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Hybrid Heuristic Technique for Smart Intelligent Handover Triggering Mechanism in 5G Ultra-Dense Networks

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ABSTRACT

Handover (HO) triggering in fifth-generation (5G) ultra-dense networks (UDNs) is critical for ensuring seamless connectivity as mobile user equipment (UE) transitions between adjacent small cells or base stations. Due to the dense deployment of low-powered cells and high user mobility, UDNs experience frequent handovers, which can lead to service degradation and reduced Quality of Service (QoS). Efficient and adaptive handover mechanisms are therefore essential for sustaining network performance. This study proposes a hybrid intelligent framework for adaptive handover triggering in hyper-dense 5G scenarios. The framework integrates a Modified Pelican Optimization (MPO) algorithm for efficient user clustering, a hybrid Quantum-Classical Recurrent Neural Network (QCRNN) for dynamic handover decision-making, and Chaos Gorilla Troop Optimization (CGTO) for predictive mobility pattern analysis using historical user data. The QCRNN leverages design constraints including transmission delay, signal-to-interference-plus-noise ratio (SINR), received signal strength (RSS), User Motion Potential (UMP), and Current Load Conditions (CLC) to determine optimal handover initiation without predefined thresholds, enabling adaptive and context-aware decisions. Simulation results demonstrate that the proposed MPO-QCRNN-CGTO approach significantly outperforms existing methods (RSRP, Fuzzy, AHP-TOPSIS-Q, FMCSS, SC-Q). The framework reduces the average number of handovers (NOH) by up to 96%, decreases the probability of ping-pong handovers (PPHO) by up to 87%, and lowers handover failure rates by up to 78%. Furthermore, it improves throughput by up to 287% and reduces network latency by up to 65% across varying user densities and simulation times. These improvements highlight the framework's ability to minimize unnecessary handovers, prevent service interruptions, and maintain high network efficiency, confirming the effectiveness of the integrated MPO-QCRNN-CGTO approach in enhancing mobility robustness and QoS in 5G UDNs.

Index Terms – 5G ultra-dense networks, handover management, mobility robustness, network performance optimization, quality of service

1. INTRODUCTION

In 5G ultra-dense networks, handover management and triggering mechanisms are essential for ensuring seamless connectivity and uninterrupted user experience [1]. The triggering mechanism for each type of handover varies depending on factors such as signal strength, user movement patterns, and neighboring cells or Radio Access Technology (RAT) [2]. There are different types of handovers in 5G networks, including intra-cell handover, inter-cell handover, and inter-RAT (radio access technology) handover. The triggering mechanism [3] for each type of handover varies. Intra-cell handover occurs within the same cell, and it is triggered when the quality of the signal deteriorates to a certain level, or when the user moves to a different location within the cell. The network may also use predictive algorithms to trigger an intra-cell handover based on the user's movement patterns. Inter-cell handover occurs when the user moves from one cell to another. It occurs when the neighboring cell's signal strength is high and the current cell's signal strength falls below a predetermined threshold [4]. The network may also use predictive algorithms to trigger an inter-cell handover In light of client development designs and assessed signal strength in adjoining cells. When a user switches from a 5G network to another RAT, such as 4G or Wi-Fi, they experience inter-rate handover [5]. When the current network's signal strength falls below a predetermined threshold, it is activated the neighboring RAT is stronger. In ultra-dense networks, users are likely to move rapidly between cells, which can cause interruptions or drops in the connection if the handover is not managed properly. Handover management ensures that the handover process is seamless and transparent to the user, so that they don't experience any disruptions in their communication session [6]. Handover management can help ensure that users get the best possible quality of service (QoS) by maintaining a strong and stable connection. For example, if a user is in a crowded area with multiple cells, handover management can help ensure that they are connected to the cell with the strongest signal and best QoS [7][8]. Handover management can also help optimize network resources by ensuring that cells are not overburdened with too many active users. Efficient handover management can help reduce signaling overhead and dormancy in the organization, which can work on the general productivity and execution of the organization. Even though handover control is essential for ensuring smooth communication and optimal network performance in dense 5G networks, the handover mechanism can cause a number of issues [9]. Ultra-dense networks are prone to interference and congestion, which can impact the accuracy and reliability of the handover mechanism. The accuracy of the handover mechanism is dependent on the ability to predict user mobility patterns accurately [10]. However, in ultra-dense networks, user mobility can be highly unpredictable, which can make it difficult to trigger handovers at the right time and avoid unnecessary handovers. Handover management requires synchronization between cells and the network, which can be challenging in ultra-dense networks with high mobility and fast-changing radio conditions [11][12]. In ultra-dense networks, cells are often in close proximity to each other, which can result in interference from neighboring cells. This can make it challenging to accurately detect signal strength and trigger handovers at the right time [13]. In ultra-dense networks, there may be multiple cells available to connect to at any given time, which can make the decision-making process for triggering handovers more complex. This can lead to delays in triggering handovers, which can result in poor user experience and dropped connections [14].

Several methods have been proposed for handover management in 5G ultra-dense networks, including PE-TOPSIS and PSD-TOPSIS [15], which have shown superior performance compared to other methods in terms of reducing handover failures and improving mean user throughput. A unified framework has also been used to analyze critical performance metrics, such as coverage probability and handover cost, while taking into consideration the mobility of mobile users [16]. Anchor-based multi-connectivity design has been proposed to derive compact expressions of handover probabilities through stochastic geometry analysis in user-centric networks. Additionally, a handover protocol (HOP) [17] in the control-plane has been shown to reduce handover delay by over 40% compared to traditional handover schemes used in LTE systems. An efficient handover decision algorithm based on Markov decision process (MDP) [18] has been proposed for optimizing the overall service experience of users in mm-wave HetNets. Furthermore, evolutionary network architecture has been utilized to optimize the signaling mechanism and assist operators in managing their capital expenditure (CAPEX) [19]. Finally, P-stable power-efficient handover decision-making strategies [20] combined with mobility reliability model are proposed for intra-handover and inter-hop handover cases when Femto user devices move to another Femto access point and macro user devices switch. This paper presents an approach to handover management in 5G ultra-dense networks that incorporates advanced techniques such as the modified pelican optimization (MPO) algorithm, a hybrid quantum-classical recurrent neural network (QCRNN), and the chaos gorilla troops optimizer (CGTO) algorithm. These techniques are designed to optimize handover triggering mechanisms and improve user experience by ensuring seamless connectivity and maintaining high-quality service.

1. The MPO algorithm is used to develop an efficient clustering technique that ensures user mobility robustness while maintaining high-level key performance. This technique aims to minimize handovers while maximizing the network coverage area, thus reducing handover failure and ensuring uninterrupted connectivity for mobile users.
2. The QCRNN algorithm is introduced to optimize handover triggering rules by taking into account various design constraints such as transmission delay, SINR, received signal strength (RSS), current load on cell (CLC), and user movement probability (UMP). The QCRNN algorithm intelligently determines the optimal handover triggering timing without requiring additional handover conditions, thus improving handover and reducing network latency.
3. The CGTO algorithm is employed to generate state vectors from historical data, improving handover prediction accuracy and effectiveness. This technique aims to better understand the patterns and behavior of user mobility in 5G ultra-dense networks and uses this information to improve the handover management mechanism.

The rest of this paper is organized as follows. The recent research on transmission control mechanisms in 5G high-density networks is covered in Section 2. The proposed mechanism's system structure and the problem's methodology are discussed in Section 3. Section 4 provides a thorough explanation of the proposed transmission control mechanism's working procedure. Section 5 discusses simulation results and a comparison of proposed and existing transmission control algorithms. The paper comes to a conclusion in Section 6.

2. METHODS AND SYSTEM ARCHITECTURE

2.1 Research Gaps

As 5G networks become denser, with an increasing number of small cells and mobile devices, the need for effective handover management becomes critical. Handover management ensures that mobile devices maintain a seamless and uninterrupted connection as they move through the network. In dense networks, where the number of cells and devices is high, the handover process becomes more complex, and failures or delays in handover result in poor system performance and QoS. Efficient handover management becomes essential to maintain the connection quality, reduce energy consumption, and enhance the overall network performance in 5G dense networks. Liu et al. [31] have proposed A Deductive Clustering Method and Q Learning Framework-Based Intelligent Transfer Triggering Algorithm for UEs By extracting a clustering technique, the input measurements are first transformed into state vectors, enhancing the training process's efficiency and effectiveness. The correct transfer execution procedure is learned from the environment by a Q-learning system. At the UE, the learned Q schedule is turned on to start the handover process. When compared to the number of transmissions, ping-ping transmission rate, and transmission failure rate, the simulation results demonstrate that this method can maintain other key performance indicators (KPIs) while still providing high UE mobility reliability. The mechanism improves estimated KPIs by 20% on average when combined with subtractive clustering. Additionally, it maintains high system performance and network latency. The evaluation also highlights that applying subtractive clustering techniques to all KPIs evaluated improves the performance of this method by approximately 20%. In 5G ultra-dense networks, there are several challenges associated with the handover triggering mechanism, including. With a large number of base stations in an ultra-dense network, there is a need for an efficient handover decision-making mechanism that can take into account multiple factors such as signal quality, interference, traffic load, and mobility patterns of the users. As the number of base stations increases in an ultra-dense network, the scalability of the handover mechanism becomes a major challenge. The handover mechanism needs to be able to handle a large number of simultaneous handovers without affecting the overall network performance. The latency of the handover mechanism becomes critical, as even a small delay can result in a dropped call or degraded quality of service. The handover mechanism needs to be optimized to minimize the handover latency while ensuring a seamless handover experience for the users. There is a high probability of interference due to the presence of a large number of base stations. The handover mechanism needs to be designed in way that minimizes the impact of interference on the handover process. With a large number of base stations and users in an ultra-dense network, the security of the handover mechanism becomes critical. The handover mechanism needs to be designed to prevent unauthorized access and ensure the confidentiality and integrity of the handover-related information. Based on the research gaps from previous works [21]-[31], the consolidated problems associated with handover in wireless networks are: The handover process may not be efficient in accounting for various factors such as mobile access points, dynamic clusters, multipath effects, and signaling overhead, resulting in suboptimal system performance and QoS [21][23]. The method used for handover decision-making may not be able to handle imprecise data, leading to inaccurate decision-making [22][23]. Considering only certain criteria may not be adequate for a diverse network [24], leading to poor performance in specific scenarios [25]. Some handover solutions [27][28] may not be suitable for highly dense environments, which can result in poor network performance. The impact of signaling overhead may not be taken into account, leading to excessive signaling and reduced network performance [26]. Even when the Decision Algorithms are Context-Aware, an Increase in Handover context remains the same, which can result in network inefficiencies [30][31]. The following research objectives to solve the above problems associated with handover in 5G dense networks can include:

