

Multivariate Kernel Regressive Opportunistic Wilcoxon Gradient Descent for Resource and Connectivity Aware Mobile Communication in 5G Networks

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Article Info

Journal of Machine and Computing (<https://anapub.co.ke/journals/jmc/jmc.html>)

Doi: <https://doi.org/10.53759/7669/jmc202606014>

Received 23 March 2025; Revised from 02 August 2025; Accepted 13 October 2025

Available online 18 October 2025.

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Abstract – Mobile computing refers to employ of portable computing tools, namely smartphones, tablets, laptops, to entrance as well as transmit information and information wirelessly over a network. These tools typically utilize wireless technologies such as cellular networks (e.g., 3G, 4G, 5G) and Bluetooth to connect to internet as well as additional devices. Among these networks, 5G represent the fifth generation of mobile communication, succeeding po and dynamically connect with other devices. Several fundamental challenges were tackled in 5G development, including low data transfer rates, high latency, intermittent connectivity, energy efficiency, and robustness. In order to enhance efficient communication in 5G, a novel Multivariate Kernel Regressive Opportunistic Wilcoxon Gradient Descent (MKROWGD) method has been developed. Major aim of MKROWGD technique is to enhance data communication among mobile devices within 5G networks by achieving minimal latency and data loss, higher throughput, and energy efficiency. MKROWGD comprises two major processes namely Multivariate kernel regressive Opportunistic Diversity Scheduling and Wilcoxon signed-rank Gradient Descent method. Firstly, Multivariate kernel regressive Opportunistic Diversity Scheduling is employed to find resource-efficient mobile devices in 5G networks based on energy and bandwidth, improving data delivery and minimizing loss rates. Secondly, the Wilcoxon signed-rank Gradient Descent method is used for seamless connectivity by applying the soft handover technique based on received signal strength estimation, enhancing throughput and minimizing latency in data communication within 5G networks. Comprehensive simulations are performed to estimate result of proposed technique by different parameters. Quantitatively explained outcomes denote MKROWGD method improves performance of 5G networks, achieving higher throughput and minimal latency as well as data loss compared to conventional methods.

Keywords – Mobile Computing, 5G Network, Data Communication, Multivariate Kernel Regressive Opportunistic Diversity Scheduling, Wilcoxon Signed-Rank Gradient Descent Method, Soft Handover Technique.

I. INTRODUCTION

5G networks are newest age group of mobile internet connectivity, providing quicker speeds and additional consistent connections than previous generations like 4G. They are designed to handle more data and connect more devices simultaneously to perform communication in distributed environments. 5G technology guarantees to deliver quicker data speeds, minimum latency, increased network capability compared to preceding generations. With lower latency and higher bandwidth, 5G networks have the potential to enable various applications such as healthcare, transportation, and manufacturing, facilitating innovations like remote surgery, autonomous vehicles, and smart factories, among others. Machine learning techniques have been integrated into 5G technologies for resource-efficient and connectivity-aware data transmission, optimizing communication systems by achieving higher energy efficiency, lower latency, and higher throughput.

The Carrier Aggregation with Support Vector Machine (CA with SVM) method was developed in [1] for 5G mobile communication with the aim of achieving higher throughput. However, resource-aware 5G mobile communication posed a major challenge in minimizing the loss rate. DLID2DC method was developed in [2] to achieve higher throughput, energy efficiency, and minimize delay. However, it failed to consider the signal strength of mobile devices to enhance connectivity and reduce latency.

A bagging ensemble mean-shift Gaussian kernelized clustering method was developed in [3] to enhance D2D Connectivity, aiming for improved packet delivery ratio. However, issue of bandwidth-aware data communication remained unaddressed, leading to minimize data loss. Software defined D2D and device to vehicle communications were performed in [4] for achieving high reliability and low latency. But the achieving higher throughput was major issue. In [5], empirical analysis on network coverage, employment, result of 5G networks was conducted using machine learning techniques. But, result of data delivery was not analyzed.

New wake-up system was designed in [6] to address tradeoff among latency and energy efficiency at 5G. But it failed to focus on improving throughput of information communication in 5G networks. A ML-basis of QoE estimation deployment in 5G was developed [7] using various regression methods. But, result of 5G networks was not enhanced. The Traffic-Driven Cell Zooming technique was developed in [8] to decrease the energy consumption of cellular networks. However, achieving bandwidth-aware data transmission in 5G mobile communication posed a challenging issue. Mobile network connectivity analysis was performed in [9] for 5G communication with the aim of reducing device congestion. However, the performance of throughput was not improved. Mobility and handover management methods were explained in [10] aimed to achieve seamless connections during user mobility. However, these techniques failed to enable the mobile tool to concurrently attach to multiple networks.

A user association scheme was developed in [11] based on game theory to enhance D2D communication by minimizing path loss and conserving device energy. However, it failed to select the appropriate link to improve network performance of 5G network. Recurrent Neural Network models were developed in [12] to analyze patterns of bandwidth evolution and address the handoff prediction problem. However, the designed model failed to minimize latency. Supervised, unsupervised, and reinforcement learning models were developed in [13] to minimize latency and enhance reliability in data transmission. However, the analysis did not include an assessment of the energy efficiency of wireless devices and computational resources. A novel modular model based on machine learning techniques was developed in [14] to enhance 5G network performance. However, it failed to minimize latency and loss rates effectively. Different machine learning techniques were developed for 5G wireless communication systems in reference [15].

Major Contributions of the Paper

A novel MKROWGD method is introduced with the following novel contributions,

- To improve D2D communication at 5G, MKROWGD method has been developed by applying a Multivariate Kernel Regressive Opportunistic Diversity Scheduling and Wilcoxon Signed-Rank Gradient Descent method.
- To enhance data delivery rates and minimize loss rates in 5G network communication, the Multivariate Kernel Regressive Opportunistic Diversity Scheduling method is utilized. This method aims to identify resource-efficient mobile devices, thereby improving data transmission and minimizing loss rates.
- To enhance throughput and minimize latency, MKROWGD employs the Wilcoxon signed-rank Gradient Descent method to analyze mobile device connectivity from the base station. This ensures seamless data transmission through a soft handover procedure.
- Finally, a comprehensive simulation assessment was carried out with a variety of evaluation parameters to illustrate the improvements of the MKROWGD method over conventional method

Outline of Manuscript

The remainder of manuscript is organized as follows: Section 2 appraisal literature survey. Section 3 gives explanation of MKROWGD method. Section 4 describes simulation setup. Section 5 discusses the performance outcomes of proposed model and conventional techniques using various evaluation metrics. Section 6 summarizes the manuscript.

