Construction of Improved Device-to-Device Communication in 5G Networks based on Deep Learning Techniques

Sajad Ali Zearah[1], Ahmed R. Hassan[2,*], Aqeel Ali[3], Saad Qasim Abbas[4], Tamarah Alaa Diame[5], Ahmed Mollah Khan[6], Mariok Jojoal[7]

[1]Scientific Research Center, Al-ayen University, Thi-Qar, Iraq
[2]Department of Medical Devices Engineering Technologies, National University of Science and Technology, Dhi Qar, Nasiriyah, Iraq
[3]Medical instruments engineering techniques, Al-farahidi University, Baghdad, Iraq
[4]Computer Technologies Engineering, Al-Turath University College, Baghdad, Iraq
[5]Technical Computer Engineering Department, Al-Kunooze University College, Basrah, Iraq
[6]Department of Computer Engineering, University of Massachusetts Dartmouth, MA 02747Inst, USA
[7]Department of Computer Science and Engineering, University of Deusto, 48007 Bilbao, Spain

Emails: sajad@alayen.edu.iq; Ahmed.r.hassan@nust.edu.iq; Aqeel Ali@uoalfarahidi.edu.iq; saad.qasim@turath.edu.iq; Tamarah. Alaa @ Kunoozu . Edu .Iq; ahmed.khan@umassd.edu; marjoj@@deusto.es

Abstract

Device-to-Device (D2D) Communication promises outstanding data speeds, overall system capacity, and spectrum and energy efficiency without base stations and conventional network infrastructures, and these improvements in network performance sparked a lot of D2D research that exposed substantial challenges before being used to their fullest extent in 5G networks. This study suggests using Deep Learning-based Improved D2D communication (DLID2DC) in 5G networks to address these issues. Reprocessing resources between Cellular User Equipment (CUE) and D2D User Equipment (DUE) can increase system capacity without endangering the CUEs. The D2D resource allocation method allows for a flexible distribution of available resources across CUEs. In addition, several CUEs can consume the same pool of resources simultaneously. Researchers utilize various deep learning techniques to handle the difficulty of constructing D2D links and addressing their interference, mainly when using millimeter-wave (mmWave), to improve the performance of D2D networks. This research aims to increase system capacity by optimizing resource allocation using the suggested DLID2DC paradigm. The model uses Deep Learning methods to overcome interference issues and make D2D link building more efficient, especially in mmWave communication. The model uses Convolutional Neural Networks (CNNs) to learn and adapt to complicated D2D communication patterns, improving performance and dependability. The experimental findings show that, compared to other conventional approaches, the proposed DLID2DC model improves connection with lower end-to-end delay, energy efficiency, throughput, and efficient convergence time.

Keywords: Device-to-Device Communication; 5G Networks; Deep Learning; Convolutional Neural Network.

1. Introduction

The transmission of data at a high rate of speed necessitates improvements in communication technology to maintain optimal performance and deal with large volumes of data. Reliable media transmission necessitates top-notch communication and cutting-edge technology. [1]. The fifth generation (5G) uses technologies to offer dependable and practical solutions. D2D communications can enable mobile networks to interact directly without base stations [2]. D2D's primary function is to reduce the price of communication by facilitating the rapid growth of systems and applications through location for locating and talking to nearby devices. [3].

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

The D2D Commission faced numerous challenges that must be addressed in an organized manner using several approaches for improving system efficiencies that include the Internet of Things (IoT), Artificial Intelligence (AI), Vehicle Vehicles technology (V2V), and millimeter-wave technologies (mmW) [4]. Mobile customers' interaction is caused while adopting D2D technology, as they access the same assets in the same region. Other challenges with D2D technologies include peer identification, delivery, radio assignment administration, optimization, and energy security [5]. As a result, several academics and mobile carriers have been concerned with D2D to improve network efficiency without infringing service criteria [6].

D2D seeks to improve the signal of smartphones in scattered environments with the actual variety of communication equipment [7]. D2D connectivity must operate with mobile network solutions to complement one other [8]. The critical element is to share the capabilities between D2D and cellular connection regarding ability and frequency while developing D2D [9]. The advantages of D2D include maintaining the security and freedom of the material. Because the centralized storage unit does not store information shared, D2D connectivity can enhance energy consumption, production, equity, and time [10]. For this innovation to succeed, the communication technology D2D confronts numerous obstacles [11]. D2D requires resource administration strategies, device search mechanisms, intelligent algorithms for mode choice, security, standards, and data transfer procedures [12].

Many studies were conducted to monitor or control system performance and interference [13]. The article examines a series of recent advances in the realm of 5G capabilities working with D2D, particularly the problems of confidentiality and protection [14]. D2D can achieve many of the 5G criteria as it supports high data rates and reduces delays between D2D user equipment (UE) to a minimum.D2D connections can enhance performance, energy consumption, time delays, equality in spectrum efficiency, capacity redistribution, and interference reduction [15]. D2D can also reduce power usage for connecting D2D devices since the communication range is smaller [16]. D2D can allow the emotion of user usage; thus, generally, it can be anticipated that non-D2D UEs can take advantage of the removal of mobile use, as they, therefore, have access to greater capacity and less congestion to communicate between them [17].

Similarly, several difficulties need to be fixed, including detection of device, mode selection, power regulation, voltage regulation, security, distribution of radio resources, cell densification & downloading and the choice of Quality of Service (QoS) & paths, mmWave connectivity, non-cooperative customers and handoffs strategic planning to fully implement D2D [18]. In recent years, Artificial Intelligence, Explanatory Artificial Intelligence (XAI), has played a significant role when transparent and interpretable.

Evolving fuzzy structures (EFS) and XAI is also the solution for complicated analysis and definition solutions, including concurrent learning, rule choosing, rule teaching, a database having to learn, and variable setting [19]. Therefore, in the 5G study, many methods, such as monitored learning, unmonitored learning, and AI-based enhancement learning, are used [20]. Therefore, this paper proposes a new technique DLID2DC in conjunction with existing AI approaches to integrate XAI to improve the efficiency of D2D communications systems [21].

The contributions to the proposed DLID2DC model are given below:

- The proposed model analyzes the requirements of D2D networks and then recommends effective methods and protocols for putting them into action.
- The DLID2DC uses AI-based methods for better protection, data collection and organization, cross-checking, and analysis of user comments.
- The architecture of a CNN permits real-time evaluation and training, ensuring the best possible outcomes by boosting transmission strength, system performance, and fairness.

The proposed DLID2DC model uses XAI to improve D2D communications efficiency by building on top of existing AI techniques. The DLID2DC model's contributions were described, offering a possible starting point for further study and advancement in this field. The relevance of direct, one-to-one communication within the context of 5G communications networks and the challenges and potential advantages of implementing such a system was emphasized.

The remaining parts of the study are as follows: The evolution of device-to-device communication is outlined in Section 2. Section 3 discusses the proposed DLID2DC models using Deep Learning techniques. Section 4 demonstrates the suggested model's software analysis and performance. Section 5 discusses the final results and potential implications.

2. Background To Device-To-Device Communications

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

Hossain et al. [22] presented the Smartphone Assisted Disaster Recovery (SmartDR) approach that uses 5G D2D communication technologies to facilitate smartphone-based post-disaster communication. By combining parameters including device discovery, route establishment, energy consumption, and delay times, the SmartDR approach significantly boosts network performance in post-disaster settings. The model has a delay of 45 timeslots when using 35 channels and delays of 55, 69, 109, and 309 timeslots when using Distributed Randomized Duty Cycle Synchronization (DRDS), Join/Select (JS), basic Asynchronous Multi-Channel Random Channel Cycling (AMRCC), and improved AMRCC, respectively. The study does not scale up to more significant crisis scenarios with more trapped people and participating smartphones, given that it emphasizes only small-scale scenarios with low smartphone numbers.