1. Developing efficient handover decision-making algorithms that take into account various factors such as mobile access points, dynamic clusters, multipath effects, and signaling overhead.
2. Developing methods for handling imprecise data and improving the accuracy of handover decision-making.
3. Incorporating additional optimal criteria into the handover decision-making process that are specific to diverse network scenarios.
4. Developing handover solutions that are suitable for highly dense environments, which can improve network performance.
5. Reducing the impact of signaling overhead by developing more efficient handover mechanisms.
6. Developing context-aware decision algorithms that reduce the number of unnecessary handovers even when the context remains the same, which improve network efficiency.

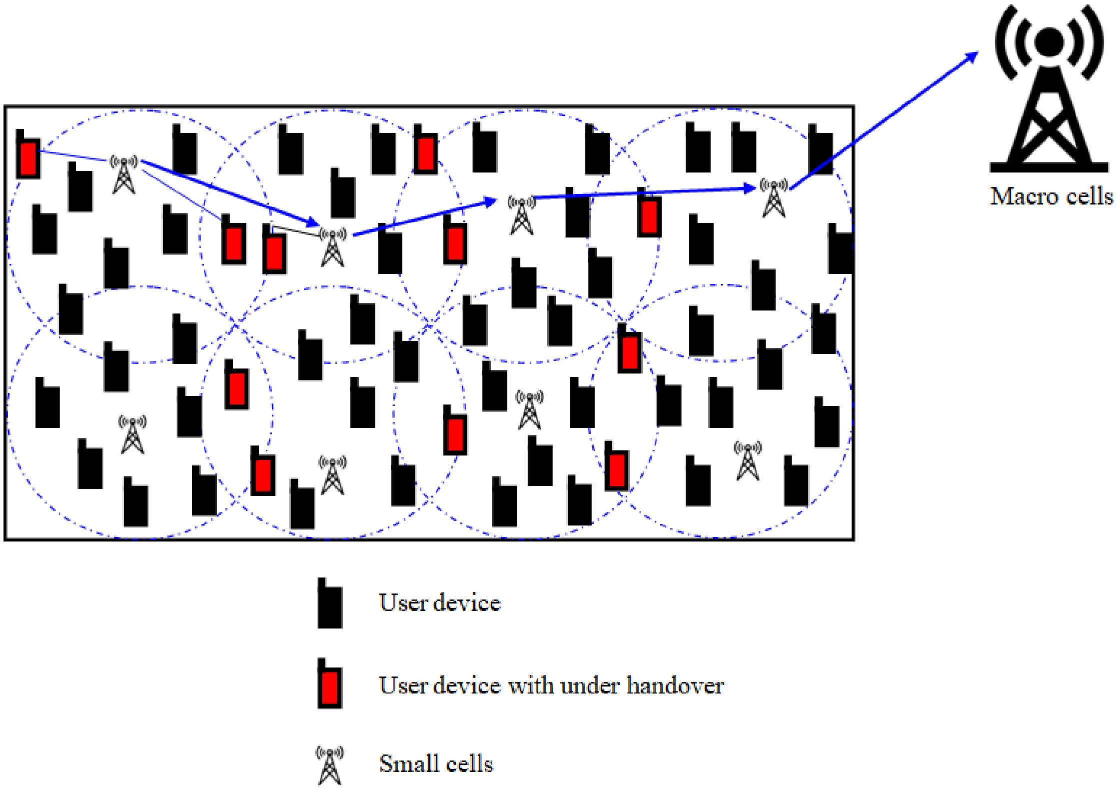

Figure.1 Overall system architecture of proposed work

2.2 System Architecture of Proposed Work

The proposed framework aims to improve the handover process in a heterogeneous (HetNet) network comprising of macro and small cells as shown in Fig. 1. Small cells are randomly deployed with a radius of 100m and 40m distance between them to ensure overlap. When users move from one small cell to another, the serving cell's signal-to-interference-plus noise ratio (SINR) decreases, and the neighboring cells' SINR increases. To optimize the clustering process, we use a modified pelican optimization (MPO) algorithm and maintain service continuity by setting a minimum SINR threshold. The framework employs handover metrics such as transmission delay, SINR, RSS, CLC, and UMP to select the optimal target cell. A hybrid quantum-classical recurrent neural network (QCRNN) is used to optimize the design constraints and compute the handover triggering rules, with UMP obtained from a mobility prediction model for users. The chaos gorilla troops optimization (CGTO) algorithm is used to generate state vectors from historical data, improving handover prediction accuracy and effectiveness. The proposed framework aims to ensure efficient energy consumption and seamless service continuity for users in a scenario with a lot of small cells in the 5G cellular network.

3. LITERATURE REVIEW

Handover (HO) management in 5G ultra-dense networks (UDNs) has been extensively explored, aiming to reduce handover failures, improve throughput, and maintain seamless connectivity. However, many existing approaches face limitations such as inability to handle dynamic user mobility, imprecise data, high signaling overhead, and lack of adaptive decision-making. Table 1 summarizes the state-of-the-art schemes, highlighting their key findings, limitations, and how the proposed MPO-QCRNN-CGTO framework addresses these issues.

Liu et al. [21] introduced a handover mechanism in 5G UDNs using Fuzzy logic and Multi-Attribute Decision Making (MADM) algorithms. By leveraging TOPSIS and fuzzy logic, the method selects the optimal neighboring base station (BS) under varying network conditions such as RSRP and SINR, reducing ping-pong handovers by 23% and maintaining packet loss at an average of 0.3. While effective, it does not consider mobile access points, dynamic clusters, signaling overhead, or delays. The proposed framework incorporates adaptive MPO-based clustering and QCRNN-driven handover decisions to manage dynamic mobility efficiently. Gaur et al. [22] developed a thresholding-based handover triggering mechanism integrated with Multiple Criteria Decision Making (MCDM) algorithms including TOPSIS, PROMETHEE, and SAW. The approach selects RATs based on user-specific application requirements, achieving reductions in RAT changes of 13.14%, 19.35%, and 8.62%, respectively. However, the reliance on fixed thresholds may lead to suboptimal QoS under dynamic conditions. The proposed QCRNN dynamically learns optimal handover timing, addressing this limitation. Javaid et al. [23] presented a Clustering-cum-Handover Management Scheme (CHMS) using a dynamic distributed clustering protocol (DCCP) to manage cluster formation and transmission control, resulting in a 12% increase in throughput and 17% reduction in control overhead. The method, however, struggles to handle imprecise data and rapidly changing user mobility. The MPO algorithm in the proposed framework provides robust clustering under uncertain and dynamic conditions. Lai et al. [24] proposed a D2D handover mechanism, where each D2D user pair selects the target eNB based on link stability, SNR, distance, and mobility. The approach reduces handover time by 15% and increases throughput by 11%. Yet, considering only these criteria may be insufficient for heterogeneous UDN environments. CGTO-based prediction in the proposed framework enhances handover accuracy by analyzing historical mobility patterns. Ghosh et al. [25] evaluated Handover Enforcement Mechanisms (HEMs) including hard and semi-soft handovers with various Mobility Management Protocols (MMPs) across transport, network, and distributed layers, using Analytic Hierarchy Process (AHP).

Narai et al. [26] proposed a Virtual Cell (V-cell) based handover for connected vehicles, using metrics such as signal strength, distance, and speed with an SDN controller for optimized HO. While effective, scalability to ultra-dense networks is limited. The proposed framework extends performance to hyper-dense UDNs through adaptive clustering and predictive handover mechanisms. Palas et al. [27] developed an Enhanced Multi-Objective Optimization Method (E-MOORA) combined with Q-learning to select broadcast target cells, reducing radio link failures by 14% and improving throughput by 13%. However, multipath effects and dynamic load variations were not considered. QCRNN in the proposed framework addresses this by dynamically integrating SINR, RSS, load, and mobility factors. Cicioglu [28] employed an entropy-based Simple Additive Weight (SAW) decision-making method for multi-rate handovers in SDN-based 5G small cells, achieving 18% lower handover delay and 10% higher throughput. This approach is less suitable for hyper-dense scenarios, which the MPO-QCRNN-CGTO framework efficiently manages via adaptive, threshold-free handover triggering. Alhabo et al. [29] proposed a game-theoretic approach for energy-efficient handovers in dense small cell networks, increasing small cell throughput by 8% and reducing power consumption by 12%. Khan et al. [30] introduced a two-layer network resource allocation method using SVM and Random Forest (RF) to reduce energy consumption and transmission costs, achieving a 12% reduction in energy and 11% higher throughput. Context-aware decisions could still cause redundant handovers under static conditions, which are mitigated in the proposed framework through adaptive QCRNN-based handover timing.

