International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2022/215917 Volume 9, Issue 5, September – October (2022)

RESEARCH ARTICLE

Energy Efficient Device to Device Data Transmission Based on Deep Artificial Learning in 6G Networks

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Received: 24 July 2022 / Revised: 24 August 2022 / Accepted: 07 September 2022 / Published: 30 October 2022

Abstract – The rising wireless service constraints and user compactness have to lead the progress of 6G communication in the modern days. The benefit of 6G over the presented technologies is a huge support for mixed applications and mobility maintenance. Device to Device (D2D) data transmission in 6G has great attention since it gives a better data delivery rate (DDR). Recently, several methods were established for D2D data transmission. However, energy consumption was not considered to improve the network throughput. To handle such problems, an artificial intelligence technique called Deep Neural Regressive Tangent Transfer Classifier (DNRTTC) model is introduced in this research for D2D data transmission in a 6G system. The designed method includes several layers to attain energy-efficient D2D data transmission. The primary layer is the input layer and it includes several mobile nodes as input. Nodes are transmitted to the hidden layer one. For each node, energy, received signal strength, and connection speed of each mobile node is calculated. Then the similarity analysis is done in the following layer where each node is analyzed with its threshold value. The result is sent to the output layer where the better resource mobile nodes are identified by using the activation function. This leads to attaining energy-efficient D2D data transmission in 6G. Results illustrate that the DNRTTC outperformed compared to conventional methods with better energy efficiency, packet delivery ratio, and throughput.

Index Terms – Artificial Intelligent, Device to Device Data Transmission, 6G Network, Energy Efficiency, Deep Neural Network, Mobile Nodes, Activation Function.

1. INTRODUCTION

Device to Device (D2D) is a significant aspect of the 6G wireless networks. 6G networks can be competent to exploit superior frequencies than 5G networks. It offers significantly superior capacity and much lesser latency. One of the goals of the 6G internet is to hold one-microsecond latency communications. It gives a peak data rate with minimum latency. 6G will be 50 times quicker than 5G, 100 times more consistent, and offer wider coverage. 6G enables network connectivity among several devices. This progress in the devices needs huge spectrum of resources to facilitate a combination of scenarios. D2D omits the data distribution to the base station and assists the devices in the transmission. This enables high-speed data communication with less latency and is used to lessen the traffic in the Base Station. D2D includes several sensible troubles and demands. Resource-efficient device selection is the foremost focus as it plays an imperative part in the performance of the system. There are many methods and algorithms designed for D2D communication but, the DDR and throughput were not improved. Therefore, to handle the open research concerns in D2D communication, a novel model is introduced.

A deep deterministic policy gradient (DDPG) based strategy was presented in [1] for examining the latency and energy of B5G/6G systems. The cost of the strategy was reduced but, the DDR was improved effectively. Advanced Virtual Multi-Purpose Network Embedding Algorithm (AVMPNEA) was described [2] for granting better services to 6G users. AVMPNEA lessen the latency but, the data delivery data was not improved.

Artificial Intelligence (AI) and optimization techniques were investigated in [3] to decrease the latency and backhaul load in a 6G system. However, robust and reliable 6G services failed to be provided. A communication resource allocation method called hybrid NOMA-assisted multi-access edge computing was employed [4] for in 6G system. The designed

RESEARCH ARTICLE

scheme enhances the energy efficiency of 6G communication but, the time was not decreased.

Multiple RPL instances were designed in [5] to improve the 6G/IoE-based health monitoring systems. But, the latency was improved. Multiple Machine Access Learning with Collision Carrier Avoidance (MMALCCA) protocol was employed in [6] to make better communication in the 6G system. The designed protocol minimizes the collision rate but, the energy efficiency was not considered. Resource allocation approaches were observed in [7] to handle resource provision for handling communication concerns.

Decentralized edge architecture named OMNIBUS was developed in [8] for the 6G system. It guarantees the constant allocation of computational ability for end devices. However, throughput was not improved. A broad analysis of the 6G technologies was provided in [9] like Pervasive AI, Ambient Backscatter Communication, and so on. New services of 6G were provided by key enabling technologies in [10]. However, additional works were mandatory to realize the expected 6G.

1.1. Problem Statement

From the above works, lower DDR, throughput, reliability, energy efficiency, and higher latency are major problems identified in D2D communication in 6G networks. Many research works have been designed for D2D communication in 6G but, the data transmission was affected by the lack of identifying resource-efficient mobile devices. To solve these issues, a new finding of the artificial intelligent method is needed for 6G D2D communication.

Contributions/novelties involved in this paper are:

- A novel model called DNRTTC for D2D communication is presented to solve the energy efficiency and latency issues in the 6G network.
- Multiple resources of mobile devices like energy received signal strength, and connection speed into proposed DNRTTC to identify the efficient devices through regression analysis in the hidden layer.
- The hyperbolic tangent sigmoid transfer activation function is employed in the DNRTTC model to significantly classify the mobile devices for ensuring a high data rate. On contrary to other activation functions, it simply identifies the devices with better resources for increasing the packet delivery ratio.
- The robustness of the DNRTTC model is demonstrated with existing methods for D2D communication in 6G.

