AI-Powered Deep Agentic Model for Resource Efficient Seamless Data Communication in 5G Networks

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Abstract **5G is an ultra-high-speed, low-latency, and reliable wireless communication systems. The rapid explosion of mobile devices in 5G network, integrated with the exponential growth of data traffic. As a result, it faces significant challenges in seamless connectivity while ensuring high-quality service delivery. The initiation of 5G technology demands major improvements in handover approach to ensure seamless connectivity and optimal performance in mobile networks. In 5G mobile networks, frequent and unnecessary handovers have emerged as a significant challenge, particularly for mobile devices based on cellular data and exhibiting complex mobility patterns. To address this issue, a novel LAplace KErnelized Regressive Agentic AI (LAKER-AAI) model is developed by statistical distribution functions. By accurately modeling user mobility and network behavior, the proposed agentic AI model dynamically adjusts handover parameters to enhance the seamless data communication. This enhances the efficiency, increased connection speed, low latency, and throughput of handovers under varying network conditions. Agentic AI model called deep reinforcement learning model is employed for analyzing each device's resources such as energy, bandwidth, memory, and spectrum. Next, identifies resource-efficient devices through the segmented regression model to enhance data delivery and minimize packet loss. Followed by, the connectivity metrics of the selected resource efficient devices is computed based on received signal strength and SINR and RSRP. Using this analysis, Laplace kernel is employed to identify better and poor connectivity of the devices. Finally, Weighted Fair Queuing handover mechanism is employed for efficient handover to maintain seamless communication. Then Agentic AI model assigns the rewards for identifying the successful handover. Finally, resource-efficient seamless communication is achieved. The performance of the proposed LAKER-AAI model is evaluated using various metrics, including energy efficiency, spectrum efficiency, handover success rate, data delivery rate, data loss, throughput, and handover latency. Quantitative results reveal that the LAKER-AAI model significantly enhances seamless communication in 5G networks, achieving higher throughput, lower latency, and packet loss compared to existing methods.**

***Keywords*: 5G network, Seamless communication, agentic AI, segmented regression model, Laplace kernel, Weighted Fair Queuing handover mechanism**

I. INTRODUCTION

The 5G wireless communication technology is designed to deliver ultra-fast data speeds, minimal latency, and massive device connectivity. In 5G networks, seamless connectivity refers to the uninterrupted and reliable data communication across different network cells or geographical regions. Maintaining a continuous connection without packet loss, delay, or service interruption plays a major role for delivering ultra-low latency and high reliability. To achieve seamless connectivity, 5G systems implement advanced handover mechanisms, and AI-driven mobility management to predict user movement, assess signal quality, and ensure smooth transitions between base stations. These mechanisms work together to maintain a stable and efficient link by changing network conditions.

A deep learning-based model known as DLID2DC was proposed in [1] to enhance device-to-device (D2D) communication by increasing throughput, optimizing energy usage, and reducing transmission delay. However, the model did not consider the signal strength of mobile devices for enhancing connectivity and further reducing communication latency. A distributed Q-learning-based reinforcement learning (RL) approach was introduced in [2] for dynamic device-to-device (D2D) communication. This designed approach achieved notable improvements in both energy and spectrum efficiency and reduced latency. However, the method lacked integration with an AI-powered deep learning framework to handle interference more effectively.

An Adaptive Handover Optimization (AHO) model was developed in [3] with the aim of increasing the data delivery through the efficient handover and achieved high Handover Probability. However, resource optimization remained a major concern for achieving seamless data delivery. A velocity-aware-fuzzy logic controller-weighted model was designed in [4] for achieving the Handover Optimization within Future Mobile Heterogeneous Network. However, the model failed to consider energy efficiency. In order to improve the energy efficiency and throughput, a novel hybrid manta ray foraging with chef-based optimization (HMRFCO) algorithm was designed in [5] for efficient relay selection and resource allocation. However, ensemble-based deep learning approach was not introduced to extend the coverage area, increase the Energy Efficiency, and throughput.

A State-Action-Reward-State- Action (SARSA)-based reinforcement learning (RL) method was introduced in [6] for device-to-device cellular communication based on resource allocation. However, the method did not examine other networking factors, such as user mobility in cellular communication. A deep learning with statistical learning model were developed in [7] for device-to-device communications within the dynamic network environment. However, the model was not applied to high-mobility scenarios and rapidly changing channel conditions. A machine learning (ML) based resource allocation framework was developed in [8] for guaranteeing fairness and minimizing interference. However, the integration of a deep reinforcement learning model to improve distributed deployments was not considered. A graph neural networks (GNNs)-based reinforcement learning (RL) was introduced in [9] for efficient device-to-device communication by minimizing the delay and packet loss. However, advanced machine learning techniques were not implemented to optimize resource allocation in next generation wireless networks. An integration of Double Deep Q-Network with LSTM model was developed in [10] to increase the spectrum efficiency and user connectivity within the dynamic wireless networks. However, the model was not tested for scalability across varied network topologies, resulting in higher computational complexity. AI-Driven Handover Management model was developed in [11] based on load balancing optimization. However, the approaches did not improve computational efficiency while reducing power consumption in AI-driven network operations. A Heterogeneous Network (HetNet) model was developed in [12] for D2D communication by achieving high energy efficiency and throughput. However, the mobility of the device and the system performance was not analyzed. A convolutional neural network was developed in [13] for efficient communication within 5G network through the vertical handover. However, the model did not achieve high throughput with minimal data loss. A deep Q-network (DQN) framework was developed in [14] based on handover management within the ultra-dense 5G networks for network optimization and interference reduction. However, avoiding unnecessary handovers in high-density networks remained a major concern. A predictive handover method was introduced in [15] using reinforcement learning algorithm for mobile communication within the dynamic network conditions. However, context-aware resource management and multi-connectivity were not considered, to further enhance overall mobility AND QUALITY OF SERVICE IN NEXT-GENERATION MOBILE NETWORKS.

A. Key contribution

The key contributions of the LAKER-AAI model are listed as follows,

- Design a LAKER-AAI model to solve resource optimized seamless data delivery in wireless network by employing an Agentic AI model.
- To simultaneously improve energy efficiency and optimize spectrum utilization, a segmented regression method is employed to identify mobile devices that offer efficient resource consumption. These chosen devices are then utilized in the communication process, leading to enhanced data delivery and a reduction in packet loss.
- To enhance the handover success rate and minimize the latency, Laplace kernel is employed for analyzing the signal strength of each mobile device and identifies the poor connectivity. A weighted fair queuing handover mechanism is applied for efficient handover to maintain seamless communication leading to increase the throughput.

- To reduce the probability of unnecessary handovers, the Agentic AI model evaluates handover events and incorporates a reward-based mechanism within its Q-value assessment framework. Specifically, the model assigns a positive reward when a handover decision leads to improved connectivity performance. This reinforcement learning approach enables the AI agent to learn optimal handover strategies that enhance stability and reduce service interruptions.
- Finally, extensive simulations are conducted to evaluate the performance of LAKER-AAI model and other deep learning models.

B. Paper organizations

The paper is structured into five key sections. Section 2 reviews relevant literature and offers necessary background information. Section 3 details the proposed LAKER-AAI model, including an architectural diagram. Section 4 outlines the simulation analysis. In Section 5, a comparative analysis of various approaches is conducted using multiple performance metrics. Lastly, Section 6 concludes the paper.

C. Related works

A Hybrid Snow Leopard and Dark Forest Algorithm (HSL-DFA) was designed in [16] for significantly increases the network performance for the management of 5G network with high throughput. However, effective resource allocation within 5G HetNets remained a major issue. In [17], an LSTM-based model was introduced to minimize handover latency and enhance throughput by reducing packet loss, thereby improving the more efficient data transmission. However, the model did not address resource optimization. AI-driven framework was introduced in [18] for optimal edge server selection while considering low latency and high throughput. However, only limited data sharing was implemented. A load-based resource sharing approach was designed in [19] for 5G communication systems. However, communication systems did not optimize network resources, leading to reduced throughput and increased latency. In order to reduce the latency during the communication, reinforcement learning-based approach was developed in [20]. However, it failed to address scalability and overhead issues in 5G networks.

A Deep Deterministic Policy Gradient (DDPG) algorithm was designed in [21] using handover parameters for increasing the throughput and low latency. However, did not considering different environmental conditions to deliver improved QoS and mobility management performance. A Deep Reinforcement Learning (DRL) algorithm was proposed in [22] for streaming data transmission. However, resource management and network optimization remained major concerns. A Handover Decision Optimization Method was developed in [23] by applying a Data-Driven multilayer perceptron. However, it did not improve robustness and applicability across diverse network environments. sAn efficient resource management scheme was designed in [24] for achieving the high throughput and minimal latency of communication. However, the data loss was not minimized. A distribution function-driven handover method was designed in [25] for 5G mobile networks aiming to improve the handover efficiency and reliability. However, machine learning techniques were not integrated to enhance the handover performance.

A machine learning model was developed in [26] for 5G mobile networks to predict handovers and achieve the better quality of service with minimal computational complexity. However, it was not possible to optimize resource allocation, reduce computational costs, and improve network utilization while simultaneously enhancing overall quality. Machine learning based Self-Optimization Handover Technique was designed in [27] to enhance the performance. However various network topologies and higher mobility speed scenarios were not considered.

