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*Original Article*

# Resource Aware Quadratic Discriminative Gentle Steepest Boost Classification for D2D Communication in 5G

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***Abstract*** - *D2D communication for 5G networks enables mobile devices to communicate directly with other devices. For effective available resources, 5G cellular networks that enable high-speed network communication are the major challenging issues. A novel Resource Aware Quadratic discriminative gentle steepest boost classification (RAQDGDBC) technique for D2D communications is introduced. For each device in the 5G network, energy, bandwidth, and connection speed is measured to improve the continuous flow of data and minimize data loss and latency during the communication. The RAQDGDBC technique uses the ensemble method called gentle adaptive steepest boost classification technique to identify the higher bandwidth, energy-efficient, and speed-aware devices by using the set of the weak learner, i.e., Quadratic discriminative classifier. Weak learner measures the device's bandwidth, energy, and connection speed with the threshold value. An optimal node is selected for efficient communication based on the likelihood measure. The ensemble method offers accurate outcomes with minimum error with the help of the steepest descent function. Therefore, the device with higher bandwidth, energy efficiency, and connection speed is chosen for data communication. These advanced features of the 5G network provide better data transmission and reduce loss. A comparison of RAQDGDBC and existing techniques indicates that the RAQDGDBC technique achieves a higher Data delivery rate (DDR), throughput, energy efficiency, and lesser Data loss rate (DLR) and latency than the conventional methods.*

***Keywords*** - *5G Network, Device-to-Device (D2D) Communication, Bandwidth Connection Speed, Quadratic Discriminative Classifier, Gentle Adaptive Steepest Boost.*

## 1. Introduction

D2D was an important function within 5G networks for offering distributed services. D2D facilitates connections among mobile terminals. Based on the wireless network, D2D is to maintain a high data rate with low latency communications in a cellular 5G network. Therefore, an efficient technique is needed to estimate the performance of the D2DCommunications

Distributed Artificial Intelligence Solution (DAIS) was developed in [1] for D2D Communication by sharing the bandwidth between the user and other user equipment. But the framework failed to estimate multiple mobile user equipment. SCMA scheme was introduced in [2]. The designed method supports large device connectivity to improve the 5G network. It maximizes the system data rate but fails to apply a reliable distributed technology to improve data communication.

### *1.1. Major Contributions*

- A novel RAQDGDBC technique is developed for improving the bandwidth and connectivity-aware D2D communication in 5G.
- To improve the DDR and loss rate, a gentle adaptive steepest boost classification technique is designed for identifying the efficient device by constructing the Quadratic discriminative classifier.
- The Quadratic discriminative classifier measures the likelihood between the bandwidth, connection speed, and energy with the threshold value. The maximum likelihood ratio is used to find the efficient node for data communication.
- To identify the higher bandwidth, energy-efficient, and speed-aware devices, the RAQDGDBC technique uses the ensemble method called the gentle adaptive steepest boost classification technique.
- Finally, a series of simulation tests are carried out with the various simulation metrics to validate the performance of the RAQDGDBC technique and existing

methods. The observed results of the RAQDGDBC technique are discussed with different performance metrics.

### 1.2. Outline of the Paper

The paper is summarized in various sections. Section 2 describes RAQDGDBC. Section 3 provides Methodology, section 4 provides simulation settings, and Section 5 outcomes proposed and existing methods. Section 6 provides the conclusion of the article.

## 2. Related Works

D2D communication in unlicensed spectrum (D2D-U) was introduced in [3] to enhance the 5G network capacity further. But it failed to achieve higher 5G network throughput. In [4], the feasibility of the D2D approach was developed to increase the cellular throughput under the various loads by maximizing the bandwidth. But it failed to improve the delivery rate.

A probabilistic integrated resource allocation approach was introduced in [5] to improve the D2D communication based on resource optimization. However, the approach was difficult as well as the consumption of time. A novel cluster-based architecture was designed in [6] for D2D communication and to improve the performance of 5G networks. Though the architecture increases the throughput and reduces end-to-end delay, it failed to achieve higher data delivery.

A new hybrid transmission mode selection approach was introduced in [7] using online reinforcement learning for obtaining better system throughput. But the approach failed to apply the machine learning technique to improve the throughput further. An intra–intercell D2D communication system was developed in [8] to enhance throughput. The designed method increases spectrum efficiency. But it failed to achieve the minimum loss rate. A novel game-theoretic method was introduced in [9] for D2D communication using common resources of various cells. The designed method failed to achieve higher throughput.

A hybrid resource allocation system was introduced in [10] to enhance throughput. However, the system only considered D2D communication. A D2D multicast system was introduced in [11] for effective D2D communication. However, it failed to reduce the DLR.

A heuristic algorithm was designed in [12] to improve the near-optimal solution with minimum computational complexity to increase spectrum efficiency and network capacity. But it failed to improve the network throughput. An intelligent building system was introduced in [13] for 5G communication to achieve optimal performance. An optimized caching policy was introduced in [14] for D2D communication. But the designed model failed to minimize the delivery latency and forwarding energy costs.