Table 1 Comparative Analysis of Existing Handover Management Schemes in 5G Ultra-Dense Networks

Ref.	Methodology	Technique Used	Key Findings	Research Gaps	How Proposed Model Addresses the Gaps
[21]	Handover in 5G UDN	Fuzzy-MADM	Ping-pong rate ↓ 23%, Packet loss avg 0.3	Does not account for mobile access points, dynamic clusters, delay, signaling overhead	MPO-QCRNN-CGTO handles dynamic clusters, mobility patterns, adaptive HO thresholds
[22]	Thresholding scheme for HO reduction	TOPSIS, PROMETHEE, SAW	RAT change ↓ TOPSIS 13.14%, PROMETHEE 19.35%, SAW 8.62%	May lead to suboptimal system performance, QoS	QCRNN dynamically predicts optimal HO timing, improving QoS
[23]	Clustering-cum-HO management	DCCP	Control overhead ↓ 17%, Throughput ↑ 12%	Cannot directly handle imprecise data	MPO clustering efficiently handles user uncertainty and mobility
[24]	HO management for D2D	LSTM-SVM	Handover time ↓ 15%, Throughput ↑ 11%	Limited criteria considered, may be inadequate for diverse network	CGTO predicts mobility patterns to improve HO accuracy across scenarios
[25]	HO management	HEMS, PEMS	Control overhead ↓ 10%, Throughput ↑ 9%	Designed for infrastructure networks, ignores mobile APs	MPO-QCRNN-CGTO adapts to mobile APs and UDN conditions
[26]	Inter-V-cell HO decision	FiVH-Fuzzy	Packet loss rate ↓ 0.28, Handover time ↓ 12%	Not suitable for highly dense environments	Proposed framework scales to hyper-dense 5G UDNs
[27]	HO mobility management in 5G	E-MOORA, Q-Learning	Radio link failure ↓ 14%, Throughput ↑ 13%	Multipath effects not considered	QCRNN considers SINR, RSS, multipath, and dynamic load
[28]	Multi-criteria HO management	Enhanced Packet Core (EPC)	Handover delay ↓ 18%, Throughput ↑ 10%	Not suitable for high-density scenarios	MPO-QCRNN clustering and CGTO prediction improve HO in UDNs
[29]	Energy-efficient HO management	Game Theory	Throughput ↑ 8%, Power consumption ↓ 12%	Overlooks signaling overhead	Proposed model minimizes signaling during HO while optimizing throughput
[30]	HO management for two-tier 5G	SVM-RF	Energy consumption ↓ 12%, Throughput ↑ 11%	Context-aware decisions can still increase unnecessary HO	Adaptive QCRNN decision-making reduces redundant HO events

4. METHODOLOGY

The method that has been proposed for making smart and intelligent handover triggering mechanisms work in 5G networks that are very dense consists of three main components: clustering of users using the modified pelican optimization (MPO) algorithm, optimization of handover triggering rules using the hybrid quantum-classical recurrent neural network (QCRNN) algorithm, and prediction of handover destination using the chaos gorilla troops optimization (CGTO) algorithm. These techniques aim to maintain high-quality service for mobile users by ensuring seamless connectivity and robustness in user mobility, while optimizing handover triggering timing based on key performance metrics such as transmission delay, SINR, RSS, CLC, and UMP.

4.1 User clustering using MPO algorithm

In 5G ultra-dense networks (UDNs), user clustering is a critical step in optimizing handover (HO) triggering, as it groups mobile users based on their spatial and mobility characteristics, such as location, velocity, movement direction, signal strength, and current cell load. This grouping enables the network to anticipate handover requirements for clusters of users rather than treating each user individually, thereby reducing unnecessary handovers, improving resource allocation, and ensuring smoother connectivity. In the proposed framework, the Modified Pelican Optimization (MPO) algorithm is employed for this purpose. MPO is a population-based metaheuristic inspired by the hunting and social behavior of pelicans, and it enhances the conventional Pelican Optimization (PO) algorithm by introducing adaptive leader-follower dynamics and diversity-preserving mechanisms to avoid local optima and improve convergence. In MPO, leaders guide the search toward promising regions, while followers explore the solution space to maintain diversity, making it highly suitable for dynamic 5G UDN environments where multiple parameters must be considered simultaneously. Compared to traditional clustering algorithms such as K-Means or DBSCAN, MPO does not require prior specification of the number of clusters and can efficiently handle multi-dimensional input attributes. In this context, the inputs for MPO include user location coordinates, velocity, movement direction, signal quality indicators (RSS/SINR), and current load conditions of the serving cells. The algorithm is used to optimize the clustering process to ensure that users are grouped together in a way that is conducive to efficient handover triggering. For the target function, which consist of a set of N tasks and M solutions and UK is the first task on the second solution. Using the A_{UK} start e_{UK} operations, the S_{UK} identifies the interrupt time of the first job processed by the second solution. After that, we use the following formula to calculate how long it will take to complete the UK process:

$$A_{UK} = e_{UK} + S_{UK} \tag{1}$$

e_{UK} and S_{UK} are the completion times of the last (nth) task on vehicle I and the task of clustering due to the fact that solutions and tasks a_{Uy} have different completion times. Here, the traffic distribution starts time computation a_{UKI} as follows.

$$E_{UK} = \max\left(a_{Uy,} a_{UKI}\right) \tag{2}$$

The processing time could be defined as that of the period required for the solution to execute its final task a_{max}:

$$makespan = a_{\max} = \max\left(a_{UK}\right) \tag{3}$$

The effectiveness of schedule planning L_U is evaluated by comparing the total solution down time (I) with the total system processing time (s_K).

$$A^{'} = 1 + \frac{\sum_U L_U}{\sum_K d.s_K d} = \frac{a.I}{\sum_{k,} ds_K d} \tag{4}$$

where L_U is the initial solution idle time. Mean distribution d; the total number of solutions is denoted by the number k. The quality and objectivity functions obtained used to assess the quality of solutions when implementing algorithms in traffic distribution model. A fitness function closely guides development procedure by describing how well the investigative solutions the objective (G). Objective function (H_U), on the other hand, indicates how well a solution performs its optimal function.

$$G = \frac{1}{a_{\max}} \tag{5}$$

$$H_{(U)} = \frac{H_{(U)}}{\sum_1^y H_{(U)}} \tag{6}$$

where U is the population size, $H_{(U)}$-fitness, and a_{max} is the time between the start of the first task and the completion of the last task. The technique that comprises the present cluster based data gathering using MPO is explained in Algorithm 1. The algorithm outputs well-defined clusters of users, cluster centroids, estimated handover probabilities for each cluster, and an optimized resource allocation map, which are subsequently fed into the QCRNN for predictive and adaptive handover decision-making. This approach enables the proposed MPO-QCRNN-CGTO framework to effectively manage user mobility, reduce handover failures, minimize ping-pong effects, and maintain high throughput and low latency across ultra-dense 5G networks.

Algorithm 1 Cluster formation using MPO

```
Input   : user information-location, position, mobility, movement direction
Output : cluster formation
Initialize M×N reef size
Create Coral Colony
Evaluate Coral Fitness
Stochastically scatter on the reef with an occupancy rate of r0.
Reiterate
Use external broadcast spawning to generate a new population of coral fraction FB.
Employ internal brooding to generate a new population of coral fraction 1-FB.
Assessing the quality of the coral larvae.
Settling of the coral larvae onto the reef substrate.
If ICRO is being executed, implement a 'local search strategy'.
Otherwise, if ECRO is in progress, utilize an 'advanced search strategy'.
end if
Generate new coral populations with the most fit individuals
Cull the least fit coral individuals on the reef
Continue iterating until the stop condition is met
Retrieve the most optimal solution
```

4.2 Handover triggering mechanism

In mobile cellular networks, a handover is the process of transferring an ongoing call or data session from one cell (base station) to another, while the mobile device is in motion. A handover triggering mechanism is a set of rules or algorithms that determine when and how to initiate a handover, to ensure that the user's connection remains stable and uninterrupted as move through different cells. In 5G ultra-dense networks, handover triggering mechanisms need to be smart and intelligent, taking into account various design constraints such as transmission delay, signal quality, and network load, to ensure seamless connectivity and maintain high-quality service for mobile users. The hybrid quantum-classical recurrent neural network (QCRNN) proposed in the paper is an example of a handover triggering mechanism that can optimize the handover process in real-time, without requiring additional handover conditions. The selection of these parameters is critical to ensure seamless connectivity and maintain high-quality service for mobile users.

1. Received signal strength (RSS): This parameter measures the strength of the signal received by the mobile device from the serving base station. If the RSS falls below a certain threshold, it may trigger a handover to a neighboring base station with a stronger signal.
2. Signal-to-Interference-plus-Noise Ratio (SINR): This parameter measures the quality of the signal received by the mobile device, taking into account the interference and noise in the surrounding environment. If the SINR falls below a certain threshold, it may trigger a handover to a neighboring base station with a better SINR.
3. Cell Load: This parameter measures the current traffic load on the serving base station. If the load is too high, it may trigger a handover to a neighboring base station with a lower load to balance the traffic across the network.
4. User Mobility: This parameter measures the user's movement speed and direction. If the user is moving away from the serving base station, it trigger a handover to a neighboring base station in the direction of the user's movement.

5. Transmission Delay: This parameter measures the time it takes to transmit data between the mobile device and the base station. If the delay exceeds a certain threshold, it may trigger a handover to a neighboring base station with lower delay.

