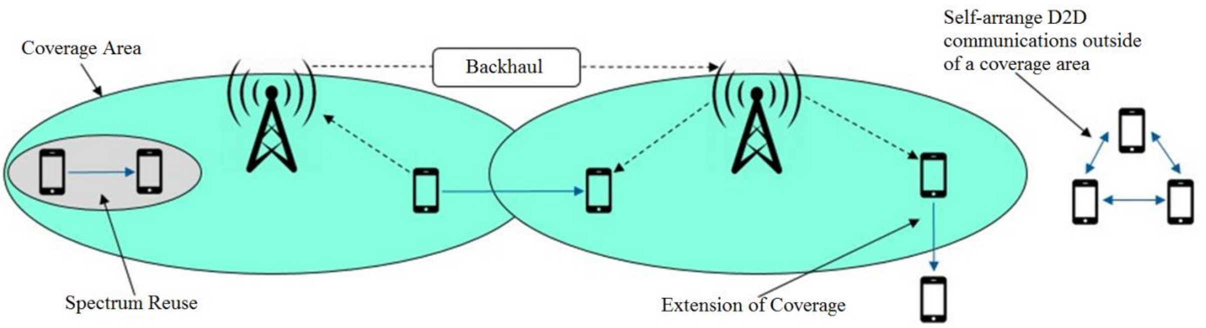

Figure 1: Illustration of possible D2D use cases [5]

The use cases are diverse and varied, as shown in Figure 1. The work of [6] uses D2D to set up an information relay for cellular networks. Some works focused on improving the spectral efficiency of cellular networks using D2D communications [7] [8] [9] [10] [11]. The authors of [12-15] use D2D to set up multicasting applications. We also see in the literature numerous applications of P2P (peer-to-peer) communications [16-17], dissemination of videos [4] [8] [18], M2M (Machine-to-Machine) or discharges from the cellular system.

D2D communication is based on short-distance communications in which the transmitter and receiver are close enough so that a link between them offers a SINR (signal to noise plus interference ratio) and indicates the ratio. between the received signal power by the sum of the noise and interference powers) high and allows direct communication. In some cases, the SINR will be superior to that offered by the link with the base station (BS), and the D2D communication becomes an alternative that presents better performance than that offered by the cellular network, and with less latency, as traditional communication needs 2 hops to complete the link. Another advantage of D2D communication is the possibility of reducing traffic in the BS and freeing up resources to be reused by the cellular network [7].

For the reuse of the resource to be possible, it is necessary that the cellular link and the D2D communication are limited to certain power levels, in order to guarantee that the interference between them is controlled. In this sense, although it is performed directly between two mobiles, the D2D communication must be done under the coordination of the BS. Coordination must ensure that the power of the D2D connection exerts limited interference on the cellular network, in addition to allowing for optimal reuse and efficient allocation of network resources.

If well-coordinated, D2D communication offers an interesting solution for increasing the global capacity of cellular systems, especially in cases where there are many users who want to establish short links within the same cell, as occurs, for example, in fairs, exhibitions, concerts, congresses and other events. Another use lies in service applications such as video streaming, online games, P2P file sharing, among others.

When establishing a link between two devices, it is necessary to satisfy link quality requirements in order to obtain satisfactory communication. More than transmitting information between these devices, it is important to do so with a sufficiently low number of errors so that it is possible to recover, upon reception, the information previously transmitted.

Thus, when talking about establishing D2D communication (secondary layer) to obtain reuse of resources from a cellular network (primary layer), it is important to consider aspects of quality of the received signal both for the cellular link and for the D2D link, establishing a protocol of priorities between both and a coordination strategy, to avoid that, when competing for the same resources, users of the two layers interfere with each other in a destructive way, making communication impossible for both.

Therefore, one way to consider the D2D system is to limit the interference that this system imposes on the primary layer to a certain value, performing a transmission power control coordinated by the BS.

In the model studied, a cellular user is occupying the available resource when two users want to establish a D2D link. Due to the scarcity of resources, the system will try to allocate this communication in the resource destined for cellular communication through reuse. To carry out this operation, the BS coordination determines the maximum power limit for the D2D transmitter.

