Artificial Neural Network based Power Control in D2D Communication

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***Abstract*—As a viable technique for next-generation wireless networks, Device-to-Device (D2D) communication has attracted interest because it encourages the usage of point-to-point communications between User Equipment (UE) without passing over base stations (BS). Device-to-device (D2D) communication has been proposed in cellular networks as a supplementary paradigm to primarily increase network connection. This research takes into account a cellular network where users are trying device-to-device (D2D) connection. A D2D pair is composed of two D2D users (DUEs), a transmitter, and a receiver. To improve spectral efficiency, we use the premise that the D2D pairs only employ one communication channel. In order to minimize interference between D2D pairs and increase capacity, a power control is required. In the scenario where only typical cellular channel gains between base stations and DUEs are known and channel gains among DUEs are completely inaccessible, we address the issue of D2D power control. For each individual D2D pair, we use an artificial neural network (ANN) to calculate the transmission power. We show that the maximum aggregate capacity for the D2D pairs may be reached while anticipating the transmission power setting for D2D pairs using cellular channel gains.**

Keywords*—Artificial Neural Network (ANN); Base Stations (BS); CUE; Device-to-Device (D2D); DUE; ML; User Equipment (UE)

I. Introduction

In general, the allocation of spectral resources and power control are two processes that are not separate from one another. Power control is a way to limit interference between network users while guaranteeing the minimal quality of service requirements. Interference between cellular and D2D users occurs when shared resources are assigned; in this scenario, the transmission power of the D2D user is lowered in accordance with the minimum reference value of the cellular communication. Thus, the network can also establish a maximum transmission value for D2D devices, depending on the impact of the different power levels of the devices on the quality of the cellular links.

Since there is minimal to no chance of interference between D2D and cellular users, the transmit power may frequently be greater when dedicated spectrum resources are allocated to D2D devices rather than shared resources. Thus, the management of spectrum resources can be carried out mainly by the network or by the devices themselves. In dedicated sharing, devices must be aware of the environment and use resources adaptively, trying to cause minimal interference to other users. Leaving resource management in the hands of the device it results in a less predictable process, but with greater flexibility and less complexity.

Power control is one of the most often used interference avoidance methods [1]. This technique allows an adjustment of maximum D2D transmission power so as not to exceed the predefined SINR limit in cellular communication that is, the transmission power level can be limited by the eNB in order to reduce potential interference to cellular receivers. In addition, the eNB can also control access to shared cellular communications resources and D2D peers, which represents greater efficiency in the use of spectrum [2].

However, this technique is simple, but not efficient, in the sense that by placing the restriction at the D2D power level, it implies that it may affect D2D communication, that is, it results that D2D communication may not always be viable.

The schematic depiction of the power control strategy is shown in Fig. 1. The distance between the D2D pairs, the distance between the D2D pairs and the eNB, or the distance between the DUE_T pairs and the cellular users (CUE) all have a significant role in how well this strategy works.

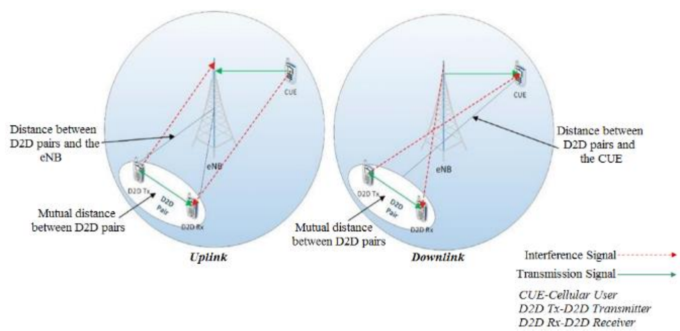

Fig. 1. D2D Power Control Technique [3].

The performance of the D2D communication is unaffected by the power reduction if the D2D pairs are close together and remote from the eNB or CUE.

The D2D power reduction can provide a very low probability of D2D communication or even completely preclude communication between the D2D pairs in the opposite scenario, when the distance between the D2D pairs is great while also being reasonably close to the eNB or CUE.

In spite of this, the power management strategy only works well for reducing D2D communication interference in cellular communication when the D2D pairs are near together and at the same time separated from the eNB and/or CUE. The

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performance of D2D communication might be harmed by severe regulations that limit the transmission power of D2D users.