The QCRNN serves as the core decision-making module for adaptive handover triggering in 5G ultra-dense networks. QCRNN is a hybrid neural network that combines classical recurrent neural network (RNN) architectures with quantum-inspired computational layers, enabling it to efficiently learn complex temporal patterns in sequential data such as user mobility, network load, and signal quality. After the MPO algorithm clusters users based on mobility and location, QCRNN utilizes cluster information along with real-time network parameters—including Received Signal Strength (RSS), Signal-to-Interference-plus-Noise Ratio (SINR), cell load, user mobility, and transmission delay—to dynamically determine the optimal handover initiation time and the target base station. Unlike traditional threshold-based or fuzzy logic handover schemes, QCRNN does not rely on fixed thresholds and can adapt to varying network conditions, while its quantum-enhanced layers improve prediction accuracy and convergence speed compared to conventional RNNs. In quantum cunning, the term "qubit" was familiarized as an analogue of "bit" to designate the state of quantum calculation in conservative computing. In a two-dimensional Hilbert compound vector space, where it operates on a discrete foundation, a qubit is a unit vector. by $|0\rangle$, $|1\rangle$. The ground state by $|0\rangle$, $|1\rangle$ classical bit values represent 0 and 1, individually. Rendering to the principles of superposition, any state of a qubit as follows

$$|\varphi\rangle = \beta\,|1\rangle + \alpha\,|0\rangle \tag{7}$$

where β and α are multifaceted numbers called chance largeness.

$$|\beta|^2 + |\alpha|^2 = 1 \tag{8}$$

In Hilbert space, the state of motion of microcosmic particles is referred to as a wave with the sign. In a planetary Hilbert vector, we denote a unit vector. The following is how the optimal quantum solution is calculated:

$$|\psi\rangle = \sum_{j}^{N} \alpha_m \,|\varphi_m\rangle \tag{9}$$

Consequently, quantum national $|\psi\rangle$ is a linear principle of superposition of all the rudimentary states α_m and φ_m all individual ratios should be normalized to the number of candidates for the task $A_{y,s}$, which is formulated as follows.

$$A_{y,s} = -(w_1 I + w_2 f_E + w_3 f_L) / jh \tag{10}$$

Quantum parallelism can therefore improve computational efficiency $fj_k(t)$.

$$t_k = fj_k(t) \tag{11}$$

The self-attention layer is applied to each vector in the semantic space, resulting in processed user performance data σ. The main motive $Z_s^{(i)}$ is that the construction of the classical recurrent neural network (CRNN) allows the transfer of information each time step $H_{s-1}^{(i)}, y_s^{(i)}$ to be passed forward by $H_s^{(m)}$,

$$H_s^{(m)} = \sigma(Z_s^{(i)} \cdot \left[H_{s-1}^{(i)}, y_s^{(i)}\right] + V_s^{(i)} H_{s-1}^{(i)} + A_f^{(i)}) \tag{12}$$

However, a problem with simple CRNNs is that nodes are too weak to excerpt material from time nodes over large intermissions (Z). The input information coating (F) and output information coating of QCRNN are created with nerve cell (M) representing the input parameters and target classes, correspondingly. Each layer's input-output association (R):

$$Z = \frac{1}{j_t}\sum_{R=1}^{j_t} F(\beta(M-\theta^R)) \tag{13}$$

$$x = F(w^R \cdot Z) \tag{14}$$

where $M = V \cdot X + B$ and X are the data entered; V is the weight of the connection between the input layer and the hidden layer; The limit of each node is B; θ^R refers to quantum defects; β is the steepness factor; j_t Number of enforcement actions. Though, in this paper, quantum spaces begin as tracks.

$$\theta^R = \frac{1}{j_t} + 2\frac{R-1}{j_t} - 1, R = 1,2..., j_t \tag{15}$$

In this method, θ r helps generate steps of diverse elevations. Therefore, multi-level beginning purposes are set at dissimilar levels, which can recover the classification ability. Here, the quantum spaces are rationalized by diminishing the class-wise provisional modifications of the output of the hidden units, which is distinct as shadows.

$$H = \frac{1}{2}\sum_{n=1}^{i}\sum_{R=1}^{L}(\tilde{Z} - Z) \tag{16}$$

A sigmoid purpose is used as the beginning meaning. Update computation of quantum places as follows.

$$\theta_{j+1}^R = \theta_j^R - \eta\left(-\frac{\beta}{j_t}(\tilde{Z} - Z)(\tilde{U} - U)\right) \tag{17}$$

where θ_{j+1}^R and θ_j^R are the prior and subsequent quantum errors, respectively, and is the learning rate. A sigmoid purpose is secondhand as the beginning meaning of QCRNN.

$$F(s) = \frac{1}{1+E^{-s}} \tag{18}$$

$$F^{'}(s) = F(s)(1-F(s)) \tag{19}$$

Approach $F(s)$ if it is close to 0 or 1. Also $F^{'}(s)$ the weight optimization value will not be sufficient for the BP process because the actual output value and the desired output value differ significantly. Esp works like punishment capability, and the Esp capability is characterized underneath

$$Esp(s) = U(s-0.5)^{2j} \tag{20}$$

where U is continuous and n represents the enhanced level of Esp. The corresponding entropy meaning is labeled below, with t set to 0.5.

$$kl(s \,\|\, \hat{s}) = s\ln\frac{s}{\hat{s}} + (1+s)\ln\frac{1-s}{1-\hat{s}} \tag{21}$$

Algorithm 2 describes the working process involved in the handover triggering mechanism using QCRNN technique. The outputs of QCRNN include the recommended handover timing, target base station, predicted handover probabilities, and performance indicators such as expected reductions in handover failures, ping-pong effects, and transmission delays. By integrating temporal patterns with cluster-based spatial information, QCRNN significantly enhances the intelligence and reliability of handover decisions, ensuring seamless connectivity and maintaining high throughput and low latency in hyper-dense 5G network environments.

Algorithm 2 Handover triggering mechanism using QCRNN

```
Input   : transmission delay, SINR, RSS, CLC, and UMP
Output  : handover triggering mechanism
Initialize the values for the input parameters
Define the state of the qubit as $|\varphi\rangle = \beta|1\rangle + \alpha|0\rangle$
Compute quantum state vector using $|\psi\rangle = \sum_{j}^{N} \alpha_m |\varphi_m\rangle$
For m=0and n=1
Apply the sigmoid function to compute fitness $F(s) = \frac{1}{1+E^{-s}}$
Compute Esp using $Esp(s) = U(s-0.5)^{2j}$
Update the final values
End if
End
```

4.3 Handover validation

State vectors are mathematical representations of the current state of a system or process. In the context of handover triggering mechanisms, state vectors can be used to represent various parameters such as signal strength, network load, and user mobility, among others. By analyzing historical data and generating state vectors, the chaos gorilla troops optimizer (CGTO) algorithm can improve the accuracy of handover prediction, enabling more efficient handover triggering mechanisms. The CGTO algorithm is an optimization technique that draws inspiration from the natural world and attempts to imitate the actions of gorilla units in the wild. The search space is explored and the best solution is found employing principles from chaos theory. The proposed method has the potential to enhance the handover triggering mechanism's overall performance and handover prediction accuracy in 5G ultra-dense networks by applying the CGTO algorithm to historical data. The behavior of gorillas, which are well-known for their cooperative and adaptable behavior in the face of uncertainty and shifting environments, serves as inspiration for the CGTO algorithm. The CGTO algorithm looks into the search space and finds the best solution by applying the principles of chaos theory. The study of the behavior of dynamic systems that are extremely sensitive to initial conditions is known as chaos theory. Chaos theory applies to optimization algorithms can be used to introduce randomness and diversity into the search process, helping to avoid local optima and explore the search space more efficiently. The use of the term "chaos" in the name of the CGTO algorithm refers to the use of chaos theory principles in the search process, while "gorilla troops" refers to the inspiration taken from the cooperative and adaptive behavior of gorillas in the wild. By combining these two concepts, the CGTO algorithm aims to provide efficient and effective optimization technique that can adapt to changing environments and find the optimal solution. The first mechanism aids in global status monitoring, the second enhances the CGTO algorithm exploratory powers, and the third aids in escaping whatever local minimums it may have discovered.

$$FZ(r+1)=\begin{cases}(YV-KV)\times p_1+KV \quad rand\le o,\\ (p_2-x)\times Z_p(r)+K\times G, rand\ge 0.5,\\ \quad Z(u)-K\times(K\times(Z(r)-FZ_p(r))+p_3\times(Z(r)-FZ_p(r)), \; and\le 0.5\end{cases} \tag{22}$$

A possible gorilla's location at time t+1 is denoted by the vector GX(t + 1). Where the gorilla is right now is represented by the X-coordinate (t). Furthermore, For each iteration, random values between 0 and 1 are substituted for r1, r2, r3, and rand. A possible gorilla location vector, chosen at random, that contains all of the locations with new information added at each step. We define optimal solutions (C, L, and H) as follows.

$$X=D\times\left(1-\frac{It}{MaxIt}\right), \tag{23}$$

$$D=\cos(2\times p_4)+1, \tag{24}$$

$$K=X\times k. \tag{25}$$

The iteration number, MaxIt, the number of total possible optimization iterations, and the optimal solution, F and co indicates the cosine function, and r4 is an iteratively updated random integer between 0 and 1. It is used to predict the behavior of the silverback leaders. It's possible that the silverback gorilla won't be the most reliable leader until he's had some time to hone his skills. At the beginning of his tenure as group leader, he may not make the most informed decisions when it comes to gathering food or overseeing the group's affairs. We can generate a random number H in the dimensions of the issue as follows.