A machine learning-based handover decision model was developed in [28] that incorporate user behavior prediction and workload balancing. However, in energy efficiency performance was not improved. In [29], integration of statistical models, and machine learning algorithms were developed to optimize handovers and reduce latency. Q-Learning algorithm was designed in [30] for enhancing the communication by minimizing the latency. However, achieving high though was major issue.

II. PROPOSED METHODOLOGY

The proposed approach for seamless data communication-based on handover optimization in 5G networks is described, reflecting changes in network conditions and user mobility behavior. This section details the core stages involved in designing and deploying the novel method for Device-to-device (D2D) communication offers notable benefits in terms of spectrum utilization, energy efficiency, overall system capacity, and high data throughput. However, several challenges are addressed before D2D is fully integrated into 5G networks. To address these challenges, a novel model called LAKER-AAI is introduced specifically designed to enhance the communication efficiency, thereby reducing the latency.

The proposed LAKER-AAI model, illustrated in Figure 1, consists of three primary stages namely resource optimization, connectivity and handover strategies. These interconnected stages work together to efficiently improve the Device-to-device (D2D) communication. This section provides an in-depth explanation of the proposed model, including its ability to analyze device resources, and accurately performs the handover strategies to reduce packet loss, prevent service disruption, and ensure consistent quality of service.

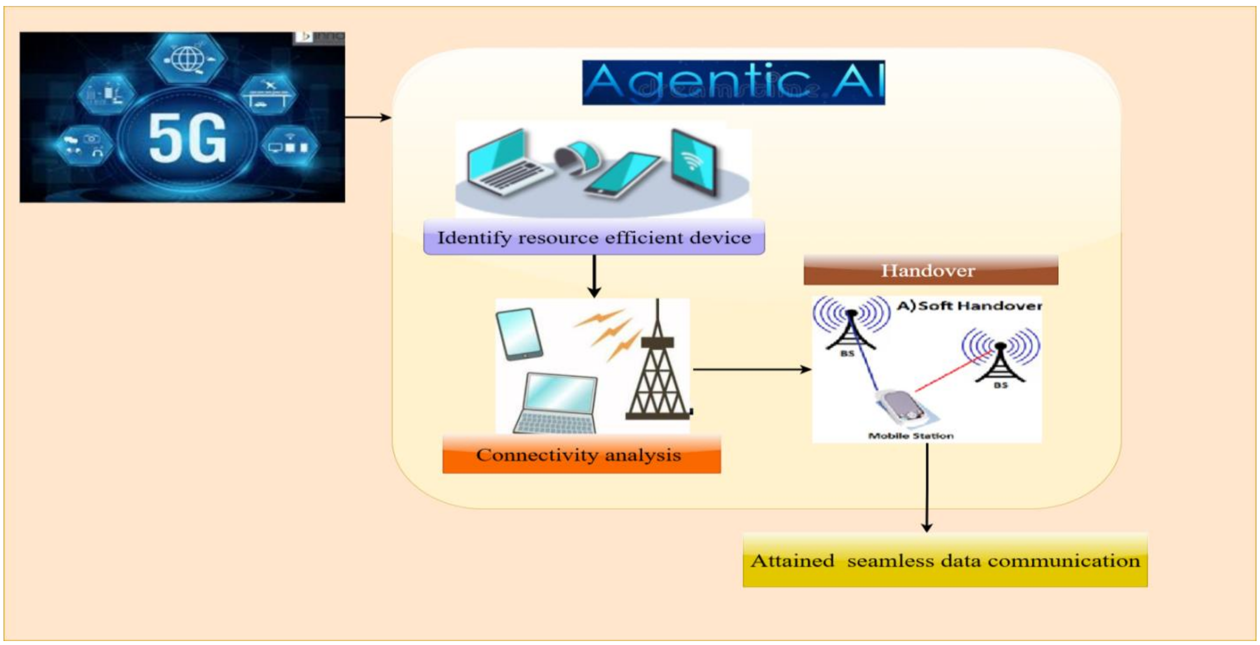

Figure 1: Architecture of proposed LAKER-AAI model

Figure 1 presents the architecture of the proposed LAKER-AAI model, developed to enable data communication within 5G networks. This LAKER-AAI model is structured around three core processes namely identifying resource-efficient devices, analyzing connectivity, and managing handovers. These components are integrated to construct a 5G system that ensures optimal resource allocation and enhanced device connectivity, thereby promoting efficient utilization of network resources and seamless communication. The network model of 5G cellular system consists of mobile devices or nodes $MN_1, MN_2, MN_3 \dots, MN_n$ to ensure seamless communication. The mobility of mobile devices often leads to variations in connection quality, with signal strength weakening as a device moves away from its current base station. To maintain uninterrupted service, the device changeover to a nearby access network using a handover mechanism. Each mobile device communicates through either an access point (AP) or a base station (BS), which is responsible for continuous data transmission. With this system model, the proposed LAKER-AAI model is described in the following subsections.

A. Laplace kernelized regressive agentic ai model

Agentic AI is a type of artificial intelligence models designed to operate autonomously, enabling systems to create decisions and perform predictive tasks without human intervention. In the proposed approach, an Agentic AI framework specifically, a Deep Reinforcement Learning model is developed to train input mobile devices and their resource estimation corresponding to different classes. The structure of the Deep Reinforcement Learning model is illustrated in Figure 2.

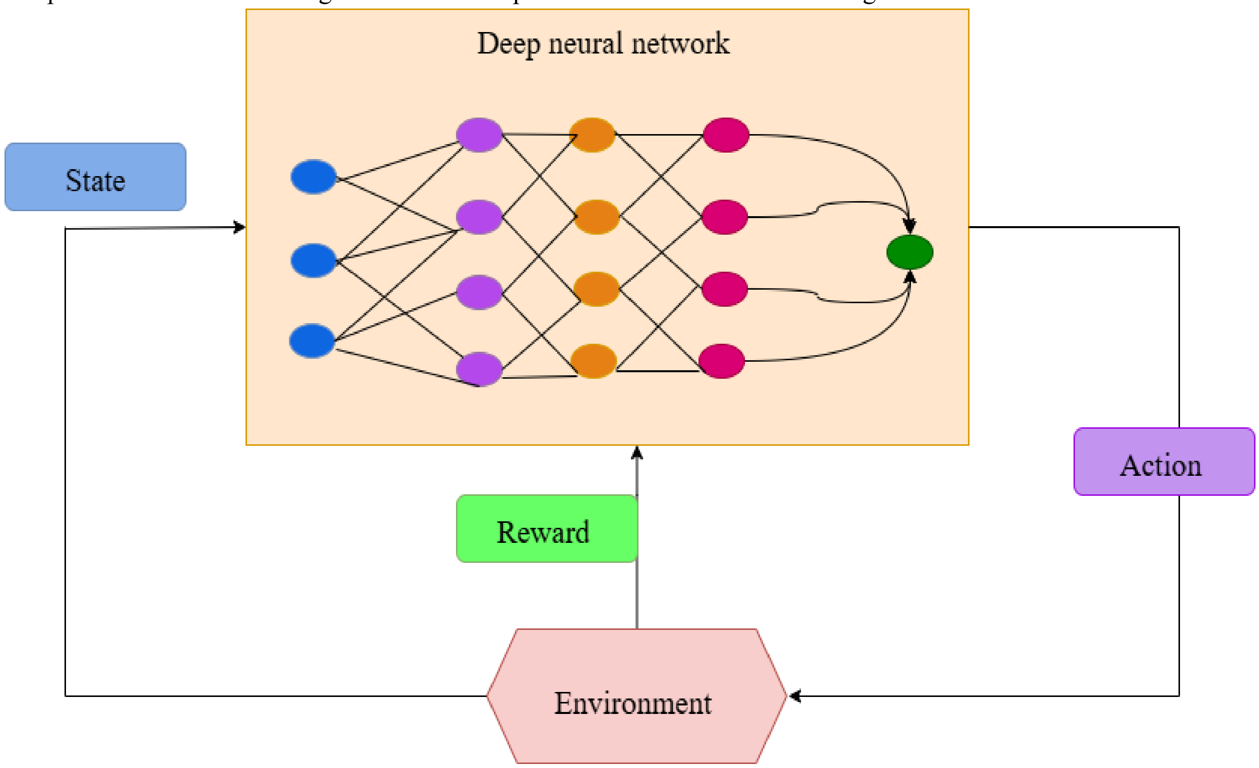

Figure 2: block diagram of the deep reinforcement learning

Figure 2 depicts the block diagram of the Deep Reinforcement Learning (DRL) model designed for accurate detection of resource efficient devices. As shown in figure 2, the system processes input mobile devices or nodes $MN_1, MN_2, MN_3 \dots, MN_n$. Within this framework, the agent leverages a deep neural network to analyze the resources of devices. DRL is a type of deep learning where multiple agents learn optimal decision-making strategies through continuous interaction with their environment. The main objective of reinforcement learning is to enable agents to take the best possible actions based on feedback received in the form of rewards. The initial structure of reinforcement learning consists of five primary components such as the agent, the environment, actions, states, and rewards.

Agent: The agent serves as the decision-making entity that employs with the environment and performs actions based on its observations.

Environment: The environment provides a reward as feedback, directing the agent to increase its prediction over time.

Actions: Actions represent the options existing to the agent for making decisions. These decisions shape the agent path and feedback it obtains from the environment.

States: A state defines the present condition or status of the environment at a given moment.

Rewards: A reward serves as the environment response to an action taken by the agent. It offers positive reinforcement for correct predictions and inaccurate ones with negative feedback.