A Flexible network architecture was introduced in [15] for QoE-aware Communications of 5G Systems. However, the designed architecture failed to perform a better delivery rate. A new interference-aware graph-based resource sharing technique was presented in [16] to enhance D2D with lesser computational complexity. But, it was unsuccessful in enhancing the performance of resource sharing during the device communications.

A reinforcement-learning technique was introduced in [17] for indoor D2D communication to increase the strong 5G connectivity and reduce the latency. Spectral efficiency techniques were developed in [18] to achieve better D2D communication.

A game-based power adjustment model was developed in [19] to improve the throughput for multi-hop relay-aided D2D communication. The designed model failed to achieve the throughput improvement of the D2D communication. Device discovery algorithms were developed in [20] for D2D communication with a higher signal success ratio and accuracy. However, the algorithm failed to ensure the data transmissions.

A 5G-QoE framework is proposed in [21] to address the QoE modeling for UHD video flows in 5G networks. A power control algorithm based on the Lambert W function was proposed in [22] to maximize the energy efficiency of a single D2D pair. The generalized quadratic discriminant analysis (GQDA) was introduced in [23] to discriminate between populations with underlying elliptically symmetric distributions. However, the classification rule in GQDA is still based on the sample mean vector and the sample dispersion matrix of a training set, which are extremely non-robust under data contamination.

The training algorithm of discriminative learning quadratic discriminant function (DLQDF) was designed in [24] to overcome the accuracy promotion for HCCR. A self-sustained RAN slicing framework was proposed in [25] to achieve an adaptive control strategy under unforeseen network conditions.

## 3. Methodology

D2D is a key communication model and provides seamless connectivity for any mobile device and application connected to the user's environment. The future 5G network will provide high data and low latency through optimized connection speed and flexible bandwidth. Such features are analyzed regarding data transmissions using different machine-learning (ML) techniques. The performance of D2D networks is the major issue for boosting. RAQDGDBC was proposed for enhancing communication between the devices with higher throughput.

This work measured D2D in 5G networks as a combination of cellular and device users. The system model includes multiple cellular devices '$D = d_1, d_2, \dots, d_n$' deployed in the 5G network. 5G enables mobile devices to directly communicate with other mobile nodes within the radio communication range. To improve communication, three major features are considered in this work such as bandwidth $(Bw)$, connectivity speed $(S)$, the energy efficiency of the device $(\alpha_{EE})$. As a result, the data communication is performed through the node with higher bandwidth and connectivity speed, improving the data delivery with minimum latency and minimizing the loss. The above-said processes are explained in the following sections.

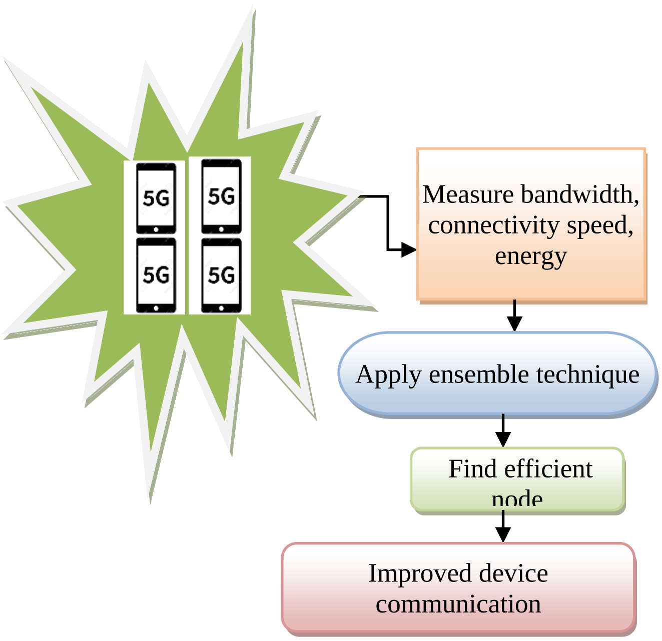


**Fig. 1 Architecture diagram of Proposed RAQDGDBC Technique**

Fig. 1 demonstrates the architecture of RAQDGDBC to improve D2Dcommunication in 5G. Dynamic movements of the cellular nodes are input to perform the communication process. Fig. 1 illustrates that each device's bandwidth, connectivity speed, and energy efficiency are measured to obtain better communication and minimize the DLR and latency. The device with higher bandwidth and the connectivity speed improves the continuous flow of data (i.e., data streaming).

### *3.1. Quadratic Discriminate Gentle Adaptive Boost Classification based D2D Communication Technique*

The proposed RAQDGDBC technique uses the Quadratic discriminative gentle adaptive boost technique to find an efficient device with higher bandwidth, connectivity speed, and energy efficiency.

