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Gibbs Haversine Reinforcement Learning Based Handover For 5g Enabled Seamless Mobility in Wireless Network.

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***Abstract:** Seamless Mobility (SM) is crucial for bringing about better Quality of Service (QoS), like minimum handover latency with maximum throughput in 5G networks. In this work, a method called Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD) is designed for the optimal selection of target cells in the handover process to ensure seamless mobility. The JIRF-RLGHD method is split into two sections. They are predicting the signal quality of both serving and adjacent wireless nodes using the Box-Jenkins Impulse Response Filtering model. The second task involves applying a Reinforcement Learning-based Gibbs Haversine Distribution for the optimal selection of target cells during handover, ensuring seamless mobility in a wireless network. The overall proposed method was simulated on a Python programming interface. The simulation results reveal that the JIRF-RLGHD method offers a higher delivery rate and handover success with lower handover latency at a minimal packet loss rate. Numerical results show that the JIRF-RLGHD method performs better in terms of data delivery rate by 18% and handover latency by 33% compared to existing methods.*

***Keywords:** Fifth Generation, Seamless Mobility, Quality of Service, Box Jenkins, Impulse Response Filter, Reinforcement Learning, Gibbs Haversine Distribution*

I. INTRODUCTION

Optimisation based on the distance (Opt. Distance) was employed as the mechanism to ensure effectiveness and convenience with divergent mobility patterns based on the User Equipment (UE) state of affairs [1]. The areas that necessitated improvement were also analysed, and the tuning of network parameters was made accordingly. Moreover, by employing antenna gain and path loss models, service quality was enhanced in response to changes in network conditions and traffic patterns, requiring minimal human intervention. Finally, better user experiences were provided through a more efficient bandwidth allocation handover process in a significant manner. Despite improvements in allocating bandwidth with a better handover process, the delay, which is considered a critical performance factor, was not taken into consideration when designing divergent mobility patterns.

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The 5G NR supports enhanced mobile broadband, low-latency communications, and a large number of mobile devices. Hence, seamless mobility must be conserved during the migration process between cells during the handover procedure. However, with the increasing number of mobile devices, high mobility management of dense networks becomes pivotal. Additionally, an active adjustment is essential, as it crucially influences the handover latency and overall throughput.

A Learning-based Intelligent Mobility Management (LIM2) was proposed in [2] for handling mobility management in 5G. Initially, a Kalman filter was applied to predict the future signal quality of both serving and adjacent cells, and an optimal selection of the target cell for the handover process was achieved using state-action-reward-state-action-based reinforcement learning. Finally, a greedy policy was employed to trigger time, thereby ensuring high throughput and low packet delay. Although high throughput with low packet delay was assured, the latency was not optimised. Next-generation wireless cellular networks are envisioned to be self-coordinated, significant, and cost-efficient. Due to the new 5G paradigm, several design issues arise, ranging from scalable mobility management to reliable resource management, ensuring seamless access to wireless services without compromising the anticipated Quality of Service (QoS). A control/data separation architecture was designed in [3] via stacked long short-term memory (LSTM). With this type of design, efficient separation between predictive and non-predictive cases was achieved through a holistic evaluation of handover costs, which in turn improved handover accuracy. An extensive number of base stations and associated sensors have been growing exponentially. This, in turn, had corresponding increased numerous types of mobility management issues, which necessitated an optimisation model to circumvent degradation of QoS. Machine learning (ML) is a promising approach for future wireless 5G networks. The robustness optimization technique was applied in [4] via key performance indicators ensuring system enhancements. In this day and age, information and communication technology extends swiftly. As a result, there is an improvement in both coverage and connectivity. On the other hand, the evolution of 5G has resulted in minimal communication latency, the highest speed, increased throughput, and more. In [5], essential and pivotal characteristics of 5G communication technology in addition to the drawbacks of prevailing methods were presented in detail.

A holistic review of seamless mobility management issues related to 5G was investigated in [6].

The domain of seamless mobility encompasses health, surveillance, and transportation. A greedy pricing scheme was applied in [7] employing a column-generated solution to obtain the optimal solution for measuring the strategic behavior of travelers and ensuring seamless mobility. A detailed literature review, along with the exploration of 5G in different industries, was conducted in [8]. Additionally, an in-depth review of the evolution and progress of wireless technology, with an emphasis on the significance of 5G networks, was presented. In recent years, healthcare has gained significant importance following the COVID-19 pandemic, with a focus on providing robust solutions utilising 5 G. The Prevailing radio access technology was improved in [9] to ensure quality of experience. Additionally, resource utilisation was improved by utilising a multi-agent reinforcement learning mechanism.

A. Contributions

Motivated by the above issues, like, handover latency, packet loss, data delivery rate, and success of handover for seamless mobility in wireless networks, in this work, a method called, Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD) is designed using Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution. The significant contributions of this work are pointed out below.

- To present a significant method for designing seamless mobility in wireless networks by ensuring optimal handover called Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD).
- To design a convergence-efficient filtered signal (i.e., eliminating the noisy signal results), to minimize handover latency and packet loss using the Box-Jenkins Impulse Response Filtering algorithm applied to the raw traffic flows obtained from the IP Network Traffic Flows dataset
- To propose a Reinforcement Learning-based Gibbs Haversine Distribution algorithm for optimally selecting target cells for performing handover, therefore ensuring seamless mobility in an accurate and precise manner.
- Finally, the performance of the proposed JIRF-RLGHD-based seamless mobility method for traffic flows is compared with the conventional state-of-the-art methods.

B. Organization of the Work

The rest of the paper is organised as follows. Section 2 provides the related works on seamless mobility, handover, machine learning, and deep learning for network traffic flows. Section 3 presents a brief description of the seamless mobility for wireless networks, known as Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD). After that, Section 4 provides experimental results, along with the corresponding implementation details in Section 5. Section 6 presents a detailed comparative study between the proposed JIRF-RLGHD method and the other state-of-the-art methods with the aid of a table and graphical representation. Finally, Section 7 concludes the paper.

II. RELATED WORKS

The mobile industry is evolving and preparing to establish 5G networks. The emerging 5G networks are becoming increasingly accessible as a powerful enabler of IoT devices. Moreover, 5G's lightning-fast connection and low latency are essential for the evolution of intelligent automation, including Artificial Intelligence (AI), driverless cars, digital reality, and other applications. The evolution of 5G yet opens a state-of-the-art world of probabilities for almost all areas of the domain.

Mobility management is one of the paramount services that necessitate awareness for the present-day 5G organizations. Moreover, the QoS essentials in 5G wireless networks are user-specific. As far as seamless mobility in 5G wireless networks is concerned, network slicing has been considered as one of the key enablers for ensuring on-demand service schemes. In [10], radio resource access was concentrated on mobile roaming users. Additionally, an integrated architecture was designed to enable seamless handover between a 5G network and a network slicing paradigm. However, two significant issues — latency and bandwidth — were not addressed. To address these two aspects, Software Defined Networking (SDN) and Network Function Virtualization (NFV) were designed for 5G networks [11]. Here, seamless mobility management was designed to shift the paradigm between SDN and another in a 5G network. Employing a distributed hash table resulted in a significant reduction in handover latency.