One of the most often utilised interference avoidance approaches is power control [19]. This technology allows the maximum D2D transmission power to be adjusted so that it does not exceed the predetermined SINR limit in cellular communication; in other words, the transmission power level may be restricted by the eNB to prevent potential interference to cellular receivers. Furthermore, the eNB may regulate access to shared cellular communications resources and D2D peers, resulting in higher spectrum efficiency [20].

However, this strategy is simple but inefficient in the sense that setting the limitation at the D2D power level indicates that it may influence D2D communication, resulting in D2D communication not always being practical.

Several studies have been carried out to increase the spectral efficiency of D2D networks utilising power regulation as a resource allocation problem [21-28]. Sum capacity-focused power management across D2D pairs is a non-convex problem. As a result, the literature has a variety of iterative strategies with varying degrees of complexity. However, iterative approaches may cause latency issues. Deep neural networks (DNN) have recently been used as an option by researchers to control instantaneous power in D2D communication [22]. The DNN reduces the complexity of power control by using supervised [23]-[24] or unsupervised [25]-[28] learning based on offline training. In terms of cumulative capacity, power control systems that mix unsupervised learning and the DNN outperform the currently deployed iterative procedures. A DNN loss function is required for unsupervised learning. The total capacity as a function of channel gains among D2D users (DUEs) and DUE transmission powers are two examples. A fundamental shortcoming of all of the aforementioned techniques, both traditional and DNN-based, is that they generally take into consideration full information of all D2D channel gains. Machine learning approaches alter transmission powers by putting the D2D channel gains into the neural network as an input. It is sometimes feasible to decrease the need that channel state information (CSI) include all distributed D2D channel gain values. In comparison to the signalling required for traditional cellular communications, even a cursory comprehension of the benefits of D2D channels reveals that they come at a substantial cost in terms of extra channel estimations and signalling.

The major claim of this research is a novel power control strategy for D2D communication based on artificial neural networks (ANNs) that requires no prior knowledge of D2D channel gains. There is no signalling overhead since the channel quality is transmitted to all neighbouring base stations during a shared network operation. The primary purpose of our proposed ANN is to link D2D and cellular channel gains. The transmission power of the D2D pairs is then modified using this relation to enhance total capacity. It is critical to remember that there is no known explanation for the relationship between cellular channel gains and total D2D pair capacity. As a result, providing a proper loss function for an ANN based on unsupervised learning is problematic. We adopt a supervised learning approach because we first identify the targeted DUEs transmission powers that boost the cumulative capacity. In order to arrive at the optimal power setting, the ANN is then trained to construct a mapping between cellular channel gains and target transmission powers. The whole training method takes place offline, and the trained ANN is used for quick power control choices in the real network without any further training during communication.

The rest of the paper is organised as follows. Section III presents the recommended methods for power control in D2D. Section IV discusses the MATLAB-based simulation results, followed by concluding remarks in Section V.

II. PROPOSED METHODOLOGY

A. Models for Calculating Energy Consumed

Initially, it is assumed that the bandwidth utilised for transmission is constant throughout time for all transmitted data. To validate the potential improvement in energy efficiency inside a 2-tier D2D network, we examine the network's overall energy usage. First, we employ Shannon's capacity formula, which was employed by the authors of [29]. This formula provides us the following relationship between the data rate communicated by user equipment i (D_i) and the power delivered by user equipment i for data rate D_i (P_i) transmission:

$$\frac{D_i}{W} = \log_2\left(1 + \frac{P_i|h|^2 k r^{-\alpha}}{N_0}\right) \tag{1}$$

Where k is an antenna gain constant, h is channel fading at the transmitter and receiver (fading is assumed to follow the same law at the transmitter and receiver), r is the distance between the transmitter and the receiver, N_0 is the power spectral density of the additive white Gaussian noise (AWGN), W is the channel bandwidth, and α is the path loss exponent.