To enhance safety and performance in MSNs over 5G networks, He et al. [23] presented a deep reinforcement learning strategy. The approach considered the system's complexity using MEC, caching, and D2D communications. According to the simulation findings, the proposed system stabilizes at a value close to 5900 as the number of episodes grows. There is a noticeable difference in the convergence rate between the 0.0001 and 0.001 learning rates. The study does not provide alternative procedures to verify the claimed method's efficacy.

Zhang et al. [24] proposed a load-balancing technique to handle the spatial-temporal unpredictability of wireless data traffic over cellular networks. The issue is formulated as a D2D routing and resource allocation problem to maximize system throughput. The authors divide the issue into a monotonic optimization problem and a related geometric programming issue and then use iterative techniques to resolve both. According to simulation results, the proposed method enhances system performance, especially data rate, by 20%. The article does not highlight scalability, robustness, and ease of deployment.

Future sixth generation (6G) mobile networks will rely heavily on intelligent automated network operations, management, and maintenance, as discussed by Zhang et al. [25], delved into the notion of intelligent device-to-device (D2D) communication. With mobile edge computing, smart network slicing, Non-Orthogonal Multiple Access (NOMA), and D2D-based cognitive networking all in the picture, this study considers the latest developments in 6G architecture and end-user devices to ensure their effective integration into communication networks. Although the article overviews potential D2D solutions and their association with 6G, it does not provide specific implementation details or empirical results.

The Efficient and Safe Integrated Mutual Authentication and Key Agreement (ESIM-AKA) method was developed by Roychoudhury et al. [26] for 5G cellular networks to ensure secure interaction between various devices. Compared to current D2D authentication techniques, the suggested scheme outperforms them regarding signaling message exchange performance, computational complexity, and bandwidth consumption. The Secure Hashing Algorithm – 256 (SHA-256 bit) yields a result of 0.659. The article summarizes possible D2D solutions and their connection to 6G, yet it needs to provide substantial empirical results or an in-depth assessment of the performance of the suggested method.

Shang et al. [27] offer CAKA-D2D, a verification and key agreement system for anonymous and private group-based D2D communications over 5G cellular networks. Certificate-Less Public Key Cryptography (CL-PKC) and Elliptic Curve Cryptography (ECC) are used in the protocol to encrypt and secure communications. The effectiveness of the security features in the proposed protocol can be evaluated using Burrows-Abadi-Needham (BAN) Logic and Automated Validation of Internet Security Protocols and Applications (AVISPA). The energy cost is 63.7n 28.5mJ, while the transmission cost is 65.114n 29.034mJ. Attack vectors and vulnerabilities are not the primary focus of this study.

Gandotra and Jha [28] suggested an adaptive resource-block (RB) allocation system for Device-to-Device communication in a 5G WCN. The approach employs a hidden Markov model for dynamic allocation to guarantee that every D2D pair accessed enough RBs. The goal is to maintain transmission power limits while maximizing resource efficiency to meet service quality and experience (QoS and QoE) needs. Enhanced energy efficiency (EE) and decreased interference in the 5G network have been demonstrated in simulations of the concept. Conversely, for d = 3 and d = 7, when inter-D2D-pair interference is extreme, the sector technique is less effective, and EE is lower than otherwise. The study needs to improve scalability, and performance needs to be investigated further in more extensive and sophisticated 5G network scenarios.

Distributed pricing-based resource allocation was proposed by Bahonar et al. [29] for high-density device-to-device communications in 5G networks. The objective is to enhance spectrum efficiency for cellular user gear and D2D pairs while minimizing quality-of-service needs. The suggested utility function is applicable for dense

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

networks since it incorporates distance-based cost parameters and admission control. Overall sum-rate improvement can be shown when the Distributed Spectrally Efficient Resource Allocation (DSERA) algorithm's utility feature and price updating mechanism are compared to comparable systems. Possible difficulties with implementation, signaling cost, and channel fading should be discussed in the study.

The communication process between gadgets was crucial at these times due to the demands arising from the growing number of mobile consumers. For major cellular networks, this became impossible to fulfill increasing requests for data transfer, thereby opening the way for connectivity technologies for D2D [30]. Then the complete D2D relaying data transmission showed an excellent way to send large amounts of data. Notably, both in-band and out-of-band wavelengths were used for D2D communications. In addition, the D2D system enabled proximity capabilities for efficient data transmissions, such as D2D discovery and D2D communications. Within a short period, D2D communications technology undoubtedly constituted the foundation of wireless communications worldwide.

The adequate capacity (EC) of a device-to-device (D2D) link is studied by Shah et al. [30], along with the effect switching between modes can have in overlay and underlay configurations. The link depends on the mode option, and the EC is the highest constant arrival rate the transmitter's queue can support. According to simulation studies, the beneficial effect of overlay D2D is reduced as EC drops precipitously as path-loss measurements get noisier. Maximum EC is achieved at r =25 bits per second rate. The research does not investigate the mode selection that affects other performance indicators or consider channel characteristics and deployment scenarios encountered in the real world.

The literature surveyed in this section represents that delivering International Mobile Telecommunications 2020 (IMT-2020) standards was difficult without massive Multiple Input Multiple Output (MIMO) technologies. MIMO systems methods were classified individually for indoor and outdoor situations to improve performance. Peak amplitude, larger bandwidth, capacity doubling, and power savings were among the notable achievements of Massive MIMO above traditional MIMO [31-33]. Therefore, the forthcoming 5G networks research DLID2DC model requires massive MIMO to improve user experiences and network efficiency with higher processing speed and lower error.

3. Proposed Deep Learning-Based Improved D2d Communication

Network identification and interruption control are The primary elements determining efficiency for D2D communications. The effectiveness of current D2D networks is problematic. Nevertheless, due to the diverse requirements of dynamic mobile device methods and protocols, the significance depends mainly on the range among nodes within the network of customers in the vicinities. Moreover, the methods and their respective algorithms can be defined beforehand without considering the existing circumstances and needs.

To handle the different needs concerning the situation: First of all, it needed to assess the current needs of the networks. Secondly, cost estimates play an essential part in the reference architecture. Therefore, an acceptable cost evaluation method for the spectral processing of filtering based on AI is used using biorthogonal spline wavelets. Thirdly, the appropriate, cost-effective technology and its protocol are selected for implementation in the D2D networks. In the smartphone included in the 5G-based D2D networks, the right technology and related protocols are ultimately used to achieve optimum efficiency. Given that the portable device's processing, computing, and memory space are insufficient, the smartphone's challenging procedure for Software Defined Radio (SDR) is complicated. The proposed system intends to use the exterior public cloud to replace automation with an Explainable Artificial Intelligence (XAI) method to analyze the communication needs, select a methodology and practice, and transfer machine language from the remote server to the smartphone as needed.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