II. LITERATURE SURVEY

ML within the mobile edge computing approach was developed in [16] to automate adaptive resource allocation and enhance energy effectiveness in 5G. In [17], various ML methods were introduced to enhance result of D2D networks, aiming for better throughput. An advanced mobility robustness optimization approach was developed in [18] for 5G mobile communication networks. However, the dual connectivity problem was not addressed to enhance the throughput.

The Artificial Intelligence Multiple Linear Regression (AI-MLR) method was developed in [19], aims to optimize the mobility robustness of 5G cellular networks and achieve higher throughput. The Cluster-based Lightweight Prediction Model was developed in [20] for concurrent traffic forecast in 5G mobile networks. Integrating robot controller communication model was developed in [21] for 5G mobile communication, aiming to enhance both data transmission efficiency and energy efficiency. But it failed to improve result of 5G technology. Important components of 5G were discussed [22] included minimizing latency, MIMO, cell distribution, and speed. However, multiple connectivity technologies were not considered.

The multi-link communication approach was developed in [23], aimed to evaluate the system's effectiveness in reducing network traffic. However, the approach failed to consider various factors, namely energy utilization, robustness. In [24], effective resource distribution method was developed for D2D communication using SCMA. However, the robustness of connectivity-based device communication was unaddressed. An effective radio resource allocation (RRA) method was developed in [25] for 5G to enhance D2D communication. The hybrid network and spatial clustering method introduced

in [26] aims to enhance automated coverage and maximize the performance of 5G capacity. Joint optimization model was presented [27] for task offloading and resource distribution depend on edge computing, but it did not prioritize minimizing communication latency performance. In [28], clustering and communication models were developed to improve the device-to-device performance, resulting in minimized delay and improved packet delivery.

A mobile network connectivity analysis was performed in [29] to improve communication and reduce congestion of tools around BS, aiming to enhance result of D2D network. A method for handover decision-making was developed [30] with the objective of minimizing redundant handovers through computing connection times to little cell network. However, this algorithm did not apply in ultra-dense state, where mobile devices moved at arbitrary directions.

III. PROPOSAL METHODOLOGY

5G networks are increasingly standard in global telecommunications with Mobile devices. To meet the demanding needs of improved data, URLLC, massive Machine-Type Communication elevated bandwidth, minimum latency, and massive connectivity requirements. Contrast to 4G technologies, 5G systems are addresses various challenges including achieving better QoS in throughput, reducing latency, supporting high device connectivity, and energy efficiency. In this manuscript, new machine learning concept named MKROWGD method is developed in 5G network architecture to analyze the mobile devices (i.e. node) and their resources status for achieving the improved QoS aware data communication.

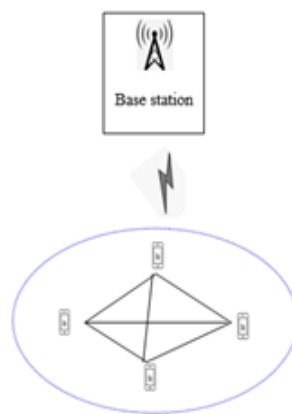


Fig 1. Architecture of Mobile Communication on 5G Network.

Fig 1 shows the architecture of the mobile communication in 5G network. The 5G offer a virtual wireless connection between the mobile devices and base stations without physical cables or dedicated links. The mobile devices communicate with each other directly using wireless communication. The base stations serve as access points in the 5G network, connecting mobile devices to the core network. They facilitate D2D communication by providing resources, managing connections, and coordinating communication between devices. Overall, the architecture of mobile communication in 5G networks enables efficient, low-latency communication between mobile devices, enhancing connectivity. In order to improve the energy aware data communication, a novel machine learning concept called the MKROWGD method is introduced in the 5G network architecture to analyze the mobile devices resource and connectivity status for improving communication.

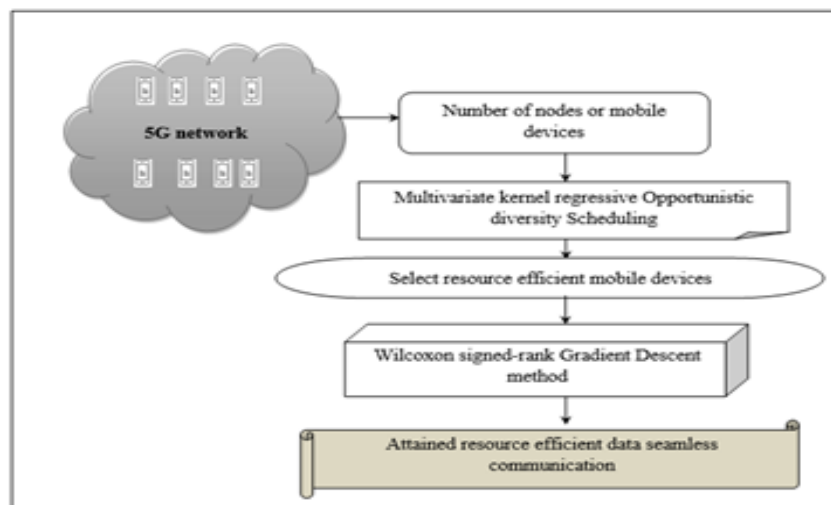


Fig 2. Architecture of Proposed MKROWGD Method.

Architecture of MKROWGD method shown in **Fig 2**. Initially, mobile devices or nodes $MN_1, MN_2, MN_3 \dots, MN_n$ deployed in 5G network and it considered as input to analyze the resources for the possibility of improving the data communication. The proposed MKROWGD method includes two major processes, namely Multivariate Kernel Regressive Opportunistic Diversity Scheduling-based resource analysis and Wilcoxon signed-rank Gradient Descent method-based connectivity analysis. These two techniques are used to design 5G architecture with optimal resource allocation and improved connectivity among devices, resulting in efficient resource utilization and seamless communication.