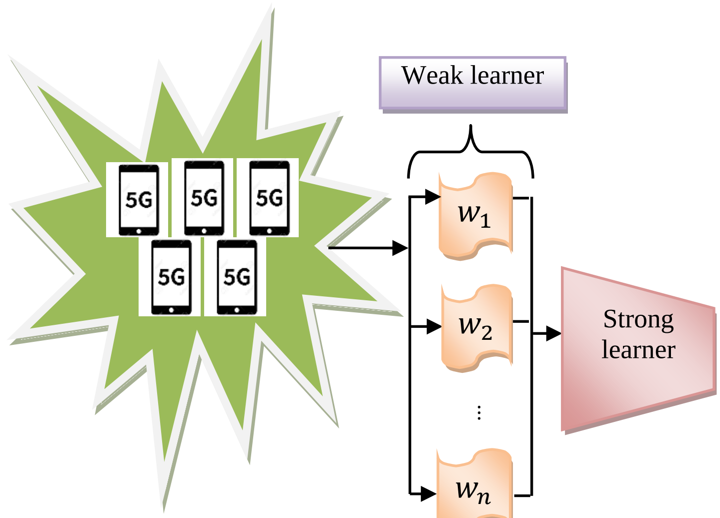


**Fig. 2 Structure of Quadratic Discriminative Gentle Adaptive Boost Technique**

The gentle adaptive boost is an ensemble technique that enhances machine learning algorithm performance by converting the results of the weak learner into strong ones. The weak learner does not provide correct results. In contrast, boosting offers correct outcomes through gathering weak learners. In the proposed RAQDGDBC technique, the Quadratic discriminative classifier was a weak learner in classifying the devices based on their bandwidth, connectivity speed, and energy efficiency.

Fig. 2 depicts the Quadratic discriminative gentle adaptive boost technique to identify the efficient device in the 5G network based on the bandwidth $(Bw)$ and connectivity speed $(S)$. The ensemble technique uses a training set $\{(d_1, y_1), (d_2, y_2), \dots, (d_n, y_n)\}$ Where '$d$' denotes the number of devices, '$y$' denotes an ensemble classification output. As shown in figure 2, the ensemble technique initially constructs 'm' weak learners $w_1, w_2, w_3, \dots w_n$. The proposed RAQDGDBC technique uses a Quadratic discriminative as a weak learner for classifying the devices.

Let us consider the mobile devices $d_1, d_2, \dots, d_n$ In 5G network. The bandwidth level of the device is calculated based on the amount of data downloaded or uploaded from the device at a given time. It is mathematically expressed as given below,

$$Bw = \left(\frac{Amount\ of\ data\ (Gb)}{time\ (sec)}\right) \quad (1)$$

Where '$Bw$ '(bandwidth) denotes a bandwidth, the amount of data in terms of Gigabytes (Gb) per one second (sec), in a 5G network, the bandwidth level of the device is greater than 1 Gbps. Then the device's connection speed is measured between access points and the wireless devices connected to those points. It is measured as given below,

$$S = \left(\frac{max_{RD}}{time}\right) \tag{2}$$

Where $S$ denotes a connection speed, $max_{RD}$ Denotes the maximum rate at which data is received over the internet at a particular time. In a 5G network, the connection speed is measured in terms of megabits per second (Mbps). The energy efficiency of each device is measured as given below,

$$\alpha_{EE} = DLR_{D2DL} - f(\varepsilon TP_{D2DL} + TP_{CP}) \tag{3}$$

The above equation (3), $\alpha_{EE}$ denotes an energy efficiency, $DLR_{D2DL}$ indicates a data loss rate of the device. '$DLR_{D2DL}$', $TP_{D2DL}$ denotes a transmission power of the device and, $TP_{CP}$Indicates a transmission power of circuit, $\varepsilon$ denotes a constant. The devices' bandwidth, connection speed, and energy efficiency are classified with the threshold value.

Quadratic discriminant classifier classifies devices. Let us consider the devices $d_1, d_2, \ldots, d_n$ And their threshold value of the bandwidth, connection speed, and energy efficiency threshold value. The likelihood ratio test was achieved among features, i.e., bandwidth, connection speed, energy efficiency, and the threshold value. Thus, the likelihood ratio test was calculated by,

below,$$\mathcal{L}\,(Bw|Bw_t) = \left(\frac{1}{D\sqrt{2\pi}}\right)^{-n} \exp\,[-\textstyle\sum_{i=1}^{n} \frac{1}{2D^2}\,\|Bw - Bw_t\|^2] \tag{4}$$

And

$$\mathcal{L}\,(S|S_t) = \left(\frac{1}{D\sqrt{2\pi}}\right)^{-n} \exp\,[-\textstyle\sum_{i=1}^{n} \frac{1}{2D^2}\,\|S - S_t\|^2] \tag{5}$$

And

$$\mathcal{L}\left(\alpha_{EE}\middle|\alpha_{EE_t}\right) = \left(\frac{1}{D\sqrt{2\pi}}\right)^{-n} \exp\,[-\textstyle\sum_{i=1}^{n} \frac{1}{2D^2}\left\|\alpha_{EE} - \alpha_{EE_t}\right\|^2] \tag{6}$$

Where $\mathcal{L}\,(Bw|Bw_t)$ denotes a likelihood ratio test between the bandwidth $Bw$ and threshold $Bw_t$. $\mathcal{L}\,(S|S_t)$indicates a speed and the threshold value. '$S_t$' of the speed, $D$ denotes a deviation, $\mathcal{L}\left(\alpha_{EE}\middle|\alpha_{EE_t}\right)$ denotes likelihood ratio test among energy efficiency as well as threshold. '$\alpha_{EE_t}$'. The likelihood ratio test among features and the threshold is calculated, achieving classification results. Weak learner classifies the devices based on the maximum likelihood ratio.

$$w_j(d) = \arg\max(\mathcal{L}\,(Bw|Bw_t) \&\& \mathcal{L}\,(S|S_t)) \&\& L\left(\alpha_{EE}\middle|\alpha_{EE_t}\right)) \tag{7}$$

Where, $w_j(d)$ be the results of weak learners, $\arg max$ Denotes an argument of maximum function. The device which has maximum likelihood is selected as optimal for better communication. In this way, the devices are classified and obtain the results.