Thus, we may deduce the power utilised by transmission equipment from equation (1):

$$P_i = \frac{N_0}{|h|^2 k \cdot r^{-\alpha}}[\exp(\ln 2 \cdot C_i) - 1] = \frac{N_0}{|h|^2 k \cdot r^{-\alpha}}\Phi(C_i) \tag{2}$$

Where $C_i = \frac{D_i}{W}$ (in bit/s/Hz) and $\Phi(x) = \exp(\ln 2 \cdot x) - 1$.

Our objective is to calculate the overall energy efficiency benefit for the whole network. As a result, we present the overall power usage of the whole network as follows.:

$$P_T = P_{UA} + P_{UB} + P_{UR} \tag{3}$$

Here, P_{UA} represents the total power spent by UA, P_{UB} represents the total power consumed by UB, and P_{UR} represents the total power consumed by UR. In this case, UA is the source device sending its own data. The destination device, UB, receives data from UA. The relay device, UR, relays data from UA to UB.

The various D2D pairs that are using the channel interfere with one another. This definition of the n^{th} D2D pair's capacity reads as follows [21]:

$$C_n = W \log_2\left[1 + \frac{p_n g_{n,n}}{N_0 W + \sum_{\substack{j=1 \\ j\neq n}}^{j=N} p_j g_{j,n}}\right] \tag{4}$$

Where,

- N_0 is symbolized for the noise power spectral density.
- p_j represents the transmission power of the j^{th} DUE_T, and $g_{j,n}$ is the channel gain between the n^{th} DUE_R and the j^{th} DUE_T.
- W is symbolized for channel bandwidth.
- p_n is the symbol for the transmission power of the n^{th} DUE_R.

Since it is challenging to predict D2D channel gains, therefore a channel between any DUE_R and DUE_T ($g_{j,n}$ and $g_{n,n}$) is thought to be unknown.

Because D2D users will continue to monitor the transmit channels to the server base station (for prediction, decoding, and so on), channel quality information between each D2D user and neighbouring base stations should be assessed and transmitted to the server base station on a regular basis. The $G_{m,l}$ represents the predicted channel gain between the m^{th} and l^{th} DUE.

B. Problem Formulation

This research endeavour intends to optimise the transmission power p_n for every n^{th} D2D pair in order to increase the overall capacity of D2D pairs. Because p_{max} and p_{min} represent the maximum and minimum transmission powers, respectively, the binary power control is assumed, yielding $p_n \in \{p_{min}, p_{max}\}$. To maximise their combined capacity, the transmission power of the D2D pairs must be configured as follows:

$$P = \arg\max \sum_{n=1}^{n=N} C_n \tag{5}$$

$$p_n \in \{p_{min}, p_{max}\}, \forall_n \in \{1,2,\dots,N\} \tag{6}$$

Where $P = \{p_1, \dots, p_N\}$ is the vector containing all D2D pair transmission powers, maximising the total number of D2D pair capacity, and the constraint of equation (6) ensures that the transmission power of each D2D pair is set to either maximum or minimum.

The purpose of the optimization problem in equation (5) is to maximise the cumulative capacity of D2D pairs. However, as seen in equation (4), C_n is dependent on the channel gains of the D2D pair.

C. Neural Network based Power Control for D2D Pairs

A computer model inspired by the brain architecture of sentient species is known as an artificial neural network (ANN). Its intelligent behaviour is derived from the interaction of processors and the environment during the learning process, the role of which is to modify the synaptic weight of the network and offer access to this information for the intended application.

Neural networks are parallel systems made up of neurons or processing units that compute certain (typically nonlinear) mathematical functions. These processor neurons can be split into one or more layers and are linked to one another by a large number of connections (synaptic weights) that store the information represented in the model and help to weight the input data received by each neuron in the network.