Multivariate Kernel Regressive Opportunistic Diversity Scheduling

The Opportunistic diversity scheduling technique aims to maximize system throughput by selecting the best mobile devices at any given time based on efficient resource utilization. This is achieved through Multivariate piecewise radial kernel regression, where Multivariate represents the regression function analyzing multiple resources such as energy and bandwidth.

Initially, all mobile devices possess identical energy levels. The total energy of MN is computed as,

$$E_T(MN_i) = E_{TX} + E_P + E_S \quad (1)$$

Where, $E_T(MN_i)$ denotes a total energy of the i^{th} mobile node, E_{TX} denotes a energy dissipated during transmission of a data, E_P denotes a energy dissipated during processing tasks, E_S denotes a energy consumption of standby mode.

$$E_{TX} = (E_{el(TX)} * K) + (E_{amp} * K_{TX} * D^2) \quad (2)$$

Where, E_{TX} denotes a energy consumed by the mobile node, K_{TX} denotes a size of the data being transmitted, measured in bits, $E_{el(TX)}$ refers to energy consumed by the electronic circuitry during the transmission of a single bit of data in communication, D denotes a distance among mobile device and BS.

Energy consumed during processing is computed through multiplying power utilization of device by the duration of processing tasks

$$E_P = (P_{(MN_i)} * T) \quad (3)$$

Where, E_P denotes an energy dissipated during processing tasks, $P_{(MN_i)}$ refers to power consumption of component (e.g., CPU, display, network) in measured in watts (W), T denotes a duration of processing tasks, measured in seconds (s).

The standby energy consumption of a mobile device involves estimating the power usage when the device is not actively performing tasks but is still powered on and maintaining essential functions like keeping the display on standby, and handling background processes. A formula for estimating standby energy consumption is expressed as follows,

$$E_S = (P_{(stand)} * T_{(stand)}) \quad (4)$$

Where, E_S denotes an energy dissipated during standby mode, $P_{(stand)}$ refers to power consumption of device in watts (W), $T_{(stand)}$ denotes a duration of standby mode measured in seconds (s).

The bandwidth of a mobile device typically is defined as amount of data which broadcasted over network in provided period, normally calculated in bps, kbps, Mbps, or Gbps.

$$BW(MN_i) = \left[\frac{D}{T(s)} \right] \quad (5)$$

Where, $BW(MN_i)$ denotes a bandwidth of a mobile device, D denotes a amount of information transferred over network (calculated in bits, bytes, kilobytes, etc.), $T(s)$ denotes a within a given time period in seconds.

Multivariate piecewise radial kernel regression is a ML method where independent variables (i.e. mobile devices) are distinguished based on the breakpoint. A breakpoint, in the context regression, refers to the boundary or threshold point between different segments.

The radial kernel function, often used in machine learning and statistical modeling that calculates relationship between resources of mobile tools. Radial kernel function is expressed as follows,

$$\phi_{RK} = \exp \left(-\frac{|K_i - \mu_i|}{2\sigma^2} \right) \quad (6)$$

Where, φ_{RK} denotes a radial kernel function, R_i denotes a resource of mobile device such as energy ($E_T(MN_i)$) and bandwidth of a mobile device ' $BW(MN_i)$ ', σ denotes a deviation, μ_i denotes an average value. The radial kernel function gives output ranges as of 0 to 1.

$$R = \begin{cases} \varphi_{RK} > \delta, & RED \\ \varphi_{RK} < \delta, & otherwise \end{cases} \quad (7)$$

Where, R denotes a piecewise regression outcome, δ denotes a threshold or breakpoint, φ_{RK} denotes a radial kernel function output. The radial kernel function yields similarity values greater than a threshold (i.e. $\varphi_{RK} > \delta$) for identifying resource-efficient mobile devices (RED). Conversely, when the similarity values are lower than the threshold (i.e. $\varphi_{RK} < \delta$), the radial kernel function is utilized to identify mobile devices that are not resource efficient.

Algorithm 1: Multivariate kernel regressive Opportunistic diversity Scheduling
Input : Number of mobile devices $MN_1, MN_2, MN_3 \dots, MN_n$
Output : Select resource efficient devices
Begin
Step 1: For each device ' MN_i '
Step 2: Measure the energy ' $E_T(MN_i)$ ' using (1)
Step 3: Measure the bandwidth ' $BW(MN_i)$ ' using (5)
Step 4: End for
Step 5: Analyze the resources of mobile device using (φ_{RK}) using (6)
Step 6: if ($\varphi_{RK} > \delta$) then
Step 7: Node is said to resource efficient for communication
Step 8: else
Step 9: Node is said to not resource efficient for communication
Step 10: End if
End

Algorithm 1 describes the Multivariate kernel regressive Opportunistic diversity scheduling for identifying resource efficient mobile device to improve the data communication in 5G network while minimizing the data delivery and loss. For each mobile device, the energy and bandwidth are measured. Then the regression function analyzes the resources using radial kernel function. The radial kernel output greater than threshold is used to find the resource efficient mobile devices. Otherwise, the mobile device is not resource efficient for better communication. With the resource efficient device, the 5G architecture design needs to be done to obtain better communication with minimum loss.

Wilcoxon Signed-Rank gradient Descent Method

After finding the resource efficient mobile device, the connectivity is measured for seamless data transmission in 5G network to increase the throughput and minimize the latency. An intermittent connectivity problem in a wireless network provides the slow or unreliable internet access, with occasional connection drops followed by reconnection after a short period. Therefore, a proposed Wilcoxon signed-rank Gradient descent method is used for analytically diagnosing and addressing intermittent connectivity issues to ensure stable or seamless communication and network connectivity for mobile devices. This, in turn, helps achieve better throughput and minimal latency.