II. Literature Review

Machine learning has application in a wide range of fields: image processing, audio, finance, economics, social behaviour analysis, telecommunications network management, the latter being one of the most promising applications of this branch of artificial intelligence [4] [5] [6].

Telecommunications networks are now able to learn from and extract information from data thanks to the discipline of machine learning's growth. The latter is of vital importance for new wireless network standards such as 5G [4] [5] [6].

Until now, the development of machine learning and telecommunications networks have been carried out as different research fields, but the application of ML in 5G networks has demonstrated the present and future potential of this combination of paradigms and technologies. It is now clear that this is the case with mobile edge computing, location-based services, contextual networking, edge caching, network traffic monitoring, and big data analytics [4] [5] [6].

Machine learning is perfect for difficult problems that need a lot of human fine-tuning to solve or for problems for which there is no traditional answer. The above problems can be addressed by replacing conventional software that contains a large number of rules with software (containing ML routines) that is capable of automatically learning from data. Automatic feature extraction, anomaly detection, scenario prediction, environment adaption, information gathering on complicated issues with enormous volumes of data, and pattern discovery are some of the distinctions between machine learning algorithms and conventional cognitive algorithms [4] [5] [6].

Many parameters in wireless and mobile networks are estimated using heuristic techniques because there is no analytical answer or because it is impractical given its complexity and related expenses. In these situations, machine learning algorithms can aid in the resolution by forecasting and estimating variables and functions based on the existing information [4] [5] [6].

Despite the advantages of using ML, this technique has limitations that prevent its widespread use in wireless communications, including the findings' interpretability, the difficulty of locating pertinent data, the needed processing power, the complexity added, and the lengthy training cycles of some algorithms, among others, which cause the cost, time, latency and delay introduced to be incompatible with some real-time applications [4].

Despite the difficulties to be overcome, it can be said that machine learning is already widely used in the modelling of a variety of technical issues of next-generation systems, including large-scale MIMO, low-latency communications, heterogeneous networks made up of femtocells and small cells, vehicular networks, D2D networks, among others [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15].

Basically AI is any technique that allows computers to imitate human behaviour; ML are those algorithms that use statistical techniques to allow machines to "learn" through experiences; and Multi-layer neural networks are used in the deep learning subfield of machine learning to carry out algorithm execution [4] [5] [6].

D2D communications were initially found to be beneficial for increasing spectral efficiency and frequency reuse, while reducing communication delays. However, this mode of communication has introduced additional interference due to multiple simultaneous communications on the same frequency bands, which is difficult to control and mitigate. This is especially true when D2D communications take place in Inband and/or Underlay circumstances, i.e., on the same frequency as the cellular network and/or concurrently with cellular communications [16].

Numerous academics have looked at resource distribution challenges in this setting, such as connecting for D2D communications and power and frequency distribution. The performance of D2D and cellular communications in a basic wireless network was examined by the authors of [17] in relation to the effect of the QoS requirement on latency. They developed the best power allocation strategies taking into account statistical QoS provisioning in order to maximise network performance while adhering to QoS limitations.

The authors of [18] described an underlying D2D-based network that allows D2D users to serve as a relay for cellular communications in order to optimize the transfer rates that D2D users may achieve while still meeting the QoS criteria of cellular users. The best power allocation technique for the base station (BS) and the D2D transmitter is found in closed mode when there is a global power restriction. Moreover, the simulation results demonstrate the superiority of using D2D devices as complete relays compared to classical cellular communications.

In order to increase the overall throughput of cellular and D2D users while maintaining the required minimum QoS for WiFi users, the authors of [19] investigated the issue of shared channel and power distribution. They proposed a particle warm optimization (PSO) algorithm, which significantly reduces interference in both licensed and unlicensed bands and improves throughput performance. This work has focused on the derivation of optimal solutions or heuristics that are applied offline, i.e., with the a priori knowledge of the state of the entire system. For online deployments, where device locations and channel conditions are constantly shifting, these techniques would be insufficient. The research has suggested increased learning methodologies as a solution to these problems.