Weak learning includes training errors in classification outcomes. The ensemble method makes strong classification results by gathering weak learners to improve classification results.

$$y = \textstyle\sum_{i=1}^{m} w_j(d) \tag{8}$$

Where $y$ denotes an output of an ensemble classifier that combines the results of weak learners $w_j(d)$. Weights were used to obtain strong results for each weak learner.

$$y = \textstyle\sum_{i=1}^{m} w_j(d) * \varphi \tag{9}$$

Where $\varphi$ indicates the weight assigned to weak learners. After that, the training error was calculated. Error is measured as the squared difference among actual as well as predicted outcomes as given below,

$$e = \left[z_a - z_p\right]^2 \tag{10}$$

Where '$e$' is the training error of a weak learner, $z_a$ indicates actual outcome, $z_p$ Indicates output of weak learner. The initial weight of each weak learner gets updated according to the error. The ensemble method increases weights if it incorrectly categorizes the device. Otherwise, the weight gets decreases. Any adjustment coefficients are not used for classification during the weight updating, which minimizes the complexity.

$$\varphi' = \varphi_t\,\exp(-y_i\, z_p(i))\,) \tag{11}$$

In (10),$\varphi'$ represents the updated weight, $\varphi_t$ indicates an initial weight, $z_p(i)$ represents the predicted classification results of $i^{th}$weak classifier, $y_i$Indicates output of strong learner. The proposed ensemble technique uses the steepest descent to reduce the objective function, i.e., error.

$$f\,(x) = \arg\min e\,(w_j(d)) \tag{12}$$

Where $f\,(x)$ denotes the steepest descent function, $arg\ min$ is an argument of the minimum function, and '$e$' denotes the training error of the weak classifier. This way, the ensemble technique correctly classifies the devices as efficient for communication in the 5G network. As a result, the devices' efficient bandwidths, connection speed, and energy are selected to improve the continuous flow of data communication in the 5G network. The algorithmic bandwidth and connectivity aware Quadratic discriminative gentle adaptive boost classification is described as follows.

Algorithm 1 explains D2D within 5G. For each 5G network, energy-efficient bandwidth and connection speed are measured. Then the ensemble technique consists of some weak learners.

| **// Algorithm 1: Quadratic discriminative gentle steepest boost classification** |
|---|
| **Input:** Device '$D = d_1, d_2, \dots, d_n$<br>**Output**: Bandwidth and connectivity aware D2D communication |
| **Begin**<br>**Step 1: for each** $d_i$<br>**Step 2:** Measure bandwidth '$Bw$' and connection speed '$S$'<br>**Step 3:** Construct 'm' set of weak learners<br>**Step 4: For each** value '$Bw$', $S$, $\alpha_{EE}$<br>**Step 5: For each threshold** $Bw_t$', $S_t$, $\alpha_{EE_t}$<br>**Step 6:** Measure the likelihood ratio test<br>**Step 7: End for**<br>**Step 8: End for**<br>**Step 9: If**<br>**(**$\arg\max(\mathcal{L}\ (Bw\|Bw_t)\&\&\ \mathcal{L}\ (S\|S_t)\&\&\ (L\ (\alpha_{EE}\|\alpha_{EE_t}))$ **then**<br>**Step 10:** Devices are classified as optimal for data communication<br>**Step 11: Else**<br>**Step 12:** Devices are classified as nonoptimal for data communication<br>**Step 13: End if**<br>**Step 14:** Combines all weak learners $y = \sum_{i=1}^{m} w_j(d)$<br>**Step 15: For each** weak learners$w_j(d)$<br>**Step 16:** Initialize a weight '$\varphi$'<br>**Step 17:** Measure the training error '$e$'<br>**Step 18:** Update the weight '$\varphi'$'<br>**Step 19:** Apply steepest descent '$f(x)$'<br>**Step 20:** Find a weak learner with minimum error $\arg\min e(w_j(d))$<br>**Step 21: End for**<br>**Step 22: Return** (strong classification results)<br>**Step 23:** Perform data communication via optimal devices<br>**End for**<br>**End** |

Weak learner measures among the estimated value of bandwidth and connection speed and the threshold value. The likelihood is higher than the threshold, and the device is categorized as resource-efficient for continuous data flow. Then ensemble method allocates weight for each device. Training error was measured for identifying classification outcomes and applied the steepest descent to detect weak learner results. Thus, bandwidth, speed, and energy-efficient devices are selected for efficient data communication and to minimize data loss.