1. Artificial Neuron

The artificial neuron model proposed interprets the function of biological neurons as a simple binary circuit that combines several inputs and one output signal. Their mathematical description gives a model with n input terminals representing dendrites and an output representing axons. To mimic synaptic behavior, the input terminal of the artificial neuron is weighted. In mathematical terms, we can describe k neurons by writing the following pairs of equations:

$$v_k = \sum_{j=1}^{m} w_{kj} x_j \quad (7)$$

$$y_k = \varphi(v_k + b_k) \quad (8)$$

Where, $x_1, x_2, \dots x_m$ are the input signals; $w_{k1}, w_{k2}, \dots, w_{km}$ are the synaptic weights of neuron k; v_k is the output of the linear combiner due to the input signals; b_k is the bias; φ is the activation function; and y_k is the neuron's output signal. A description of the artificial model of a neuron is illustrated in Figure 2.

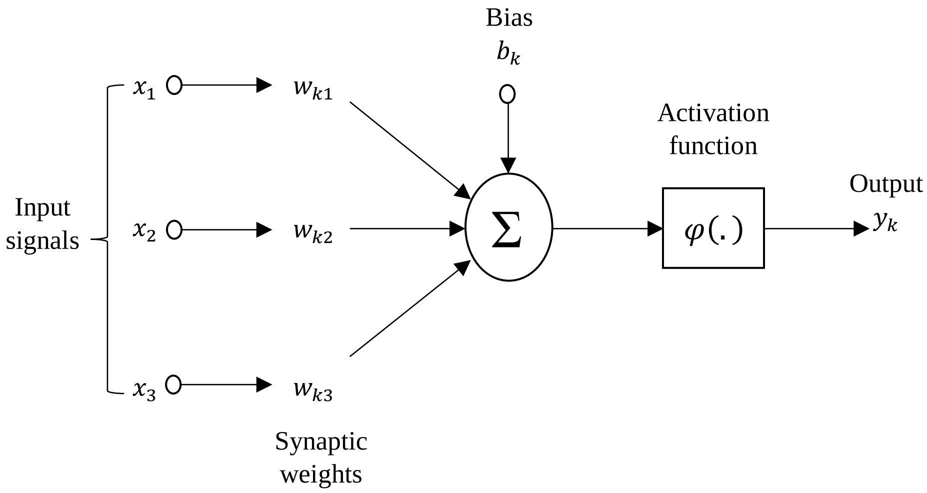

Figure 2: Nonlinear structure of an artificial neuron

2. Activation Function

The main job of the artificial neuron, or processor element, is to sum the components of the input vector, weighted by synaptic weights, and feed this result into a nonlinear function called the activation function.

The activation function, represented by φ, restricts the amplitude of the signal at the output of a neuron in terms of the induced local field v. It is defined as:

$$\varphi(v) = \frac{1}{1 + e^{-av}} \quad (9)$$

Where a is the slope parameter of the sigmoid function and v is the value of the neuron activation function. The logistical function is of the unipolar type, where the output of the model varies between [0, 1].

3. Multilayer Perceptron Architecture of Neural Network

The performance of the ANN is determined by the number of training data, learning rule, selection of evaluation data (input) and the consideration of classification conditions (output). In the scientific community, the development of methodologies from data mining for industrial application is carried out mainly based on an artificial neural network, called Multilayer Perceptron (MLP). MLP is widely used due to its accuracy and performance in numerical modeling problems [30].

Recalling, the MLP is a basic network of the ANN and widely used in classification tasks, being defined as multilayered because the network architecture contains a successive number of layers, in which each one has a finite number of processing units called neurons (Figure 3).