Initially, the agent in the network model selects the action as prediction tasks by utilizing the deep neural network model.

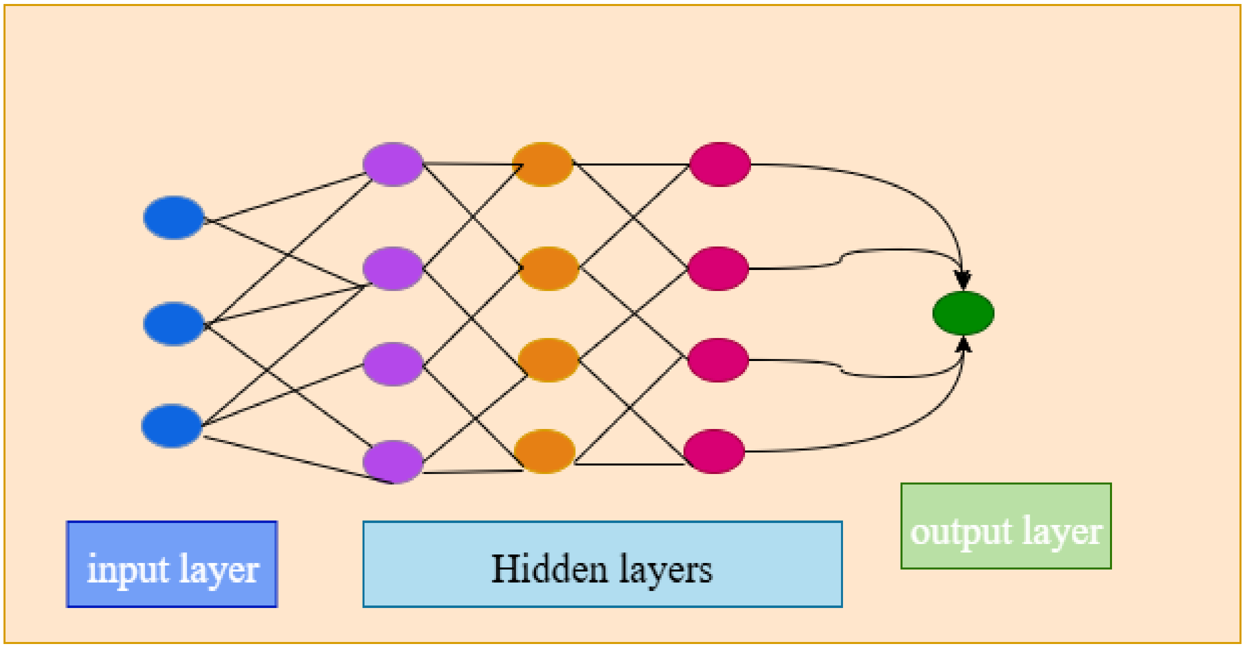

Figure 3: structure of deep neural network

Figure 3 illustrates the architecture of a deep neural network (DNN), which is composed of three main types of layers namely the input layer, numerous hidden layers, and the output layer. The input layer receives the mobile devices within the 5G network. The layers positioned between the input and output layers are known as hidden layers. These layers consist of multiple neurons (also referred to as nodes) that process the input through weighted connections and activation functions. Finally, the output layer generates the prediction results based on the transformations learned throughout the network. The proposed deep neural network considers the training set $\{MN_i, Y_k\}$ where MN_i indicates input mobile devices and Y_k indicates a result.

Each neuron in the input layer receives the mobile devices and transfers it to the hidden layer after applying the relevant weights and biases. In the hidden layer, each neuron determines a weighted sum of inputs as follows,

$$X = \sum_{i=1}^{n} MN_i * \omega_{ih} + b \quad (1)$$

Where, X represents a weighted sum output, MN_i indicates a mobile devices, ω_{ih} denotes a weight between neuron in input layer and hidden layer, and b denotes a bias. By applying deep reinforcement learning, Q-values are first initialized with arbitrary fixed value for each state-action pair.

$$Q: (s, a) \quad (2)$$

Where, Q-values 'Q' initialized with state-action pair(s, a). At each time step, the agent selects an action, obtains a reward from the environment, transitions to a new state, and then updates the corresponding Q-value based on the knowledge.

- *Identification of device with optimal resource utilization*

First, the input mobile devices are transferred into first hidden layer where the resource efficient devices are determined. Initially, the residual energy of the mobile device is measured as follows,

$$RE = E_{MN} - E_T\,(MN_i) \quad (3)$$

Where, RE represents a residual energy of device, E_{MN} denotes a total energy of device, $E_T\,(MN_i)$ represents an energy consumed by each mobile device.

Bandwidth refers to the capacity of a network to transfer data over a given period. It is typically expressed in bits per second (bps), kilobits per second (kbps), megabits per second (Mbps), or gigabits per second (Gbps).

$$BW\,(MN_i) = \left[\frac{\mathrm{D}}{T\ (\mathrm{s})}\right] \quad (4)$$

Where, $BW\,(MN_i)$ represents a bandwidth of a mobile device, D indicates an amount of data transferred over the network (bits, bytes, kilobytes, etc.), T (s) represents a time period in seconds.

Memory in a mobile device plays a vital role in enabling data processing and storage performance. It represents the device's capacity to retain data over the long term, including files such as photos, videos, and applications. In the 5G network, the available memory of a mobile device is calculated as follows,

$$MA = M_{MN} - M_c\,(MN_i) \quad (5)$$

Where, MA refers to a memory availability of mobile device in Giga bytes (GB), M_{MN} indicates an original or total memory of the device, $M_c\,(MN_i)$ represents a memory consumed by mobile device. Spectrum is a critical resource in 5G networks, significantly influencing both network speed and coverage. Higher spectrum availability enables higher data transmission rates and increased capacity, allowing more efficient communication. It is typically measured in bits per second per Hertz (bps/Hz), which reflects the data rate achieved per unit of frequency.

$$S = \frac{DR\ (\text{bps})}{BW\ (Hz)} \quad (6)$$

From (6), S represents a spectrum, DR indicates a channel capacity or data rate in bits per second (bps), BW indicates bandwidth of the channel in hertz (Hz).

Processor speed of the mobile device refers to rate at which the device processer executes instructions.

$$PS = \frac{No.of\ clock\ cycles}{time\ (\text{sec})} \quad (7)$$

Where, PS indicates a processor speed of the mobile device. It is measured in Hertz (Hz), typically Gigahertz (GHz).

$$R(MN) = \{(RE)\&\&(BW)\&\&\,(MA)\&\&(SA)\&\&(PS)\} \quad (8)$$

Segmented regression is a machine learning technique used to describe relationships between independent variables i.e. resources of mobile devices and dependent variables i.e. target output. Followed by which, two segments are made such as resource efficient and resource inefficient generating the following equations.

$$RE_{MN} = \delta_1 . R(MN) + c_1, if\ R(MN) > BP \quad (9)$$

$$RIE_{MN} = \delta_2 . R(MN) + c_2, if\ R(MN) < BP \quad (10)$$

Where,'RE_{MN}' represent the resource efficient of mobile devices 'MN' and their resources '$R(MN)$' via regression coefficient 'δ_1', 'δ_2' and regression constants 'c_1', 'c_2' with respect to breakpoints 'BP' (i.e. threshold). From the analysis, the resource efficient mobile devices 'RE_{MN}' results are observed for further processing. Otherwise, resource inefficient mobile devices 'RIE_{MN}' is not considered for further processing. The resource efficient mobile devices are transferred into the next hidden layer for connectivity analysis.

- *Connectivity metric analysis*

In second hidden layer, connectivity analysis is carried out particularly in dynamic 5G environments for ensuring seamless communication. This connectivity analysis helps to achieve higher throughput and lower latency. Effective connectivity management also minimizes interruptions during handovers. To assess the connectivity performance of a mobile device, three key parameters are considered such as Received Signal Strength (RSS), Signal-to-Interference-plus-Noise Ratio (SINR) and RSRP (Reference Signal Received Power).

Received Signal Strength (RSS) indicates the amount of power present in a wireless signal when it reaches a mobile device. It serves as a center measurement for assessing the reliability and performance of a wireless connection.

$$RSS = p_{Tx} - G_T + G_r + 20\ log_{10}\left(\frac{\lambda}{4\pi D}\right) \quad (11)$$

From (11), RSS represents a received signal strength or power, p_{Tx} indicates a transmitted power in dBm, G_T represents a gain of the transmitting antenna, G_r denotes a receiving antenna gain, λ represents a wavelength of the signal (in meters), D indicates a distance between the mobile device and base station in meter.

Signal-to-Interference-plus-Noise Ratio (SINR) is another important metric used to evaluate the quality of a mobile device's connection. It represents the ratio of the power of the intended signal to the combined power of interference from other signals and background noise. SINR is typically expressed in decibels (dB).

$$SINR = P_r - 10\ log_{\ 10}\,(I + \vartheta_N) \quad (12)$$

From (12), P_r represents as received signal power, 'ϑ_N' denotes a noise power, and 'I' represents the interference power from all nearby base stations. A higher SINR value signifies a stronger and more stable communication link, which is crucial for maintaining high data speeds, low latency, and reliable connectivity in 5G networks.