### *3.2 System Model*

The system model of the proposed RAQDGDBC technique is presented. Let us consider the squared sensing area n*n, where the vehicle nodes are randomly deployed. A VANET is represented by a graph $G = (v, e)$ where '$v$' denotes the number of nodes and '$e$' represents the edges, i.e., links between vehicle nodes. The source vehicle node $(SN)$ routes the data packets $D = d_1, d_2, \dots, d_n$ To the destination node $(DN)$ through optimal neighboring nodes.

## 4. Experimental Setting

The RAQDGDBC and DAIS [1] SCMA scheme [2] was simulated with a MATLAB simulator. To conduct the simulation, the Movie streaming datasets iflix datasets is used and taken from the Kaggle dataset[https://www.kaggle.com/datasets/aungpyaeap/movie-streaming-datasets-iflix]. The dataset consists of five data explorers: Assets, demographics, Plays, Psychographics, and Users. Each user has a unique ID. The different parameters considered for simulation are listed below,

**Table 1 Simulation parameters**

| S No. | Parameter | Value |
|---|---|---|
| 1 | Number of cellular users | 100,200,300,400,500,600,700,800,900,1000 |
| 2 | Network area | 500m * 500m |
| 3 | Input energy | 2000J |
| 4 | Data sent | 512KB |
| 5 | Transmission range | 500m |

Dataset identifies psychographic and demographic tags about some iflix users. Each user-tag pair has an associated confidence score (1 is the highest and 0 is the lowest confidence).

Each trait can consist of up to 3 levels, depending on its granularity. Some traits can be identified by only considering the first 2 levels,

While others make more sense when all the 3 levels are considered, e.g. 'iflix Viewing Behaviour' is a level 2 psychographic trait that only makes sense when it is looked at in combination with the level 3 traits corresponding to it ('casual,' 'player' and 'addict'). Traits are available corresponding to a user_id in the dataset only if the user has a certain confidence that the user belongs to the trait.

The simulations for movie streaming with the devices and consumption platform are arranged in a stipulated area for D2D communication in a 5G network. Each content genre varies from reality, comedy, and kids to different genres with different content runtime. The simulations are studied for varying the users within a range of 50 to 150 devices

## 5. Results and Discussion

The performance analysis of RAQDGDBC and DAIS [1] SCMA scheme [2] is discussed. To measure the performance, the following three parameters are used: DDR, DLR, throughput, energy efficiency, and latency. These metrics are described as given below,

**Data delivery rate**: The first metric for D2D communication is the DDR. A considerable number of data is said to be delivered during D2Dcommunication. The data delivery is mathematically expressed as given below,

$$DDR = \frac{D_d}{D_s} * 100 \tag{13}$$

Where, $D_d$ number of data delivered, $D_s$ Denotes data sent at a particular time interval. It was calculated by percentage (%).

**Data loss rate**: Second important metric for D2D communication is the DLR. A considerable number of data is said to be lost during D2Dcommunication. The DLR is formulated as given below,

$$DLR = \frac{D_l}{D_s} * 100 \tag{14}$$

Where, $D_d$ data lost, $D_s$ Denotes data sent at a particular time interval. DLR was calculated by percentage (%).

**Throughput** refers to the amount of data transferred from one location to another in time. The formula for calculating the throughput is given below,

$$\boldsymbol{T_{put}} = \left[\frac{\text{amount of data transferred}}{time}\right] \tag{15}$$

Where, $T_{put}$ Denotes a throughput. It is measured in terms of bits per second (bps).

**Energy efficiency:** EE of a device was measured by the proportion of the output energy to input energy as given below.

$$EE = \frac{E_{out}(J)}{E_{in}(J)} * 100 \tag{16}$$

Where $EE$ denotes an energy efficiency '$EE$,' energy. '$E_{out}$' denotes output energy, '$E_{in}$' denotes total input energy. It is measured in terms of percentage.

**Latency**: Latency refers to the time consumed for a number of data transmitted between two devices. It is mathematically expressed as given below.

$$L = \sum_{i,j=1}^{n} Data * Time\left[D_i \cup D_j\right] \tag{17}$$

Where '$L$' denotes a latency is measured based on the data, and the time consumed for performing the data transmission '$Time\left[D_i \cup D_j\right]$'. It was calculated by milliseconds (ms).

**Table 2. Comparison of data delivery rate**

| Number of cellular users | Data delivery rate (%) | | |
|---|---|---|---|
| | DAIS | SCMA scheme | RAQDGDBC |
| 100 | 94.1 | 92.8 | 96.2 |
| 200 | 93.8 | 92.5 | 95.8 |
| 300 | 93.45 | 92.2 | 95.58 |
| 400 | 93.2 | 91.9 | 95.4 |
| 500 | 93.1 | 91.6 | 95.2 |
| 600 | 92.8 | 91.4 | 94.95 |
| 700 | 92.6 | 91.18 | 94.87 |
| 800 | 92.34 | 91.09 | 94.4 |
| 900 | 92.2 | 90.9 | 93.8 |
| 1000 | 91.8 | 90.85 | 93.65 |

Table 2 describes the data delivery rate versus the number of cellular users. During the simulation scenario, the number of cellular users ranges from 100 to 1000. The tabulated results indicate that the data delivery rate of the proposed RAQDGDBC technique is higher than the other two existing methods. This is proved through statistical analysis. Simulations were conducted with 100 numbers of cellular users and the data to be sent is 512KB; the data delivered using the proposed RAQDGDBC technique is 492.54KB, and the delivery rate is 96.2%. By applying the existing DAIS [1] SCMA scheme [2], the amount of data delivered is 481.792 KB and 475.136 KB, and the delivery rate is 94.1% and 92.8%, respectively.