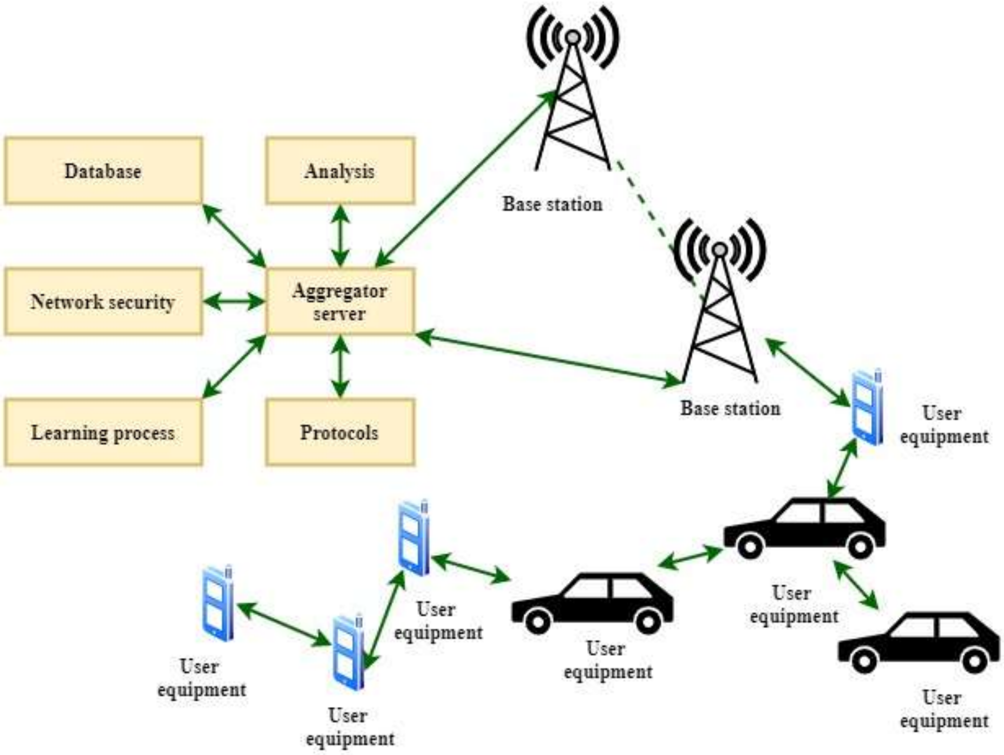

Figure 1: Architecture of the DLID2DC Model

Fig. 1 depicts the suggested DLID2DC model's architecture. It comprises a base station, end-user devices, and a server aggregating data. The aggregator server is connected to the database, analysis module, protocols, learning process, and network security module. On the other side, XAI aggregators in the super-fast distant central server control and regularly monitor the whole activity. This XAI Aggregator Unit links and controls four aggregator sites: auto-learning and Processor, the Network Databases, Transmission of Techniques and Procedures (TTP), and Performance Assessment.

The TTP comprises all the protocols and techniques used to improve system effectiveness. In addition, profound Q-learning, together with supervised methods, is used in the assessment to make final decisions. In addition, AI-based path search techniques are utilized to analyze the current internet traffic. Because of the difficulties of linking each D2D network node to the XAI Aggregate Unit, the Transitional Masters node (TMN) via aggregator by Linear Programming is picked as one device in various D2D Networks. TMN is able, using the IEEE802.11b specifications and the MIMO-based 5G data Networks, to relevant questions namespaces to the XAI aggregating unit. This TMN connectivity aims to decrease the danger of interfering and to improve D2D effectiveness.

Network attributes and metrics such as D2D subscriber profiles, Radio Access Network (RAN) viewpoint, path loss and interference, and performance evaluation are inputs in the proposed methodology—multiple components exchange information inside the DLID2DC model's design. Information about user devices, network metrics, training information, TTP building blocks, and based artificial intelligence path search methods are all passed back and forth for processing. The learning process component transmits the training data and model parameters to the aggregator server, while the aggregator server receives data from the user equipment. In contrast, the AI-based path search techniques evaluate internet traffic data to establish the best data transmission paths; the TTP component boosts system efficiency.

3.1 XAI Aggregation Unit

The aggregator operates as the core of the whole XAI Aggregation site unit and makes its final choices. The activities and methods provided in each system model's aggregators are shown below.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

3.1.1. Security Connection

The AI processor improves safety on the D2D connection and analyses the 3-step aggregators given below:

a) Gathering Network information: Efficient routing assaults like Eavesdroppings, Tapping, and Denial of Service (DoS) are tracked regarding the data collection methodology. Data collection is monitored. In particular, AI management improves the surveillance system's effectiveness and is implemented to capture attackers or their tactics. AI analyzed even the content written in social networks to examine ads or traps used by attackers to draw attention to their virus connection or program.

b) Information organization: it is not easy to arrange computer security data effectively without deep learning after data collection. Therefore, massive data storage and organizations based on artificial intelligence and cloud computing are recommended. Other blocks of safety aggregation can utilize massively parallel techniques to increase the system organization skills through algorithms and approaches applied in the big data platform.

c) Implementation of cross-checks and protocols: cross-checks are conducted regularly to assess interruptions of perceived attacks and identify problems in existing networks. Appropriate security procedures are subsequently applied using AI through the algorithms of the tree structure, as choices based on the classification values are required.

3.1.2. Network Database

D2D Subscriber Profiling, Subscriber's Outlook, Radio Access Network (RAN) Viewpoint, and Subscriber's Mobility Patterns are the most frequent metrics to monitor and save for additional reference. Cellular radius, capacity, Ground Station Transmitters power, Radio environmental mapping, Transport Profile, Subscriber-centered wireless offloading, and Submitter power are also used. Noise in primary user, Thermal sound power D2D pair length, carriers' frequency, the expression for path loss among sensors, the indication for path loss among base station devices, loss of coefficient of determination between equipment, loss of pathway between base station operating systems, efficiency enhancement, independent loading energy in the base station, antenna energy, cellphone power per customer device are analyzed.

The database saves all parameters. The Integrated AI concept in a Big Data Lagoon is utilized efficiently in network connectivity. It refers to administrative systems engineering based on the lengthy descriptions of variables, customer satisfaction, and data from various connections, local entrances, SDRs, routers, and more. Data are collected from several servers, gates, and outcomes that allow the 5G cloud based SDR system to be founded using the same approach.

3.1.3. Techniques and Protocols Transmission

Signal Noise Ratio (SNR) based D2D development, cell orthogonal receptive disclosure (pull), and proactive, reactive institutional development techniques are the most used. Federal-funded intervention canceled flights, based minimum electronic systems, Genetic Algorithm (GA) based user-assignment and worksheet, marketing techniques, and centralized power electronics are used for interference-mitigation ways. The TPT encodes all such techniques required for executable files. Moreover, the created processes are also kept in TPT after the authorization of the aggregator to continue the implementation. Cloud computing pond is also utilized for server installation.

3.1.4. Performance Assessment

The D2D systems' findings are considered with two different techniques and are improved frequently by the aggregator and database.

A) Self-evaluation: Q-learn method combined with adaptive-greedy is used to assess strategies of the Transmission Control Protocol (TCP) based D2D networks that contain many complex methodologies such TCP Tahoe, TCP NewReno, TCP Westwood, TCP Compound, TCP Vegas, etc. In this circumstance, it is now impossible to determine specific approaches from the necessary network needs. The adaptive greedy system based on Q-learning is used for quick evaluation and understanding.

b) Behavioral analysis: The analysis is compelling and like the false emotional patterns as the D2D systems behave in identical situations and settings in many respects. The choice of artificial conduct is made following a

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

moral assessment. In addition, brain structure is formed, and the same self-learning approach is utilized afterward for emotional network psychology.

c) Evaluation of feedback: Increasing the use of D2D cellular telephones is unavoidable. Proper feedback systems are necessary to handle these network activities. The critical feedback aspects, continuous rate adaptation method, and QoS increase the efficiency of the D2D system are evaluated.

3.1.5. Self-Learning and Processing

An understandable, deep-learning architecture is created to understand Cellular User Equipment (CEU) behavior and grasp the primary theoretical conventions on D2D systems to utilize XAI for self-learning. In addition, the D2D self-paradigm offers the framework for adaptive Advanced Analytics and AI that contribute to complex activities such as resource optimization, data-based coverage, etc. A stochastic convergence technique is also created to finalize the processing procedures.

3.1.6. Main Server Aggregation

MAS takes the last option to select an optimal approach based on profound enhanced training through many Deep Q-Networks for outstanding system functioning aside from choices advised by aggregation in specific PA and SLP. Moreover, MAS retains precedence for decision-making based on D2D network performances based on bargaining strategy from multiple collections.