The reminder of the paper is structured as follows. Section 2 explores the related works. Section 3 provides the proposed methodology with an architecture diagram in the 6G network. Section 4 gives the simulation outcomes and their results and inferences. At last, the conclusion and future scope of the paper are provided in section 5.

2. RELATED WORK

SEmi-Dynamic Mobile Anchor Guiding (SEDMAG) for drones was employed in [11] to localize 6G IoT devices. The drone tracks the shortest path through the connected graph. The complexity and positioning delay was reduced. Though the SEDMAG has lower localization latency, the error rate was not effectively minimized. Smartphone Assisted Disaster Recovery (SmartDR) technique was introduced in [12] for D2D communication in a cellular network. It enables direct communication of devices without relaying through a network infrastructure. It enhances the network lifetime. However, the data loss rate remained unaddressed. A comprehensive review of AI-enabled 6G communication technology was employed in [13]. AI was incorporated into diverse scenarios like object finding, UAV communication, security, etc investigated. AI combined 6G architecture by highlighting diverse application scenarios. Also, several problems and implementation concerns in 6G were highlighted.

6G enabled technologies in various applications such as crop growing, learning, media and activity, logistics and moving, and sightseeing were described in [14]. A broad study of the social, psychological, health and commercialization disputes associated with 6G were examined. But, a more explicit version of 6G was not discussed. A framework combining energy, computation, and communication (ECC) was described in [15] for 6G cellular IoT. But, the DDR was not improved. AI methods were employed in [16] to provide the application of wearable devices in the 6G network. First, the design of wearable sensors was proposed. Then, the human behavior recognition model was introduced to enhance behavior detection.

Serial polynomial programming (SPP) based energy allocation scheme was employed in [17] for the 6G network. It assists to boost the energy of all the points in the network. SPP significantly improved the spectral performance without concerning the QoS. However, throughput was not improved. Novel network architectures of the 6G network were introduced in [18] for wireless communication. Energy-efficient resource allocation strategy was employed in [19] for handling the energy-related issues in the 6G system. However, the time requirement was not minimized. Analysis of transfer learning algorithms was described in [20] for future 6G communications. But, the mutual connection between TL and 6G was not discussed.

The novel technologies were developed [21] towards 6G for numerous cases. A full-stack, system-level perception on 6G was evaluated and selected 6G machinery through designing new communication schemes. QC-assisted and QML-based

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RESEARCH ARTICLE

model was employed in [22] for 6G networks to tackle challenges. Optical wireless communication provided5GB communication system requirements. OWC technologies were applied in [23] for the operation of 5G/6G and IoT. The Blockchain and IoT models were combined in [24] with high-level solutions to solve the inadequacies and failures of both models. A secure and intelligent architecture was employed in [25] for wireless networks via joining AI and blockchain to tolerate secure resource sharing. A blockchain-empowered content caching intricate was solved to boost the system effectiveness and create caching model through deep reinforcement learning. The new technologies were introduced in [26] with wireless networks towards 6G for numerous cases. A full-stack, system-level opinion on 6G requirements was analyzed and selected 6G machinery via initiating new communication models.

3. METHODOLOGY

The budding wireless service constraints and user compactness have guided growth of 6G communication in modern days. The assistance of 6G over the offered models is its high-level preservation for mobility sustain. The design of 6G communications enhances the QoS constraints by increasing data rates and controlling delay. This advantage is employed in different scenarios such as medical care, industry mechanization, smart homes and urban, intelligent transportation, etc. The incorporation of multi-level complex networks, information and communication technologies, and computational methods maintain through the cloud guarantees elastic and mobility-aware access to the 6G users. In a 6G network, D2D is referred to as the straight transmission of data among two devices. This assists high-speed data transmission.