RSRP (Reference Signal Received Power) is defined as the average strength the reference signal received by the device's antenna. It serves as an important indicator of the quality of the radio link between the device and its connected cell.

$$RSRP = \frac{1}{m}\sum_{j=1}^{m} P_j \quad (13)$$

$$RSRP\ (dBm) = 10log_{10}\ RSRP (14)$$

From (13), P_j denotes a Power of the j^{th} reference signal resource element, m denotes a total number of reference signal resource elements considered. It measured in terms of dBm stands for decibel-milliwatts. The estimated connectivity metric or signal metric is transferred to another hidden layer for executing the handover.

- *Weighted Fair Queuing handover mechanism*

The mobile device plays an active role by periodically measuring and reporting key connectivity metric such as RSRP, SINR, and RSS. These reports include measurements from both the serving base station and neighboring base station, allowing the network to evaluate the quality of the current connection and detect stronger or more stable alternatives. Based on these measurements, the serving base station evaluates whether a handoff is necessary based on Laplace kernel function.

The Laplace kernel is a type of radial basis function (RBF) kernel used to measure similarity between connectivity metric and their threshold value. Based on kernel, handoff decision is taken by base station.

$$K = \exp\left[\sum_{j=1}^{m} - \left(\frac{|C_M - T_{CM}|}{D}\right)\right] (15)$$

Where, K represents a Laplace kernel, C_M indicates a connectivity metrics, T_{CM} indicates a threshold for connectivity metrics, D symbolizes deviation. The Laplace kernel function returns the output from 0 to 1. Based on kernel output, the connection quality is determined as given below,

$$K = \begin{cases} 1, & better\ connection\ quality \\ 0, & poor\ connection\ quality \end{cases} \quad (16)$$

The kernel 'K' provides the output as 1 represents the mobile device has better connection quality and no handoff needed. The output '0' represents the poor connection quality and handoff is triggered to another base station.

Poor connectivity severely impact communication quality by reducing signal strength and, which in turn minimizes data communication efficiency. This degradation often leads to increased packet loss and higher latency. To address this issue, Weighted Fair Queuing handover mechanism is employed. This allows a device with weak connectivity is switched from its current base station to a neighboring one offering stronger signal quality. This process helps to maintain uninterrupted connectivity and enhances overall network performance.

Queuing based handover mechanism is designed to manage congestion by handling numerous handover requests in base station. First the number of handover requests $HR_p \in HR_1, HR_2, HR_3, \dots HR_b$ is considered as input to the queuing model. Then compute the weighted score for each request based on computed metrics such as RSRP, SINR, and RSS.

$$WC = \alpha_1.\left(\frac{1}{\text{RSRP}}\right) + \alpha_2.\left(\frac{1}{\text{SINR}}\right) + \alpha_3.\left(\frac{1}{\text{RSS}}\right) \quad (17)$$

Where, WC denotes a weighted score of each handoff request, $\alpha_1, \alpha_2, \alpha_3$ indicates a weights. Based on score value, the handoff requests are prioritized and stored in queue. The requests with higher score are prioritized first than those with lower weights. In this way, the requests are prioritized and stored in queue. After that, each request in the high-priority is switched to nearby base station, which minimizes network congestion across networks. This approach aims to enhance data transmission efficiency and minimize latency and packet loss effectively. Finally, the handover results are observed at the output layer.

Depending on the handover outcomes, the environment provides a reward that serves as feedback for the agent's actions. This feedback enables the agent to reduce the unwanted handovers. When the agent makes a correct handover, it is rewarded positively, whereas unwanted handover result in negative rewards. Based on these rewards, the initial Q-value gets updated to reflect the effectiveness of the action taken in that particular state. The Q-value is updated accordingly based on the rewards observed from the environment as follows.

$$Q_{t+1}\,(s,a) = Q_t\,(s_t,a_t) + \eta\,[\,\vartheta\,(s_t,a_t) + f.\ max\ Q\,(s_{t+1},a_t) - Q_t\,(s_t,a_t)] \quad (18)$$

Where, $Q_{t+1}\,(s,a)$ represents an updated Q-Value, $Q_t\,(s_t,a_t)$ denotes a current Q value, η denotes a learning rate (0< η <1), $\vartheta(s_t, a_t)$ represents a reward observed from environment, f denotes a discount factor includes slightly lesser than 1, $max\ Q\ (s_{t+1}, a_t)$ denotes a maximum Q-value of the next state 's_{t+1}' for a particular action 'a_t', (s_t, a_t) represents a current action and state space respectively. The process repeats for every new state until a predefined maximum number of iterations get reached. Afterward, the final Q-values are used to identify successful handovers, helping to maintain seamless connectivity and enhance overall network performance. The algorithm is described as given below.

// Algorithm 1: Laplace Kernelized Regressive Agentic AI
Input: Number of mobile devices $MN_1, MN_2, MN_3 \dots, MN_n$, data packets $Dp_1, Dp_2, Dp_{3,\dots}Dp_n$
Output: Increase the seamless data delivery ratio
Begin Step 1: For each mobile devices $MN_1, MN_2, MN_3 \dots, MN_n$ Step 2 Initialize Q table with state and action pair (s, a) Step 3: While $(t \ \leq \ max\_t)$ do Step 4: For each pair (s, a) do Step 5: Agent utilizes the deep neural network Step 6: Mobile devices $MN_1, MN_2, MN_3 \dots, MN_n$ given to input layer Step 7: Measure the weighted sum using (1) Step 8: End for Step 9: For each device Step 10: Compute multiple resources RE, $BW\ (MN_i)$, MA,S, PS using (3) (4) (5) (6) (7)--[first hidden layer] Step 11: Formulate regression with estimated resources '$R(MN)$' Step 12: If $(R(MN) > BP)$ then Step 13: Device is said to be resource efficient using (9) Step 14: else if$(R(MN) < BP)$ then Step 15: Device is said to be resource inefficient using (10) Step 16: End if Step 17: For each resource efficient devices– [second hidden layer Step 18: Measure the connectivity metric using (11) (12) (14) Step 19: End for Step 20: For each device with connectivity analysis Step 21: Apply kernel function using (15) Step 22: if $(K = 1)$ then Step 23: Devices have better connectivity Step 24: else Step 25: Devices have poor connectivity Step 26: End if Step 27: For each device with poor connectivity---- [third hidden layer] Step 28: Initiate the Handover requests Step 29: End for Step 30: For each Handover request Step 31: Compute the weighted score 'HR_p' using (17) Step 32: Assign priority to request and stored into queue Step 33: End for Step 34: For each request in high priority queue Step 35: Switched device from current to new base station Step 36: End for Step 37: For each handover

Step 38: Assign reward
Step 39: Update the Q value '$Q_{t+1}(s,a)$' using equation (18)
Step 40: Increment t=t+1
Step 41: Go to step 3 until it converges
Step 42: End while
Step 43: Return (successful handover)
End

Algorithm 1 outlines a Laplace Kernelized Regressive Agentic AI model designed to achieve resource-efficient and seamless data communication in 5G networks. The process begins with the initialization of Q-values for various state-action pairs. The action space includes the number of mobile devices, which are provided as input to the deep neural network's input layer. Each input sample is initialized with weights and biases before transferred to the hidden layers of the network. Within the hidden layers, various resource metrics such as energy, bandwidth, memory, spectrum availability, and processor speed of each mobile device are evaluated. Segmented regression is then applied to identify the most resource-efficient mobile devices. Subsequently, signal strength metrics are computed to estimate the connectivity of the selected devices with the base station. The Laplace kernel is utilized to assess whether the connectivity is strong or weak. For devices exhibiting poor connectivity, a Weighted Fair Queuing (WFQ) handover mechanism is employed to switch to nearby base stations offering better signal quality, thereby reducing congestion. Rewards are then assigned based on the effectiveness of the handover decisions. The Q-values are continuously updated according to the received rewards until the model converges, effectively minimizing unnecessary handoffs. After reached the convergence, the algorithm significantly enhances the overall handover performance, ensuring efficient and reliable data communication in 5G networks.

III. SIMULATION SETUP

This section presents a simulation-based evaluation of the proposed LAKER-AAI model, compared against existing approaches, namely DLID2DC [1], a Q-learning-based reinforcement learning method [2], and AHO [3]. The simulations were conducted using the NS-3 network simulator to evaluate the performance of these techniques. In the simulation environment, a total of 500 mobile devices were randomly distributed within a square area of 1100 by 1100 meters. Device mobility is directed by the Random Waypoint model, which allowed for realistic movement patterns across the defined space. For data transmission, the Dynamic Source Routing (DSR) protocol is implemented to facilitate effective and adaptive communication between the devices in 5G network. Each simulation scenario is executed over a time span of 100 seconds. A comprehensive list of the simulation parameters and their respective configurations is outlined in Table 1.

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 dBm
Number of runs	10

A. Simulation results

This section provides a detailed explanation of the different stages involved in the proposed LAKER-AAI model. Initially, 50 mobile devices or nodes are randomly distributed within an 1100m × 1100 m area, as depicted in Figure 4.

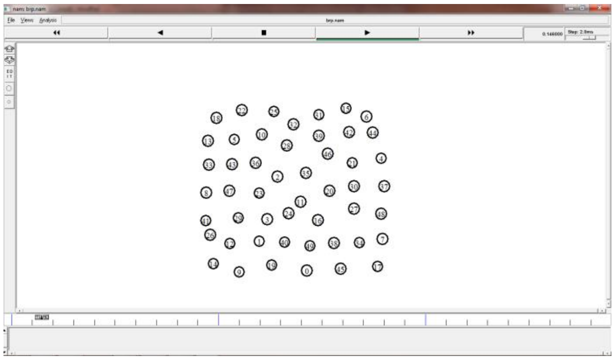

Figure 4: sensor node deployments

Once the mobile devices have been deployed within the designated network area, the data communication is initiated by defining the source and destination nodes, as illustrated in Figure 5.