In [20], the authors proposed a Q-learning method that jointly assigns channels and power levels to D2D devices to maximize end-to-end traffic flow in an underlying scenario D2D. They showed that their method outperforms benchmarks in terms of average system capacity. The authors of [21] employed Q-learning with logarithmic regret to minimize total transmission power and associations to SB. Then they extended their proposal to distribute Q-learning to reduce complexity. The results obtained demonstrated the superiority of their approaches compared to benchmarks, in terms of reduction of transmission energy consumption. Additionally, the authors of [22] looked at the issue of power distribution in D2D underlying networks. The authors suggested a D2D power control based on extreme hierarchical machine learning that, in terms of communication speed and energy efficiency, surpasses both distributed Q-learning and CART decision trees. Finally, in order to maximise the D2D sum throughput, [23] developed a deep reinforcement learning strategy for scheduling D2D connections in a cellular underlay network. The results of the simulation showed that the suggested strategy outperformed the conventional procedures.

D2D communications would offload content and traffic off the cellular network, reduce recovery and content delivery, and enhance the energy efficiency of the cellular network, all of which would considerably improve system performance in caching cellular systems. These benefits have been demonstrated in several recent works.

In [24], the authors proposed to cache content either in the cellular BS or in D2D devices. Next, they studied the co-design of the content caching and delivery policy, given their prior knowledge of user demands. The authors described in [25] the D2D cognitive communications underlying cellular transmissions in order to cache files between devices transparently. On BS and D2D devices, they then assessed the delay and queue length. Additionally, the authors in [26] suggested a caching method that reduces the typical content delivery time in a D2D-supported cellular network. They demonstrated the superiority of their proposed greedy algorithm over the naive popularity-based caching policy. In order to maximize the probability of successful transmission, which gauges the percentage of users meeting their QoS delay criteria, the authors of [27] took use of the collaboration between BS caching and D2D caching. They showed that by using the proposed block coordinate descent algorithm, they can achieve significant performance gains over conventional caching methods.

In contrast, the authors of [26] used a user behaviour learning algorithm that predicts user requests and estimates file popularity. Thus, this information is used to adjust the caching policy between D2D devices, with the aim of minimizing transmission delays for file delivery. Simulations demonstrate that the suggested strategy performs better than both probabilistic and naïve caching. In [28], the authors examined the combined cache placement and resource allocation problem in heterogeneous networks with D2D support. In terms of average content delivery times, they suggested two imperfect heuristic methods that outperform D2D-unsupported systems. Authors of [29] examined content placement in the context of a D2D-assisted Hetnet with the goal of reducing the average content delivery time. For a single content library, the optimal solution is obtained and then used to design a low-complexity heuristic for a larger content library. They demonstrated through simulations the advantages of storing popular data in D2D devices inside the cellular system that had the best connectivity to other D2D devices.

The authors of [30] investigated content caching and delivery in a D2D network. They used a deep-Q network (DQN) method to improve content distribution with respect to delays and energy restrictions, and echo-state networks for predicting user mobility and content popularity. In [31-32], the authors formulated a Multi-Agent Reinforcement Learning (MARL) D2D caching problem, aiming to improve the average latency content delivery rate and cache hit rate, without prior knowledge of content popularity. To solve it, they proposed Q-learning for independent learning devices and joint action learning devices. Through simulations, they found that joint action learning algorithms outperform individual learning algorithms and other basic approaches.

Numerous research have been conducted to improve the spectral efficiency of D2D networks using power regulation as a resource allocation problem [33-40]. A non-convex issue, sum capacity-focused power management over D2D pairs. Because of this, a number of iterative techniques with varied degrees of complexity are provided in the literature. But latency problems might arise with iterative techniques. Deep neural networks (DNN) are being employed as an alternative lately by researchers to regulate instantaneous power in D2D communication [34]. Through supervised [35]–[36] or unsupervised [37]–[40] learning based on offline training, the DNN significantly decreases the complexity of power control. Importantly, power control approaches that combine unsupervised learning and the DNN surpass the presently used iterative strategies in terms of cumulative capacity. For unsupervised learning, a DNN loss function is necessary. Examples include the overall capacity as a function of channel gains among DUEs and DUE transmission powers. The fact that all of the aforementioned approaches, both conventional and DNN-based, typically take into account full information of all the D2D channel gains is a significant disadvantage. By feeding the D2D channel gains into the neural network as an input, machine learning techniques change the transmission powers. Sometimes it is possible to reduce the need that channel state information (CSI) contain all distributed D2D channel gain values. In contrast to the signalling needed for conventional cellular communications, even a partial understanding of the benefits of D2D channels indicates that they come at a significant expense in terms of extra channel estimates and signalling.