With the mushrooming expansion of traffic load and associated devices in the wireless network, 5G should reliably minimise latency. Specifically, seamless mobility is highly required for attaining low handover latency. In [12], a generalized RACH-less handover method was presented for arriving at seamless mobility without the need for a synchronized network. Yet another holistic review of user localization equipment, along with standardized reference signals to ensure localization accuracy, was presented in [13]. A survey of handover optimization mechanisms was investigated in [14].

The primary objective of 5G communication remains to bring a revolution in QoS (Quality of Service) through mobile broadband, low-latency, and reliable communication processes, as well as extensive communication between machines. In [15] a comprehensive survey of 5G communication networks for addressing routing-based interference was designed. A detailed study of the handover management to ensure seamless mobility in 5G was detailed in [16]. Additionally, specific performance metrics, such as throughput, delay, and traffic load, involved in the handover process were detailed. Moreover, the challenges involved in designing handover to counteract the attacks during handover were also presented. Seamless mobility management in 5G networks for massive wireless data from numerous application scenarios was presented in [17].

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A regression model for seamless mobility deploying heterogeneous networks was designed in [18]. The evolution of the 5G wireless network, with its seamless mobility, has led the way to numerous advantages. However, it gave rise to new issues with the 5G wireless network, thereby making the prevailing methods for handling data obsolete. Due to this, research was conducted to explore deep learning methods in addressing issues in the 5G network.

In [19] a survey of deep learning methods for addressing issues concerning 5G in wireless networks for seamless mobility was proposed. However, seamless mobility for complicated urban environments was still not a focus. To address this issue, a network-slicing strategy for machine communication was researched in [20].

Although machine learning methods have been widely used and applied in the area of seamless mobility with 5G, only a few researchers have endeavoured to utilise these methods. As discussed earlier, we will demonstrate that machine learning can be used to ensure seamless mobility with optimal handover in a 5G wireless network.

III. MATERIALS AND METHODOLOGY

A. Dataset description

The proposed method utilises the IP Network Traffic Flows Labelled with 75 Apps dataset, extracted from https://www.kaggle.com/jsrojas/ip-networktraffic-flows-labelled-with-87-apps, to facilitate seamless wireless network mobility in 5 G. The corresponding raw data were obtained both in the morning and afternoon over a six-day period in April and May 2017. The dataset comprises a total of 87 features, with 3577296 instances gathered, accumulated, and stored in a CSV file. The sample instance comprises IP information flow, including the source and destination IP addresses, ports, inter-arrival times, and Layer 7 protocols. Numeric data types represent several features, but nominal data types are also included, along with the date types known as Timestamp. The features included in the dataset are source port, source IP, flow ID, flow duration, timestamp, destination IP, destination port, total forward and backwards packets, and the length of forward and backwards packets, respectively. The input vector for the corresponding IP Network Traffic Flows Labelled dataset is subjected to the input vector matrix as given below.

$$IV = \begin{bmatrix} S_1F_1 & S_1F_2 & \dots & S_1F_n \\ S_2F_1 & S_2F_2 & \dots & S_2F_n \\ \dots & \dots & \dots & \dots \\ S_mF_1 & S_mF_2 & \dots & S_mF_n \end{bmatrix} \quad (1)$$

From the above formulation (1), the input vector 'IV' matrix includes 'm' samples with 'n' features as input with which further processing is said to be performed.

B. Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD)

Seamless mobility refers to the potential to change the wireless node's point of attachment to an IP-based network without losing track of ongoing connections (i.e., current connections) and without disruptions in communication (i.e., between current cells and adjacent cells). Seamless mobility management, with facilities for seamless handoff and QoS guarantees, is a crucial issue that significantly aids the global roaming of wireless nodes (WNs) between multiple wireless systems.

As far as the 5G network is concerned, mobility is not only a physical postulation but also a logical one. It is hence pivotal to provide seamless mobility and QoS guarantee support stemming from intelligent and efficient mobility management mechanisms. To enable seamless mobility and QoS provision, a seamless handoff (i.e., minimal service disturbance in the course of handoff) is of considerable significance. Seamless handoff refers to minimal data packet loss, moderate handoff latency, and reasonable signalling traffic overhead. To align with proliferating projections and emerging requirements, 5G encompasses a wide range of performance-influencing characteristics.

Evaluating the correlation between these influencing characteristics and validating every probability is a prerequisite for determining the constraints and issues that must be addressed to ensure 5G achieves its objectives. These, in addition, enable the accurate and precise pre-selection of characteristics based on the needs before the network is deployed, which in turn results in the appropriate performance level. Nevertheless, while the association of several contributing characteristics leads the way to 5G organisation, accurately and precisely predicting performance based on all these associated characteristics remains a significant challenge in practice. To address this challenge, this work proposes a 5G model comprising five distinct modules.

a. System model

Let 'SN' be the serving node, 'TN' be the target node, and 'α_{ISD}' represents the Inter Site Distance between the serving node and the target node. Let the wireless node 'WN' be positioned at coordinates '(A_i, B_i)' and supposed to progress in a straight line, making an angle of 'β' for the 'α_{ISD}' where '$\beta = 0^{\circ}$' associates the straight line movement of the wireless node 'WNToward the target node. One of the pivotal digital framework building blocks for 5G includes microcells, picocells, and femtocells. As a substitute for restoring conventional macrocells, employing small cells (i.e., microcells, picocells, and femtocells) enhances this framework to improve both network coverage and capacity in densely populated areas. To provide targeted wireless network coverage and capacity, three types of cells — femtocells, picocells, and microcells —are used. As the name implies, femtocells cover a diameter of up to 10 meters, picocells cover a diameter of up to 200 meters, whereas microcells cover a diameter of up to 2 km. In our work, picocells and microcells are employed to design seamless mobility patterns with minimal interference, utilising flow statistics and deep packet inspection of application layer protocol information obtained from the raw dataset for further processing. Figure 1, given below, illustrates the sample system model deployment for wireless network seamless mobility.