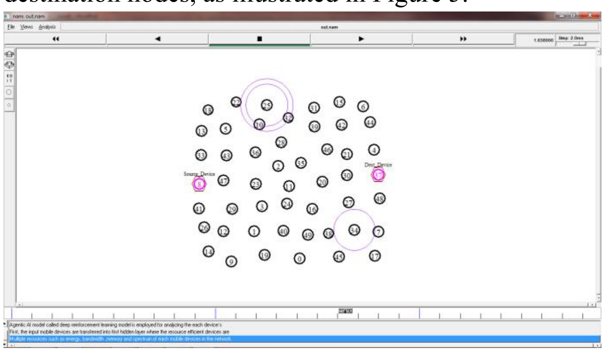

Figure 5: Initialization of source and destination

A deep Agentic AI model is employed to evaluate multiple resources of mobile devices, including residual energy, bandwidth, and memory, spectrum and processor speed. Based on this analysis, the mobile devices are classified according to their resource efficiency using segmented regression as shown in figure 6.

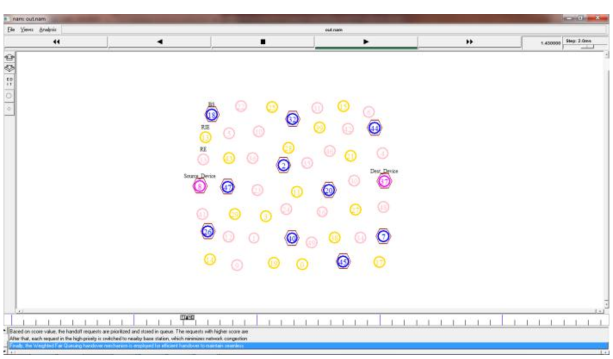

Figure 6: segmented regression based resource efficient node identification

As depicted in Figure 6, the pink colored nodes represent mobile devices that are efficient in terms of resource utilization, whereas the yellow nodes indicate those that are less efficient for resource utilization within the 5G network.

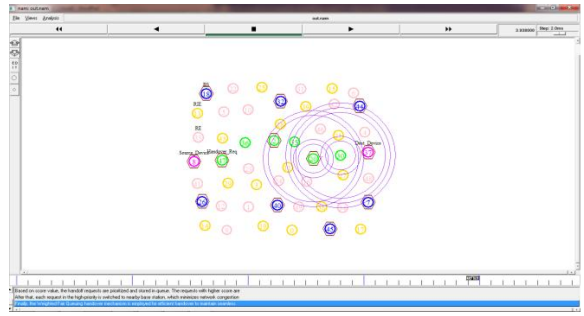

Figure 7: Handover requests arrival

Handover request arrival refers to the process in which a mobile device initiates a request to transfer its ongoing connection from one base station to another. The mobile device periodically reports their connectivity metrics such as RSRP, SINR, and RSS to evaluate the quality of the current connection. This device with poor connectivity is sends a handover requests and it switched from its current base station to a neighboring one offering stronger signal quality. The high priority requests are processed first than other.

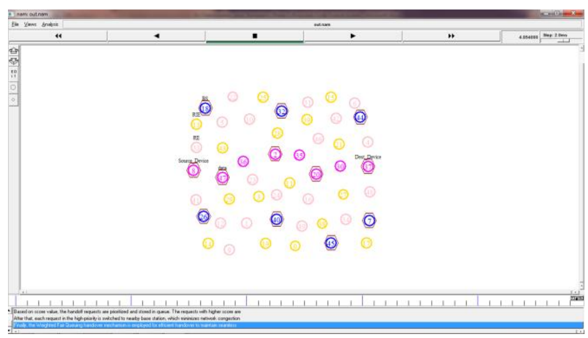

Figure 8: seamless data communication

Once the successful handover achieved, seamless data transmission is carried out to ensure resource efficient and uninterrupted data communication between the source and destination.

IV. PERFORMANCE ANALYSES

This section provides a comparative performance analysis of different approaches namely the proposed LAKER-AAI model, compared against existing approaches, namely DLID2DC [1], a Q-learning-based reinforcement learning method [2], and AHO [3]. The evaluation focuses on a range of performance metrics, including energy efficiency, spectrum utilization, handover success rate, handover latency, handover probability, data delivery rate, data loss, throughput. These metrics are employed to comprehensively assess the effectiveness of each method. The results of the analysis are presented using both tabular data and graphical visualizations for clear interpretation and comparison.

A. Analysis of energy efficiency

Energy efficiency is measured as the ratio of the total amount of data successfully transmitted through the 5G communication channel to the amount of energy consumed. It is calculated using the following formula:

$$EE = \frac{Data\ transmitted\ (MB)}{Energy\ consumed\ (Joule)} \quad (19)$$

From (19), EE denotes energy efficiency. It measured in terms of Mega bytes per joule (MB/J).

Table 2: Energy efficiency versus data size

Data size (MB)	Energy efficiency (MB/J)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO [3]
1000	76.33	63.29	69.93	71.42
2000	77.85	65.33	72.32	74.65
3000	79.63	67.05	74.65	76.84
4000	82.78	68.03	75.02	77.45
5000	84.23	69.12	76.04	78.63
6000	87.31	70.3	78.06	80.96
7000	89.63	71.42	80.12	82.63
8000	91.05	73.06	81.36	84.96
9000	93.45	75.06	82.05	85.78
10000	94.85	77.74	83.62	86.65

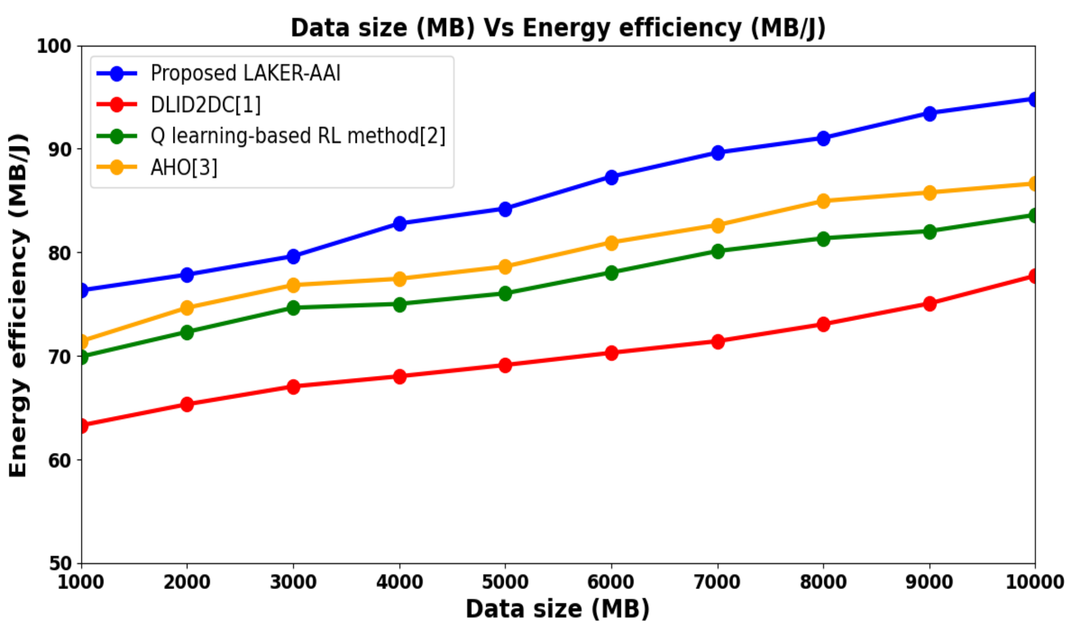

Figure 9: graphical results of energy efficiency

Figure 9 given above presents a comparative analysis of energy efficiency across different approaches, including the proposed LAKER-AAI model, compared against existing approaches, namely DLID2DC [1], a Q-learning-based reinforcement learning method [2], and AHO [3]. Energy efficiency is measured based on varying data sizes ranging from 1000 MB to 10,000 MB. Among four methods, LAKER-AAI model consistently demonstrates superior performance in terms of achieving energy efficiency across all data sizes. For example, at a data size of 1000 MB, the LAKER-AAI model achieves an energy efficiency of 76.33 MB/J, [1], [2], and [3], observed 63.29 MB/J, 69.93 MB/J, and 71.42 MB/J respectively. Finally, the average energy efficiency improvement of the LAKER-AAI model is approximately 22% compared to [1], 11% over LAKER-AAI model [2], and 7% compared to [3]. This enhanced performance is achieved due to the integration of a segmented regression within the deep neural network architecture of the Agentic AI model. This model effectively selects the most resource efficient mobile device for better data transmission, thereby minimizing energy consumption and improving overall system efficiency. The consistent outperformance of the LAKER-AAI model across multiple evaluations highlights improved energy-efficient data transmission.

Analysis of spectrum efficiency It refers to the amount of data transmitted per unit of bandwidth within a communication system. It is determined using the following formula,

$$SE = \frac{Data\ transmitted\ (MB)}{bandwidth\ (Hz)} \quad (20)$$

From (20), SE represents spectrum efficiency. It measured in the unit of Mega bits per Hertz (MB/Hz).