This paper's main proposition is a unique power control technique for D2D communication based on artificial neural networks (ANNs) that requires no further understanding of the D2D channel gains. Since the channel quality to all nearby base stations is sent during a shared network operation, there is no signalling overhead. Our suggested ANN's main goal is to establish a connection between D2D and cellular channel gains. In order to increase the total capacity, the transmission power of the D2D pairs is then changed using this relation. It is vital to keep in mind that there is no known explanation for the association between cellular channel gains and the overall D2D pair capacity. Therefore, it is difficult to provide a suitable loss function for an ANN based on unsupervised learning. Because we first identify the targeted DUEs transmission powers that increase the cumulative capacity, we employ a supervised learning technique. The ANN is then trained to create a mapping between cellular channel gains and the target transmission powers in order to arrive at the correct power setting. The whole training procedure takes place offline, and without any further training during communication, the trained ANN is used for swift power control decisions in the real network.

The remainder of the paper is laid out as follows. The proposed methodology for power control in D2D is presented in Section III. Section IV states the problem under study. Section V talks about power control for D2D pairs using ANN. Section VI discusses the MATLAB based simulation outcome of the research followed by the conclusive remarks in Section VII.

III. Proposed Methodology

A. System Model

We take into account a model with M D2D users (DUEs) and L base stations producing N D2D pairings inside a square area (i.e., $N = M/2$ provided M is an even number). To ensure the viability of the D2D connection, the distance D_{max} between the receiver DUE_R and transmitter DUE_T that make up the D2D pair is restricted. It is expected that the common channel is used by D2D pairs. 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 [33]:

$$C_n = B\log_2\left[1 + \frac{p_n g_{n,n}}{\sigma_0 B + \sum_{\substack{j=1 \\ j\neq n}}^{j=N} p_j g_{j,n}}\right] \tag{1}$$

Where,

- σ_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.
- B 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.

Since D2D users will continue observe the transmit channels to the server base station (for prediction, decoding, etc.), the channel quality information between each D2D user and neighbouring base stations should be periodically measured and reported to the server base station. The $G_{m,l}$ stands for the equivalent expected channel gain between the l^{th} and the m^{th} DUE.

IV. Problem Formulation

To boost the overall capacity of D2D pairs, this study effort aims to optimize the transmission power p_n for every n^{th} D2D pair. Since p_{max} and p_{min} are the maximum and minimum transmission powers, respectively, the binary power control is assumed resulting in $p_n \in \{p_{min}, p_{max}\}$. To optimize their combined capacity, the D2D pairs' transmission power must be set up as follows:

$$P = \arg\max \sum_{n=1}^{n=N} C_n \tag{2}$$

$$p_n \in \{p_{min}, p_{max}\}, \forall_n \in \{1,2,\ldots,N\} \tag{3}$$

Where $P = \{p_1, \ldots, p_N\}$ is the vector holding all D2D pair transmission powers, maximizing the total number of D2D pair capacity, and constraint of equation (3) guarantees that each D2D pair's transmission power is set to either maximum or minimum.

Maximizing the cumulative capacity of D2D pairings is the goal of the optimization problem in Eq. (2). But as we can see from Eq. 1, C_n is reliant on the channel gains of D2D pair. We focus on the case when the developers of current systems presuppose full or at least partial knowledge of the channel gains of D2D pairs.

V. Power Control for D2D Pairs using Artificial Neural Networks

Based on biological neural structures, artificial neural networks are arrangements popularly used in machine learning. A Neural Network is made up of neurons, which in turn are organized into layers. Each layer can contain one or multiple neurons, and its position in the neural network dictates which class it belongs to: input layer, hidden layer, or output layer. Input layer and output layer are terms used to describe the first and last layers, respectively. Between the input and output layers, there are several layers, each of which is referred to as a hidden layer.