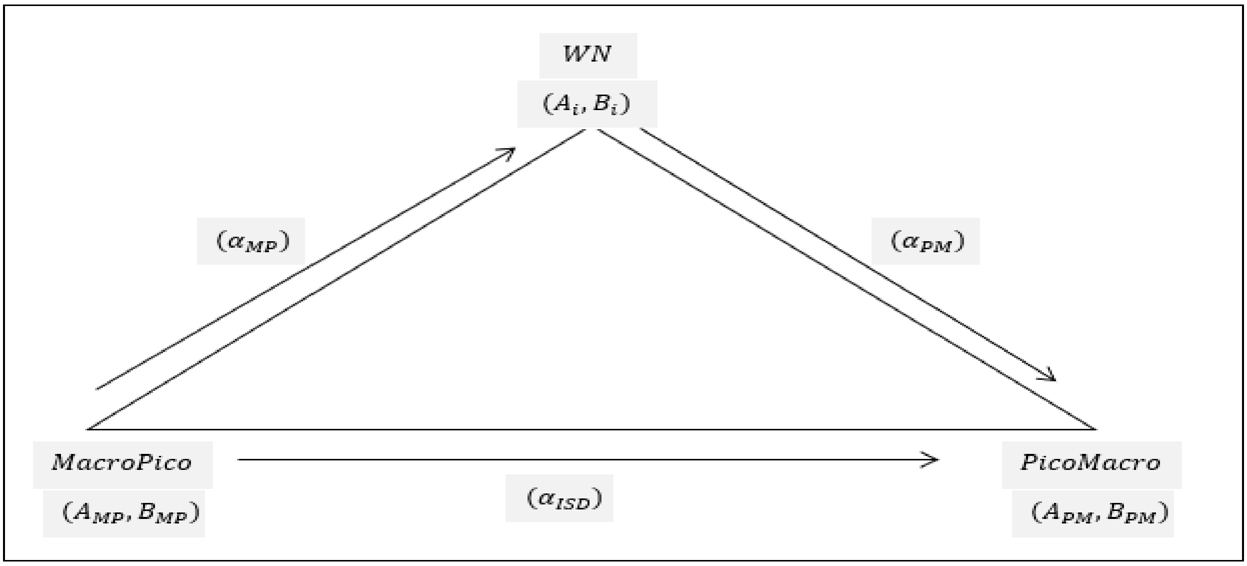

Fig. 1: System Model of Wireless Network Seamless Mobility

As illustrated in the above figure, with the wireless node 'WN' positioned at coordinates '(A_i, B_i) The picocell is represented as '(A_{PC}, B_{PC})' whereas the microcell is represented as '(A_{MC}, B_{MC})'. The wireless node 'WN' is supposed to travel between the serving node 'SN' and target node 'TN' at a constant velocity and angle. At any instance, the wireless node 'WN' is considered to be at a distance 'α_{MP}' from the microcell and 'α_{PM}' from the picocells. Finally, the Inter-Site Distance 'α_{ISD}' represents the distance between two adjacent sites or adjacent nodes. Then, the distance between the wireless node 'WN' and 'α_{MP}' from the microcell and 'α_{PM} The picocells are mathematically formulated as given below.

$$\alpha_{MP} = \sqrt{(A_i - A_{MP})^2 + (B_i - B_{MP})^2} \qquad (2)$$

$$\alpha_{PM} = \sqrt{(A_i - A_{PM})^2 + (B_i - B_{PM})^2} \qquad (3)$$

From the above equations (2) and (3), 'α_{MP}' and 'α_{PM}' represents the location coordinates of macro pico '(A_{MP}, B_{MP})' and picomacro '$PicoMacro$' respectively.

b. Box-Jenkins Impulse Response Filtering model

Following this, with the above system model in consideration for predicting the future signal quality of both service and adjacent cells or nodes, this work applies a scalable and reliable impulse response filter modelling technique called Box-Jenkins Impulse Response Filtering. By applying this scalable and reliable impulse response filtering, a scalable and dependable link quality is ensured, which in turn not only reduces handover latency but also significantly minimises packet loss. Figure 2 shows the structure of the Box-Jenkins Impulse Response Filtering model.

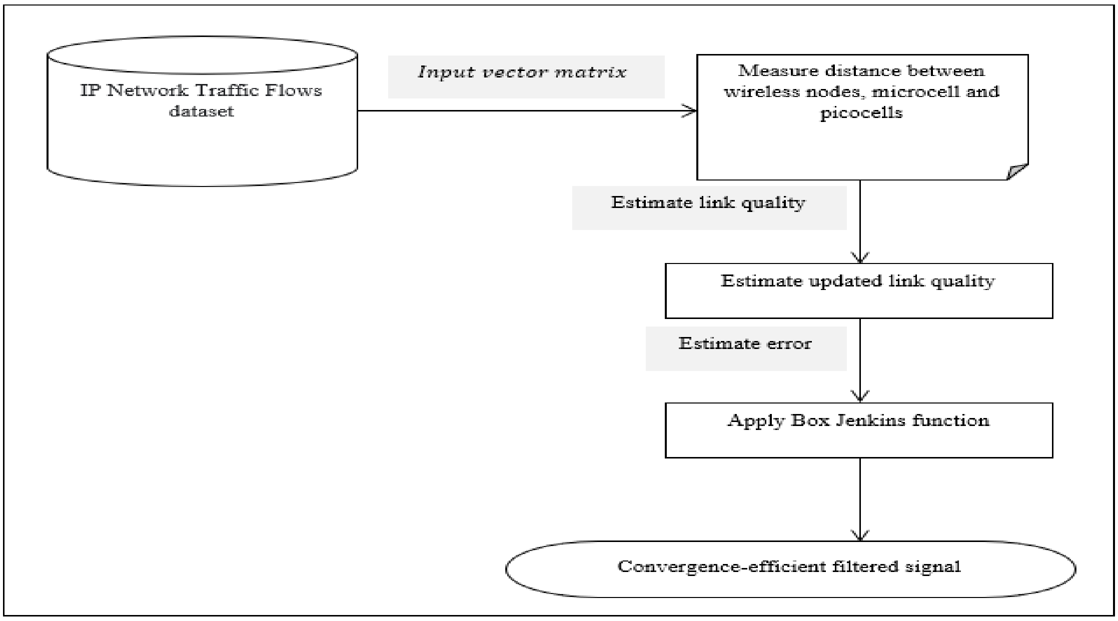

Fig. 2: Structure of Box-Jenkins Impulse Response Filtering Model

As illustrated in the above figure, first, with the input vector matrix 'IV' obtained from the raw dataset 'DS', and location coordinates obtained, a scalable and reliable impulse response filter is designed. This formulation is generated in such a manner as to predict the future signal quality of '$RSSI[n]$' and the duration

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below which '$RSSI[n]$The threshold remains a mathematical statement as given below.

$$RSSI_{pred}[n] = \sum_{l=1}^{M} h_n[l] RSSI[n-l] \; (IV) \quad (4)$$

From the above equation (4), 'M' refers to the number of data packets necessary for prediction, whereas '$RSSI[n-1]$' refers to the measured RSSI value at time '$n-1$' and '$h_n[l]$' represents the '$l-th$' coefficient of the filter for '$n-th$' round respectively. Additionally, the filter coefficient values are updated arbitrarily, and the updated link quality estimate results are then mathematically stated as follows.

$$RSSI(n) = RSSI_{Pred}[n+1] = RSSI_{Pred}[n] + \gamma(RSSI[n] - RSSI_{Pred}[n]) \quad (5)$$