In 5G wireless communication, connectivity often depends on the strength of the signal between devices and a network infrastructure (e.g., base station). Stronger signal strength typically results in more reliable and faster communication. In the proposed method, the signal strength of the mobile devices is computed using Friis transmission for each communication session.

$$RSS = p_{Tx} - G_T + G_r + 20 \log_{10} \left(\frac{\lambda}{4\pi D} \right) \quad (8)$$

Where, RSS indicates a received signal strength, p_{Tx} denotes a transmitted power in dBm, G_T denotes a gain of broadcasting antenna, G_r indicates gain of getting antenna, λ denotes a wavelength of signal (in meters), D indicates a distance among mobile device as well as BS in meter. Friis transmission equation provides a useful starting point for estimating signal strength in wireless systems.

Wilcoxon signed-rank test is employed to test the received signal strength of the mobile device. The function assigns the rank to received signal power of mobile device. Rank of the smallest signals strength is one, the rank of the next smallest is two, and so on.

$$Q = [RSS^1, RSS^2, RSS^3 \dots \dots RSS^n] \quad (9)$$

Where, Q denotes a ranked vector model of 'n' signal strength of mobile device represented by $RSS^1, RSS^2, RSS^3 \dots \dots RSS^n$. After that, the sign is assigned to each output.

$$S = \begin{cases} -1, & RSS < \beta_{RSS} \\ +1, & RSS > \beta_{RSS} \end{cases} \quad (10)$$

Where, S denotes Wilcoxon signed-rank test outcome, if computed signal strength of mobile device is superior than threshold ' β_{RSS} ', test returns the positive value '+1'. If estimated signal strength of mobile device is lesser than the threshold ' β_{RSS} ', then the test returns the negative value '-1'. The positive signed results are utilized to identify the mobile device with the stronger signal strength, thus enhancing connectivity. This improvement facilitates seamless data communication within the 5G network.

The negatively signed results indicate lower signal strength, leading to intermittent connectivity. The proposed technique identifies the mobile device with lower signal strength and switches it over to the nearest base station to ensure continued data transmission with minimal latency. Soft handover, also known is a technique used in 5G communication networks to ensure seamless continuity of communication. The soft handover allows the mobile device to maintain connections with multiple neighboring base stations simultaneously when the signal strength is weak.

The taxicab distance is employed to compute distance current location of the mobile device and the locations of nearby base stations. Let us consider the coordinate of the mobile device represented as (x_1, y_1) and the coordinate of the base stations denotes as (x_2, y_2) in a two-dimensional Cartesian coordinate system. Therefore, the distance is measured as follows,

$$D = |x_1 - x_2| + |y_1 - y_2| \quad (11)$$

The Gradient descent in machine learning is used to find the minimal distance between mobile device and the locations of nearby base stations.

$$f(x) = \arg \min D \quad (12)$$

Where, $f(x)$ denotes a Gradient descent function, $\arg \min D$ denotes a argument minimum of distance. After finding the nearest base station, the mobile device switched as of old BS to novel nearest BS. This aids to enhance seamless continuity of communication.

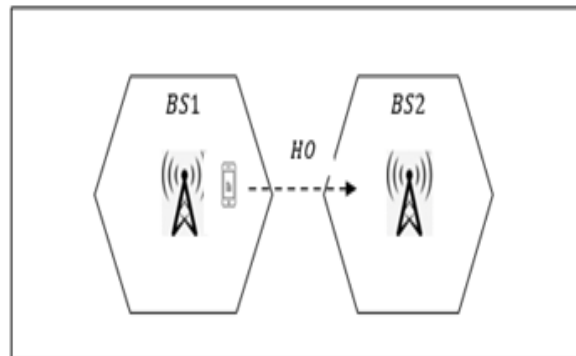


Fig 3. Soft Handover in 5G Communication.

Fig 3 illustrates the soft handover process in 5G communication, a crucial concept used for seamless evolution of mobile tools connection as of single BS to another while maintaining continuous communication with previous base stations. From the above **Fig 3**, the mobile device with weaker signal strength is immediately handed over 'HO' to the nearest base station 'BS2'. Once the connection with the target base station 'BS2' is stable and reliable, the mobile device completes the handover process by terminating the connection with the previous base station 'BS1'. This process solved the intermittent connectivity issues and improves the stable communication with minimal latency. The algorithm of Wilcoxon signed-rank Gradient descent seamless connectivity method is described as follows, Algorithm 2, described above, outlines the various processing steps involved in Wilcoxon signed-rank Gradient descent seamless connectivity method in a wireless. Number of resource efficient mobile tools is taken as input. For every MN received signal strength is measured. Wilcoxon signed-rank statistical method is employed for analyzing the signal strength with threshold and finds the weak signal strength and strong signal strength mobile devices. Based on this analysis, the algorithm identifies the weak signal strength mobile devices requiring handoff for continuous data communication. Subsequently, the nearest base station is identified by measuring the taxicab distance. Finally, handover is executed to transition mobile device as of

single BS to nearby base station. Throughout this process maintains connectivity and improve the data transmission and minimize latency.

Algorithm 2: <u>Wilcoxon signed-rank Gradient descent seamless connectivity method</u>
Input: Number of resource efficient mobile devices $MN_1, MN_2, MN_3 \dots MN_n$, data packets $Dp_1, Dp_2, Dp_3, \dots Dp_n$
Output: Improve seamless data communication
Begin
Step 1: Number of resource efficient mobile devices $MN_1, MN_2, MN_3 \dots MN_n$ taken as input
Step 2: For each device MN_i
Step 3: Measure the received signal strength using (8)
Step 4: End for
Step 5: Sort the mobile devices MN_i based on 'RSS'
Step 6: if ($RSS > \beta_{RSS}$) then
Step 7: S returns '+1' indicates strong signal strength
Step 8: else
Step 9: S returns '-1' indicates weak signal strength
Step 10: End if
Step 11: For each mobile device ' MN_i ' <u>with weak</u> signal strength
Step 12: Find nearest base station using (11) (12)
Step 13: Handoff mobile device ' MN_i ' into nearby base station
Step 14: Establish stable communication between the device
Step 15: End for
End

IV. SIMULATION SETUP

Simulation of three different methods namely the proposed MKROWGD models, an existing method referenced as CA with SVM [1], and another method referenced as DLID2DC [2], all conducted using the NS3 simulator. Random Waypoint mobility method is employed to enable device communication, and the simulation duration is set to 100 seconds. To facilitate seamless data communication, the Dynamic Source Routing (DSR) protocol is employed, ensuring optimal data transmission.