3.2 Convolutional Neural Networks

The proposed method uses CNN to improve its effectiveness. Border Node (BN) processing is the method of normalizing each node in the CNN structure that adapts the digital output values of each layer's kernel function to the correct range. Techniques such as droppings are substituted through BN, increasing the acquisition rate. The BN system can therefore increase the learning pace and address the weight reduction and losing weight issue.

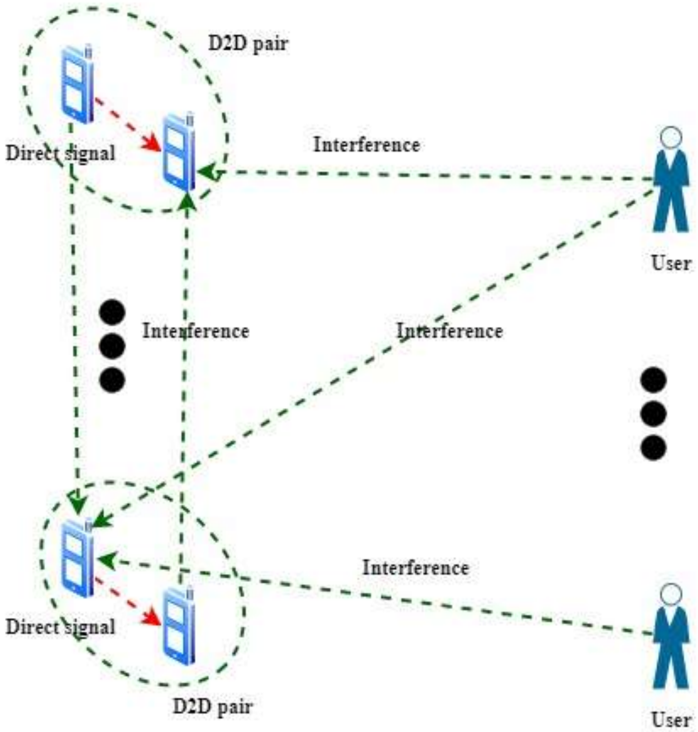

Figure 2: D2D communication model of the DLID2DC system

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

Fig. 2 depicts the user and user devices in the DLID2DC system's D2D communication model. The user equipment receives a signal from a direct signal and an interference signal. The first element in the system is learned after switching to a dB scale. It gets the normalized channels. The standardized channel energy $\hat{c}_{xy}$ is shown in Equation (1)

$$\hat{c}_{xy} = \frac{\log(c_{xy})}{\sqrt{E(\log(c_{xy}))}} - \frac{E(\log(c_{xy}))}{1-\sqrt{E(\log(c_{xy}))}} \quad (1)$$

The channel power is denoted c_{xy} , and the expected value is denoted as $E()$. It conducted the BN procedure that normalizes the neural network architecture by each batch of information's independent and dependent variables. The convolutional procedures used BN. The picture shows that the outcome is normalized by connecting additional BN procedures in a basic convolutional approach. Equations (2) and (3) show the convolutional function

$$G_{\alpha\beta} = \frac{\hat{c}_{xy}-\alpha}{\sqrt{\beta^2+\alpha}} \quad (2)$$

$$G_{\alpha\beta} = \delta G_{\alpha\beta} + J_{xy} - B_x \quad (3)$$

Where $\alpha, \beta, and\ \delta$ are a median mini-batch, mini-batch default, and a numerator value, respectively, that does not reach 0. The convolutional function is denoted $G_{\alpha\beta}$. Then, it derived the result of the BN procedure for x and y recipients, J_{xy}, using $\hat{c}_{xy}$. Specifically, the trainable B_x determines the scaling and shift of normalized data where B_x, is the stratum index of $x = 1,2,\cdots,8$. The BN outputs are utilized for the source of linear constraints corrected ReLU layer and subsequently for the outputs of the ReLU level expressed in Equation (4)

$$J_{xy}(ReLU) = maximum\ (J_{xy}, 0) \quad (4)$$

It is observed that, while doing the $max(.,0)$function, the ReLU layer avoids a negative value and gives CNN nonlinearity. The received power is denoted as, J_{xy}. The ReLU level output flows to the convolutional where the $3x3$ weighted level matrix is B^D, employed. The depth of the convolutional is supposed to be eight in this study. The outcome is then given as follows from the convolutional component and expressed in Equation (5)

$$J_{xy}(conv) = \sum_{m=0}^{2} \frac{J_{xy}(ReLU)}{{B_{m,y}}^D} \quad (5)$$

Here, ${B_{m,y}}^D$, is the D's mth component. The received power is denoted as J_{xy}. The overlapping layer is performed in the linear combination by the scale factor 1 and the null buffering equal to the corresponding size. The CNN architecture is more beneficial than the overall genetic algorithm if two-dimensional incoming information is provided in the form of the products in two dimensions than the one-dimensional output of this compression layer. It is observed that for all normed chain powers, i.e., $\hat{c}_{xy}$for $x = 1,2,\cdots,M, and\ y = 1,2,\cdots,M$ should be executed.

The length of $J_{xy}(conv),$ is $MxMx8$, if the outcome matrices of the coevolutionary layer are named as $J_{xy}(conv)$. Since it comprises eight levels, the operation occurs eight times in sequence. After completing the eight-layer compression portion, its output re-enters the BN procedure. The result is then designated as $J_{xy}(conv)$, and the $J_{xy}(conv)$, $MxMx8$ matrix is converted into the v^D, $1x8M^2$ vector (completely connected) portion input). The D part outputs are therefore generated with the support vectors v^D. The output is denoted in Equation (6)

$$z^D = \frac{v^D B^D}{w^D} \quad (6)$$

When the D portion is B^D and $w^D$and the lengths for both B^D and $w^D$are set to $8M^2xM$, $1xM$ correspondingly. The result vector length for the D portion, z^D, is therefore $1xM$. Lastly, the D section is placed in the sigmoid, and the sigmoid section is represented in Equation (7)

$$z_x(s) = \frac{1}{1-\exp(-z^D)}; x = 1,2,\cdots,M \quad (7)$$

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

$z_x(s)$, outputs are restricted from 0 to 1. The outcome received from the previous layer is denoted as z^D. Therefore, the transmitting power is increased by T_{mx} to change 0 to T_{mx}. The intended power of transmission is therefore represented in Equation (8) for transmitters x:

$$T_x = T_{mx} \times z_x(s) \quad (8)$$

The transmitted power is denoted as T_{mx}, and the output of the hidden layer is denoted $z_x(s)$. Our CNN architecture, an adaptable time assessment, answered the optimizing issue using the backpropagation technique outside the system. Furthermore, B^D and w^D, are started by a standard distribution in weight vector ratios. The approach of deep learning minimization reduces the value of the failure parameter, described by Equation (9):

$$K_D = \beta \sum_{x=0}^{Y} S_x - (1+\beta)H_x \quad (9)$$

In the failure functions, Y determines the most important in optimum S_x and optimal H_x , of the CNN and $0 < \beta < 1$. The bias variable is denoted as β. The incoming and outgoing variable input is denoted as $S_x \; and \; H_x$.