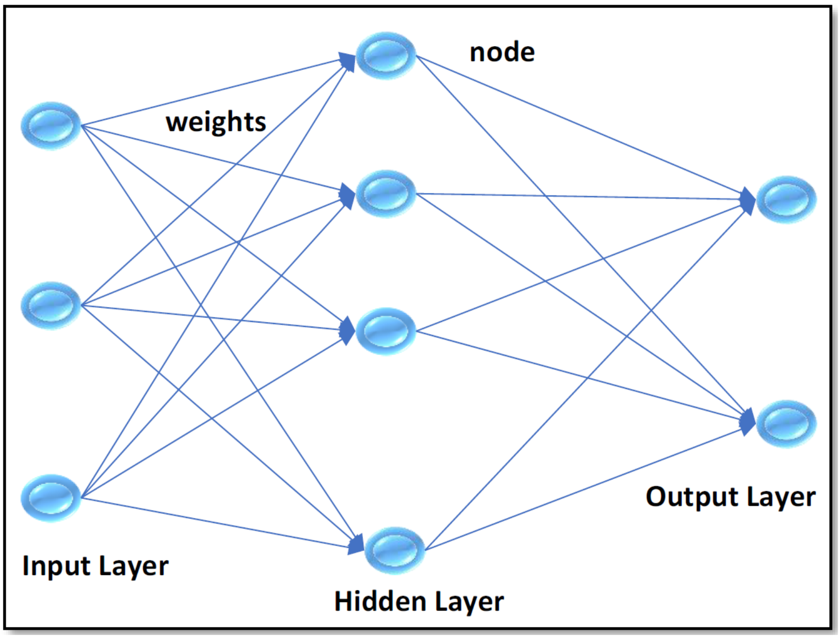

Figure 3: Three-layer multilayer perceptron [30]

The number of neurons in the input and output layers can be observed to be determined by the amount of input variables and the classification condition suggested for a certain job. The number of neurons in the hidden layer is chosen at random or by applying an optimization strategy that allows you to reach your objectives.
An input layer $X = (X_1, X_2, \dots X_n)$, hidden layers $H = (H_1, H_2, \dots H_n)$, and an output layer $Y = (Y_1, Y_2, \dots Y_n)$ make up the proposed ANN. The suggested ANN features an input layer that contains an input vector, and this input layer aligns the cellular channel gains from the D2D users to the base stations.
The term, $Out_{X_0} = P_{1,1}, P_{1,2}, \dots, P_{C,D}$ with a length of $C \times D$ is a vector representing the cellular channel gains between base stations and D2D users and is produced by the input layer.
Because the value of the sigmoid function is between 0 and 1, the output of the ANN will be $out_Y \in [0,1]$, displays the probability that $p_n = p_{max}$. Consequently, the n^{th} D2D pair's transmission power is set to:

$$p_n = \begin{cases} p_{max} & if\ out_Y > 0.5 \\ p_{min} & otherwise \end{cases} \tag{10}$$

4. *ANN Learning Rule*
Following the analysis from the perspective of the interaction of the ANN as a learning machine, the efficiency of the ANN is also determined by the learning rule, that is, the scope and speed of convergence of the mean square error (MSE), given by:

$$MSE(x) = \left(a - y(k)\right)^t \left(a - y(k)\right) \tag{11}$$

Where, x : Synaptic weight vector (unknown variable), a: desired output, y : output in iteration k.
In the training process, the MSE of the ANN is adjusted to a user-defined error precision. This adjustment is possible by updating the unknown variable (synaptic weights and bias) that guarantees the correct classification of the data. In mathematical terms, the ANN learning rule can be seen as an optimization problem [31].
The mathematical relationship between cellular channel gains and D2D channel gains serves as the foundation for the optimization problem in equation (5). The link between cellular channel gains and D2D channel gains in mobile networks is unclear, and it cannot even be inferred analytically from any known mobile network features. We recommend using an Artificial Neural Network to automatically understand this relationship and alter the transmission intensity of the D2D pairs accordingly (ANN). More specifically, the ANN may be viewed as a regulator that adjusts the transmission power of the D2D pair solely based on the information supplied to base stations by D2D users regarding cellular channel gains.
When employing the binary power control, the purpose of equation (5) optimization is to adjust the transmission power of each D2D pair to either $p_n = p_{min}$ or $p_n = p_{max}$. As a result, the difficulty of N identical binary classification is determining how to adjust the transmission power for N D2D pairs. We suggest using a fully-connected ANN to develop the mapping between cellular channel gains and the optimum binary transmission power setting for every n^{th} D2D pair that optimises the cumulative capacity of D2D pairs.
There is no clear mathematical link between D2D pair cumulative capacity and cellular channel gains that can be utilised to determine D2D pair transmission power. As a result, we provide an offline supervised learning-based approach for identifying the ideal binary transmission powers after a thorough search in order to maximise the sum capacity of D2D pairs. The transmission power of the n^{th} D2D pair is then sent to the proposed artificial neural network as a targeted class associated with the set of cellular channel gains. The features and targeted class are combined into a single learning sample. Testing and training sets are generated from the gathered learning samples.