From the above equation results (5) using the filter coefficient values '$0 < \gamma < 1$' the predicted RSSI value for '$n+1$' determines the anticipated error between the predicted RSSI and the actual RSSI values, hence taking into consideration both the service and adjacent cells or nodes. With this improved future signal quality, results are achieved, thereby significantly minimising handover latency and data packet loss rate. The output '$y(n)$' From the above-updated link quality, the estimate remains an additive sum of the signal '$RSSI(n)$' disturbance '$Dis(n)$' The noise measured '$v(n)$'. This is mathematically stated as given below.

$$y(n) = RSSI(n) + Dis(n) + v(n) \quad (6)$$

$$RSSI(n) = G_{RSSI}(n) + IV(n) \quad (7)$$

$$Dis(n) = G_w(n)w(n) \quad (8)$$

From the above equations (6), (7), and (8), the signal '$RSSI(n)$' and the disturbance '$Dis(n)$Models are obtained taking into consideration the sample input vector.$IV(n)$', white noise '$w(n)$', transfer matrix or order 'n_{RSSI}' and 'n_w' respectively. Finally, using the Box-Jenkins function, an efficient mathematical model that forecasts the signal quality is obtained from the following formula as given below.

$$D_{RSSI\,w}(n) = D_w(n) N_{RSSI\,w}(n) IV(n) + \epsilon(n) \quad (9)$$

$$D_w(n) = D_{RSSI}(n) D_w(n) \quad (10)$$

$$N_{RSSI\,w}(n) = D_w(n) N_{RSSI}(n) \quad (11)$$

From the above equations (9), (10), and (11), future signal forecasting results are predicted based on the denominator. $D_{RSSI\,w}(n)$ ' and numerator ' $N_{RSSI\,w}(n)$ ' polynomials. The pseudo-code representation of Box-Jenkins Impulse Response Filtering for generating scalable and reliable filters is given below.

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \ldots, S_m\}$', Features '$F = \{F_1, F_2, \ldots, F_n\}$', Data packets '$DP = \{DP_1, DP_2, \ldots, DP_M\}$'
Output: filtered signal results '$D_{RSSI\,w}(n)$' with minimal handover latency and packet loss
Step 1: **Initialize** '$m = 3557297$ ', '$n = 87$', serving node 'SN', target node 'TN', 'M', coefficient '$0 < \gamma < 1$' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Samples 'S' and Features 'F' Step 4: Formulate the input vector matrix as given in equation (1) Step 5: Formulate distance between wireless node 'WN' and 'α_{MP}' from the microcell as given in equation (2) Step 6: Formulate distance between wireless node 'WN' and 'α_{PM}' from the picocells as given in equation (3) Step 7: Evaluate link quality as given in equation (4) Step 8: Evaluate updated link quality estimate results as given in equation (5) Step 9: **If** '$RSSI[n] - RSSI_{Pred}[n]$ *are highly correlated*' Step 10: **Then, the** predicted signal results are correct and make 'γ' purposefully small Step 11: **Return** predicted future signal quality Step 12: **End if** Step 13: **If** '$RSSI[n] - RSSI_{Pred}[n]$ *are less correlated*' Step 14: **Then, the** predicted signal results are not correct and make 'γ' purposefully large Step 15: **Go to** step 5 Step 16: **End if** Step 17: Evaluate signal and output error as given in equations (6), (7) and (8) Step 18: Formulate the Box-Jenkins function to the evaluated signal and output error to predict signal quality results as given in equations (9), (10) and (11) Step 19: **End for** Step 20: **End**

Algorithm-1: Scalable and Reliable Impulse Response Filter

As outlined in the above algorithm, which aims to minimise both handover latency and packet loss, a scalable and reliable impulse response filter is applied. First, with the raw data obtained from the dataset and formulated as an input vector matrix, the distance between the wireless node and the microcell is initially measured. Second, the list quality is estimated for each round with different numbers of data packets and time instances. Third, according to the updated link quality estimates, filter coefficient values are updated arbitrarily. Finally, according to the correlated results, predicted future signal quality is either returned or proceeds with other sets of data. With the predicted future signal quality results, the signal and the output error are evaluated. From the identified results, minimal realisations of the signal, the disturbance, and the filter are obtained using the Box-Jenkins function, which not only minimises the handover latency but also significantly reduces the packet loss rate.

c. Reinforcement Learning-based Gibbs Haversine Distribution for optimal selection of the target cell for the handover process to ensure seamless mobility

Handover enhancements were explored to handle frequent handovers owing to seamless mobility in wireless networks. Therefore, the major problem of handover towards seamless mobility was the signalling storm generated by handing over all wireless nodes in a wireless network from an old cell to a new cell, because when a wireless node intersects the boundary between the serving and adjacent cells, handover occurs.

With this frequent handover, the data delivery rate and, consequently, the success of the handover are compromised. To address this issue, in this work, a Reinforcement Learning-based Gibbs Haversine Distribution for optimal selection of target cells for the handover process to ensure seamless mobility is designed. Figure 3 shows the structure of the Reinforcement Learning-based Gibbs Haversine Distribution model.