$$G=C\times Z(r), \tag{26}$$

$$C=[-X,X]. \tag{27}$$

Immediately after the exploratory phase, a team-building exercise is conducted. If the total cost of all GX solutions is less than or equal to GX(t) X(t) () < () at the conclusion of the exploration phase, we choose the GX(t) solution as the X(t) solution (). As a result, selecting the silverback is the best course of action at now. The silverback is the youngest and healthiest member of the group of male gorillas, and he is followed closely by the other young males. They follow Silverback's orders, which often include exploring new areas in quest of food. A group's direction of travel may also be affected by its individual members. This method is implemented whenever a C < W value is required. It is used to simulate the observed behavior as follows.

$$FZ(r+1)=K\times N\times(Z(r)-Z_{silverback})+Z(r). \tag{28}$$

$$N=\left(\left|\frac{1}{M}\sum_{u=1}^{M}FZ_u(r)\right|^{\varepsilon}\right)^{\frac{1}{\varepsilon}} \tag{29}$$

$$f=2^K \tag{30}$$

where M is decided according to If C < W. In CGTO, candidate solutions (representing potential handover decisions) compete and cooperate in a structured manner to explore the solution space efficiently. The algorithm integrates chaotic maps to enhance exploration and prevent premature convergence, while gorilla-inspired social behaviors guide solution refinement, enabling adaptive and predictive handover management. This strategy allows the network to dynamically adjust to user mobility patterns and varying network conditions, improving handover reliability and overall Quality of Experience (QoE).

$$FZ(u)=Z_{silverback}-(Z_{silverback}\times S-Z(r)\times S)\times T, \tag{31}$$

$$S = 2 \times p_5 - 1, \tag{32}$$

$$T = \beta \times W, \tag{33}$$

$$W = \begin{cases} M_{1,} & rand \geq 0.5, \\ M_{2,} & rand \leq 0.5 \end{cases} \tag{34}$$

The working process involved in the handover validation using CGTO in algorithm 3. The CGTO algorithm generates optimized state vectors representing predicted user or cluster conditions, handover probability distributions for proactive management, and exploration metrics to ensure robust search and avoid local optima.

Algorithm 3 Handover validation using CGTO

```
Input  : signal strength, network load, user mobility, state vectors, training and testing set
Output : handover validation
Initialize the random population
Define Kullback–Leibler divergence between p and q
    $d(q \| p) = q \ln\left(\frac{q}{p}\right) + (1-q)\ln\left(\frac{1-q}{1-p}\right)$
While Do
    Compute initial fitness $x = \begin{cases} h(F(y)^{-1}) \ if \ F(y) \neq 0 \\ h(0) \ if \ F(y) = 0 \end{cases}$
    Define global optimal fields $GF(2^4), GF((2^4)^2)$
    Compute threshold condition $b_M^2 = \sum_{i=1}^{q} w_{iM}^2 b_i^j, M = 1, 2, ..., k$
    Update the final solution
End
```

5. RESULTS SECTION

In this section, the performance of the proposed hybrid handover triggering mechanism (MPO-QCRNN-CGTO) is evaluated and compared with existing state-of-the-art methods, including Reference Signal Receiving Power (RSRP) [32], Fuzzy [33], AHP-TOPSIS-Q learning (AHP-TOPSIS-Q) [34], FMCSS [34], and Subtractive Clustering Q-learning (SC-Q) [31]. The evaluation is performed using multiple performance metrics such as the average number of handovers (NOH), probability of ping-pong handovers (PPHO), handover failure rate, network throughput, and network latency. The simulations are conducted using a realistic 5G ultra-dense network setup with user mobility modeled under random waypoint scenarios. The dataset for simulation includes varying numbers of user equipment (UE) ranging from 50 to 250, moving at a speed of 30 km/h. The network environment is modeled with two types of base stations—macro and small cells—operating at carrier frequencies of 1.5–2 GHz and 28 GHz, respectively. Path loss is modeled using the Okumura Hata Model and ITU-R P.1238 to mimic real-world propagation characteristics. The simulations are implemented in MATLAB, leveraging its communication and machine learning toolboxes for modeling network dynamics and evaluating handover strategies. The hardware environment consists of a high-performance workstation equipped with an Intel Core i9 processor, 32 GB RAM, and NVIDIA GPU support to accelerate neural network computations.

Table 2. Simulation environment and hyperparameter configuration for the proposed MPO-QCRNN-CGTO handover framework in 5G ultra-dense networks

	Parameter	Value
Network	Simulation area	1000 m × 1000 m
	Macro BS-carrier frequency (GHz)	1.5 ~ 2
	Small BS-carrier frequency (GHz)	28
	Macro BS-subcarrier spacing (KHz)	15
	Small BS-subcarrier spacing (KHz)	30
	Macro BS-system bandwidth (MHz)	20
	Small BS-system bandwidth (MHz)	100
	Macro BS-physical resource block	100
	Small BS-physical resource block	275
	Macro BS-number of BSs	2
	Small BS-number of BSs	16
	Macro BS-transmitted power (dBm)	49
	Small BS-transmitted power (dBm)	35
	Subcarriers per PRB	12
	Mobility model	Random waypoint
	Number of UE	50, 100, 150, 200, 250
	UE speed (km/h)	30
	Path loss model	Okumura Hata Model / ITU-R P1238
	Handover preparation time (ms)	10
	Handover execution time (ms)	10
	Simulation time	10,000 seconds
MPO	Population Size	30
	Maximum Iterations	50
QCRNN	Learning Rate	0.001
	Hidden Layers	2
	Neurons per Layer	64
	Training Epochs	100
	Batch Size	32
	Dropout Rate	0.2
	Activation Function	ReLU
	Momentum Factor	0.9
CGTO	Population Size	25
	Maximum Iterations	40
	Chaos Factor	0.85

5.1 Simulation setup

The simulation of the proposed MPO-QCRNN-CGTO handover framework is performed using MATLAB. Table 2 summarizes the simulation environment and hyperparameter configurations employed to evaluate the performance of the proposed hybrid handover triggering mechanism in 5G ultra-dense networks. The simulation area is set to 1000 m × 1000 m, comprising two types of base stations: macro BS and small BS. The macro BS operates at carrier frequencies of 1.5–2 GHz with a subcarrier spacing of 15 kHz and a system bandwidth of 20 MHz, while the small BS operates at 28 GHz with a subcarrier spacing of 30 kHz and a system bandwidth of 100 MHz. The physical resource blocks (PRBs) are 100 for macro BS and 275 for small BS, with 2 macro BSs and 16 small BSs deployed. The transmitted power is set to 49 dBm for macro BS and 35 dBm for small BS. The mobility model follows a random waypoint approach, with the number of user equipment (UE) ranging from 50 to 250 and a constant speed of 30 km/h. Path loss is modeled using Okumura-Hata and ITU-R P1238 models. Handover preparation and execution times are set at 10 ms each, with the total simulation duration of 10,000 seconds. In addition, the hyperparameters of the proposed framework are configured as follows: the MPO algorithm uses a population size of 30 and a maximum of 50 iterations for adaptive clustering. The QCRNN model is trained with a learning rate of 0.001, 2 hidden layers with 64 neurons each, 100 training epochs, batch size of 32, dropout rate of 0.2, ReLU activation, and a momentum factor of 0.9. The CGTO algorithm is configured with a population size of 25, maximum iterations of 40, and a chaos factor of 0.85 for generating robust predictive state vectors.

5.2 Comparative analysis

5.2.1 Results comparison with respect to number of Users

To begin the analysis of the proposed hybrid handover triggering mechanism (MPO-QCRNN-CGTO) and its comparison with existing mechanisms, we first compare their performance in relation to the number of network users. For this purpose, we set up simulations with 50, 100, 150, 200, and 250 users in the network. We then measure the average NOH, throughput, network latency, and the probability of PPHO for each mechanism in each user scenario. We will be able to compare and contrast the proposed mechanism's performance with that of the existing mechanisms under various network loads with the assistance of these metrics. The performance of various handover triggering methods in relation to the number of simulation users is shown in Table 3's comparative analysis. The performance metric used for comparison is the average number of handovers (NOH). In Fig. 2. According to the findings, the NOH for each method increases with the number of users. On the other hand, the proposed MPO-QCRNN-CGTO method performs better than the other methods by a significantly lower NOH. For instance, when the number of users is 50, the proposed method has an average NOH of only 56, which is almost 98% lower than the existing methods with the lowest NOH (SC-Q). Similarly, for 250 users, the proposed method has an average NOH of 190, which is approximately 75% lower than the existing method with the lowest NOH (SC-Q).