III. SIMULATION RESULTS

The neural network based model is developed utilising training set samples of cellular channel gains and their related predicted transmission powers. To avoid overfitting, the trained NN is next evaluated using a test set of data with cellular channel gains that were not utilised during training. This graph depicts the categorization accuracy of the collection of samples.

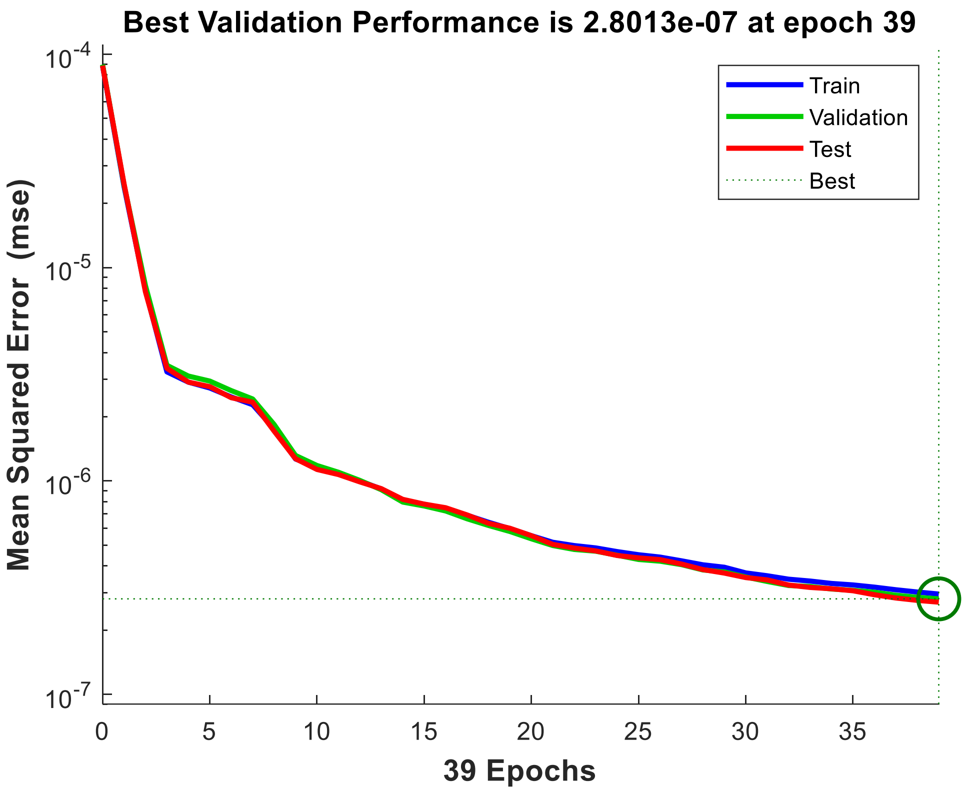

Figure 4: Training and testing performance of proposed approach

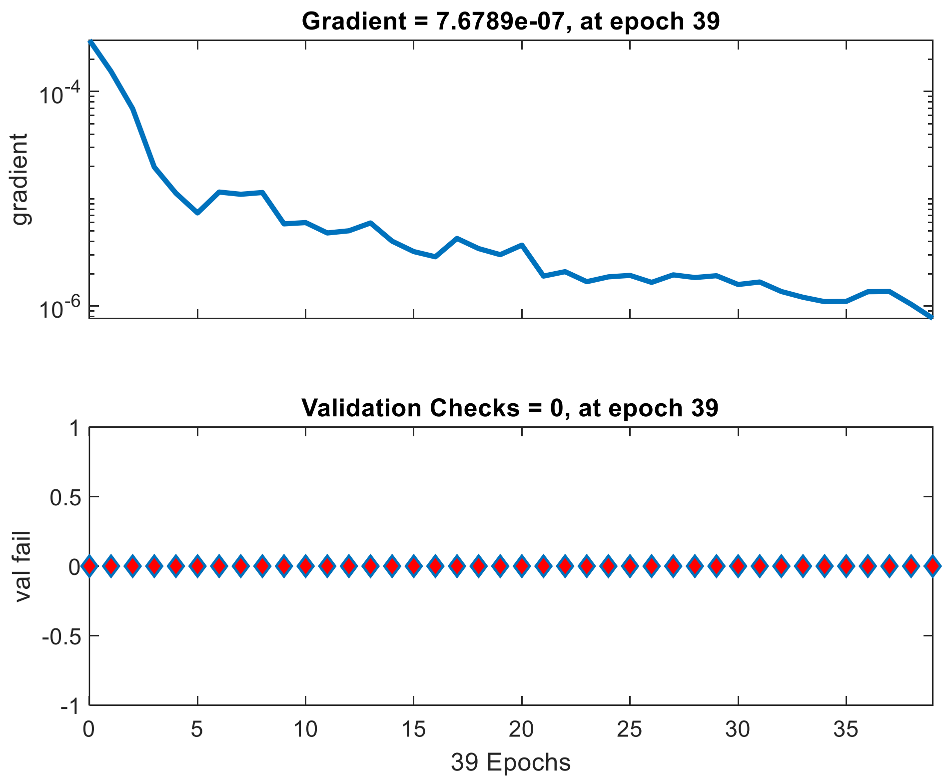

Figure 5: Performance measures of proposed classifier

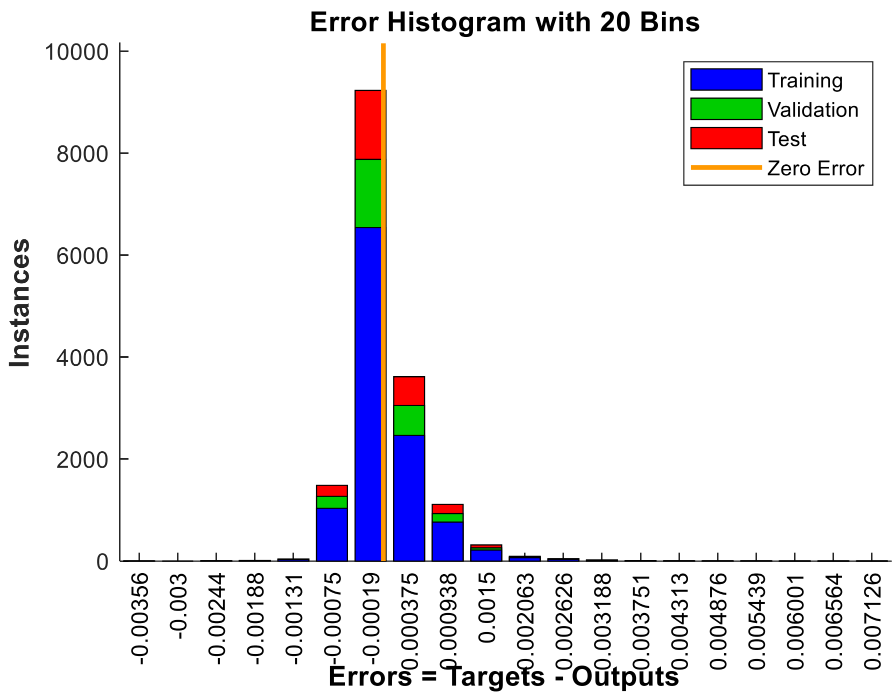

Figure 6: Error histogram graph

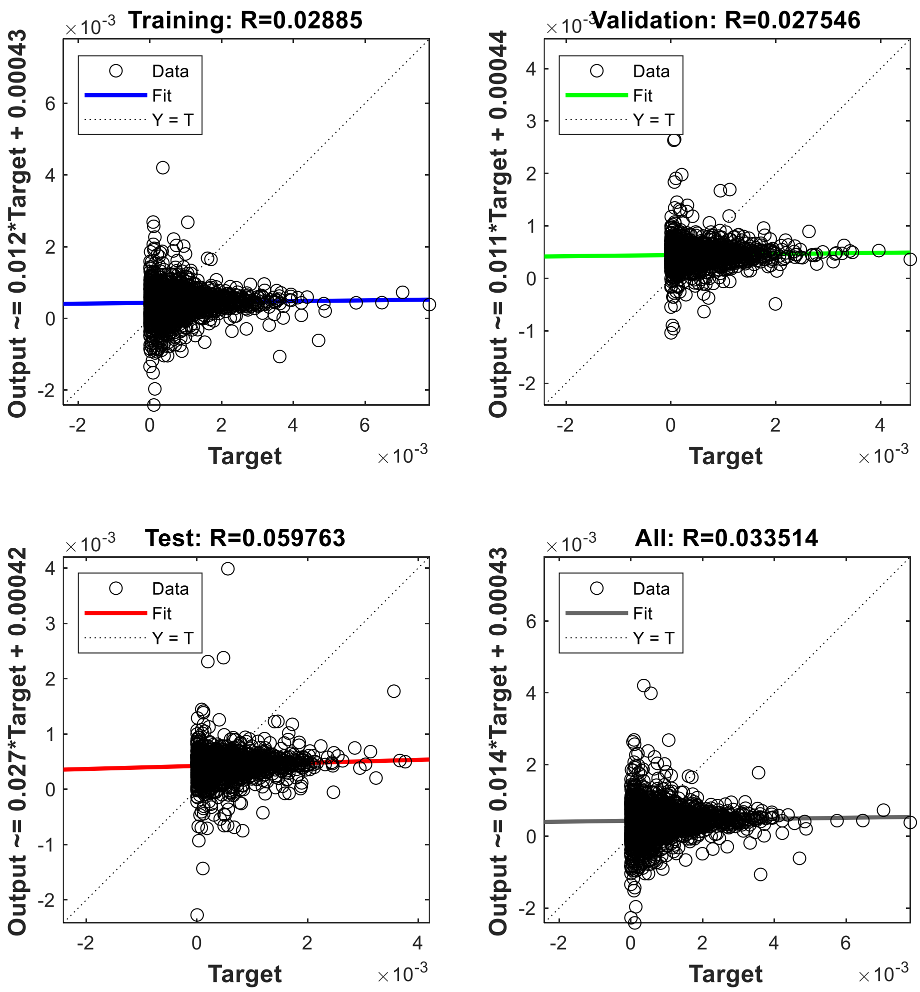

Figure 7: Final output

Table 1: Final results

Optimal result obtained by NN (System Efficiency)		63.0430