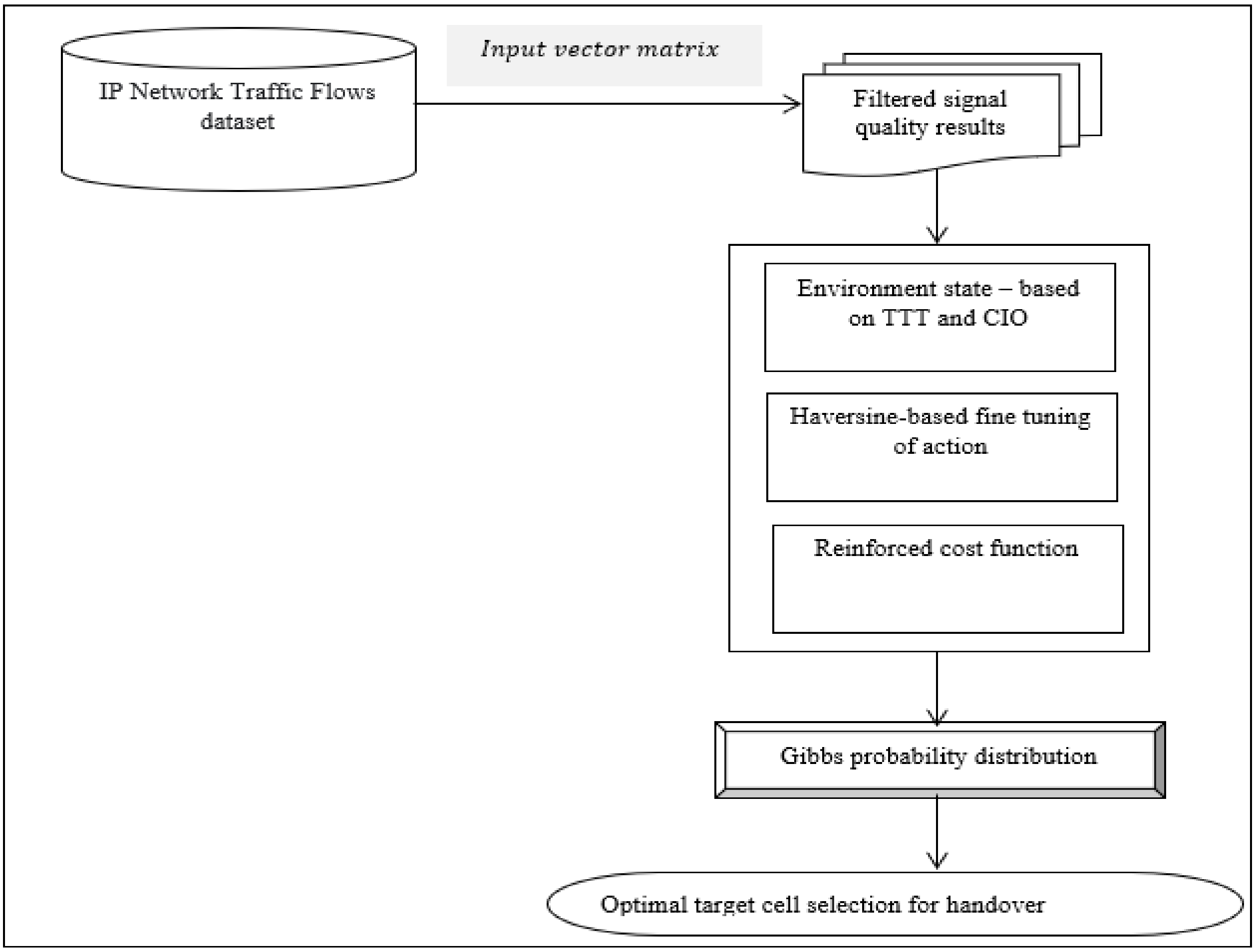

Fig. 3: Structure of Reinforcement Learning-based Gibbs Haversine Distribution Model

As illustrated in the above figure, the environment state is assessed based on the handover optimization costs (e.g., too late handovers and too early handovers). Accordingly, it selects an action to optimise handover parameters (e.g., Time To Trigger (TTT) and Cell Individual Offsets (CIO)) in harmony with the measured state by employing prior knowledge (i.e., from the impulse response filter).

The knowledge is updated based on optimization costs to reflect the optimal selection of target cells for the handover process. To fine-tune mobility between cells 'i' and cell 'jThe optimal selection of the target cell for the handover process includes four features: the environment state.$es_{ij} \in ES$', action '$a_{ij} \in A(ES_{ij})$', dataset '$DS(a_{ij})$' that provides the belief distribution of optimal features and cost function 'C_{ij}' that considers the quality of an action in a given state, respectively.

The proposed algorithm selects the optimal action.$A(ES_{ij})$' to reduce handover cost (i.e., maximising data delivery rate and success of handover) based on optimisation costs. Environment state '$es_{ij} \in ES$' is sensed based on the handover to reduce unwanted handovers. The environment state ' $es_{ij} = (ES_{CIO+}, ES_{CIO-}, ES_{TTT+}, ES_{TTT-})$' that refers to the increase in CIO, decrease in CIO, increase in TTT, and decrease in TTT respectively, from their prevailing values, to control both too late and too early handover, therefore ensuring seamless mobility extensively. Following this, the action '$A_{ij} \in A(ES_{ij})$' fine-tunes the resultant 'CIO' and 'TTT' Values to reduce unwanted handovers as claimed by the current state 'ES_{ij}' via Haversine function. Hence, the action '$A(ES_{ij})$' is set to change based on the state 'ES_{ij}' via Harvard sine function.

$$\theta = \frac{Dis}{Radius} \tag{12}$$

From the above equation (12), 'Dis' and '$Radius$Refer to the distance and radius between two wireless nodes on a sphere. Finally, the fine-tuned results are obtained by measuring the haversine of 'θ' from the latitude and longitude of two points as given below.

$$Hav(\theta) = Hav(\alpha_1 - \alpha_2) + \cos\alpha_1 \cos\alpha_2 (\beta_1 - \beta_2) \tag{13}$$

From the above equation (13), 'α_1' and 'α_2' represents the latitude of the wireless node 'WN_i' and the latitude of the wireless node 'WN_j', 'β_1' and 'β_2' representing the longitude of the wireless node 'WN_i' and the latitude of the wireless node 'WN_j' respectively. Based on the latitude and longitude of the serving and adjacent nodes for the fine-tuned Haversine results, a greedy strategy for optimal action is selected as follows.

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$$A'_{ij} = argmin\ Q(A_{ij})[Hav(\theta)] \quad (14)$$

Finally, the cost function reflects the quality of action in a given state, taking into account too-late handovers and too-early handovers between serving cells (i.e., a wireless node).WN_i' and adjacent cell (i.e., a wireless node) 'WN_j' are mathematically stated as given below.

$$RL_{ij} = \frac{NTooLate_{ij}}{NTot_{ij}}; RE_{ij} = \frac{NTooEarly_{ij}}{NTot_{ij}}; R_{ij} = RL_{ij} + RE_{ij} \quad (15)$$

From the above equation (15), the reinforced cost function 'R_{ij}' between serving cell (i.e., a wireless node) 'WN_i' and adjacent cell (i.e., a wireless node) 'WN_j' are obtained based on the reinforced too-late handovers 'RL_{ij}' and too early handovers 'RE_{ij}' respectively. Finally, the haversine function '$hav(\theta)$' is applied to both the central angle and the differences in latitude and longitude to obtain the optimal selection as given below.

$$hav(\theta) = Sin^2\left(\frac{\theta}{2}\right)[R_{ij}] \quad (16)$$

With the above haversine-induced reinforced cost function results '$hav(\theta)$As given in Equation (16), the Gibbs probability distribution function is applied to select higher-probability results, ensuring a better handover towards seamless mobility. This is mathematically stated as given below.

$$Prob(es_{ij}, A'_{ij}) = \frac{\exp\left[-\frac{\theta(a'_{ij})}{\tau}\right]}{\sum_{b'_{ij} \in A(ES_{ij})} \exp\left[-\frac{\theta(b'_{ij})}{\tau}\right]} \quad 17)$$

From the above equation (17), the probability of taking an action (i.e., selecting a target cell for the handover process) is measured based on the Gibbs function and the probability results. Higher probability results are chosen over the lower probability results. In our work, 'τ' refers to the positive parameter called time to trigger 'TTT'. A higher 'TTT' causes the actions to have a more equal probability. On the other hand, a lower temperature leads to a greater difference in the selection probability for actions, which stimulates making use of prior knowledge. The pseudo-code representation of the Reinforcement Learning-based Gibbs Haversine Distribution for the optimal selection of target cells in the handover process, ensuring seamless mobility, is provided below.