Similarly, other runs are performed with different cellular users, and the size of data being sent is 512KB. Ten results of the data delivery rate of the proposed technique are obtained and compared. The average of ten comparison results proves that the data delivery rate is increased by2% and 4% using the proposed technique compared to two related works DAIS [1] SCMA scheme [2]. Based on the observed simulation result, the graph is plotted in figure 6.

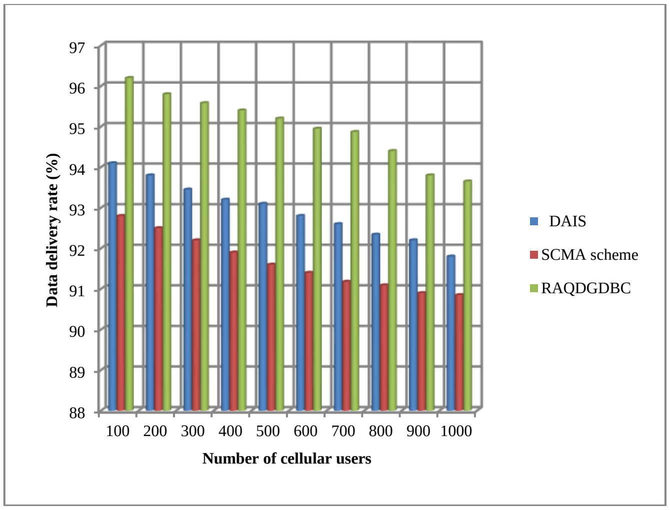


**Fig. 3 Performance results of data delivery rate versus number of users**

Figure 3 performance of data delivery rate concerning the number of cellular users. As shown in figure 3, the data delivery rate of three methods as proposed and two existing methods are illustrated with three columns of lines, green, blue, and red, respectively. The observed figure illustrates that the proposed technique increases the data delivery rate more than the conventional methods. This significant improvement is achieved by identifying the energy, bandwidth, and connectivity-aware devices through the Quadratic discriminative gentle steepest boost classification technique. The ensemble technique finds that devices with higher bandwidth and connection speeds are chosen for efficient data transmission. This helps to improve the data delivery.

**Table 3. Comparison of Data loss rate**

| Number of cellular users | Data loss rate (%) | | |
|---|---|---|---|
| | DAIS | SCMA scheme | RAQDGDBC |
| 100 | 5.9 | 7.2 | 3.8 |
| 200 | 6.2 | 7.5 | 4.2 |
| 300 | 6.55 | 7.8 | 4.42 |
| 400 | 6.8 | 8.1 | 4.6 |
| 500 | 6.9 | 8.4 | 4.8 |
| 600 | 7.2 | 8.6 | 5.05 |
| 700 | 7.4 | 8.82 | 5.13 |
| 800 | 7.66 | 8.91 | 5.6 |
| 900 | 7.8 | 9.1 | 6.2 |
| 1000 | 8.2 | 9.15 | 6.35 |

Table 3 describes the performance results of the data loss rate using the proposed RAQDGDBC technique and two existing methods, DAIS [1] and SCMA scheme [2]. The different numbers of cellular users are taken from 100 to 1000 to calculate the data loss rate. When the simulation is conducted with 100 users and 512KB data being sent, the data loss rate is found to be 3.8% using the proposed RAQDGDBC technique, 5.9% with the aid of [1], and 7.2% using [2]. The observed result showed that the data loss rate is minimized using the proposed technique than the conventional methods. For each method, ten results are observed with different inputs. The average of ten results indicates that the proposed technique reduces the data loss rate by 29% and 40% compared to state-of-the-art methods.