The cellular channel gains and D2D channel gains are related mathematically, which is the basis of the optimization issue in equation (2). For mobile networks, the relationship between cellular channel gains and D2D channel gains is unknown, and it cannot even be deduced analytically from any known mobile network characteristics. In order to automatically learn this relation and adjust the transmission strength of the D2D pairs in accordance, we advise employing an Artificial Neural Network (ANN). More specifically, the ANN may be thought of as a regulator that manages the transmission power of the D2D pair based only on the information provided by the D2D users to the base stations regarding cellular channel gains.

When using the binary power control, the goal of Eq. (2)'s optimization is to set each D2D pair's transmission power to either $p_n = p_{min}$ or $p_n = p_{max}$. Thus, the challenge of N identical binary classification is how to set the transmission power for N D2D pairs. In order to build the mapping between cellular channel gains and the ideal binary transmission power setting for every n^{th} D2D pair that maximises the cumulative capacity of D2D pairs, we propose the utilization of a fully-connected ANN.

The suggested ANN for binary classification is shown in Fig. 2. An input layer $X = (X_1, X_2, \ldots X_n)$, hidden layers $H = (H_1, H_2, \ldots H_n)$, and an output layer $Y = (Y_1, Y_2, \ldots Y_n)$ 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.

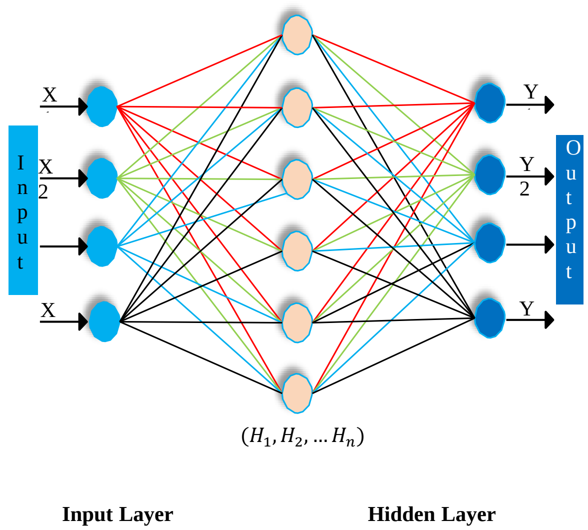

Fig. 2. Proposed ANN Architecture for Binary Classification, Matching to a Single D2D Pair's Transmission Power.

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:

$$p_n = \begin{cases} p_{max} & if\ out_Y > 0.5 \\ p_{min} & otherwise \end{cases} \tag{4}$$

A basic model of a neuron is described by applying an activation function Φ on a linear combination F of the input data, $X = (X_1, X_2, \dots X_n)$, with their corresponding weights, $W_1, W_2, \dots W_d$, and a bias constant b. Thus getting the output Y such that $Y = \Phi(F)$, in which $F = b + \sum_{i=1}^{d} W_i X_i$. This output is then passed along with the other outputs of this layer as input data to the next layer; this chain is perpetuated until the final output is generated by the output layer.

The best-known neuron model is called the sigmoid neuron, whose activation function Φ is the sigmoid function, that is, $\Phi(F) = \frac{1}{1+e^{-\eta F}}$, and therefore the output Y is calculated as follows:

$$Y = \frac{1}{1+e^{-\eta \sum_{i=1}^{d} W_i X_i - b}} \tag{5}$$

The popularity of the sigmoid neuron is due to the ease of obtaining the partial derivative of this function, since the technique used by many to adjust the weights and bias is gradient descent. These adjustments are made by the back-propagation and feed-forward processes.

There is no simple mathematical relationship between the cumulative capacity of the D2D pairs and the cellular channel gains that can be used to calculate the transmission power of the D2D pairs. We therefore provide an offline supervised learning-based technique in which the optimum binary transmission powers are identified following a comprehensive search in order to maximise the sum capacity of D2D pairs. The transmission power of the n^{th} D2D pair is then provided as a targeted class associated with the set of the cellular channel gains as features to the proposed artificial neural network. A single learning sample is comprised of the features and targeted class. From the collected learning samples, testing and training sets are produced.