Input: Dataset 'DS', Samples '$S = \{S_1, S_2, \dots, S_m\}$', Features '$F = \{F_1, F_2, \dots, F_n\}$', Data packets '$DP = \{DP_1, DP_2, \dots, DP_M\}$'
Output: delivery improved optimal target cell or wireless node selection

Step 1: **Initialize**predicted filtered signal results '$D_{RSSI\ w}(n)$'
Step 2: **Begin**
Step 3: **For** each Dataset 'DS' with Samples 'S', Features 'F' and predicted filtered signal results '$D_{RSSI\ w}(n)$'
//Environment
Step 4: Formulate environment based on the increase in CIO, decrease in CIO, increase in TTT and decrease in TTT
//Action
Step 5: Apply the Haversine function from the latitude and longitude of two points as given in equations (12) and (13)
Step 6: Evaluate greedy strategy-based optimal action as given in equation (14)
//Cost evaluation
Step 7: Formulate the cost function as given in equation (15)
Step 8: Apply the haversine function to obtain the optimal selection as given in equation (16)
Step 9: Formulate the Gibbs probability distribution function to select higher probability results as given in equation (17)
Step 10: **End for**
Step 11: **End**

Algorithm-2: Reinforcement Learning-based Gibbs Haversine Distribution

As outlined in the above algorithm, to ensure optimal handover and thereby significantly improve the data delivery rate, the Gibbs-Haversine Distribution function is applied to the Reinforcement Machine Learning model. First, the predicted filtered signal results are subjected to the given environment based on four environment states: an increase in CIO, a decrease in CIO, an increase in TTT, and a reduction in TTT, respectively. Second, a greedy strategy-based optimal action is taken using the Haversine function, which considers the latitude and longitude of two points (i.e., serving nodes and adjacent nodes). By applying this greedy strategy-based optimal action, the cost function is formulated, and following which the Gibbs probability distribution function results in higher probabilities. This, in turn, improves handover success, thereby significantly increasing the data delivery rate.

IV. EXPERIMENTAL SETUP

The proposed Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD) method for the handover process to ensure seamless mobility, along with the conventional method, optimization based on the distance (Opt. Distance) [1] and Learning-based Intelligent Mobility Management (LIM2) [2] is implemented in Python, a high-level general-purpose programming language, for fair comparison, samples obtained from the IP Network Traffic Flows Labelled with 75 Apps dataset [https://www.kaggle.com/jsrojas/ip-networktraffic-flows-labeled-with-87-apps] are used to handle the simulation for all three methods. Additionally, the results are evaluated based on performance metrics, including handover latency, packet loss, data delivery rate, and the success of the handover. Additionally, for evaluation purposes, the maximum number of samples is set at 10,000, and the maximum data packet size is considered to be 1.5 MB. The performance of the JIRF-RLGHD method is compared with the other competing methods, Opt. Distance [1] and LIM2 [2] and evaluated.

V. IMPLEMENTATION DETAILS

In this study, we developed a machine learning-based handover method for 5G-enabled seamless mobility in wireless networks, called Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD), which achieves low packet loss, reduced handover latency, and improved data delivery and handover success rates.

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- The JIRF-RLGHD method comprises two sections, namely, future signal quality prediction and optimal handover process.
- The JIRF-RLGHD method is compared with two existing methods, optimization based on the distance (Opt. Distance) [1] and Learning-based Intelligent Mobility Management (LIM2) [2] using IP Network Traffic Flows Labeled with 75 Apps dataset to validate the results.
- Initially, the network traffic flows were obtained from the input dataset.
- In the first part, the Box Jenkins Impulse Response Filtering model is employed to initially measure the distance between the wireless nodes, microcells, and picocells, respectively. Next, with the aid of RSSI, the link quality is estimated, and updates are made according to the threshold to smooth the prediction of future signal quality. Finally, the Box-Jenkins function is applied to forecast the signal quality, thereby corroborating the objectives of scalability and reliability.
- Second, with the predicted future signal quality taking into consideration both the servicing node and the adjacent nodes, the Reinforcement Learning-based Gibbs Haversine Distribution algorithm is applied to ensure robust and smooth handover, therefore providing seamless mobility.

According to the above implementation patterns, four different evaluation metrics are detailed in the next section.

VI. RESULTS AND DISCUSSION

In this section, the results are evaluated based on performance metrics, including handover latency, packet loss rate, data delivery rate, and handover success rate. Additionally, for evaluation purposes, the maximum number of samples is set at 10000. The performance of JIRF-RLGHD is compared with the other competing methods, Opt. Distance [1] and LIM2 [2]. A simulation of 10 runs is performed.

A. Performance of Handover Latency

Handover latency refers to the delay that happens between when a user takes an action on a network and when it reaches its destination. It is measured in milliseconds. To be more specific, handover latency is defined as the difference in time consumed in discovering the new cell in a wireless network and the serving cell in the same network, respectively. Handover latency is measured by taking into consideration the time of WN in the new cell and the time of WN in the old cell. This is mathematically formulated as given below.

$$HOL = WN_{NewCell} - WN_{OldCell} \tag{18}$$

From the above equation (18), the handover latency 'HOL' is measured based on the time of WN in the new cell '$WN_{NewCell}$' and the old cell '$WN_{OldCell}$' respectively. It is measured in terms of milliseconds (ms). Table 1, presented below, compares the handover latency using the three methods.

Table 1: Handover Latency Comparison Using Three Methods, JIRF-RLGHD, Opt. Distance [1] and LIM2 [2]

Methods	Handover latency (without filter)	Handover latency (with filter)
JIRF-RLGHD	0.15	0.10
Opt. Distance [1]	0.28	0.20
LIM2 [2]	0.35	0.25

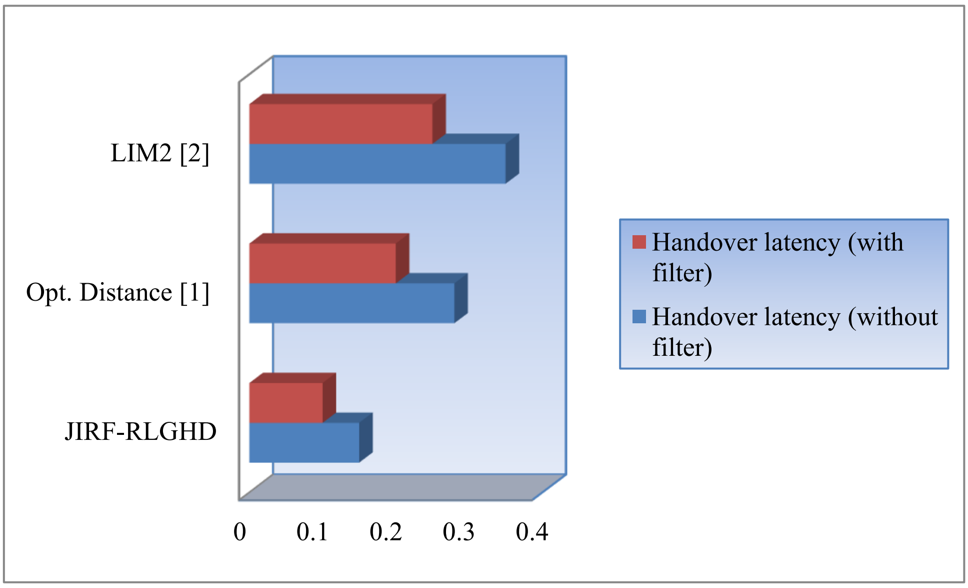

Fig. 4: Simulation Results of Handover Latency

Figure 4, shown above, illustrates the graphical representation of handover latency using the proposed method, JIRF-RLGHD, and the existing process, Opt. Distance [1] and LIM2 [2] respectively. To validate the handover latency, results were obtained both with and without a filter mechanism in place. From the above figurative representation, the handover latency with a filter was found to be comparatively reduced than without a filter. With 10,000 samples used, the handover latency without a filter, using the proposed method, was found to be 0.15 ms, whereas it was 0.10 ms when applied with a filter. Similarly, Opt.