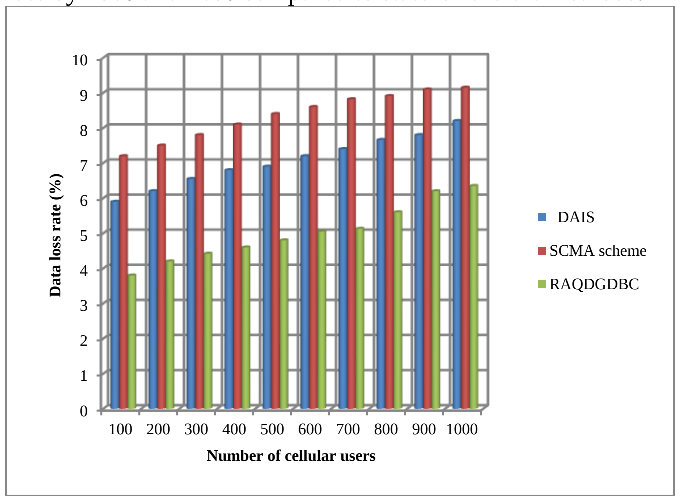


**Fig. 4 Performance results of data loss rate versus number of users**

The comparison of data loss rate using three different methods is illustrated concerning the number of cellular users, as shown in figure 4. As shown in the graph, the numbers of users are taken on the horizontal axis, whereas the performance of the data loss rate is observed on the vertical axis. The plot indicates that the data loss rate of the proposed RAQDGDBC technique is minimized then the other two existing methods. The reason for this improvement is to select the devices with higher bandwidth. The maximum rate of data transfer of the device increases the data delivery and minimizes the packet loss.

**Table 4. Comparison of Throughput**

| Number of cellular users | Throughput (bps) | | |
|---|---|---|---|
| | DAIS | SCMA scheme | RAQDGDBC |
| 100 | 120 | 115 | 125 |
| 200 | 138 | 130 | 143 |
| 300 | 155 | 146 | 165 |
| 400 | 172 | 161 | 182 |
| 500 | 185 | 175 | 193 |
| 600 | 192 | 185 | 210 |
| 700 | 210 | 195 | 245 |
| 800 | 245 | 222 | 283 |
| 900 | 280 | 255 | 315 |
| 1000 | 310 | 280 | 340 |

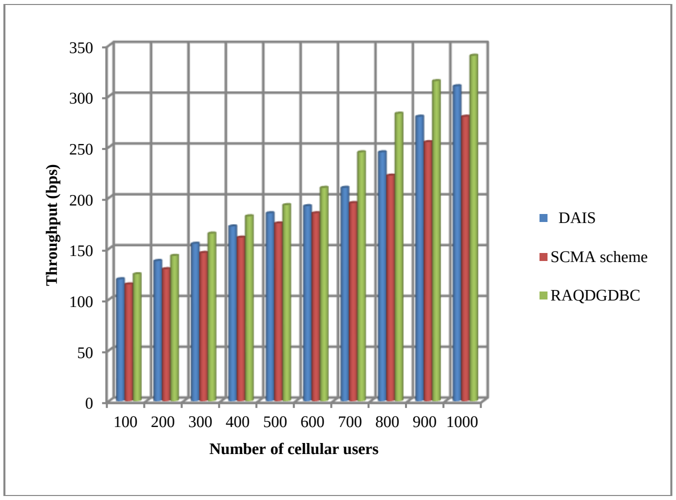


**Fig. 5 Performance results of throughput versus the number of cellular users**

Table 4 and figure 5 show the comparative analysis of the throughput of the three different methods. The above graphical chart indicates that the performance of throughput is higher using the proposed technique. Let us consider 100 users and 512 $KB$ of data packets being sent. Applying the proposed RAQDGDBC technique, 125 bits of the data packets are transmitted in 1 second. But the throughput of DAIS [1] and SCMA scheme [2] are achieved by 120 bps and 115bps. This improvement is achieved using the ensemble classification technique and identifying the optimal device for effective communication. Besides, efficient bandwidth-aware data transmission is performed for continuous data flow. This helps to improve the data transmission rate.

**Table 5. Comparison of Energy efficiency**

| Number of cellular users | Energy efficiency (%) | | |
|---|---|---|---|
| | **DAIS** | **SCMA scheme** | **RAQDGDBC** |
| 100 | 90 | 87 | 94 |
| 200 | 89.5 | 86.5 | 93.2 |
| 300 | 88.3 | 85.4 | 91.5 |
| 400 | 87.5 | 84.3 | 90.4 |
| 500 | 86.2 | 84.9 | 89.3 |
| 600 | 85.5 | 83.3 | 88.5 |
| 700 | 85.2 | 82.1 | 88 |
| 800 | 84.3 | 81.5 | 87.8 |
| 900 | 83 | 80 | 87.3 |
| 1000 | 83.5 | 79.5 | 86.2 |

Table 5 above illustrates the energy efficiency concerning the number of cellular users from 100 to 1000. From the observed results, the energy efficiency is considerably improved using the RAQDGDBCtechnique than the other existing methods. Let us consider 100 cellular users, and the input energy provided being '2000J', the input energy is '1920J'; therefore, the energy efficiency of the RAQDGDBC technique is 96%, whereas the energy efficiency of DAIS [1] and SCMA scheme [2] are 90% and 87% respectively. Similarly, the various results are observed for each method, and the results are compared. The overall results indicate that the RAQDGDBCtechnique achieves higher energy efficiency by 6% when compared to [1] and 9% when compared to [2]