VI. Simulation Results

A. Simulation Parameters

TABLE I. SIMULATION PARAMETERS

The radius of the cell	500 meters
Maximum transmit power of all devices P_{max}	0.2 Watt
Minimum data rate requirement of all D2D pairs	3 bps/Hz
The proportion of CUE's minimum rate requirement to CUE's achievable data rate	0.2
Maximum iterations of Dinkelbach's method	3
Maximum iterations of condensation method	2

B. Simulation Results

The proposed ANN is trained using samples of cellular channel gains and their associated expected transmission powers from the training set. In order to prevent overfitting, the trained ANN is next assessed on a test set of data using cellular channel gains that were not used during the training. This illustrates the set of samples' classification accuracy. The simulation results of our study are illustrated in Fig. 3 to 6 and Tables I and II.

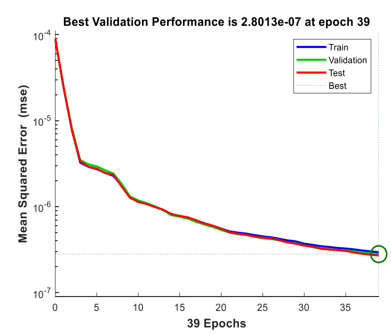

Fig. 3. Training and Testing Performance of Proposed Approach.

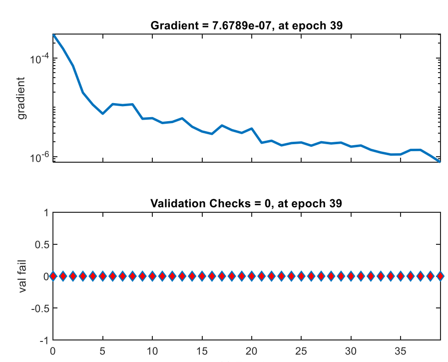

Fig. 4. Performance Measures of Proposed Classifier.

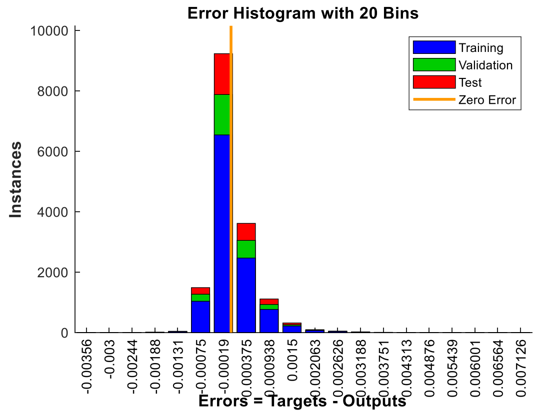

Fig. 5. Error Histogram Graph.

TABLE II. PERFORMANCE 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%	

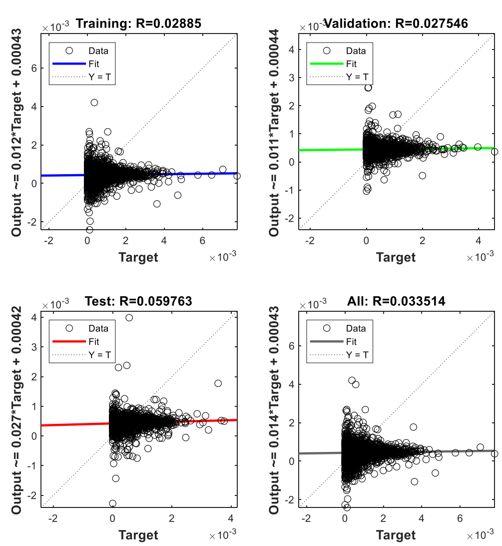

Fig. 6. Final Output.

VII. CONCLUSION

For D2D communication, we have developed a novel power control method in this paper that doesn't require any understanding of the channel gains. In order to determine the transmission power of each D2D pair using an artificial neural network, the suggested method simply utilises the cellular channel gains between D2D users and nearby base stations. The main advantage of the suggested plan over current practises is that the network does not experience any additional signalling overhead. It is only necessary to be aware of the cellular channel gains, which are reported on a regular basis for a variety of objectives connected to conventional communication and handover. The suggested method surpasses the scenario with no power control and achieves a D2D pair sum capacity that is almost ideal with a maximum classification accuracy of 92.25%. Expanding the applicability of the suggested strategy to the estimation of D2D channel gains, which can then be applied to any radio resource management issue, should be the primary focus of future study.

VIII. CONFLICTS OF INTEREST

Declare conflicts of interest or state "The authors declare no conflict of interest."

AUTHOR CONTRIBUTIONS

All authors had contributed to this work.

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