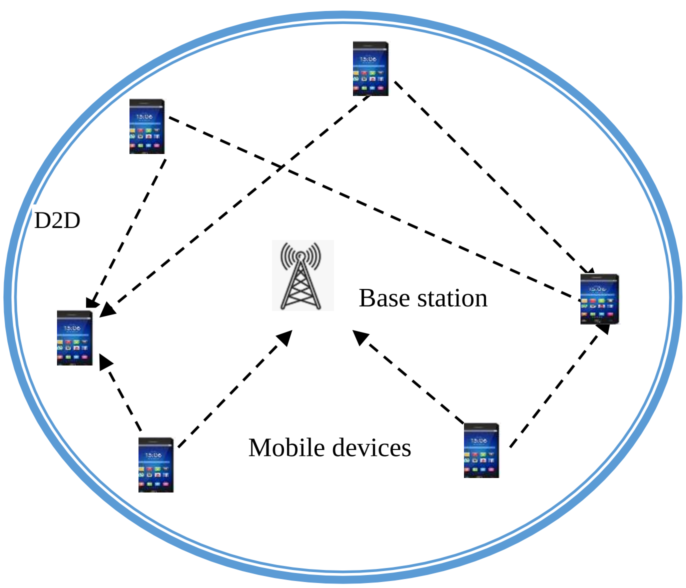

Figure 1 Architecture of Communication in 6G Network

Figure 1 shows the D2D communication over the 6G network. In a 6G network, D2D communication guarantees a direct connection among the users for lessening the traffic. 6G makes the network connectivity among several devices. In a cellular network, D2D links want to allocate the same spectrum of resources as the cellular link. The applications of D2D embrace online video clip distribution, traffic offloading, and etc. In D2D communications, the nearby users are communicated instantly without using any base stations. Owing to the short distance transmission, D2D communications can diminish energy utilization and progress the DDR. When increasing the distance between the devices, offering energy efficiency is a key concern in the 6G network. For that reason, novel technology is designed for 6G networks to dedicate better D2D communication.

The deep neural learning model or deep artificial learning observes the data to discover features that associate and then combine them to promote faster learning without being told to do so explicitly. It includes diverse kinds of layers to analyze given input. Also, the regression function is employed for computing the relationship between two variables for finding resource-efficient mobile devices. Motivated by this fact, deep neural regressive transfer classifier is preferred in the 6G network. The foremost reason of the study is to enhance D2D communication in the 6G network based on resource constraints. Accordingly, Deep Neural Regressive Tangent Transfer Classifier (DNRTTC) model is developed for the 6G network for providing resource-aware communication with a better data rate.

Figure 2 shows the block diagram of the Deep Neural Regressive Tangent Transfer Classifier to obtain resource-aware communication. The designed DNRTTC model is simple and easy to implement. As illustrated in above figure 2, the structure of the DNRTTC model is explained to classify the devices with better energy, received signal strength, and connection speed for achieving D2D communication in a 6G network. DNRTTC model includes three types of layers. The input layer comprises the number of nodes. These nodes forward the data about the mobile devices to the hidden layer. First, the input layer acquires the number of mobile devices as input. Then, this input is forwarded to the hidden layers. In that layer, resources such as energy efficiency received signal strength, and connection speed of mobile devices are computed. Here, the resources of mobile devices are deeply examined using regression analysis. Then the regression analyzed result is sent to the output layer for identifying resource-efficient devices for D2D communication. The activation function is applied to classify the given into relevant classes. If the resources of mobile devices are higher than the threshold, then the device is considered for D2D communication. Otherwise, the device is not considered. In this way, better D2D communication is achieved in 6G with maximum DDR.

RESEARCH ARTICLE

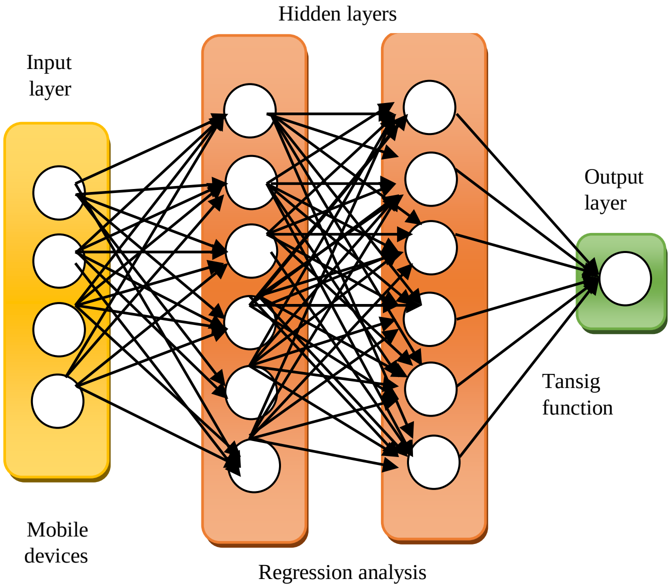

Figure 2 Deep Neural Regressive Tangent Transfer Classifier

Let us consider several mobile devices as $m_i = \{m_1, m_2, m_{3,...}, m_N\}$ in 6G network. The DNRTTC model is used for improving the device to device communication with better energy and less latency. The deep artificial neural network includes several mobile devices m_i as input. With this, the neurons' activity at the input layer is expressed as follows (equation (1)).

$$a(t) = \sum_{i=1}^{n} m_i \, \varepsilon_{ab} + \theta \quad (1)$$

Where, $a(t)$ indicates the activity of neurons at the input layer at time t, m_i is the no. of mobile devices, 'ε_{ab}' is the weights between the $a(t)$and hidden layer, 'θ_j' is the bias. The input layer forwards number of mobile devices m_i to the hidden layer one to identify the efficient devices. This is carried out by computing resources (B) of devices i.e., energy efficiency, received signal strength, and connection speed for each device. The energy of the device is expressed as follows (equation (2)).