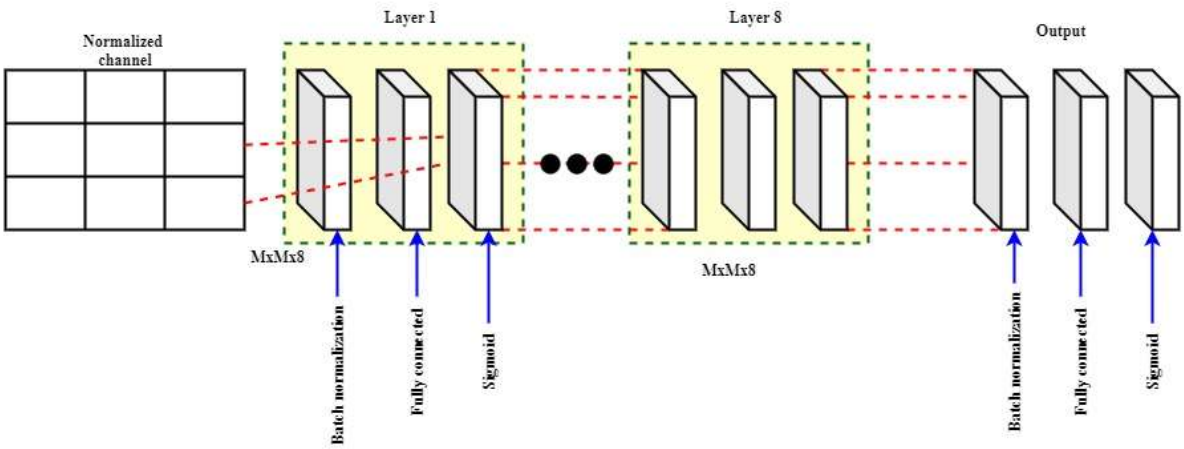

Figure 3: CNN Architecture in DLID2DC Framework

The proposed DLID2DC model's eight-layer CNN architecture is depicted in Fig. 3. Each layer has batch normalization, fully connected, and sigmoid functions. In particular, when β is near 1, the transmitting power of the gadget is selected without regard to fairness, but when β is near 0, total equity might prevail. At the same time, maximizing system efficiency (SE) is complex. To maximize H_x, the H_x, the value of the suggested model would be one. In other terms, meeting the optimum H_x, requires to discover $\beta^{\#}$. Upon discovering all feasible $\beta^{\#}$, values, it selects the highest $\beta^{\#}$, values to maximize the SE number while at the same time attaining full equality. Following the abovementioned approach, the suggested CNN-based learning scheme has been taught. The training set can calculate the transmission rate by monitoring the stream instantaneously. Note that, even on a trained network, the suggested model offered adequate transmitting power for multiple channels, the well-trained weights and binocular values of B^D and w^D, in CNN are used. Based on the inputs and after being processed by the convolutional neural network (CNN) architecture, the output is the optimum transmission power for each transmitter in the D2D network. A critical parameter affecting the efficacy and effectiveness of the D2D communication system is the intended transmission power, which the CNN outputs as T_x , in Equation (8).

3.3 Methodologies

Without going via the ground station, connecting cellular customers may communicate in a Device-to-device connectivity system and could increase bandwidth usage. In addition, if the D2D connection is not correctly built, interference is created with the existing online services. The research studied all through the research a resource assignment problem for optimizing network performances by guaranteeing both D2D clients and conventional wireless users the criteria for customer satisfaction. In a decentralized way, the Mobile Ad Hoc Network (MANET) can link all intelligent devices. MANET is a self-organized collection of mobile communication nodes that establish a transitory network without the help and centralization of fixed network facilities.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

Fig. 4 depicts the suggested system's D2D decision-making model, including a perceptual module, a D2D environment analysis model, a behavioral choice module, and an artificial internal emotion module estimate. Texts with a source outside this neighborhood zone must be skipped or sent by those neighbours who function as gateways to the right destination. As implied by using physically connected devices, raising resource usage, and improving cell wireless coverage, the D2D interactions underlying a cell network were recommended. D2D use scenarios are divided into two broad regions. In the first segment, the pair-in-peer method is termed where the D2D devices are transmitters and recipients of the transmitted information. The second portion of the transmission example involves the transmission to the targeted gadgets of data disseminated by one of the participating D2D gadgets to the Nodes.

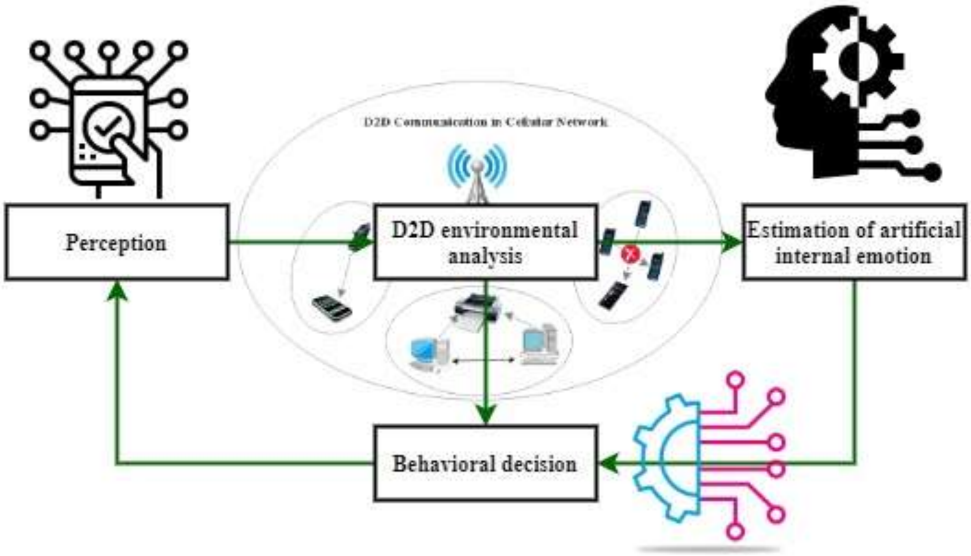

Figure 4: D2D Decision-Making Model

3.3.1. Intelligent Gadgets Probabilities

Assume that the probability-based system is a MANET and that the Internet of Things (IoT) module has three-dimensional orientations on the functional axis (y and z). The entire area is split into cells across the cellular network. This area is maintained to allow intelligent gadgets to move inside the cell. IoT nodes will detect neighbouring devices in the same cell field in hexadecimal numbers.

The licensed intelligent device limits data to another gadget. The findings demonstrated that conscious movement could only happen among neighbouring cells. Furthermore, data are distributed with a particular weighted angle and motion likelihood. The angle advantages from the easiness of an IoT device that monitors the objective splits the designated target, and adjusts the inclination.

3.3.2. Discover the Clever Gadgets of the Markov Chain

In the 2-dimensional planar area, the secret Markov algorithm finds intelligent gadgets. The modeling is linked to the working environment and devices moving in the neighbourhood, and the modeling is included in the spectrum of neighbourhood gadgets. It built the transition probability matrices through the wireless connection, detecting and converting all intelligent objects.

3.3.3. Find out the Intelligent Gadgets Utilizing Gradient Models

The gradation model identifies the gadgets and shares knowledge to create and send data to find the connected devices. This trend is maintained via communication between intelligent Android phones and simply through the adaptability of the smart Android phone intrinsic in the MANET. The gradation value set to 1 is also used to identify Android-connected devices in an area where an ad hoc connection is formed and where the destination is recognized by an Android computing phone. Its gradient data is the field time that has been concentrated. It utilized the intelligent gadget to reduce this power exponentially over time.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

Thus, while evaluating the gradient systems, the performance rate of the proposed model is better. Consequently, it utilized the gradient model to define the ad hoc network between intelligent Android phones. The WiFi association has launched emerging innovations such as WiFi Direct that enhance direct D2D interaction in wireless internet. The efficient use of enormous capacity to increase data circulation is essential for D2D communication through directed millimeter-wave technologies.

In this section, the proposed DLID2DC is an enhanced D2D communication system based on deep learning, particularly emphasizing network detection and interruption control. Problems caused by the ever-changing protocols and procedures of mobile devices are addressed. For analysis of communication requirements, methodology selection, and transfer of machine language from the distant server to the smartphone, the system uses external public cloud resources and Explainable Artificial Intelligence (XAI). The DLID2DC model architecture comprises many interconnected parts, such as a base station, user equipment, and an aggregator server. The CNN architecture boosts the proposed system speed through batch normalization, fully connected, and sigmoid functions.