Table 1. Simulation Parameters

Simulation parameters	Value
Simulator	NS3
Network area	1100m * 1100m
Number of mobile devices	500
Number of data	1000
Protocol	DSR
Simulation time	100sec
Mobility model	Random Way Point model
Nodes speed	0-20m/s
Communication range of a device	30m
Transmission power	3 <u>dBm</u>
Number of runs	10

V. PERFORMANCE COMPARISON ANALYSES

This section presents a performance comparison of three methods namely MKROWGD models, an existing method referenced as CA with SVM [1], and DLID2DC [2]. Various evaluation metrics are used to assess performance. The analysis of these evaluation metrics is conducted using both **Table 1** and graphical representations.

Data Delivery Rate

It is referred as ratio of number of data correctly received at the destination mobile device to total number of information sent from source mobile device. It is measured as follows:

$$DDR = \sum_{j=1}^m \left[\frac{DP_{received}}{DP_j_{sent}} \right] * 100 \quad (13)$$

Where DDR indicates a data delivery rate, $DP_{received}$ represents the data correctly received at the destination mobile device and DP_j_{sent} denotes a number of information sent as of source mobile device a calculated in percentage (%).

Data Loss Rate

It is described as ratio of number of information lost at the destination mobile device to total number of information sent from source mobile device. It is measured as follows,

$$DLR = \sum_{j=1}^m \left[\frac{DP_{lost}}{DP_j_{sent}} \right] * 100 \quad (14)$$

Where DDR indicates a data delivery rate, DP_{lost} represents the data lost at the destination mobile device and DP_j_{sent} denotes a number of information sent as of source mobile device a calculated in percentage (%).

Throughput

Is rate of successful information transmission over network in certain period. It is calculated in megabits per second (Mbps), depending on scale of network. Higher throughput indicates a greater amount of data successfully transmitted within a specific time frame, reflecting the efficiency and capacity of the network.

$$TP = \left[\frac{Succ_Trans_data (Mb)}{time (s)} \right] \quad (15)$$

Where, TP denotes a throughput, $Succ_Trans_data (Mb)$ denotes a successful transmission of data in Mb in one seconds (Mbps).

Latency

Latency in networking refers to time takes for information packet to travel as of source to destination transversely a network. Lower latency leads to faster data transfer.

$$LC = |Time_S - Time_{DS}| \quad (16)$$

Where, LC denotes a latency, $Time_S$ denotes a time of data to travel from the source, $Time_{DS}$ denotes a time of data received at the destination. It is calculated in milliseconds (ms).

Energy Efficiency

It is referred as quality of being capable to carry out data broadcast tasks effectively with no wasting time. Energy efficiency is defined as ratio of number of information received to number of information sent. It is calculated in percentage. It is expressed as,

$$EnergyEfficiency = \frac{Numberofdatareceived}{Numberofdatasent} * 100 \quad (17)$$

Where, efficiency level of each technique is calculated. When efficiency is superior, technique is more effective **Table 2** shows Comparison of DDR.

Table 2. Comparison of DDR

Number of data	DDR (%)		
	MKROWGD	CA with SVM	DLID2DC
100	92	86	89
200	92.5	87.5	90
300	91.66	86.66	88.66
400	92.75	86.25	89
500	92.6	86.6	88.8
600	92.66	85.16	87.5
700	91.71	87.85	89.28
800	92	87.62	89.37
900	92.88	87.22	89.44
1000	92.2	86.6	88.6

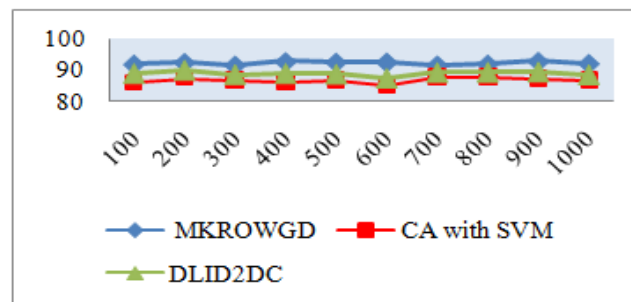
**Fig 4.** Graphical Representation of DDR.

Fig 4 illustrates the simulation analysis showing the DDR plotted against the number of information sent as of the source node. Data delivery rate is measured using three methods namely proposed MKROWGD method, CA with SVM [1], and DLID2DC [2]. According to **Fig 4**, DDR of MKROWGD method exhibits important development in DDR performance analysis compared to other techniques. This improvement is achieved because of relevance of the multivariate kernel regressive Opportunistic diversity scheduling for identifying resource efficient mobile device. For every mobile device, different resources namely energy and bandwidth are measured. Then, the piecewise radial kernel regression function examine these resources through a threshold. Depend on this analysis, mobile devices with better resource efficiency are selected to improve data delivery. A total of ten runs were conducted for each method, and the results were compared. The comparison reveals that DDR of MKROWGD method is significantly enhanced by 6% and 4% than the [1],[2].

Table 3. Comparison of DLR

Number of data	DLR (%)		
	MKROWGD	CA with SVM	DLID2DC
100	8	14	11
200	7.5	12.5	10
300	8.33	13.33	11.33
400	7.25	13.75	11
500	7.4	13.4	11.2
600	7.33	14.83	12.5
700	8.28	12.14	10.71
800	8	12.37	10.62
900	7.11	12.77	10.55
1000	7.8	13.4	11.4

Simulations outcomes of DLR are illustrated in **Fig 5** for three dissimilar methods. As depicted in **Fig 5**, data loss rate of the proposed outperforms others by achieving a significantly lower data loss rate during the transmission source to the destination mobile device in 5G network. This is because of the MKROWGD method efficiently select energy-efficient sensor nodes for data transfer. Additionally, ensures higher bandwidth availability which further enhances data delivery and reduces data loss. Considering 100 data, MKROWGD method achieved a data loss rate of 8%, whereas existing methods [1] and [2] obtained 14% and 11%, respectively. Similarly, different performances were observed across all methods. The results of the MKROWGD method are compared to conventional techniques. Average of ten outcomes shows MKROWGD method reduces data loss rate by 42% and 30% than the [1],[2] **Table 3** shows Comparison of DLR.