$$E_e = Loss_{m_j} - f(\varepsilon TP_m + TP_c) \quad (2)$$

Where, E_e is the energy efficiency, $Loss_{m_j}$denotes data loss rate of the j th device, ε is a constant, TP_m is the transmission power of the device and TP_c is the transmission power of the circuit. Then the RSS of the device is calculated in the DNRTTC model. The signal strength refers to a transmitter output power. The RSS is computed as follows (equation (3)).

$$R_{SS} = \frac{T_g \times R_g \times T_g^2 \times R_g^2}{d} \times T_{SP} \quad (3)$$

Where, $R_{ss}$is the received signal strength of the device, T_{SP}denotes transmitted signal power of the device, T_g, R_g denotes the gain of the transmitter and receiver antenna, T_g^2, R_g^2denotes the transmitter and receiver antenna height correspondingly, d denotes the distance among transmitter and receiver antenna. RSS is inversely proportional to the distance. In other words, as improving the distance between the two nodes, the signal strength is decreased. After that, the connection speed of the device is detected for enhancing the device-to-device communication in the 6G system. Connection speed is determined as the link between wireless devices and their access points. It is formulated as follows (equation (4)).

$$C_S = \left(\frac{M_D}{t}\right) \quad (4)$$

Where the connection speed is denoted as C_S, maximum rate of data obtained at a certain time is denoted as M_D. Connection speed is calculated using unit of megabits per second (Mbps). After computing the resources of mobile devices such as energy efficiency, connection speed, and received signal strength, the results are given to the hidden layer two for carrying out the regression analysis. In regression analysis, the association between dependent and independent variables is computed. Here, resources are analyzed with their threshold values to determine the current status of the mobile devices. Thus, the regression analysis is carried out as below (equation (5)).

$$R_a = \left((E_e > T_{E_e}) \&\& (R_{SS} > T_{R_{SS}}) \&\& (C_S > T_{C_S})\right) \quad (5)$$

Regression analysis is denoted as R_a, the threshold of energy is symbolized as T_{E_e}, the threshold of received signal strength is symbolized as $T_{R_{SS}}$ and threshold of connection speed is denoted as T_{C_S}. Subsequently, the result of hidden layers is expressed by (equation (6)),

$$b_2(t) = R_a \sum_{i=1}^{n} a(t) + \varepsilon_2 * b_1(t) \quad (6)$$

Where, $b_2(t)$denotes the output of hidden layer two, ε_2 is the weight of the second hidden layer and $b_1(t)$denotes output of hidden layer one. Besides, the output of hidden layers is fed into output layer in which the activation function is employed for identifying the better resource devices for D2D communication. In the DNRTTC model, activation function is employed and neurons activity of the layer is provided as (equation (7)),

$$c(t) = H(\varepsilon_{bc} * b_2(t)) \quad (7)$$

Where, $c(t)$ is the neuron activity in the output layer at a time$t$, ε_{bc} denotes the weight between the hidden and $c(t)$layer and H is the hyperbolic tangent sigmoid transfer activation (Tansig) function. The result of tangent sigmoid transfer activation is obtained as follows (equation (8)),

$$Tansigfunction = \frac{1}{1+e^{B}} \quad (8)$$

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RESEARCH ARTICLE

Where, ‘B’ is the resources i.e. energy, connection speed, and received signal strength of devices. Here, the activation function effectively analysis the resources of the devices. Lastly, the results of the output layer are formulated as (equation (9)),

$$c(t) = \begin{cases} +1 & device\ is\ selected\ for\ D2D\ communication \\ -1 & device\ is\ not\ selected for D2D\ communication \end{cases} \quad (9)$$

From (9), the activation function provides a ‘+1’ value when the energy, received signal strength and connection speed of the device are higher than the threshold. It means that the device has better resources and is selected for communication. Besides, another output of activation function i.e., ‘-1’ is obtained when the device has lesser energy, RSS, and connection speed than the threshold. From this, the device with superior energy received signal strength and connection speed is selected for communication in a 6G network. Through the selected energy-efficient devices, a promising data rate is obtained with lesser latency in the DNRTTC model. The algorithm of the deep neural regressive tangent transfer classifier model is given as follows.

Algorithm 1 explains the process of a deep neural regressive tangent transfer classifier for performing D2D communication. Initially, several mobile devices are considered in the input layer. Then the inputs are given to the hidden layer for computing the energy, communication speed, and received signal strength of the devices. After that, the regression analysis is carried out to examine the above three factors with their threshold values. Besides, the output layer obtains the regression results for classifying the devices using the tangent activation function. Depending on the analysis, the devices with better energy, communication speed, and signal strength is considered for D2D communication. This enhances the DDR with less latency.