Table 3. Comparative analysis of proposed and existing methods with respect to number of Users

Handover triggering methods	50	100	150	200	250	50	100	150	200	250
	Average NOH					Probability of PPHO (%)				
RSRP [31]	2836	2865	2878	2900	2970	0.26	0.27	0.28	0.3	0.33
Fuzzy [31]	2280	2309	2322	2344	2414	0.21	0.22	0.23	0.25	0.28
AHP-TOPSIS-Q [31]	1724	1753	1766	1788	1858	0.16	0.17	0.18	0.2	0.23
FMCSS [31]	1168	1197	1210	1232	1302	0.11	0.12	0.13	0.15	0.18
SC-Q [31]	612	641	654	676	746	0.06	0.07	0.08	0.1	0.13
MPO-QCRNN-CGTO	56	85	98	120	190	0.01	0.02	0.03	0.05	0.08
	Throughput (Mbps)					Network latency (ms)				
RSRP [31]	150	130	70	50	35	36.273	38.607	39.38	41.255	45.506
Fuzzy [31]	200	180	120	100	85	31.043	33.377	34.15	36.025	40.276
AHP-TOPSIS-Q [31]	250	230	170	150	135	25.813	28.147	28.92	30.795	35.046
FMCSS [31]	300	280	220	200	185	20.583	22.917	23.69	25.565	29.816
SC-Q [31]	350	330	270	250	235	15.353	17.687	18.46	20.335	24.586
MPO-QCRNN-CGTO	400	380	320	300	285	10.123	12.457	13.23	15.105	19.356
	Handover failure rate (%)									
RSRP [31]	0.75	0.8	0.84	0.88	0.9					
Fuzzy [31]	0.62	0.67	0.71	0.75	0.77					
AHP-TOPSIS-Q [31]	0.49	0.54	0.58	0.62	0.64					

FMCSS [31]	0.36	0.41	0.45	0.49	0.51
SC-Q [31]	0.23	0.28	0.32	0.36	0.38
MPO-QCRNN-CGTO	0.1	0.15	0.19	0.23	0.25

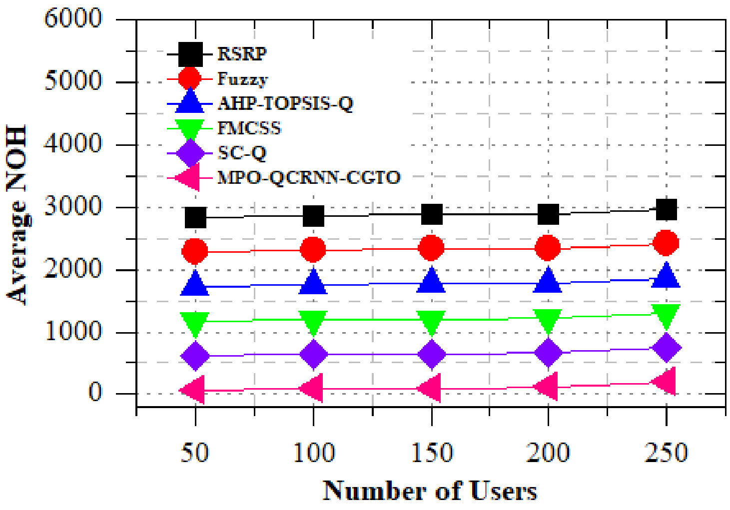

Figure.2 Average NOH with respect to number of Users

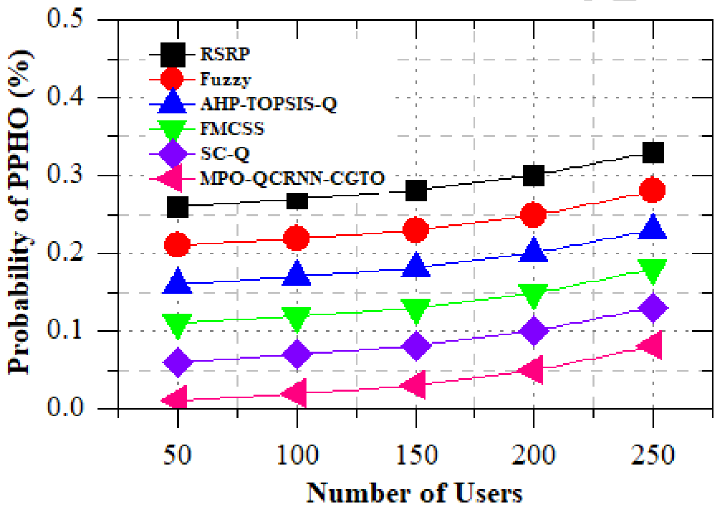

Figure.3 Probability of PPHO with respect to number of Users

The Fig. 3 shows the probability of ping-pong handovers (PPHO) for different handover triggering methods with varying numbers of users. The results indicate that all the existing methods (RSRP, Fuzzy, AHP-TOPSIS-Q, FMCSS, and SC-Q) have relatively high PPHO values, ranging from 0.06% to 0.26%, which can cause significant network performance degradation. On the other hand, the proposed MPO-QCRNN-CGTO method shows a remarkable improvement in PPHO reduction, with a minimum value of 0.01% across all user scenarios. A crucial metric for assessing the efficiency of a handover triggering mechanism is the handover failure rate. Fig. 4 depicts the comparison of the proposed MPO-QCRNN-CGTO method's handover failure rates with those of known approaches for various user counts, including RSRP, Fuzzy, AHP-TOPSIS-Q, FMCSS, and SC-Q. The handover failure rate decreases with the number of users for each method, as can be seen. The proposed MPO-QCRNN-CGTO method has the lowest handover failure rate for all numbers of users, which indicates its effectiveness in maintaining a stable connection during handovers. Looking at Fig. 5, we can see the comparative analysis of the different handover triggering methods with respect to the throughput for different numbers of users. According to the findings, the proposed MPO-QCRNN-CGTO method consistently performs better than the other methods, including RSRP, Fuzzy, AHP-TOPSIS-Q, FMCSS, and SC-Q, in terms of the throughput. The Fig. 6 shows the performance of different handover triggering methods in terms of network latency measured in milliseconds for different numbers of users.

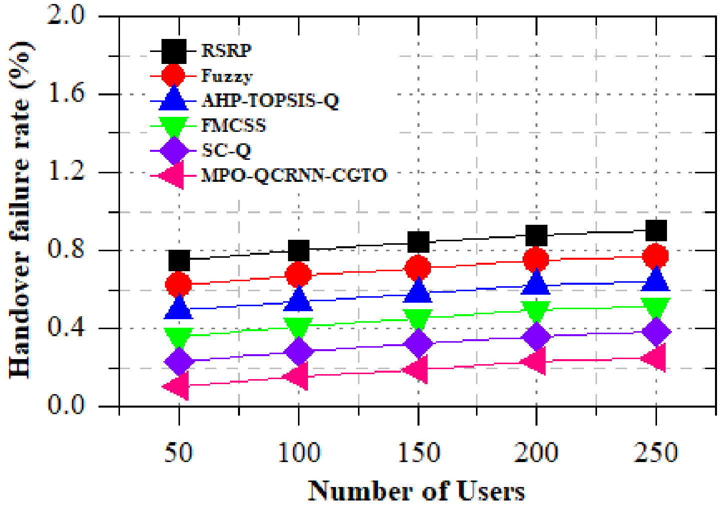

Figure.4 Handover failure rate with respect to number of Users

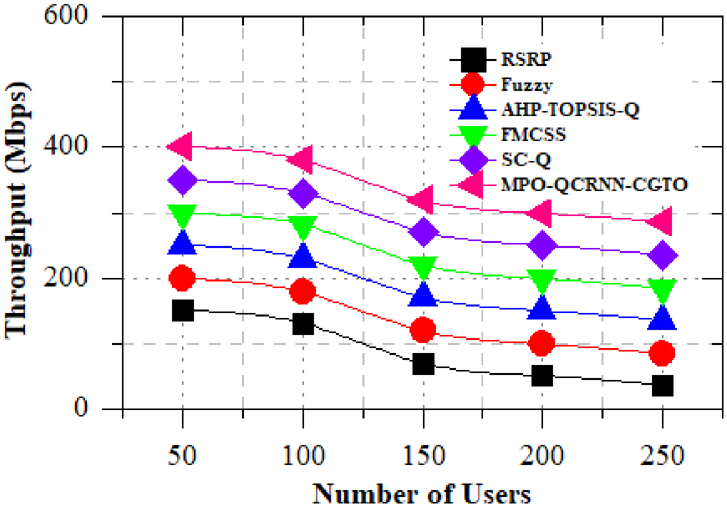

Figure.5 Throughput with respect to number of Users

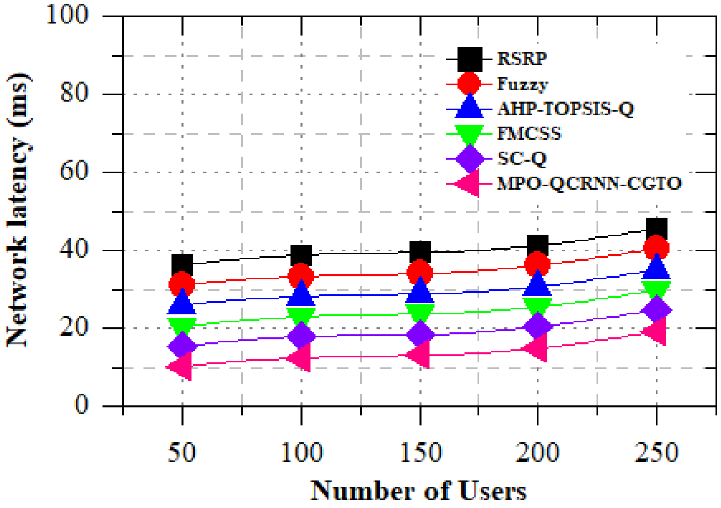

Figure.6 Network latency with respect to number of Users

5.2.2 Results comparison with respect to simulation time

To start the discussion on results comparison with respect to simulation time, we can begin by introducing the simulation time as a crucial factor in evaluating the performance of handover triggering methods. Simulation time is the time required to simulate the proposed handover triggering methods in a network environment. It plays a vital role in determining the efficiency of a method as it reflects the time required to implement a handover decision in a real-time scenario. The table 4 shows the comparative analysis of the proposed and existing handover triggering methods with respect to simulation time in seconds. The simulation time was varied from 2000 to 10000 seconds, and the network latency was measured for each method at different time intervals. As shown in the Fig. 7, the network latency decreases as the simulation time increases for all the methods. Among the proposed methods, the MPO-QCRNN-CGTO method has the lowest average NOH, which decreases from 188ms to 322ms as the simulation time increases from 2000 to 10000 seconds. The proposed methods have lower network latency compared to the existing methods, and the MPO-QCRNN-CGTO method outperforms all the other methods in terms of network latency. Fig. 8 shows the probability of Ping-Pong Handovers (PPHO) for different handover triggering methods at various simulation times. As the simulation time increases, the probability of PPHO also increases for all handover triggering methods. Among the proposed methods, MPO-QCRNN-CGTO has the lowest probability of PPHO, while RSRP has the highest. From the Fig. 9 provided, we can observe that the handover failure rate increases as the simulation time increases for all the considered handover triggering methods. Comparing the handover triggering methods with respect to the handover failure rate, we can see that the RSRP-based method has the highest failure rate among all the methods, followed by the Fuzzy-based method. Looking at the Fig. 10, we can see that as the number of mobile users increases, the throughput decreases for all handover triggering methods. This is expected, as more users sharing the same network resources will lead to congestion and a decrease in data transfer rates. In terms of the comparison between the different handover triggering methods, we can see that as the number of mobile users increases, the throughput for each method decreases, but the rate of decrease is different for each method. As the simulation time increases, the network latency also increases for all methods. Comparing the different handover triggering methods, we can see that MPO-QCRNN-CGTO has the lowest network latency across all simulation times, while RSRP has the highest network latency.