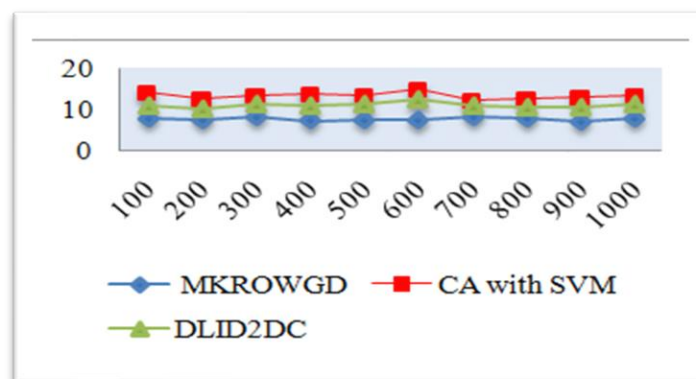


Fig 5. Graphical Representation of DLR.

Table 4. Comparison of Throughput

Data size (MB)	Throughput (Mbps)		
	MKROWGD	CA with SVM	DLID2DC
1000	256	189	212
2000	478	278	369
3000	689	452	578
4000	758	574	698
5000	812	678	752
6000	1045	789	956
7000	1236	944	1065
8000	1489	1056	1236
9000	1865	1278	1412
10000	2356	1565	1745

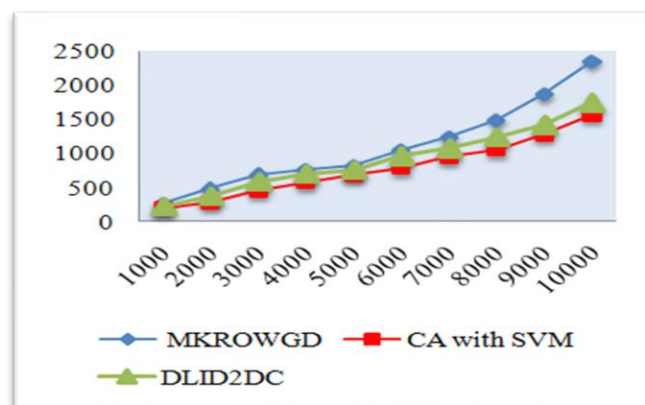
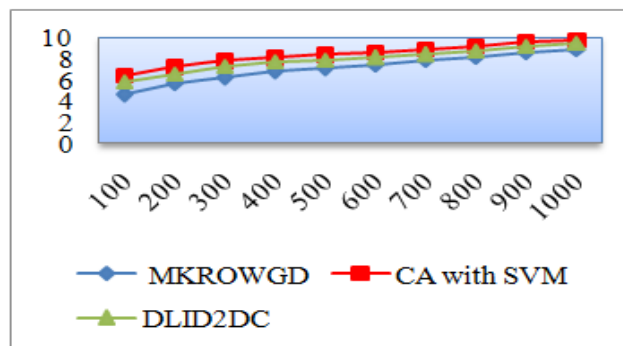


Fig 6. Graphical Representation of Throughput.

Fig 6 illustrates simulation results of throughput versus the size of the data being sent as of source to destination mobile device. Size of the data packet varies from 1000MB to 10000MB. Along with obtained outcomes, MKROWGD technique increased throughput performance. Let's consider a data size of 1000MB transmitted from the source node. By applying the MKROWGD method, 256MB of data is delivered to the destination device. In comparison, the throughput of [1] and [2] was found to be 189Mbps and 212Mbps, respectively. Various throughput results were obtained and compared. The comparison indicates that the MKROWGD method increases throughput by 41% and 22% than the [1],[2]. This enhancement is achieved due to application of Wilcoxon signed-rank Gradient Descent method. This statistical method is employed to measure the received signal strength of mobile devices, enhancing connectivity during data transmission. Mobile devices with weak signal strength require handoff for continuous data communication. Consequently, the nearest base station is identified, and the mobile device is handed over from one base station to the nearby base station to maintain connectivity and improve data transmission throughput **Table 4** shows Comparison of Throughput.

Table 5. Comparison of Latency

Number of data	Latency (ms)		
	MKROWGD	CA with SVM	DLID2DC
1000	4.6	6.4	5.8
2000	5.7	7.2	6.6
3000	6.2	7.8	7.3
4000	6.8	8.1	7.7
5000	7.1	8.4	7.9
6000	7.4	8.6	8.1
7000	7.9	8.9	8.4
8000	8.2	9.2	8.8
9000	8.6	9.6	9.2
10000	8.9	9.8	9.5

**Fig 7.** Graphical Representation of Latency.

The results illustrated in **Fig 7** above depict the simulation outcomes of latency in data transmission. According to the observed results, the proposed MKROWGD method demonstrates superior performance in minimizing latency during data transmission in 5G networks compared to conventional methods **Table 5** shows Comparison of Latency. In **Fig 7**, it is evident that latency increases for all three methods as the number of data increases. However, the MKROWGD method exhibits minimized latency during data broadcast as of source to destination. In a simulation involving 100 data, the MKROWGD method consumed 4.6ms latency, while existing methods [1] and [2] consumed 6.4ms and 5.8ms, respectively. This improvement is achieved by enhancing the connectivity between mobile devices to ensure seamless information transmission. Received signal strength of mobile devices is continuously monitored, and the soft handover process is executed when the mobile device goes beyond the signal strength threshold. This process minimizes the latency of data communication in 5G networks. The observed results validate the superiority of the proposed MKROWGD method compared to conventional techniques. Average comparison outcomes indicate latency in data broadcast is minimized with MKROWGD method by 16% and 11% than the [1],[2].