Input: Mobile devices $m_i = \{m_1, m_2, m_{3,\dots,}, m_N\}$
Output: Resource aware D2D communication

Begin
For each mobile devicem_i
Measure $E_e = L_{m_j} - (kTP)$
Compute $R_{SS} = \frac{T_g * R_g * T_h^2 * R_h^2}{d} * T_{SP}$
Calculate $C_S = \left(\frac{M_D}{t}\right)$
Perform $R_a = \left((E_e > T_{E_e}) \&\& (R_{SS} > T_{R_{SS}}) \&\& (C_S > T_{C_S})\right)$

Hidden layer analysis the resources of devices
Apply activation function at the output layer
Activation function analysis the resources of the devices
If$c(t)$ returns ‘+1’
Energy, received signal strength and connection speed of the device are higher than the threshold
m_i Selected for D2D communication
Else
$c(t)$ Returns ‘-1’
The device has poor resources
Device (m_i) is not selected for D2D communication
End if
End for
End

Algorithm 1 Deep Neural Regressive Tangent Transfer Classifier

4. RESULTS AND DISCUSSION

The simulation assessment of the proposed DNRTTC model with the existing DDPG based strategy [1] and AVMPNEA [2] is performed using Network Simulator (NS3). In the simulation analysis, 10000 mobile devices are considered to perform the data transmission. Simulations are conducted using KDD 99 Cup dataset. It includes 4000000 data and 42 attributes. The dataset characteristics are multivariate and the attribute characteristics are categorical and integer. From this dataset, data preprocessing is performed to reduce the noisy data and fill the missing values. Followed by this, feature extraction is performed to decrease the no. of features by picking relevant ones for further processing.

The mobile devices in the network are deployed within the range of $1000\text{m} \times 1000\text{msize}$. The number of data packets is considered as 30 to 300. The mobility model is used as a random waypoint model and the routing protocol is used as DSR for conducting the simulation. The simulation time is set as 300 seconds.

The assessment of the DNRTTC model with the existing methods namely DDPG based strategy [1] and AVMPNEA [2]. This assessment is performed as a comparative study by considering the metrics of energy efficiency, DDR data loss rate, throughput, and latency for the varying devices.

Energy efficiency (E_e): It means minimal energy to perform communication in the network. In other words, EE indicates the evasion of energy waste. It is mathematically calculated as follows (equation (10)),

$$E_e = \frac{O_e}{I_e} \times 100 \quad (10)$$

From (10), E_e is calculated as the proportion of output energy $O_e$to the input energy I_e.

Data delivery rate (D_{DR}): It is estimated as the proportion of no. of data sent to the no. of data delivery and it is mathematically expressed as (equation (11)),

$$D_{DR} = \frac{Delivered_D}{Sent_D} \times 100 \quad (11)$$

RESEARCH ARTICLE

From (11), $Delivered_D$ is the no. of data delivered and $Sent_D$ is the no. of data sent. $D_{DR}$is determined in the unit of percentage (%).

Data loss rate (D_{LR}): It is defined as the no. of data lost at the receiving end. D_{LR} is mathematically given as follows (equation (12)),

$$D_{LR} = \frac{Lost_D}{Sent_D} \times 100 \quad (12)$$

In (12), D_{LR} is the data loss rate, $Lost_D$ is the no. of data lost and $Sent_D$ is the no.of data sent. D_{LR} is computed in the unit of percentage (%).

Latency: It is calculated as the variation among the data received time and data sending time. It is mathematically calculated as (equation (13)),

$$Latency\ (ms)\ = (\sum_{p=1}^{n}(RT(p) - ST(p)) \quad (13)$$

In (13), L is the latency and p is the number of data. It is estimated in milliseconds (ms).

Throughput: It is described as the no. of data transmitted from one device to another device at a specified period. It is given by (equation (14)),

$$Throughput\ (bps) = \frac{no.of\ data\ transmitted}{X} \quad (14)$$

Where $X$is the time.

Table 1 shows the results of energy efficiency depending on the number of mobile devices 1000, 2000, 3000, 4000, 5000, 6000...10000. Results of energy efficiency using the DNRTTC are compared with the existing DDPG based strategy [1] and AVMPNEA [2]. From the comparative analysis, the energy efficiency of the DNRTTC model is said to be higher than the other methods. In the first run, the energy efficiency of DDPG based strategy [1] and AVMPNEA [2] is obtained as 92.3% and 90.1%. Besides, the proposed DNRTTC model provides 97.9% of energy efficiency in the D2D communication process. From that, the DNRTTC model gives better efficiency than the other methods.