Table 3: spectrum efficiency versus data size

Data size (MB)	Spectrum efficiency (MB/ Hz)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO [3]
1000	29.41	20.83	24.39	26.31
2000	31.52	21.05	26.36	27.45
3000	33.85	22.66	27.05	28.96
4000	34.96	23.04	28.66	30.23
5000	36.87	24.74	30.02	31.85
6000	40.56	25.06	32.78	33.63
7000	42.32	27.65	33.45	35.75
8000	45.78	29.04	36.05	37.85
9000	47.56	31.07	37.24	39.65
10000	51.65	32.45	39.78	41.56

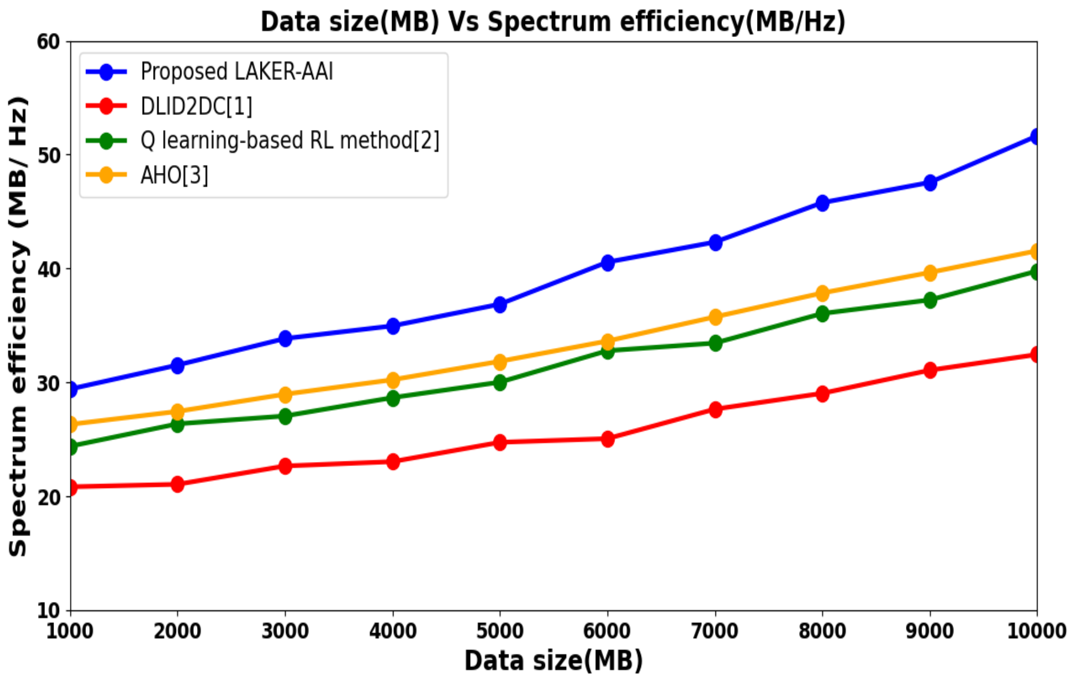

Figure 10: analysis of spectrum efficiency

Figure 10 demonstrates the performance evaluation of spectrum efficiency versus varying data sizes. The x-axis represents data sizes, while the y-axis denotes the corresponding spectrum efficiency. The experimental results clearly demonstrate that the proposed LAKER-AAI model achieves significantly higher spectrum efficiency compared to existing techniques. This improvement is to intelligently identify resource-efficient mobile devices that improve the communication within a 5G environment. This selection process is obtained by a applying a segmented regression in Agentic AI model, which effectively identifies spectrum-efficient mobile devices for data transmission, thereby enhancing overall efficiency. For example, when processing 1000 MB of data during the initial run, the LAKER-AAI model attained a spectrum efficiency of 29.41 MB/Hz. In contrast, the spectrum efficiency for the existing methods DLID2DC [1], Q learning-based RL method [2], and AHO [3] were 20.83 MB/Hz, 24.39 MB/Hz, and 26.31MB/Hz respectively. After getting the ten experimental runs, the LAKER-AAI model consistently outperformed the other existing methods. Therefore, the average of ten comparison results indicates that the spectrum efficiency of LAKER-AAI model was improved by approximately 53%, 24%, and 18% over the methods [1], [2], and [3], respectively. These results confirm the effectiveness of LAKER-AAI model in enhancing spectrum utilization in 5G wireless networks.

B. Analysis of handover success rate

The handover success rate represents the proportion of successful handovers relative to the total number of handover attempts in a wireless communication network. It is calculated using the following formula,

$$HSR = \frac{(Success\ HO\ )}{(HO_{attempts})} * 100 \quad (21)$$

Where, 'HSR' denotes a handover success rate, $Success\ HO$ represents a successful handover, $HO_{attempts}$ indicates a number of handovers attempted. It is measured interms of percentage (%).

Table 4: Handover success rate versus mobile devices

Number of mobile devices	Handover success rate (%)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO[3]
50	96	80	84	92
100	97	84.2	90.05	93.56
150	97.23	83.63	89.05	92.45
200	95.63	84.05	89.74	93.65
250	96.3	85.05	90.05	94.05
300	98.02	86.05	88.74	92.56
350	97.23	87.65	89.74	92.63
400	97.63	88.74	90.05	92.48
450	97.56	86.56	88.69	91.56
500	96.74	87.04	89.45	92.63

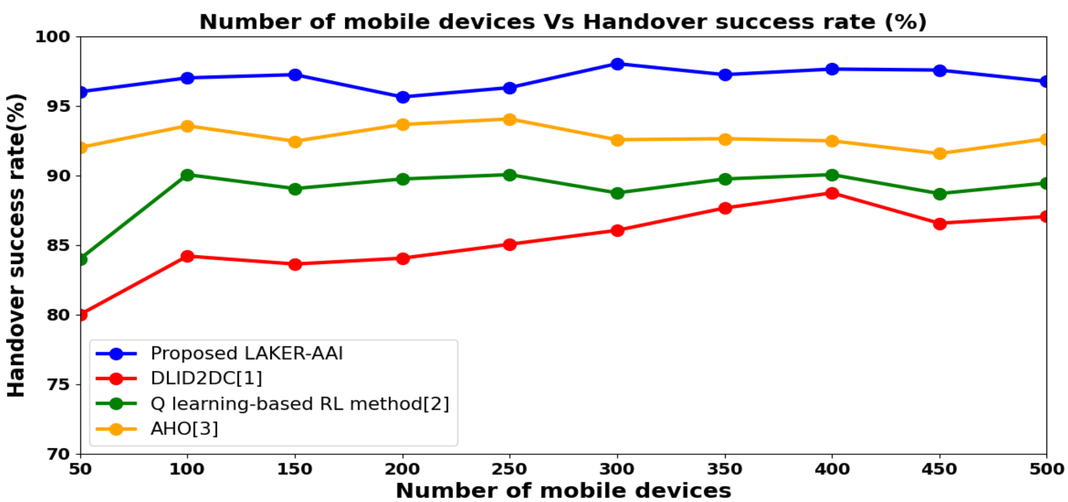

Figure 11: analysis of Handover success rate

Figure 11 illustrates the analysis of handover success rates achieved using four different approaches namely the proposed LAKER-AAI model, DLID2DC [1], Q-learning-based RL method [2], and AHO [3]. The handover success rate is evaluated by mobile devices varied from 50 to 500. Among all four methods, LAKER-AAI model, consistently demonstrates superior performance in ensuring successful handovers. For example, considering 50 mobile devices in the initial experiment, LAKER-AAI model, achieved a handover success rate of 96%, whereas [1], [2], and [3] observed success rates of 80%, 84%, and 92%, respectively. After obtaining ten experimental runs, LAKER-AAI model increased success rates by 14% compared to [1], 9% compared to [2], and 5% compared to [3]. This improved performance is largely achieved due to the integration of a Laplace kernel model within the Agentic AI model, which evaluates the connectivity status of each resource efficient mobile device compared with its current base station. When weak connectivity is identified, the device is quickly handed over to a nearest optimal base station. The nearest base station is identified using the Weighted Fair Queuing handover mechanism, facilitating seamless and efficient data transmission. This dynamic and adaptive handover mechanism embedded in LAKER-AAI model significantly enhances reliability compared to conventional approaches.

C. ANALYSIS OF HANDOVER LATENCY

Handover latency is determined by calculating the time difference between when a device disconnects from the old cell and when it successfully connects to the new cell. This metric reflects the delay experienced during the handover process. The handover latency is mathematically represented as follows:

$$HL = T(MN_{NewCell}) - T\ (MN_{OldCell}) \tag{22}$$

From the above equation (22), the hand over latency 'HL' is computed based on the time of mobile device 'MN' in the new cell '$T(MN_{NewCell})$' and the old cell '$T\ (MN_{OldCell})$' respectively. It is measured in terms of milliseconds (ms).