Table 6. Comparison of Energy Efficiency

Number of data	Energy efficiency (%)		
	MKROWGD	CA with SVM	DLID2DC
100	90	82	86
200	92.45	84.38	87.58
300	92.65	84.55	88.11
400	94.24	86.43	88.98
500	94.75	86.88	89.11
600	95.55	87.47	89.62
700	96.42	88.63	90.35
800	96.51	88.89	91.65
900	97.11	90.44	92.34
1000	97.88	91.11	93.55

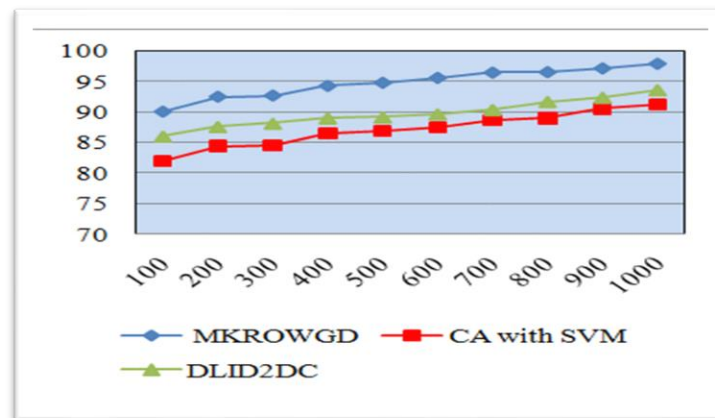


Fig 8. Graphical Representation of Energy Efficiency.

Fig 8 demonstrates simulation outcomes of energy efficiency with amount of data. The data packet is considered to range from 100 to 1000. Let us consider number of data is 200, energy efficiency obtained for proposed MKROWGD method, CA with SVM [1], and DLID2DC [2] is 92.45%, 84.38%, and 87.58%, respectively. When the number of data gets increased, the efficiency gets increased correspondingly. This is due to the application of the MKROWGD method efficiently choosing energy-efficient sensor nodes for data transfer. In this way, efficiency gets improved. A total of ten iterations were estimated with each method. The average of ten results shows that the MKROWGD method improves energy efficiency by 9% and 6% than the [1],[2] **Table 6** shows Comparison of Energy Efficiency.

VI. CONCLUSION

5G mobile communications are destined to deliver elevated data rates, minimum latency, seamless connectivity. To achieve this promise and provide a better experience, a novel MKROWGD method is employed. Initially, the MKROWGD method undergoes Multivariate Kernel Regressive Opportunistic Diversity Scheduling for resource analysis during data transmission, resulting in improved data delivery and minimized data loss. Subsequently, the Wilcoxon signed-rank Gradient Descent method is employed in 5G mobile communications to maintain stable connectivity by applying the soft handover technique. This helps enhance the throughput of data transmission and minimize latency. The paper conducts a comprehensive simulation evaluation using various metrics such as DDR, DLR, throughput, and latency. Statistical analysis confirms that the MKROWGD method outperforms existing methods, achieving a higher delivery rate while also minimizing loss rate during data transmission. Furthermore, the MKROWGD method proves to be efficient in minimizing latency and increasing throughput for efficient data communication in 5G networks compared to existing approaches.

CRedit Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Ramasamy G and Chandrasekar C; **Methodology:** Ramasamy G; **Software:** Chandrasekar C; **Data Curation:** Ramasamy G; **Writing- Original Draft Preparation:** Ramasamy G and Chandrasekar C; **Visualization:** Ramasamy G; **Investigation:** Chandrasekar C; **Supervision:** Ramasamy G; **Validation:** Chandrasekar C; **Writing- Reviewing and Editing:** Ramasamy G and Chandrasekar C; All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest

Data Availability Statement

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Funding

No funding agency is associated with this research.

Consent to publish

All the authors gave permission to Consent to publish.

Reference

- [1]. S. Mathur, Y. Chaba, and A. Noliya, "Performance Analysis of Support Vector Machine Learning Based Carrier Aggregation Resource scheduling in 5G Mobile Communication," *Procedia Computer Science*, vol. 218, pp. 2776–2785, 2023, doi: 10.1016/j.procs.2023.01.249.