Table 1Analysis of Energy Efficiency

No. of mobile devices	Energy Efficiency (%)		
	AVMPNEA	DDPG based strategy	DNRTTC model
1000	90.1	92.3	97.9
2000	88.3	90.7	97.1
3000	87.4	90.3	96.4
4000	87.1	89.5	95.1
5000	86.6	89.2	94.6
6000	86.2	88.3	94.2
7000	85.9	87.8	93.9
8000	85.6	87.5	93.5
9000	85.1	87.2	93.1
10000	84.9	86.7	92.8

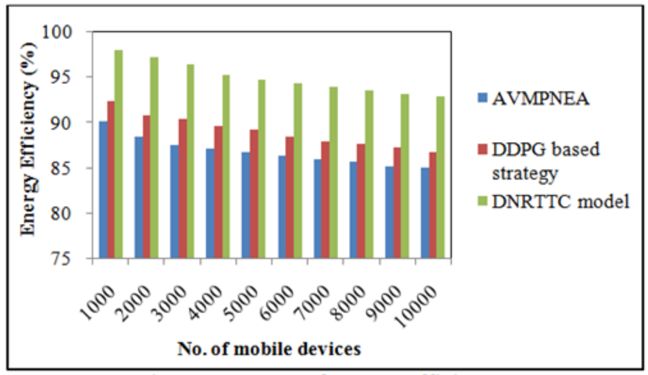

Figure 3 Impact of energy efficiency

Figure 3 demonstrates the results of energy efficiency for the DNRTTC, existing DDPG based strategy [1], and AVMPNEA [2]. As obtained in the figure, the horizontal axis explains the number of mobile nodes and the vertical axis explains the energy efficiency. In the graph, green color, yellow color, and blue color indicates the DNRTTC model, DDPG based strategy, and AVMPNEA respectively. The energy efficiency of DNRTTC model is increased than the other methods. Contrary to existing works, the DNRTTC model measures the energy level for finding better resource devices for data communication. With this, the mobile device with a better energy level is chosen for communication. Besides, the device with better energy than the threshold is chosen for transmission. The device with higher energy increases the overall performance of data communication in 6G. As a result, the energy efficiency of the DNRTTC model is increased by 7% and 9% to the existing DDPG based strategy [1] and AVMPNEA [2] correspondingly.

Table 2 Data Delivery Rate

No. of mobile devices	Data Delivery Rate		
	AVMPNEA	DDPG based strategy	DNRTTC model
1000	91.1	92.6	96.4
2000	90.6	91.5	96.1
3000	89.9	90.7	95.7
4000	89.3	90.2	94.3
5000	88.5	89.6	93.5
6000	88.1	89.2	92.4
7000	87.6	88.8	92.1
8000	87.1	88.6	93.8
9000	86.3	88.2	93.4
10000	85.7	87.4	93.1

A comparative analysis of the DDR for proposed and existing methods is given in table 2. By noticing the above table, the DDR of the proposed DNRTTC model is maximum compared existing DDPG based strategy [1] and AVMPNEA [2]. 96.4% of DDR is obtained in the DNRTTC model in the primary run whereas 92.6% and 91.1% of data delivery rate for existing

RESEARCH ARTICLE

[1] and [2] respectively. In comparison with DDPG based strategy, the DNRTTC model increased the DDR with a difference of 3.8%. Likewise compared with AVMPNEA, the DNRTTC model improved the data delivery rate with a difference of 5.3%. On the whole, the DNRTTC model provides a higher data delivery rate than the other methods.

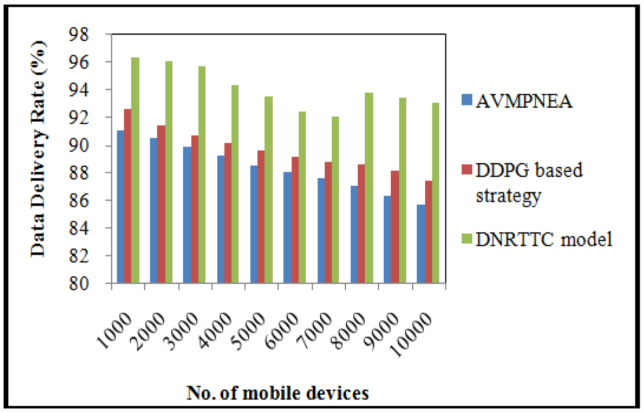

Figure 4 Impact of data delivery rate

Figure 4 depicts the DDR evaluation of 10000 mobile devices. As shown in the figure, the DNRTTC model outperformed in terms of increasing data delivery rate of the existing DDPG based strategy [1] and AVMPNEA [2]. The reason behind the improvement is to carry out the regression analysis for finding the devices with better resources for communication. The designed deep artificial learning model calculates signal strength, connection speed, and energy of the devices is computed to choose a better one among the others. As a result, the percentage of data received is increased in DNRTTC model. The simulation outcome of the DDR using the DNRTTC is improved by 5% and 6% than the other methods.