4. Software Analysis And Performance

4.1 Experimental Setup

The efficiency of this suggested method is investigated in this section. Java and Matlab are used for simulations. The scenarios include a surface area of 1500x1500 meters, one, and user equipment from 10 to 1000. The specifications for WiFi Connect, LTE Direct, and LTE communications are derived from the specifications.

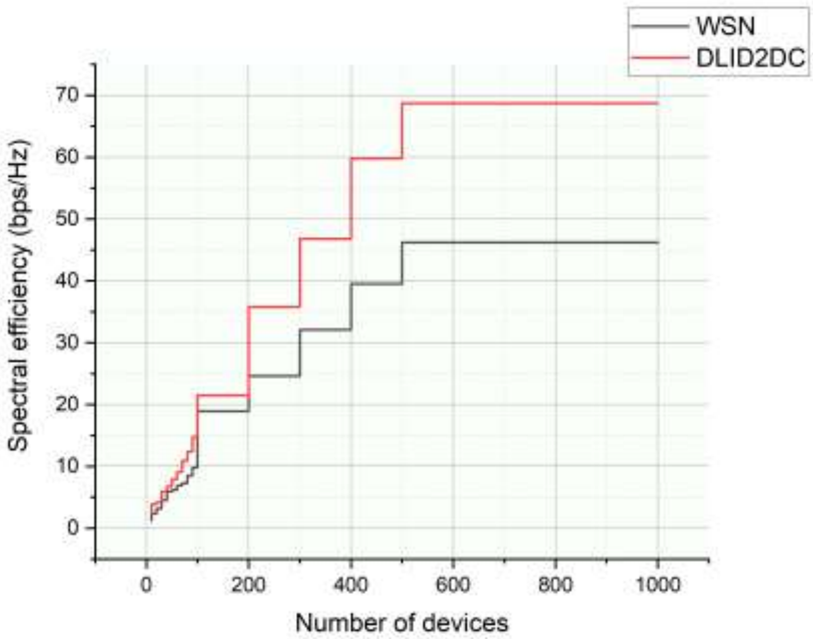

Figure 5(a): Spectral Efficiency Analysis of the Proposed and WSN Model

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

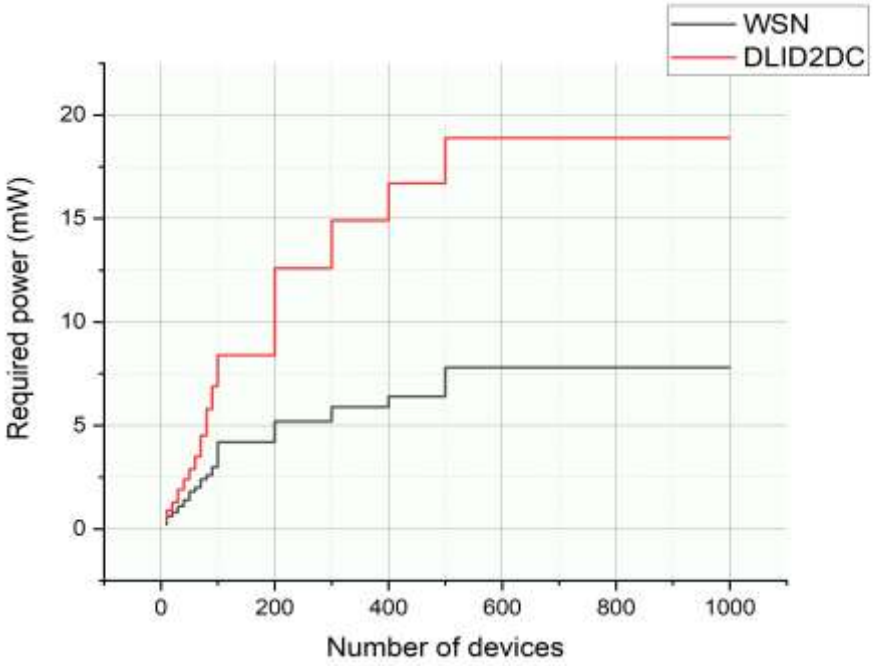

Figure 5(b): Power Requirement of the DLID2DC and WSN Model

4.2 Results and Discussion

The spectrum efficiency and necessary power assessment of the proposed DLID2DC system are depicted in Figs. 5(a) and 5(b), respectively. The number of devices in the simulation space varied from 10 to 1000 to conduct the simulation analysis. The respective spectral efficiency and required power of the proposed DLID2DC system are analyzed and plotted. As the number of devices in the simulation area increases, the individual performance of the system increases. The increased number of devices helps to better communication and coverage.

Table 1: Spectral efficiency of the proposed DLID2DC and WSN system

Number of devices	WSN (bps/Hz)	DLID2DC (bps/Hz)
10	1.2	2.4
20	2.4	3.9
30	3.2	4.2
40	4.5	5.9
50	5.9	6.8
60	6.2	7.9
70	6.9	9.1
80	7.3	10.9
90	8.5	12.4
100	9.8	14.8

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

200	18.9	21.5
300	24.6	35.8
400	32.1	46.8
500	39.5	59.8
1000	46.2	68.7

The spectrum efficacy of the DLID2DC system is displayed in Table 1. As a result of the simulation analysis, the number of nodes is adjusted from its initial minimum to its final maximum. The spectral performance of the WSN and the planned DLID2DC system are compared and contrasted in relation to the total number of nodes. According to the findings, the DLID2DC system makes better use of the available spectrum than the WSN. The proposed DLID2DC system with CNN architecture and artificial intelligence uses a higher spectrum in 5G communication.

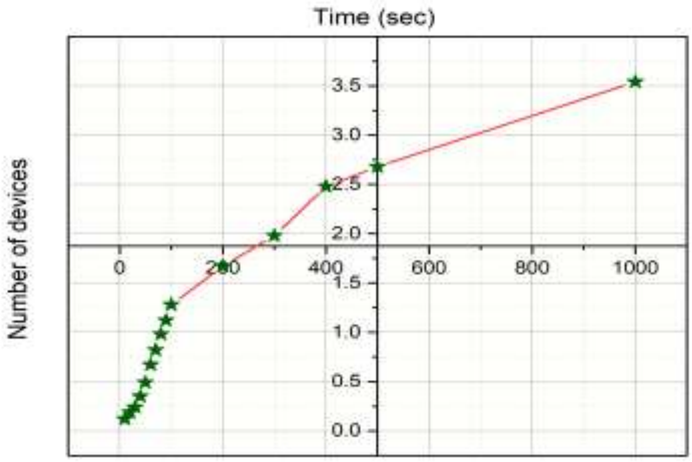

Figure 6(a): Evaluation of Delay - WSN Model

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

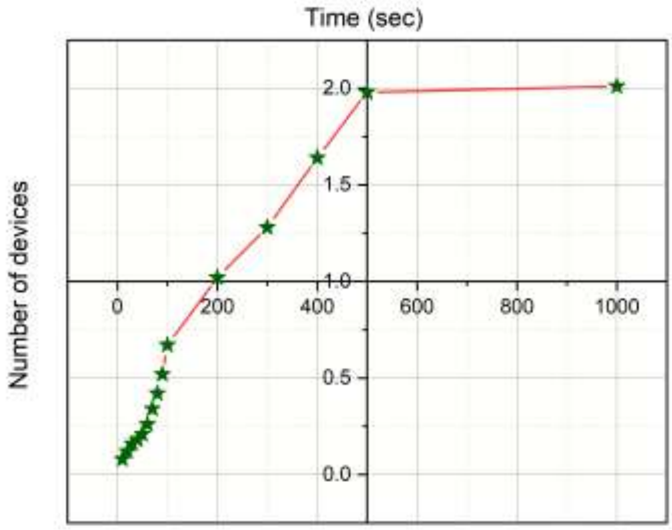

Figure 6(b): Evaluation of Delay – Proposed DLID2DC System

Figs. 6(a) and 6(b) depict the time delay evaluation of the WSN model and the proposed DLID2DC system, respectively. The simulation area's number of nodes is varied from 10 to 1000, and the delay of both the proposed and the current models is compared and contrasted. Each result is examined and displayed graphically. Complexity and delay are reduced in the DLID2DC system due to the use of AI and a CNN model with an error-analyzing mathematical model. As the number of devices increases due to processing delay in every node, the overall delay of the system increases.