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Distance [1] observed a handover latency of 0.28ms (without filter) and 0.20ms (with filter) and the LIM2 [2] method observed a handover latency of 0.35ms (without filter) and 0.25ms (with filter). The reason behind the improvement was the application of the Box-Jenkins Impulse Response Filtering algorithm for the JIRF-RLGHD method. By applying this algorithm, raw sample traffic flow data was subjected to designing seamless mobility via an input vector matrix. With the available data, the distance between the wireless node and the microcell and picocells was measured. Following this, the link quality was evaluated for different numbers of data packets, which in turn improved the scalability of the handover process. Finally, based on the evaluation of the updated link quality filter, the coefficients were updated randomly. This, in turn, improved the handover latency using the JIRF-RLGHD method by 33% upon comparison to [1] and 35% upon comparison to [2].

B. Performance of Packet Loss Rate and Data Delivery Rate

Packet loss rate refers to the number of data packets lost during transmission and is evaluated as follows.

$$PL = \frac{DP_{lost}}{DP_{sent}} * 100 \quad (19)$$

From the above equation (19), the packet loss rate 'PL' is measured based on the data packet sent 'DP_{sent}' and the data packet lost 'DP_{lost}'. It is measured in terms of percentage (%). The data delivery rate is calculated as the percentage ratio of data packets that were efficiently delivered from the service node. This is mathematically stated as given below.

$$DD = \frac{DP_{RC}}{DP_{SN}} * 100 \quad (20)$$

From the above equation (20), the data delivery rate 'DD' is measured by taking into consideration the data packets sent from the serving node 'DP_{SN}' and the data packets received correctly 'DP_{RC}'. It is measured in terms of percentage (%). Table 2, presented below, compares packet loss and data delivery rates using the three methods.

Table 2: Packet Loss and Data Delivery Rate Comparison Using Three Methods, JIRF-RLGHD, Opt. Distance [1] and LIM2 [2]

Methods	Packet loss (%)	Data delivery rate (%)
JIRF-RLGHD	3.25	96.75
Opt. Distance [1]	4.40	96
LIM2 [2]	4.85	95.15

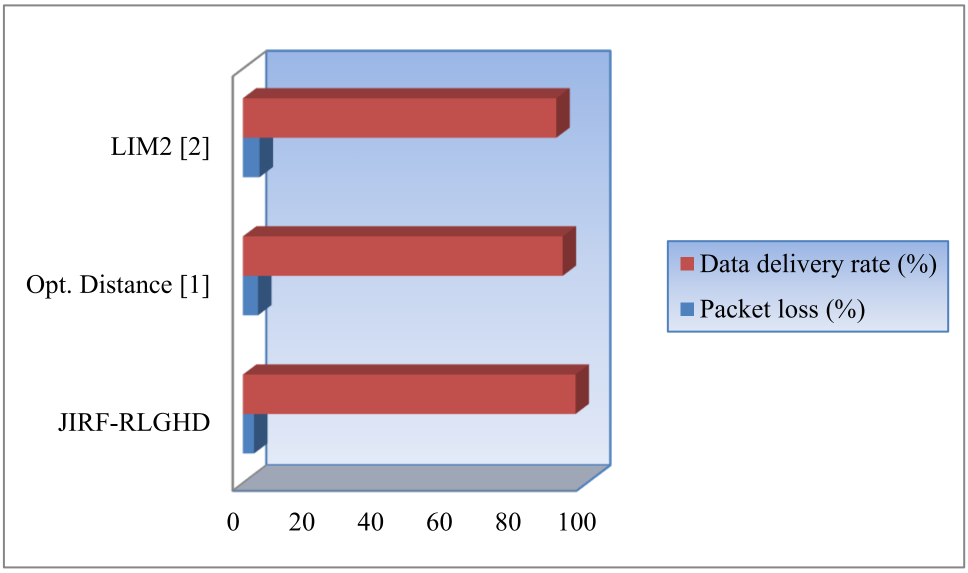

Fig. 5: Simulation Results of Data Delivery Rate and Packet Loss

Figure 5, given above, illustrates the data delivery rate and packet loss using the proposed JIRF-RLGHD and existing methods, Opt—distance [1] and LIM2 [2]. While performing the process of seamless mobility, a certain amount of packet loss is said to occur during handover, resulting in a significant compromise in data delivery rate. However, simulations performed with 10000 sample traffic flows observed data packet loss of 325, 440, and 485 using the three methods. With this, the overall packet loss rates were found to be 3.25%, 4.40%, and 4.85% using JIRF-RLGHD and Opt. Distance [1] and LIM2 [2]respectively. Similarly, the data delivery rates were observed to be 96.75%, 93%, and 91.15% using JIRF-RLGHD and Opt. Distance [1] and LIM2 [2]respectively. From these results, the packet loss and data delivery rate were observed to be comparatively lower using the JIRF-RLGHD method upon comparison to [1] and [2]. The reason behind the minimisation of packet loss and maximisation of data delivery rate was due to the application of the Reinforcement Learning-based Gibbs Haversine Distribution algorithm. By applying this algorithm, the predicted filtered signals were subjected to four distinct environment states. Following this, a greedy strategy-based optimal action employing the Haversine function, considering both the latitude and longitude of both serving nodes and adjacent nodes, was used.

This, in turn, reduced the packet loss considerably using the JIRF-RLGHD method by an average of 18% upon comparison to [1] and [2]. Additionally, a greedy strategy-based optimal action, employing the Gibbs probability distribution

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function, was applied to achieve higher probability results that evolved with better handover. This, in turn, improved the data delivery rate using the JIRF-RLGHD method by an average of 3% upon comparison to [1] and [2], ensuring reliability to a greater extent.