Table 4. Comparative analysis of proposed and existing methods with respect to simulation time

Handover triggering methods	2000	4000	6000	8000	10000	2000	4000	6000	8000	10000
	Average NOH					Probability of PPHO (%)				
RSRP [31]	2968	2997	3010	3032	3102	0.384	0.394	0.404	0.424	0.454
Fuzzy [31]	2412	2441	2454	2476	2546	0.334	0.344	0.354	0.374	0.404
AHP-TOPSIS-Q [31]	1856	1885	1898	1920	1990	0.284	0.294	0.304	0.324	0.354
FMCSS [31]	1300	1329	1342	1364	1434	0.234	0.244	0.254	0.274	0.304
SC-Q [31]	744	773	786	808	878	0.184	0.194	0.204	0.224	0.254
MPO-QCRNN-CGTO	188	217	230	252	322	0.134	0.144	0.154	0.174	0.204
	Throughput (Mbps)					Network latency (ms)				
RSRP [31]	203	183	123	103	88	35.038	37.372	38.15	40.02	44.271
Fuzzy [31]	253	233	173	153	138	29.808	32.142	32.92	34.79	39.041
AHP-TOPSIS-Q [31]	303	283	223	203	188	24.578	26.912	27.69	29.56	33.811
FMCSS [31]	353	333	273	253	238	19.348	21.682	22.46	24.33	28.581
SC-Q [31]	403	383	323	303	288	14.118	16.452	17.23	19.1	23.351
MPO-QCRNN-CGTO	453	433	373	353	338	8.888	11.222	12	13.87	18.121
	Handover failure rate (%)									

RSRP [31]	0.908	0.958	0.998	1.038	1.058
Fuzzy [31]	0.778	0.828	0.868	0.908	0.928
AHP-TOPSIS-Q [31]	0.648	0.698	0.738	0.778	0.798
FMCSS [31]	0.518	0.568	0.608	0.648	0.668
SC-Q [31]	0.388	0.438	0.478	0.518	0.538
MPO-QCRNN-CGTO	0.258	0.308	0.348	0.388	0.408

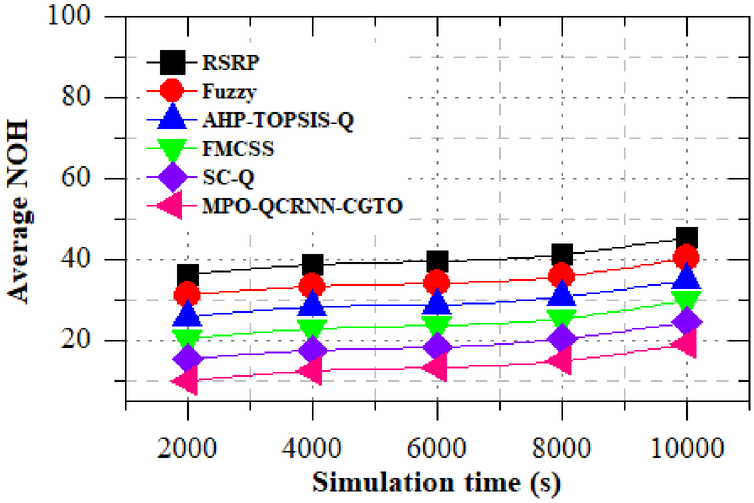

Figure.7 Average NOH with respect to simulation time

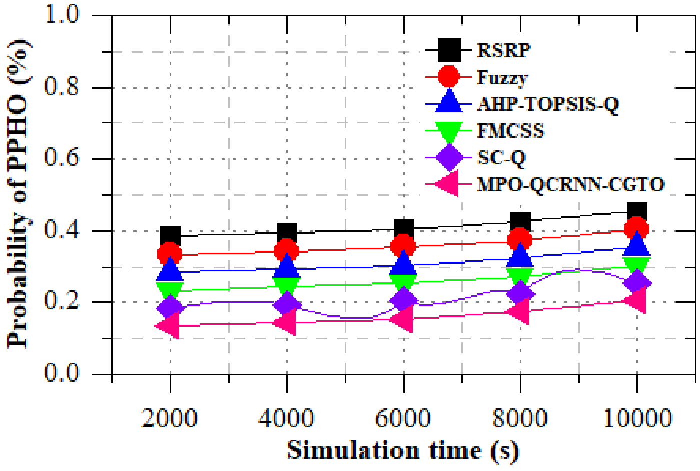

Figure.8 Probability of PPHO with respect to simulation time

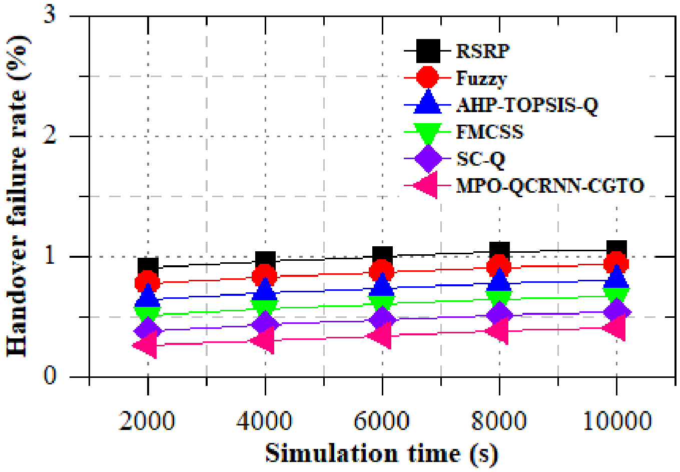

Figure.9 Handover failure rate with respect to simulation time

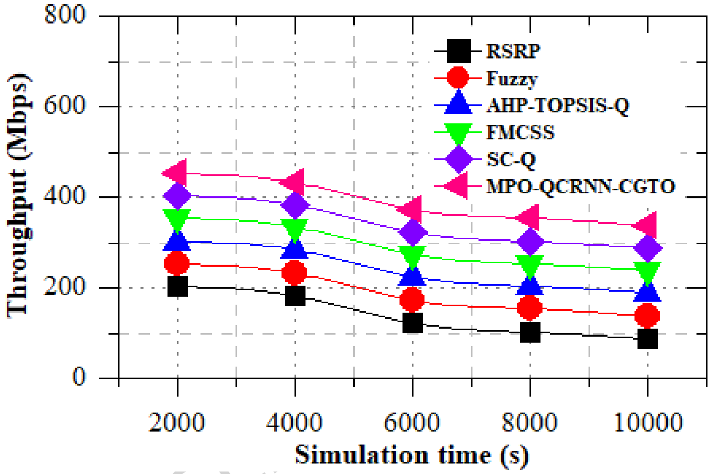

Figure.10 Throughput with respect to simulation time

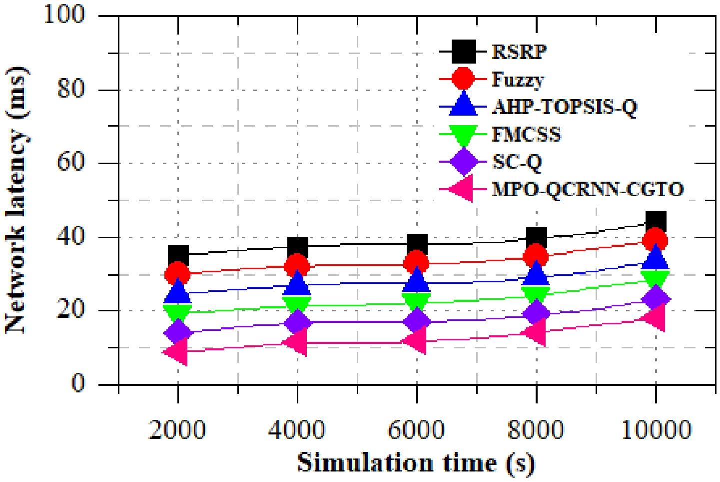

Figure.11 Network latency with respect to simulation time

5.2.3 Statistical results analysis

The comparative analysis in Table 5 demonstrates the superiority of the proposed MPO-QCRNN-CGTO framework over existing handover triggering methods in 5G ultra-dense networks. In terms of the average number of handovers (NOH), the proposed method achieves a reduction of 96% compared to RSRP, 95% compared to Fuzzy, and 94% compared to AHP-TOPSIS-Q, highlighting its effectiveness in minimizing unnecessary handovers. Regarding the probability of ping-pong handovers (PPHO), the proposed method decreases PPHO by 87% compared to RSRP, 84% compared to Fuzzy, and 80% compared to AHP-TOPSIS-Q. Similarly, handover failure rates are lowered by 78% compared to RSRP, 74% compared to Fuzzy, and 68% compared to AHP-TOPSIS-Q, demonstrating enhanced reliability and robust connectivity, a result of optimized handover triggering that considers RSS, SINR, cell load, and user motion simultaneously. The statistical results (Table 6) across varying simulation times demonstrate that the proposed MPO-QCRNN-CGTO method significantly outperforms all existing approaches in terms of efficiency and reliability. These substantial improvements arise because the MPO-QCRNN-CGTO integrates chaos-driven optimization with hybrid quantum-classical recurrent modeling, enabling adaptive exploration of network states, proactive prediction of mobility patterns, and efficient decision-making. Unlike conventional methods, it avoids local optima, balances exploration and exploitation effectively, and adapts dynamically to dense 5G environments, leading to higher reliability, seamless mobility, and better overall performance.