Table 2: Required power analysis of the proposed DLID2DC and WSN system

Number of devices	WSN (mW)	DLID2DC (mW)
10	0.2	0.4
20	0.6	0.9
30	0.8	1.3
40	1.1	1.9
50	1.4	2.4
60	1.8	2.9
70	2	3.5
80	2.4	4.5
90	2.6	5.8
100	3	6.9
200	4.2	8.4
300	5.2	12.6

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

400	5.9	14.9
500	6.4	16.7
1000	7.8	18.9

Table 2 specifies the required power investigation of the DLID2DC system. The research changes the number of nodes in the simulation area from 10, 20, 30, 40, and 50 to 100, 200, 300, 400, 500, and 1000. The power required to transmit a single message is analyzed for the proposed DLID2DC system and compared with the current one. The DLID2DC system with CNN model and artificial intelligence reduces error, thus resulting in lower utilization of power. The mathematical model of the proposed DLID2DC system is utilized to predict the necessary power to transmit a message.

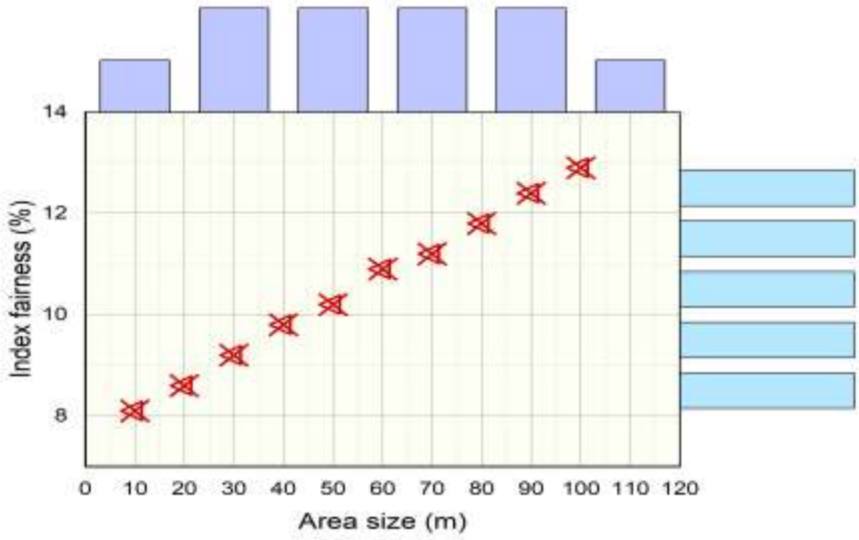

Fig. 7(a): Evaluation of the WSN Model for Index Fairness

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

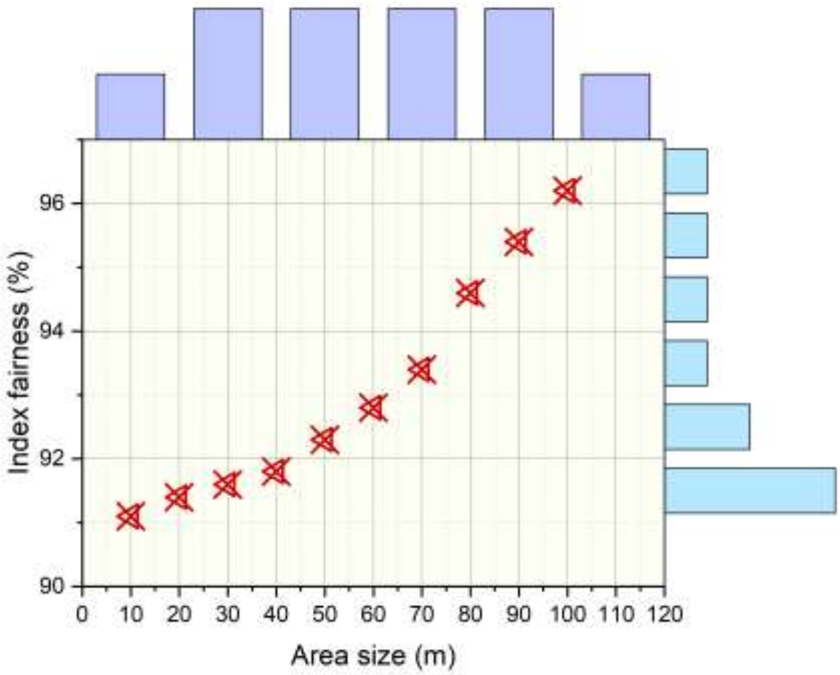

Figure 7(b): Evaluation of the DLID2DC Model for Index Fairness

Figures 7(a) and 7(b) exhibit the index fairness analysis of the current WSN and the proposed DLID2DC system, respectively. The simulation region for the study is varied between 10 and 100 meters in length. The system's fairness index is calculated and compared to the current WSN model for an equal number of nodes. There is greater index fairness in the planned DLID2DC system. The proposed DLID2DC system with artificial intelligence and CNN model assures better fairness. As the simulation area increases, the index fairness also increases.

This section evaluates and discusses the proposed DLID2DC system's performance. In this analysis, the effectiveness of a proposed system is compared to that of a WSN model. Increased spectrum efficiency, less power consumption, shorter delays, and a better fairness index are only some of the benefits of the DLID2DC system. The DLID2DC solution improves 5G communication performance and spectrum efficiency through AI and a CNN model. The simulation results indicate the superior performance of the DLID2DC system with the CNN model, AI, and mathematical model in the 5G communication domain.

5. Conclusion And Future Scope

The DLID2DC model was developed to resolve the problems of network authentication and interruption control in Device-to-Device (D2D) connections. The need to determine what kind of network is needed, estimate costs, and pick the right technology and protocols for D2D networks is emphasized. The approach utilizes an external public cloud to analyze communication requirements, shortlist techniques, and transfer machine language to mobile devices in an Explainable Artificial Intelligence (XAI) based model. The XAI Aggregator Unit monitors and manages the system, ensuring everything runs well regarding security links, network database administration, transmission methods, performance evaluation, self-learning, and processing. Convolutional Neural Networks (CNN) improve performance by altering digital output values and boosting learning efficiency through batch normalization, fully linked, and sigmoid functions. The DLID2DC framework considers a wide range of factors to improve D2D communications, including but not limited to network identification, interruption control, security, database administration, transmission methods, performance evaluation, self-learning, and processing. In addition, the recommended procedures and approaches in particular aggregator sites cannot be confined to these methods. They might be modified or extended to deep study teaching methods based on simulations and real investigation in some other notable ways in the future.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

References

[1] Seemanthini, K., Shoba, N., Sowmyalakshmi, B. S., & Karthik, S. A. (2022). Role of Internet and Communication Technologies (ICT) to Support Clinical Practice and Research in Hospitals. In Information and Communication Technology (ICT) Frameworks in Telehealth (pp. 61-77).

[2] Abdel-Basset, M., Mohamed, R., Elhoseny, M., Chakrabortty, R. K., & Ryan, M. J. (2021). An efficient heap-based optimization algorithm for parameters identification of proton exchange membrane fuel cells model: Analysis and case studies. International Journal of Hydrogen Energy, 46(21), 11908-11925.