Table 3 Analysis of Data Loss Rate

No. of mobile devices	Data Loss Rate		
	AVMPNEA	DDPG based strategy	DNRTTC
1000	8.9	7.4	3.6
2000	9.4	8.5	3.9
3000	10.1	9.3	4.3
4000	10.7	9.8	5.7
5000	11.5	10.4	6.5
6000	11.9	10.8	7.6
7000	12.4	11.2	7.9
8000	12.9	11.4	6.2
9000	13.7	11.8	6.6
10000	14.3	12.6	6.9

Table 3 reports the output of the data loss rate for 600 mobile devices. The outcomes of the data loss rate using the DNRTTC model are computed and validated with the existing DDPG based strategy [1] and AVMPNEA [2]. All three methods minimize the loss rate during the D2D communication in 6G. Ten runs are conducted with various mobile devices. In the table, the loss rate of the DNRTTC model is minimized in all the runs than the existing DDPG based strategy [1] and AVMPNEA [2].

Figure 5 demonstrates the outcomes of data loss rate with several mobile devices. To verify the competence of the proposed DNRTTC model, it is compared with conventional methods. The figure confirms that the data loss rate of the DNRTTC model is reduced than the other methods. For example, we take 10000 mobile devices which show a data loss rate difference of 3.8% in the existing DDPG based strategy [1] and 5.3% in the existing AVMPNEA [2]. In order words, the loss rate of the DNRTTC model is obtained as 3.6% whereas existing methods provide 7.4% and 8.9% respectively. The other runs show the data loss rate difference similar to 100 mobile devices. This is reduction is achieved by employing a deep artificial learning concept where the regression analysis and activation function is employed to identify the resource efficient devices. The data loss rate of DNRTTC model is reduced by 43% and 49% compared to existing DDPG based strategy [1] and 5.3% in existing AVMPNEA [2] correspondingly.

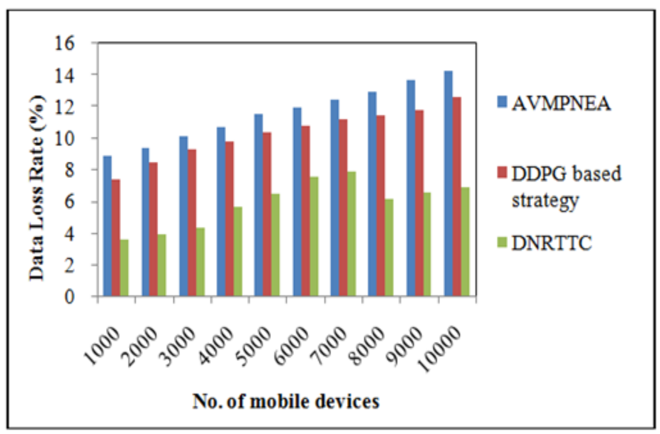

Figure 5 Impact of data loss rate

Table 4 describes comparative outputs of latency using three methods. Latency outputs of the DNRTTC model are evaluated with conventional methods. The evaluation of latency is done by considering the number of mobile devices 1000, 2000, 3000,…, 10000. The DNRTTC model obtains 14.3ms of latency whereas 17.4ms and 20.1ms of latency are attained in the existing DDPG based strategy [1] and existing AVMPNEA [2] in the first iterations. In the same way, the remaining iterations are computed and compared. The comparison shows the minimal in the DNRTTC model to the other methods.

RESEARCH ARTICLE

Table 4 Analysis of Latency

No. of mobile devices	Latency		
	AVMPNEA	DDPG based strategy	DNRTTC model
1000	20.1	17.4	14.3
2000	21.2	18.3	16.2
3000	22.6	20.5	18.3
4000	24.8	22.7	20.5
5000	27.3	25.6	22.6
6000	29.8	27.4	24.7
7000	30.4	28.2	25.3
8000	31.4	29.3	26.1
9000	33.6	31.5	26.6
10000	34.2	32.3	27.2

Figure 6 exposes the simulation output of latency proposed and existing methods. In the above figure, no. of data packets and latency are taken on the horizontal axis and vertical axis. As observed from figure, data packets increased the latency also getting increased. However, the proposed DNRTTC model gives lower latency than the existing DDPG based strategy [1] and AVMPNEA [2]. The reasonable latency is obtained by choosing the devices with the highest resources to accomplish communication. Also, the device with connection speed is considered to lessen the latency. The average latency of the proposed DNRTTC model is decreased by 12% and 20% than the existing [1] and [2] methods.

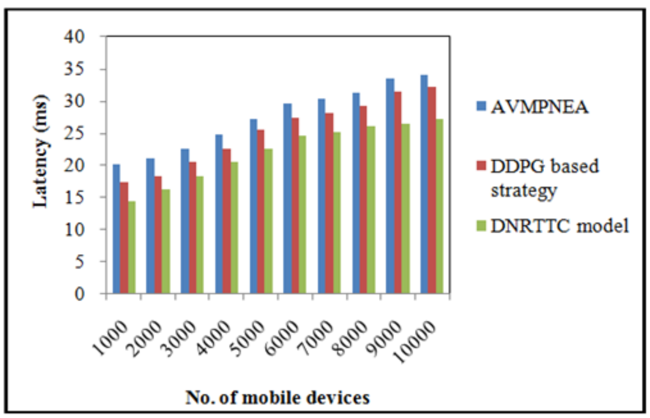

Figure 6 Impact of latency

Comparative evaluation of throughput using the proposed DNRTTC model with existing DDPG based strategy [1] and AVMPNEA [2] is shown in table 5. When increasing the number of mobile devices, the throughput of the network is improved in all the methods. But, the comparatively proposed DNRTTC model gives better throughput than the other methods. For instance, 1000 mobile devices with 480KB of data are sent. Then the 170 bits of data are sent in 1 second whereas the existing DDPG based strategy [1] and AVMPNEA [2] transmit 120bits and 100 bits per second. Similarly, all the iterations are computed. From that, it is concluded as the DNRTTC model achieves maximum throughput compared to other methods.