C. Performance of Handover Success Rate

The success of a handover or handover success rate refers to the rate of successfully transferring an ongoing call or data session from one channel to another in a wireless network. The formula for measuring the handover success rate is mathematically formulated as given below.

$$HOSR = \frac{(Success_{InterCellHO} + Success_{IntraCellHo})}{(Attempt_{InterCellHO} + Attempt_{IntraCellHO})} * 100 \quad (21)$$

From the above equation (21), the handover success rate '$HOSR$' is measured taking into consideration the successful inter-cell handover '$Success_{InterCellHO}$' Successful intra-cell handover '$Success_{IntraCellHo}$', attempted inter-cell handover '$Attempt_{InterCellHO}$' and the attempted intra-cell handover '$Attempt_{IntraCellHO}$' respectively. It is measured in terms of percentage (%). Finally, Table 3, given below, provides the handover success rate using the three methods.

Table 3: Handover Success Rate Comparison Using Three Methods, JIRF-RLGHD, Opt. Distance [1] and LIM2 [2]

Methods	Handover success rate (without optimal distribution) (%)	Handover success rate (with optimal distribution) (%)
JIRF-RLGHD	85.35	92.15
Opt. Distance [1]	80.15	83.55
LIM2 [2]	75.25	85.45

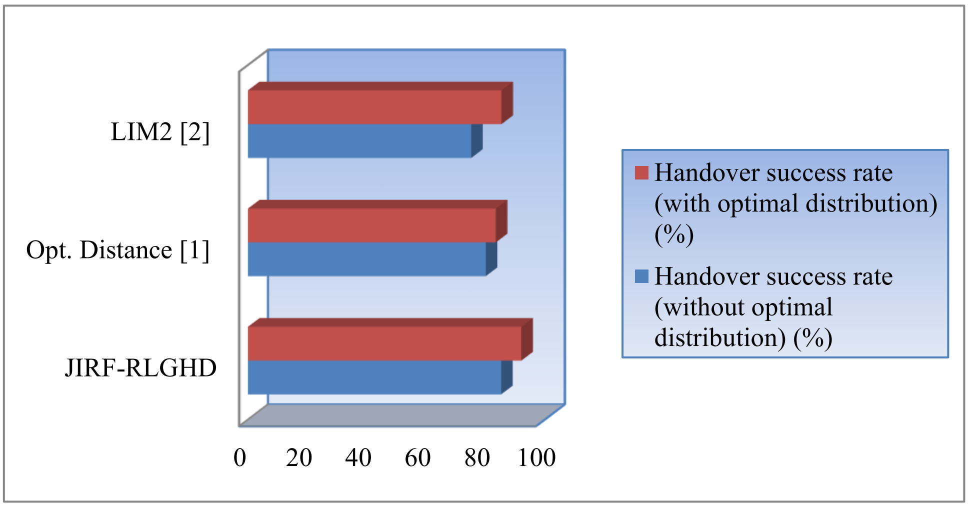

Fig. 6: Simulation Results of Handover Success Rate Using JIRF-RLGHD, Opt. Distance [1] and LIM2 [2]

Figure 6, given above, shows the handover success rate for an average of 10,000 network traffic flows using the three methods: JIRF-RLGHD and Opt. Distance [1] and LIM2 [2]. The handover success rate, as illustrated in the above figure, involves validation analysis both with and without optimal distribution. By performing optimal distribution, the handover success rate using the three methods JIRF-RLGHD and Opt. Distance [1] and LIM2 [2] were observed to be 92.15%, 83.55%, and 85.45%, respectively. Similarly, without the application of optimal distribution, the handover success rates were found to be 85.35%, 80.15%, and 75.25%, respectively. With this, the handover success rate using the JIRF-RLGHD method was found to be comparatively better than [1] and [2]. The reason behind the improvement was due to the application of the Reinforcement Learning-based Gibbs Haversine Distribution algorithm. By applying this algorithm, the Gibbs Haversine Distribution function was applied to the Reinforcement Machine Learning model. Additionally, a greedy strategy-based optimal action evolution model was employed, which in turn improved both successful inter-cell handovers and intra-cell handovers. With this, both the scalability and reliability of seamless mobility in wireless networks are said to be ensured using the JIRF-RLGHD method.

Table 4: Overall Comparative Analysis of Proposed And Existing Methods

Metrics/Methods	JIRF-RLGHD	Opt. Distance [1]	LIM2 [2]
Handover latency (without filter) (ms)	0.15	0.28	0.35
Handover latency (with filter) (ms)	0.10	0.20	0.25
Packet loss (%)	3.25	4.40	4.85
Data delivery rate (%)	96.75	96	95.15
Handover success rate (without optimal distribution) (%)	85.35	80.15	75.25
Handover success rate (with optimal distribution) (%)	92.15	83.55	85.45

Table 4 presents an overall comparative analysis of various methods, including JIRF-RLGHD and Opt. Distance [1] and LIM2 [2] to ensure seamless mobility in wireless networks. The performance of proposed and existing methods is evaluated in terms of four key metrics: handover latency, packet loss, data delivery rate, and handover success rate. As observed from the above figure, the proposed JIRF-RLGHD method outperformed the existing Opt. Distance [1] and LIM2 [2] methods. The handover latency of the JIRF-RLGHD method is obtained as

0.15 ms without using a filter, whereas a 0.10 ms handover latency is obtained for the JIRF-RLGHD method with a filter. Also, the data delivery rate is achieved as 96.75% for the JIRF-RLGHD method, whereas 96% and 95.15% are achieved for existing [1] and [2]. In addition, the Handover success rate is achieved as 92.15%, 83.55%, and 85.45% for JIRF-RLGHD, existing [1] and [2] respectively with optimal distribution whereas 85.35%, 80.15%, and 75.25% for without optimal distribution. From the above results, it is inferred that the performance of the proposed JIRF-RLGHD method is found to be better than that of the state-of-the-art methods. The Box-Jenkins Impulse Response Filtering algorithm is used in JIRF-RLGHD to get a convergence-efficient filtered signal. With this, noisy signals are eliminated, and handover latency and packet loss are minimised. In addition, the target cell is chosen optimally using a Reinforcement Learning-based Gibbs Haversine Distribution algorithm to carry out the handover with minimum latency and a higher success rate than conventional methods.

VII. CONCLUSION

In this study, a Jenkin Impulse Response Filtering and Reinforcement Learning-based Gibbs Haversine Distribution (JIRF-RLGHD) method is proposed for seamless mobility in a 5G wireless network, aiming to achieve low packet loss and a high handover success rate. The future signal quality of both serving and adjacent cells is predicted in a computationally efficient manner employing the Box-Jenkins Impulse Response Filtering algorithm. Here, a combination of updated link quality estimates based on the distance factor and the Box-Jenkins function was applied to the raw traffic signals to obtain probable signal results. Second, with the obtained probable signal results, the Reinforcement Learning-based Gibbs Haversine Distribution algorithm was employed to ensure optimal target cell selection, thereby providing a reliable and scalable handover process. The IP Network Traffic Flows Labelled with 75 Apps dataset was utilised for the experimental assessment, and the results were also compared with those of conventional state-of-the-art methods. The proposed CS-AGNN method performs better overall in terms of execution time, key storage cost, and throughput.

DECLARATION STATEMENT

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Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence.
Availability of Data and Materials	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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