[3] Amudha, G. (2021). Dilated Transaction Access and Retrieval: Improving the Information Retrieval of Blockchain-Assimilated Internet of Things Transactions. Wireless Personal Communications, 1-21.

[4] Meenakshi, N., Jaber, M.M., Pradhan, R., Kamruzzaman, M.M., Maragatham, T., Ramamoorthi, J.S., and Murugesan, M., 2023. Design systematic wireless inventory trackers with prolonged lifetime and low energy consumption in future 6G network. Wireless Networks.

[5] Hussein, H. H., Elsayed, H. A., & Abd El-kader, S. M. (2020). Intensive benchmarking of D2D communication over 5G cellular networks: prototype, integrated features, challenges, and main applications. Wireless Networks, 26, 3183-3202.

[6] Sultana, A., Woungang, I., Anpalagan, A., Zhao, L., &Ferdouse, L. (2020). Efficient resource allocation in SCMA-enabled device-to-device communication for 5G networks. IEEE Transactions on Vehicular Technology, 69(5), 5343-5354.

[7] Rachini, A.S., and Jaber, M.M., 2019. Performance of FBMC in 5G mobile communications over different modulation techniques. 2019 International Symposium on Networks, Computers and Communications, ISNCC 2019, pp.1–6.

[8] Elfatih, N. M., Hasan, M. K., Kamal, Z., Gupta, D., Saeed, R. A., Ali, E. S., & Hosain, M. S. (2022). Internet of vehicle's resource management in 5G networks using AI technologies: Current status and trends. IET Communications, 16(5), 400-420.

[9] Pizzi, S., Suraci, C., Iera, A., Molinaro, A., & Araniti, G. (2020). A sidelink-aided approach for secure multicast service delivery: From human-oriented multimedia traffic to machine type communications. IEEE Transactions on Broadcasting, 67(1), 313-323.

[10] Cao, L. (2022). Decentralized ai: Edge intelligence and smart blockchain, metaverse, web3, and desci. IEEE Intelligent Systems, 37(3), 6-19.

[11] Nguyen, D. C., Pathirana, P. N., Ding, M., & Seneviratne, A. (2020). Blockchain for 5G and beyond networks: A state of the art survey. Journal of Network and Computer Applications, 166, 102693.

[12] Khan, M. I., Qayyum, S., Farooq, S., Chu, Y. M., & Kadry, S. (2021). Modeling and simulation of micro-rotation and spin gradient viscosity for ferromagnetic hybrid (Manganese Zinc Ferrite, Nickle Zinc Ferrite) nanofluids. Mathematics and Computers in Simulation, 185, 497-509.

[13] Fourati, H., Maaloul, R., & Chaari, L. (2021). A survey of 5G network systems: challenges and machine learning approaches. International Journal of Machine Learning and Cybernetics, 12, 385-431.

[14] Salahdine, F., Han, T., & Zhang, N. (2023). Security in 5G and beyond recent advances and future challenges. Security and Privacy, 6(1), e271.

[15] Chakraborty, C., & Rodrigues, J. J. (2020). A comprehensive review on device-to-device communication paradigm: trends, challenges, and applications. Wireless Personal Communications, 114(1), 185-207.

[16] Gheisari, M., Najafabadi, H. E., Alzubi, J. A., Gao, J., Wang, G., Abbasi, A. A., & Castiglione, A. (2021). OBPP: An ontology-based framework for privacy-preserving in IoT-based smart city. Future Generation Computer Systems, 123, 1-13.

[17] Li, A., &Luk, K. M. (2020). Single-layer wideband end-fire dual-polarized antenna array for device-to-device communication in 5G wireless systems. IEEE Transactions on Vehicular Technology, 69(5), 5142-5150.

[18] Selmi, S., & Bouallègue, R. (2021). Energy and spectral efficient relay selection and resource allocation in mobile multi-hop device to device communications: Energy and spectral efficient multi-hop D2D communications. IET Communications, 15(14), 1791-1807.

[19] Alibraheemi, A. M. H., Hindia, M. N., Dimyati, K., Izam, T. F. T. M. N., Yahaya, J., Qamar, F., & Abdullah, Z. H. (2023). A Survey of Resource Management in D2D Communication for B5G Networks. IEEE Access, 11, 7892-7923.

[20] Pawar, P., &Trivedi, A. (2019). Device-to-device communication-based IoT system: benefits and challenges. IETE Technical Review, 36(4), 362-374.

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023

[21] Pedhadiya, M. K., Jha, R. K., & Bhatt, H. G. (2019). Device-to-device communication: A survey. Journal of Network and Computer Applications, 129, 71-89.
[22] Hossain, M. A., Ray, S. K., & Lota, J. (2020). SmartDR: A device-to-device communication for post-disaster recovery. Journal of Network and Computer Applications, 171, 102813.
[23] He, Y., Yu, F. R., Zhao, N., & Yin, H. (2018). Secure social networks in 5G systems with mobile edge computing, caching, and device-to-device communications. IEEE Wireless Communications, 25(3), 103-109.
[24] Zhang, H., Song, L., & Zhang, Y. J. (2018). Load balancing for 5G ultra-dense networks using device-to-device communications. IEEE Transactions on Wireless Communications, 17(6), 4039-4050.
[25] Zhang, S., Liu, J., Guo, H., Qi, M., & Kato, N. (2020). Envisioning device-to-device communications in 6G. IEEE Network, 34(3), 86-91.
[26] Roychoudhury, P., Roychoudhury, B., &Saikia, D. K. (2021). A Secure Device-to-Device Communication Scheme for Massive Machine Type Communication. Computers & Security, 102370.
[27] Shang, Z., Ma, M., & Li, X. (2020). A secure group-oriented device-to-device authentication protocol for 5G wireless networks. IEEE Transactions on Wireless Communications, 19(11), 7021-7032.
[28] Gandotra, P., &Jha, R. K. (2019). Energy-efficient device-to-device communication using adaptive resource-block allocation. International Journal of Communication Systems, 32(8), e3922.
[29] Bahonar, M. H., &Omidi, M. J. (2021). Distributed pricing-based resource allocation for dense device-to-device communications beyond 5G networks. Transactions on Emerging Telecommunications Technologies, e4250.
[30] Shah, S. W. H., Rahman, M. M. U., Mian, A. N., Imran, A., Mumtaz, S., &Dobre, O. A. (2019). On the impact of mode selection on the effective capacity of device-to-device communication. IEEE Wireless Communications Letters, 8(3), 945-948.
[31] Ameen, A.H., Mohammed, M.A. and Rashid, A.N., 2023. Dimensions of artificial intelligence techniques, blockchain, and cyber security in the Internet of medical things: Opportunities, challenges, and future directions. *Journal of Intelligent Systems*, *32*(1), p.20220267.
[32] Yassine, S., & Stanulov, A. (2024). A Comparative Analysis Of Machine Learning Algorithms For The Purpose Of Predicting Norwegian Air Passenger Traffic. International Journal of Mathematics, Statistics, and Computer Science, 2, 28–43. https://doi.org/10.59543/ijmscs.v2i.7851
[33] Nezhad, M. Z., Nazarian-Jashnabadi, J., Rezazadeh, J., Mehraeen, M. & Bagheri, R. (2023). Assessing Dimensions Influencing IoT Implementation Readiness in Industries: A Fuzzy DEMATEL and Fuzzy AHP Analysis. Journal of Soft Computing and Decision Analytics, 1(1), 102-123. https://doi.org/10.31181/jscda11202312

Doi: https://doi.org/10.54216/FPA.130116
Received: April 27, 2023 Revised: July 13, 2023 Accepted: September 10, 2023