Table 5: Handover latency versus mobile devices

Number of mobile devices	Handover latency (ms)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO[3]
50	0.22	0.3	0.28	0.26
100	0.24	0.32	0.3	0.28
150	0.26	0.36	0.34	0.32
200	0.28	0.37	0.35	0.33
250	0.31	0.41	0.38	0.36
300	0.33	0.43	0.39	0.37
350	0.35	0.45	0.42	0.38
400	0.37	0.47	0.45	0.42
450	0.4	0.5	0.47	0.44
500	0.43	0.52	0.49	0.46

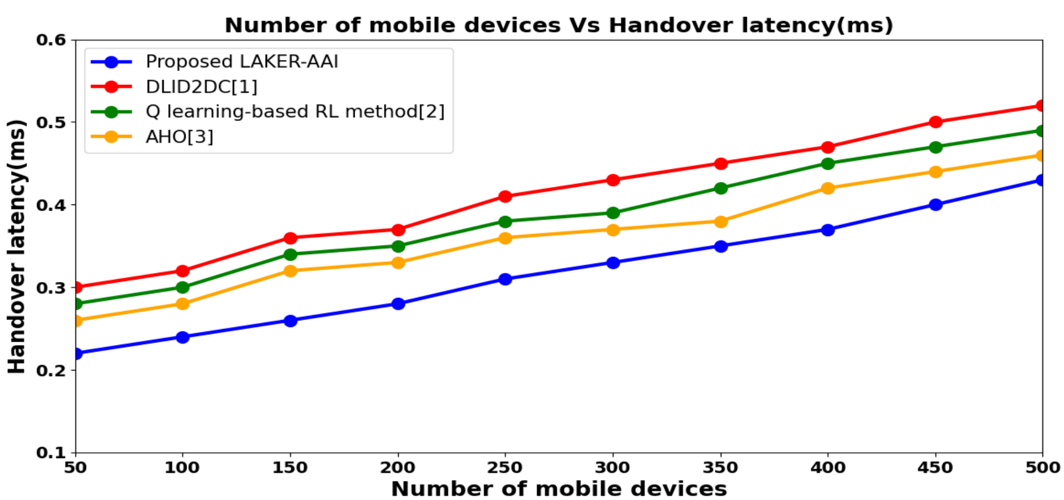

Figure 12: analysis of Handover latency

Figure 12 given above demonstrates the graphical analysis of handover latency using four proposed method, LAKER-AAI model, DLID2DC [1], Q-learning-based RL method [2], and AHO [3] respectively. As revealed in figure 12, the latency of the four methods gets increases while increasing the number of mobile devices. But comparatively, the latency of is found to be lesser using the LAKER-AAI model than the other existing methods. This is proved using statistical assessment and the results are obtained. In a simulation involving 50 mobile device, the LAKER-AAI model achieved a handover latency of 0.22milliseconds, whereas the methods in [1] and [2] [3] recorded latency of 0.3ms, 0.28ms and 0.26ms, respectively. Various data samples counts were tested and the results show that the handover latency is minimized using LAKER-AAI model by approximately 23% and 18%, 12% when compared to [1] and [2] [3]. This significant improvement is achieved by continuously connecting the mobile device to the base station. Queuing based handover mechanism is employed in LAKER-AAI model to manage congestion by handling many handover requests in base station. For each handoff requests, weighted score is computed for assigning the priority. In this way, the numerous requests are prioritized and stored in queue which minimizes network congestion across networks. This approach aims to enhance data transmission efficiency while minimizing the latency effectively.

D. Analysis of ping-pong handover probability

It measures the frequency of unnecessary handovers between serving base station and the neighboring target base station. It measured as the ratio of the unnecessary handovers between adjacent base stations to the number of handovers attempted

$$PPHP = \frac{(\text{unnecessary } HO)}{(HO_{attempts})} \quad (23)$$

Where, '$PPHP$ 'denotes a Ping-Pong Handover Probability, unnecessary HO represents a unnecessary handover, $HO_{attempts}$ indicates a number of handovers attempted.

Table 6: Ping-Pong Handover Probability versus mobile devices

Number of mobile devices	PPHP			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO[3]
50	0.08	0.2	0.16	0.12
100	0.09	0.22	0.17	0.14
150	0.12	0.23	0.18	0.15
200	0.13	0.25	0.19	0.16
250	0.15	0.26	0.2	0.17
300	0.16	0.27	0.22	0.18
350	0.18	0.29	0.23	0.2
400	0.19	0.3	0.25	0.21
450	0.2	0.32	0.26	0.22
500	0.22	0.33	0.27	0.24

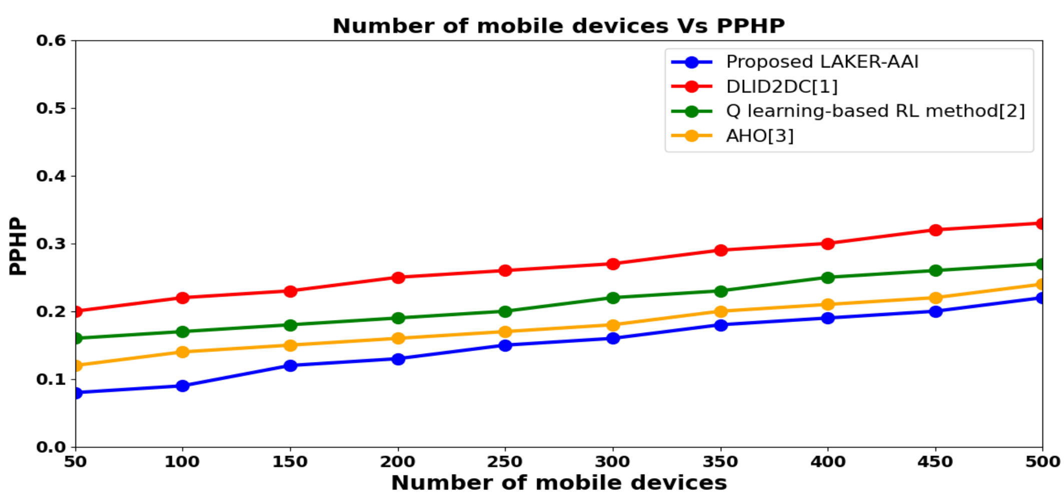

Figure 13: analysis of Ping-Pong Handover Probability

Figure 13 provides a comparative analysis of Ping-Pong Handover Probability across the LAKER-AAI model, DLID2DC [1], Q-learning-based RL method [2], and AHO [3]. The Ping-Pong effect refers to the unnecessary handovers between neighboring base stations, which degrade network stability and increase signaling overhead. In this analysis, the number of mobile devices is varied from 50 to 500 to evaluate the flexibility of each method to determine unnecessary handovers. The results indicate that the LAKER-AAI model significantly reduces the occurrence of Ping-Pong handovers compared to the other techniques. For instance, with 50 devices, the Ping-Pong handover probability for LAKER-AAI model was observed to be as low as 0.08. In contrast, [1], [2], and [3] recorded probabilities of 0.2, 0.16, and 0.12, respectively. Across ten experimental runs, LAKER-AAI model showed an average reduction in Ping-Pong probability by 44%, 30%, and 17% when compared to methods [1], [2], and [3], respectively. This reduction is mainly due to the LAKER-AAI model intelligent handover decision-making process, which incorporates connectivity stability assessments. By leveraging the agentic AI, The environment provides a positive reward that serves as feedback for the agent's actions to avoids unnecessary handovers and ensures that transitions between base stations occurred only when absolutely necessary.

E. Performance analysis of data delivery rate

It represents the proportion of data packets that are successfully delivered to the destination to the total number of packets transmitted by the source device. The calculation is given by the following formula:

$$DDR = \sum_{j=1}^{m} \left[\frac{DP\ received}{DP_j\ sent}\right] * 100 \quad (24)$$

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 data sent from the source mobile device a measured in terms of percentage (%).

Table 7: data delivery rate versus number of data

Number of data	Data delivery rate (%)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO [3]
100	96	89	91	92
200	97.36	90	92.05	93.52
300	95.56	88.66	90.05	92.56
400	96.58	89	91.06	93.45
500	97.63	88.8	90.05	92.23
600	97.72	87.5	90.78	92.74
700	96.56	89.28	91.03	93.41
800	97.56	89.37	91.36	92.45
900	97.56	89.44	91.05	93.56
1000	97.23	88.6	90.74	92.23

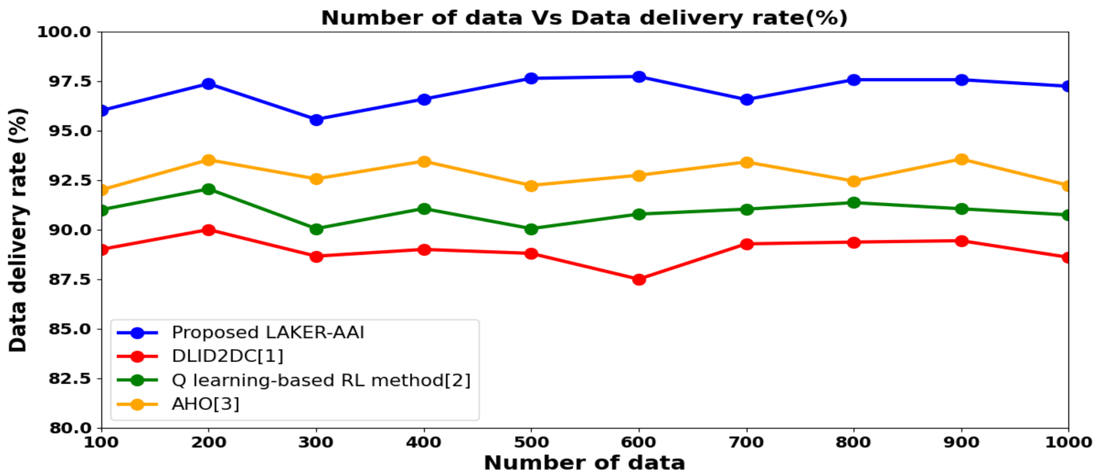

Figure 14: analysis of data delivery rate

Figure 14 displays the seamless data delivery rate performance of four approaches namely the proposed LAKER-AAI model, DLID2DC [1], Q-learning-based RL method [2], and AHO [3]. In this figure, the x-axis denotes the number of data, ranging from 100 to 1000, while the y-axis represents the corresponding data delivery rate achieved by each method. The results clearly show that the LAKER-AAI model outperforms the existing techniques in terms of achieving high delivery rate. Specifically, LAKER-AAI model achieves an improvement of approximately 9%, 7% and 4% when compared to [1] [2] [3]. This enhancement is achieved due to the model's an integration of the segmented regression algorithm into the LAKER-AAI model, which evaluates various resources various resources such as energy, bandwidth, memory, and spectrum, processor speed. The algorithm identifies mobile devices with optimal resource accessibility, leading to higher data delivery success.