- [2]. S. Mishra, “Artificial Intelligence Assisted Enhanced Energy Efficient Model for Device-to-Device Communication in 5G Networks,” *Human-Centric Intelligent Systems*, vol. 3, no. 4, pp. 425–440, Sep. 2023, doi: 10.1007/s44230-023-00040-4.
- [3]. V. Sridhar, T. Annamani, M. Renuka, V. V. Kumar, and A. Madupu, “Bagging ensemble mean-shift Gaussian kernelized clustering based D2D connectivity enabled communication for 5G networks,” *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 7, p. 100400, Mar. 2024, doi: 10.1016/j.prime.2023.100400.
- [4]. Y. He et al., “D2D-V2X-SDN: Taxonomy and Architecture Towards 5G Mobile Communication System,” *IEEE Access*, vol. 9, pp. 155507–155525, 2021, doi: 10.1109/access.2021.3127041.
- [5]. K. Kousias et al., “Empirical performance analysis and ML-based modeling of 5G non-standalone networks,” *Computer Networks*, vol. 241, p. 110207, Mar. 2024, doi: 10.1016/j.comnet.2024.110207.
- [6]. S. Rostami, K. Heiska, O. Puchko, K. Leppanen, and M. Valkama, “Novel Wake-up Scheme for Energy-Efficient Low-Latency Mobile Devices in 5G Networks,” *IEEE Transactions on Mobile Computing*, vol. 20, no. 4, pp. 1511–1528, Apr. 2021, doi: 10.1109/tmc.2020.2964218.
- [7]. S. Schwarzmann, C. C. Marquezan, R. Trivisonno, S. Nakajima, V. Barriac, and T. Zinner, “ML-Based QoE Estimation in 5G Networks Using Different Regression Techniques,” *IEEE Transactions on Network and Service Management*, vol. 19, no. 3, pp. 3516–3532, Sep. 2022, doi: 10.1109/tnsm.2022.3179924.
- [8]. M. S. Dahal, “Energy saving in 5G mobile communication through traffic driven cell zooming strategy,” *Energy Nexus*, vol. 5, p. 100040, Mar. 2022, doi: 10.1016/j.nexus.2022.100040.
- [9]. A. Laguidi, T. Hachad, and L. Hachad, “Mobile network connectivity analysis for device to device communication in 5G network,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, p. 680, Feb. 2023, doi: 10.11591/ijece.v13i1.pp680-687.
- [10]. S. A. Khan, I. Shayea, M. Ergen, and H. Mohamad, “Handover management over dual connectivity in 5G technology with future ultra-dense mobile heterogeneous networks: A review,” *Engineering Science and Technology, an International Journal*, vol. 35, p. 101172, Nov. 2022, doi: 10.1016/j.jestech.2022.101172.
- [11]. J. Sanyal and T. Samanta, “Game Theoretic Approach to Enhancing D2D Communications in 5G Wireless Networks,” *International Journal of Wireless Information Networks*, vol. 28, no. 4, pp. 421–436, Aug. 2021, doi: 10.1007/s10776-021-00531-w.
- [12]. L. Mei, J. Gou, Y. Cai, H. Cao, and Y. Liu, “Realtime mobile bandwidth and handoff predictions in 4G/5G networks,” *Computer Networks*, vol. 204, p. 108736, Feb. 2022, doi: 10.1016/j.comnet.2021.108736.
- [13]. S. Sriharan, H. Weligampola, and H. Gacanin, “A Study on Deep Learning for Latency Constraint Applications in Beyond 5G Wireless Systems,” *IEEE Access*, vol. 8, pp. 218037–218061, 2020, doi: 10.1109/access.2020.3040133.
- [14]. M. Malekzadeh, “Performance prediction and enhancement of 5G networks based on linear regression machine learning,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2023, no. 1, Aug. 2023, doi: 10.1186/s13638-023-02282-z.
- [15]. J. Kaur, M. A. Khan, M. Iftikhar, M. Imran, and Q. Emad Ul Haq, “Machine Learning Techniques for 5G and Beyond,” *IEEE Access*, vol. 9, pp. 23472–23488, 2021, doi: 10.1109/access.2021.3051557.
- [16]. M. McClellan, C. Cervelló-Pastor, and S. Sallent, “Deep Learning at the Mobile Edge: Opportunities for 5G Networks,” *Applied Sciences*, vol. 10, no. 14, p. 4735, Jul. 2020, doi: 10.3390/app10144735.
- [17]. S. Hashima, B. M. ElHalawany, K. Hatano, K. Wu, and E. M. Mohamed, “Leveraging Machine-Learning for D2D Communications in 5G/Beyond 5G Networks,” *Electronics*, vol. 10, no. 2, p. 169, Jan. 2021, doi: 10.3390/electronics10020169.
- [18]. W. Tashan, I. Shayea, S. Aldirmaz-Colak, O. A. Aziz, A. Alhammadi, and Y. I. Daradkeh, “Advanced Mobility Robustness Optimization Models in Future Mobile Networks Based on Machine Learning Solutions,” *IEEE Access*, vol. 10, pp. 111134–111152, 2022, doi: 10.1109/access.2022.3215684.
- [19]. S. A. Saad, I. Shayea, and N. M. O. Sid Ahmed, “Artificial intelligence linear regression model for mobility robustness optimization algorithm in 5G cellular networks,” *Alexandria Engineering Journal*, vol. 89, pp. 125–148, Feb. 2024, doi: 10.1016/j.aej.2024.01.014.
- [20]. X. Wu and C. Wu, “CLPREM: A real-time traffic prediction method for 5G mobile network,” *PLOS ONE*, vol. 19, no. 4, p. e0288296, Apr. 2024, doi: 10.1371/journal.pone.0288296.
- [21]. Y. Chen, “Application of 5G Mobile Communication Technology Integrating Robot Controller Communication Method in Communication Engineering,” *Journal of Robotics*, vol. 2023, pp. 1–9, Apr. 2023, doi: 10.1155/2023/1857590.
- [22]. K. Kaur, S. Kumar, and A. Baliyan, “5G: a new era of wireless communication,” *International Journal of Information Technology*, vol. 12, no. 2, pp. 619–624, May 2018, doi: 10.1007/s41870-018-0197-x.
- [23]. W. Zhao, M. Wang, and R. Othman Yahya, “Data traffic reduction for D2D communications in 5G networks using a multilink approach,” *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 9, p. 101759, Oct. 2023, doi: 10.1016/j.jksuci.2023.101759.
- [24]. A. Sultana, I. Woungang, A. Anpalagan, L. Zhao, and L. Ferdouse, “Efficient Resource Allocation in SCMA-Enabled Device-to-Device Communication for 5G Networks,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5343–5354, May 2020, doi: 10.1109/tvt.2020.2983569.
- [25]. F. Nizam et al., “Efficient radio resource allocation scheme for 5G networks with device-to-device communication,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 6, p. 5588, Dec. 2021, doi: 10.11591/ijece.v11i6.pp5588-5600.
- [26]. A. Margaris, I. Filippas, and K. Tsagkaris, “Hybrid Network-Spatial Clustering for Optimizing 5G Mobile Networks,” *Applied Sciences*, vol. 12, no. 3, p. 1203, Jan. 2022, doi: 10.3390/app12031203.
- [27]. S. Yang, “A joint optimization scheme for task offloading and resource allocation based on edge computing in 5G communication networks,” *Computer Communications*, vol. 160, pp. 759–768, Jul. 2020, doi: 10.1016/j.comcom.2020.07.008.
- [28]. M. Alnabhan, S. Al-Jaafreh, A. Abadleh, M. Atoum, A. Hammouri, and M. Al-dalahmeh, “Enhanced D2D Communication Model in 5G Networks,” *International Journal of Computing and Digital Systems*, vol. 10, no. 1, pp. 217–222, Feb. 2021, doi: 10.12785/ijcds/100122.
- [29]. A. Laguidi, T. Hachad, and L. Hachad, “Mobile network connectivity analysis for device-to-device communication in 5G network,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, p. 680, Feb. 2023, doi: 10.11591/ijece.v13i1.pp680-687.
- [30]. M. I. Goh et al., “Handover Decision-Making Algorithm for 5G Heterogeneous Networks,” *Electronics*, vol. 12, no. 11, p. 2384, May 2023, doi: 10.3390/electronics12112384.

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