Throughput		78.9144
Total Power Consumption		1.2518 Watt
Channel Gain of First Cell's CUEs	First CUE	2.6703

	Second CUE	1.9669
Channel Gain of Second Cell's CUEs	First CUE	2.0554
	Second CUE	2.2861
Channel Gain of First Cell's D2D Devices	First Device	1.5199
	Second Device	6.8406
	Third Device	9.6770
	Fourth Device	12.1281
Channel Gain of Second Cell's D2D Devices	First Device	4.3259
	Second Device	13.7552
	Third Device	11.8723
	Fourth Device	9.8168
Classification Accuracy	p_{min}=93.6%	**Total Accuracy = 92.25%**
	p_{max}=90.9%	

IV. CONCLUSION

In this study, we provide a unique power control strategy for D2D communication that does not require any knowledge of channel gains. The proposed technique simply uses the cellular channel gains between D2D users and adjacent base stations to estimate the transmission power of each D2D pair using an artificial neural network. The key advantage of the proposed method over existing practises is that there is no additional signalling overhead on the network. It is simply essential to be aware of the cellular channel gains, which are regularly published for a range of goals related to traditional communication and handover. The proposed technique outperforms the scenario with no power control and achieves a nearly optimal D2D pair sum capacity with a maximum classification accuracy of 92.25%. The key focus of future research should be on expanding the applicability of the proposed technique to the estimate of D2D channel gains, which can subsequently be applied to any radio resource management challenge.

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