Table 5 Analysis of Throughput

No. of mobile devices	Throughput		
	AVMPNEA	DDPG based strategy	DNRTTC model
1000	100	160	190
2000	140	160	190
3000	190	210	240
4000	315	330	360
5000	375	390	420
6000	490	510	560
7000	540	570	610
8000	590	620	720
9000	680	710	840
10000	720	790	950

Figure 7 illustrates the performance of throughput for varied methods depending on the mobile devices. The throughput value of each method is indicated in different colors. The above figure evident that the throughput of the proposed DNRTTC model is increased than the existing DDPG based strategy [1] and AVMPNEA [2]. In contrast to existing works, the proposed DNRTTC model computes the energy, signal strength, and connection speed for identifying efficient devices. Through the identified devices, the communication is successfully done by transmitting the data. This leads to enhancing the throughput in the DNRTTC model than the other methods. Therefore, the average throughput of the proposed DNRTTC model is improved by 16% and 26% than [1] and [2] respectively.

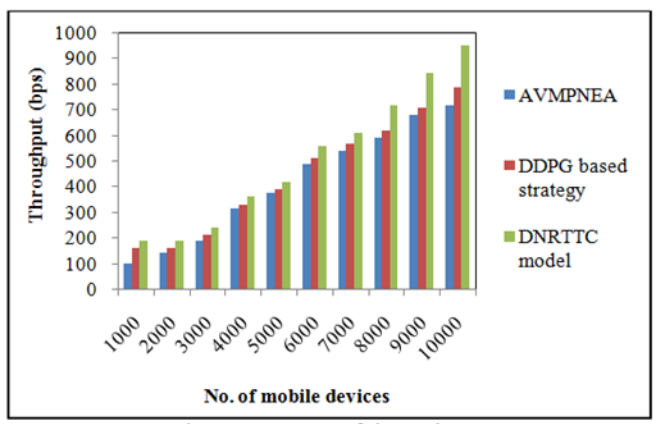

Figure 7 Impact of throughput

From the analysis of the results, the throughput of DNRTTC is found to be better than the conventional methods for the following reasons. DNRTTC is comprised of multiple layers to effectively determine the resource-efficient devices for communication. The significant resource of devices such as

RESEARCH ARTICLE

energy, RSS and connection speed is computed in our research work. This identifies the resource-efficient devices for communication. Also, regression analysis is applied to choose the appropriate devices for 6G communication. This helps to attain a higher DDR than, throughput, and lesser latency and loss rate (LR) than the other methods.

5. CONCLUSION

The research work is concludes to achieve resource-aware D2D communication in a 6G network by using the Deep Neural Regressive Tangent Transfer Classifier (DNRTTC) model. The designed classifier uses the different types of layers to deeply analyze the resources of the device whether it is used for communication or not. The calculation of energy, connection speed, and RSS of the device assists to decrease the data loss rate and latency. The utilization of regression analysis discovers the devices with the greatest resources for data transmission. As well, foremost target of rising the DDR in the 6G network is demonstrated along with the appropriate model. The throughput is enhanced using the activation function. Here, only resource-efficient devices are chosen to carry out the communication. This boosts the energy efficiency of the network. Implementation of DNRTTC is carried out using an NS3 network simulator. Implementation of the DNRTTC model is observed with various metrics. The implementation results show that the proposed DNRTTC is outperformed for 6G D2D communication in increasing DDR, throughput, EE, and decreasing latency and LR than the state-of-the-art methods. The designed model is more suitable for many real-time applications in 6G such as optimization, data analytics, driving applications, tactile communications, indoor positioning, and so on. The proposed DNRTTC model is designed with the advantages of attaining higher data packet delivery with minimal loss and delay. Despite the proposed DNRTTC model performing efficient D2D communication, computational complexities involved in the method are not analyzed. Therefore, in future enhancement, an optimization algorithm is incorporated into the deep learning model to find the optimal resources for mobile devices for 6G communication.

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How to cite this article:

Varadala Sridhar, S. Emalda Roslin, "Energy Efficient Device to Device Data Transmission Based on Deep Artificial Learning in 6G Networks", International Journal of Computer Networks and Applications (IJCNA), 9(5), PP: 568-577, 2022, DOI: 10.22247/ijcna/2022/215917.