F. Analysis of data loss rate

It indicates the percentage of data packets did not successfully arrive at the destination device, from the total number of packets sent. This metric is calculated using the following formula,

$$DLR = \sum_{j=1}^{m} \left[\frac{DP\ lost}{DP_j\ sent}\right] * 100 \quad (25)$$

From (25), DLR indicates a data loss rate, $DP\ lost$ indicates the data lost at the destination and $DP_j\ sent$ denotes a number of data sent. It is measured in terms of percentage (%).

Table 8: data loss rate versus number of data

Number of data	Data loss rate (%)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO
100	4	11	9	8
200	2.64	10	7.95	6.48
300	4.44	11.34	9.95	7.44
400	3.42	11	8.94	6.55
500	2.37	11.2	9.95	7.77
600	2.28	12.5	9.22	7.26
700	3.44	10.72	8.97	6.59
800	2.44	10.63	8.64	7.55
900	2.44	10.56	8.95	6.44
1000	2.77	11.4	9.26	7.77

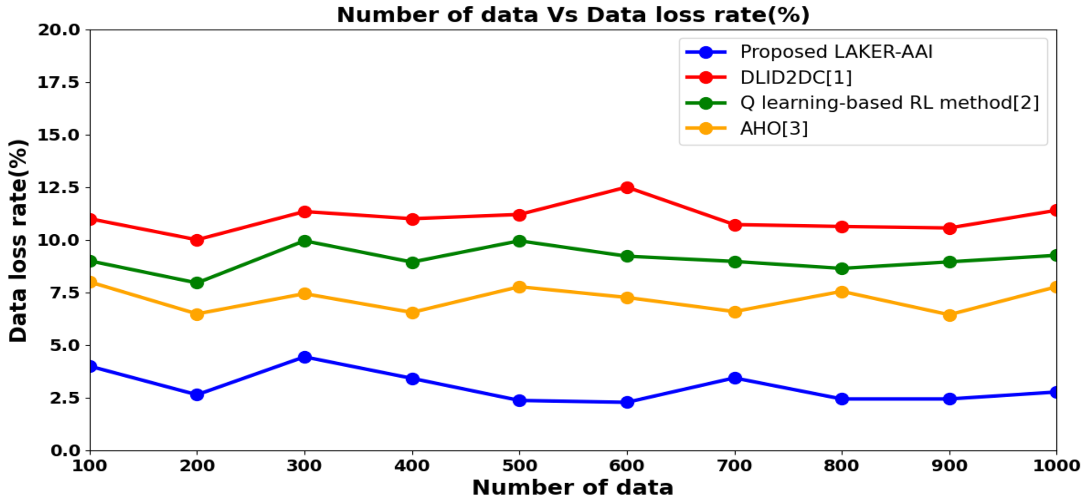

Figure 15: analysis of Data loss rate

Figure 15 illustrates the data loss rate performance of four approaches namely the proposed LAKER-AAI model, DLID2DC [1], Q-learning-based RL method [2], and AHO [3]. Among the four methods, the LAKER-AAI model demonstrates the less data loss rate, highlighting its efficiency in managing network resources. The comparative results indicate that the LAKER-AAI model reduces data loss by approximately 73% compared to [1], and by 67% compared to [2], and by 58% compared to [3], confirming its effectiveness in enhancing data reliability in distributed environments. The LAKER-AAI model utilizes a segmented regression integrated with an agentic AI model to accurately select high-performing mobile devices for data transmission. This model significantly enhances seamless data delivery efficiency while minimizing data loss within 5G network environments.

G. Analysis of throughput:

It measures the amount of data successfully transmitted over a network within a given period of time. It is typically represented in megabits per second (Mbps), depending on the network's bandwidth and capacity.

$$TP = \left[\frac{Succ\_Trans\_data\ (Mb)}{time\ (s)}\right] \quad (26)$$

Where, TP denotes a throughput, $Succ\_Trans\_data\ (Mb)$ denotes a successful transmission of data in Mb in one seconds (Mbps).

Table 9: throughput versus data size

Data size (MB)	Throughput (Mbps)			
	Proposed LAKER-AAI	DLID2DC[1]	Q learning-based RL method [2]	AHO
1000	292	212	245	255
2000	636	369	455	512
3000	785	578	658	685
4000	912	698	788	823
5000	1012	752	856	963
6000	1154	956	1032	1078
7000	1523	1065	1148	1285
8000	1932	1236	1398	1589
9000	2123	1412	1723	1896
10000	2745	1745	2145	2363

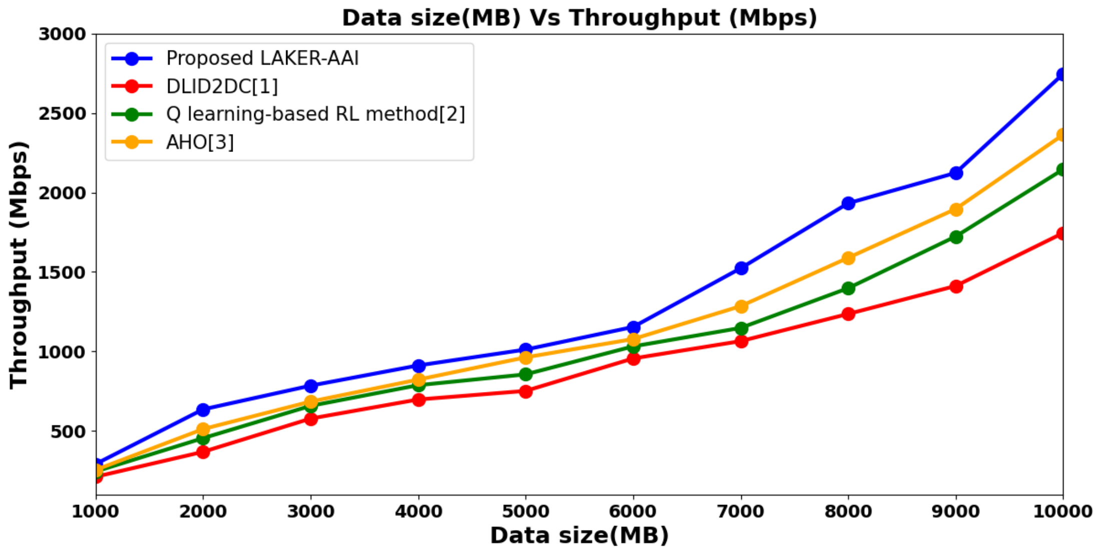

Figure 16: analysis of Throughput

Figure 16 depicts the measurement of throughput versus the size of data, ranging from 1000MB to 10000 MB. The horizontal axis indicates the size of data, while the vertical axis represents the performance outcomes of throughput. The graphical analysis exposes that the LAKER-AAI model consistently outperforms conventional methods in terms of achieving better throughput. In the first run, where 1000B data for calculating throughput, the LAKER-AAI model achieved a throughput of $292Mbps$, while the throughput of existing methods [1] [2] [3] was observed to be $212Mbps$, $245Mbps$ and $255Mbps$respectively. The statistical evaluation results show a significant improvement in throughput using the LAKER-AAI model. Overall throughput results indicate that the LAKER-AAI model outperforms existing methods [1] [2] [3] by 44%, 25% and 14% respectively. The improvement achieved by the LAKER-AAI model includes its ability to continuously monitoring of key connectivity metrics for each mobile device. When device has poor connectivity, the system automatically initiates a smooth handover to the nearest optimal base station, ensuring stable and uninterrupted data transmission. This process improves overall throughput within 5G network communications.

V. CONCLUSION

This paper addressed the resource optimized seamless data delivery problem in the 5G network architecture. The seamless data delivery is modeled as a LAKER-AAI with the objective of improving the data delivery while minimizing data loss and latency. In order to meet this objects, the LAKER-AAI model employed by applying agentic AI framework to evaluate each device's resource parameters. Following this, a segmented regression model is applied to identify the most resource-efficient devices, aiming to boost data delivery performance and reduce packet loss. Once the resource efficient devices are selected, their connectivity is further evaluated. To distinguish weak connections, the system employs a Weighted Fair Queuing (WFQ) handover strategy to facilitate smooth and effective transitions between base stations, ensuring continuous and reliable communication. A thorough simulation analysis was carried out using multiple performance metrics such as energy efficiency, spectrum efficiency, handover success rate, handover latency, Ping-Pong Handover Probability, data delivery rate, data loss rate and throughput. The findings reveal that the LAKER-AAI model outperforms conventional deep learning techniques by offering higher data delivery rate, with minimal loss as well as latency.

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