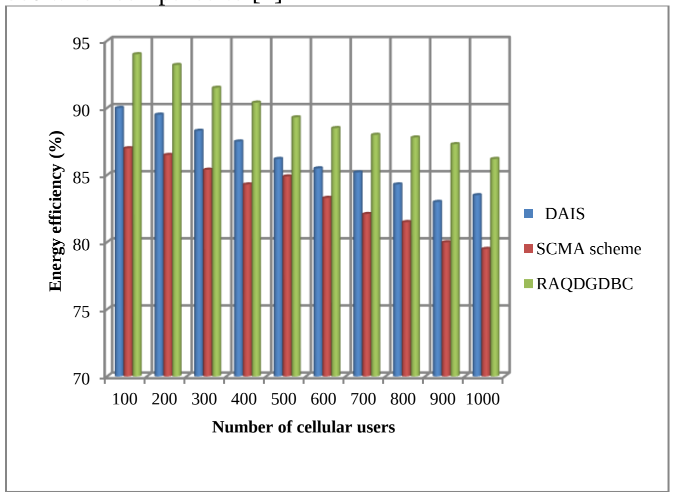


**Fig. 6 Performance results of energy efficiency versus the number of cellular users**

Figure 6 illustrates the energy efficiency versus the number of cellular users participating in the data communication. As shown in figure 6, the energy efficiency of three methods, namely the RAQDGDBC technique, DAIS [1], and SCMA scheme [2], are represented by three different colors: green, blue, and red. From the graphical illustration, the energy efficiency of the RAQDGDBC technique is improved than the other two existing methods. The significant reason for this improvement is to apply the Quadratic Discriminative Gentle Steepest Boost classifier to find resource-efficient devices for communicating the data.

**Table 6. Comparison of Latency**

| **Number of cellular users** | Latency (ms) | | |
|---|---|---|---|
| | **DAIS** | **SCMA scheme** | **RAQDGDBC** |
| 100 | 63 | 65 | 60.5 |
| 200 | 68.32 | 70.25 | 65.3 |
| 300 | 75.4 | 78.4 | 72.41 |
| 400 | 88.42 | 92.1 | 83.56 |
| 500 | 95.11 | 99.52 | 92.12 |
| 600 | 102.51 | 104.3 | 98.23 |
| 700 | 108.4 | 112.52 | 102.8 |
| 800 | 115.3 | 120.41 | 108.5 |
| 900 | 120.53 | 125.3 | 112.2 |
| 1000 | 128.32 | 133.5 | 120.3 |

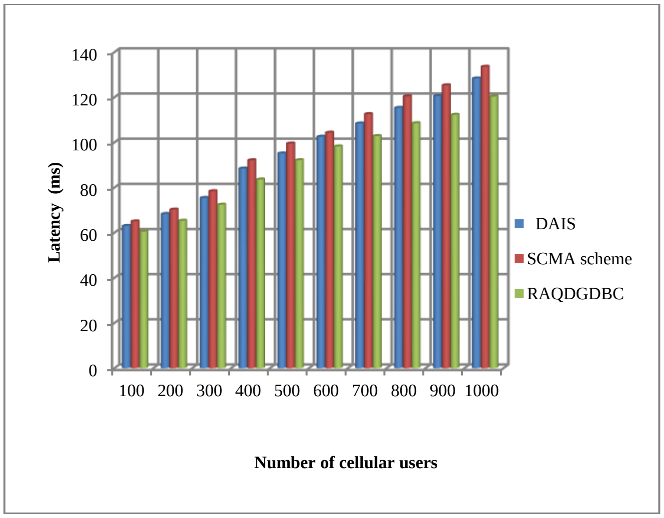


**Fig. 7 Performance results of latency versus the number of cellular users**

Table 6 and figure 7 illustrate the performance analysis of latency versus the number of cellular users in the ranges from 100 to 1000. The graphical chart indicates the latency of different methods observed in the vertical axis. The graphical plot indicates that the data transmission latency is increased with the increasing number of users. However, with the simulation conducted for 100 users and 50 data, the latency of data transmission was '$60.5ms$' using the RAQDGDBC technique, and the latency using DAIS [1] and SCMA scheme [2] was observed to be $63ms$ and $65ms$. Similarly, the remaining nine results are performed with the number of cellular users. The observed results of the proposed RAQDGDBC technique are compared to the existing results. The average comparison results inferred that the overall latency using the RAQDGDBC technique is considerably minimized by 5% when compared to [1] and 8% when compared to [2]. The reason behind improving the RAQDGDBC technique is finding a resource-efficient device for data communication.

## 6. Conclusion

As the number of communication devices has been growing rapidly with the emergence of varied wireless services, D2D allows devices in closeness to converse directly. A novel technique is applied to the 5G system to achieve higher throughput and lesser DLR. A novel RAQDGDBC technique improves the D2D communications with higher delivery and minimum loss rate. The ensemble technique uses different resources such as bandwidth, connection speed, and energy efficiency of the devices as 5G network features. The Quadratic discriminative classifier measures the likelihood and classifies the devices as optimal for better communication. Weak learner outcomes are compared to strong ones by applying the steepest descent to detect the lesser error. Therefore, the device with higher bandwidth and connection speed is selected for efficient data communication, increasing the network throughput. Experimental assessment is performed to analyze the RAQDGDBC with existing methods using different parameters. The observed result is that the proposed RAQDGDBC is more efficient for providing efficient D2D than the earlier ones, having a higher delivery rate, throughput, energy efficiency, and lesser error rate and latency.

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