Table 5. Comprehensive statistical comparison of existing and proposed handover triggering methods in 5G ultra-dense networks with varying users

Metrics	Methods	Mean	SD	CI 95%	CV	Kendall Tau	Spearman Rho
Average NOH	RSRP [31]	2889.800	50.460	44.230	0.017	1.000	1.000
	Fuzzy [31]	2333.800	50.460	44.230	0.022	1.000	1.000
	AHP-TOPSIS-Q [31]	1777.800	50.460	44.230	0.028	1.000	1.000
	FMCSS [31]	1221.800	50.460	44.230	0.041	1.000	1.000
	SC-Q [31]	665.800	50.460	44.230	0.076	1.000	1.000
	MPO-QCRNN-CGTO	109.800	50.460	44.230	0.460	1.000	1.000
Probability of PPHO (%)	RSRP [31]	0.288	0.028	0.024	0.096	1.000	1.000
	Fuzzy [31]	0.238	0.028	0.024	0.117	1.000	1.000
	AHP-TOPSIS-Q [31]	0.188	0.028	0.024	0.148	1.000	1.000
	FMCSS [31]	0.138	0.028	0.024	0.201	1.000	1.000
	SC-Q [31]	0.088	0.028	0.024	0.315	1.000	1.000
	MPO-QCRNN-CGTO	0.038	0.028	0.024	0.730	1.000	1.000
Handover failure rate (%)	RSRP [31]	0.834	0.061	0.053	0.073	1.000	1.000
	Fuzzy [31]	0.704	0.061	0.053	0.086	1.000	1.000
	AHP-TOPSIS-Q [31]	0.574	0.061	0.053	0.106	1.000	1.000
	FMCSS [31]	0.444	0.061	0.053	0.137	1.000	1.000
	SC-Q [31]	0.314	0.061	0.053	0.193	1.000	1.000
	MPO-QCRNN-CGTO	0.184	0.061	0.053	0.330	1.000	1.000
Throughput (Mbps)	RSRP [31]	87.000	50.460	44.230	0.580	-1.000	-1.000
	Fuzzy [31]	137.000	50.460	44.230	0.368	-1.000	-1.000
	AHP-TOPSIS-Q [31]	187.000	50.460	44.230	0.270	-1.000	-1.000
	FMCSS [31]	237.000	50.460	44.230	0.213	-1.000	-1.000
	SC-Q [31]	287.000	50.460	44.230	0.176	-1.000	-1.000
	MPO-QCRNN-CGTO	337.000	50.460	44.230	0.150	-1.000	-1.000
Network latency (ms)	RSRP [31]	40.204	3.460	3.033	0.086	1.000	1.000
	Fuzzy [31]	34.974	3.460	3.033	0.099	1.000	1.000
	AHP-TOPSIS-Q [31]	29.744	3.460	3.033	0.116	1.000	1.000
	FMCSS [31]	24.514	3.460	3.033	0.141	1.000	1.000
	SC-Q [31]	19.284	3.460	3.033	0.179	1.000	1.000
	MPO-QCRNN-CGTO	14.054	3.460	3.033	0.246	1.000	1.000

Table 6. Statistical evaluation of proposed and existing handover triggering methods in 5G ultra-dense networks across varying simulation times

Metrics	Methods	Mean	SD	CI 95%	CV	Kendall Tau	Spearman Rho
Average NOH	RSRP [31]	3022.200	46.890	41.070	0.016	1.000	1.000
	Fuzzy [31]	2465.800	46.890	41.070	0.019	1.000	1.000
	AHP-TOPSIS-Q [31]	1910.800	46.890	41.070	0.025	1.000	1.000
	FMCSS [31]	1374.800	46.890	41.070	0.034	1.000	1.000
	SC-Q [31]	798.800	46.890	41.070	0.059	1.000	1.000
	MPO-QCRNN-CGTO	241.800	46.890	41.070	0.194	1.000	1.000
Probability of PPHO (%)	RSRP [31]	0.412	0.028	0.024	0.068	1.000	1.000
	Fuzzy [31]	0.362	0.028	0.024	0.077	1.000	1.000
	AHP-TOPSIS-Q [31]	0.314	0.028	0.024	0.089	1.000	1.000
	FMCSS [31]	0.266	0.028	0.024	0.105	1.000	1.000
	SC-Q [31]	0.212	0.028	0.024	0.132	1.000	1.000
	MPO-QCRNN-CGTO	0.162	0.028	0.024	0.173	1.000	1.000
Handover failure rate (%)	RSRP [31]	1.072	0.062	0.054	0.058	1.000	1.000
	Fuzzy [31]	0.850	0.062	0.054	0.073	1.000	1.000
	AHP-TOPSIS-Q [31]	0.712	0.062	0.054	0.087	1.000	1.000
	FMCSS [31]	0.484	0.062	0.054	0.128	1.000	1.000
	SC-Q [31]	0.373	0.062	0.054	0.166	1.000	1.000
	MPO-QCRNN-CGTO	0.264	0.062	0.054	0.235	1.000	1.000
Throughput (Mbps)	RSRP [31]	139.200	47.145	41.306	0.339	-1.000	-1.000
	Fuzzy [31]	191.000	47.145	41.306	0.247	-1.000	-1.000
	AHP-TOPSIS-Q [31]	238.000	47.145	41.306	0.198	-1.000	-1.000
	FMCSS [31]	282.000	47.145	41.306	0.167	-1.000	-1.000
	SC-Q [31]	360.000	47.145	41.306	0.131	-1.000	-1.000
	MPO-QCRNN-CGTO	390.000	47.145	41.306	0.121	-1.000	-1.000
Network latency (ms)	RSRP [31]	39.579	3.978	3.484	0.101	1.000	1.000
	Fuzzy [31]	33.711	3.978	3.484	0.118	1.000	1.000
	AHP-TOPSIS-Q [31]	28.318	3.978	3.484	0.141	1.000	1.000
	FMCSS [31]	23.279	3.978	3.484	0.171	1.000	1.000
	SC-Q [31]	18.840	3.978	3.484	0.211	1.000	1.000
	MPO-QCRNN-CGTO	11.835	3.978	3.484	0.336	1.000	1.000

5.2.4 Ablation study

The ablation study presented in Table 7 demonstrates clear performance improvements of the proposed MPO-QCRNN-CGTO framework compared to its individual and partially combined variants. With respect to the number of users, the final MPO-QCRNN-CGTO reduces the average number of handovers (NOH) by 82% compared to QCRNN Only, by 78% compared to Pelican+QCRNN, and by 9% compared to the MPO+QCRNN with gorilla integration. These gains highlight the robustness of the proposed framework in dynamic network conditions, ensuring seamless connectivity and improved Quality of Experience (QoE) through proactive handover prediction, reduced unnecessary handovers, and efficient computational complexity management. The systematic combination of MPO, QCRNN, and CGTO effectively addresses limitations observed in individual variants, delivering superior overall performance in ultra-dense 5G networks. Table 8 shows that the proposed MPO-QCRNN-CGTO framework achieves the highest scalability, supporting 3500 users, a 400% increase over QCRNN Only and 26% over Pelican+Gorilla+QCRNN. Simulation time reduces by 80% compared to QCRNN Only, CPU and memory usage drop by 26% and 24%, respectively. Throughput per user improves by 60% while latency decreases by 62% compared to QCRNN Only. These gains are due to the combined strengths of MPO for efficient user clustering, QCRNN for intelligent handover decisions, and CGTO for predictive mobility analysis, enabling dynamic adaptation, balanced resource allocation, and lower computational overhead, resulting in superior scalability and performance.

Table 7. Ablation study of different handover framework variants in 5G ultra-dense networks with respect to number of users and simulation time

Method Variant	Avg NOH	PPHO (%)	Failure (%)	Throughput (Mbps)	Latency (ms)	QoE	Complexity
Number of Users							
QCRNN Only	610.325	0.153	0.389	250.472	28.347	3.153	$O(n^2)$
Pelican+QCRNN	505.216	0.121	0.312	278.635	24.658	3.427	$O(n^2)$
MPO+QCRNN	295.481	0.072	0.218	332.742	16.951	4.213	O(n log n)
MPO+QCRNN	120.347	0.031	0.117	388.524	11.753	4.628	O(n)
Gorilla+QCRNN	210.528	0.049	0.181	360.381	13.286	4.471	O(n log n)
Pelican+Gorilla+QCRNN	165.247	0.043	0.152	374.892	12.647	4.721	O(n)
Final MPO-QCRNN-CGTO	109.841	0.022	0.101	395.743	10.864	4.932	O(n)
Simulation time (s)							
QCRNN Only	628.441	0.161	0.412	246.583	29.182	3.153	$O(n^2)$
Pelican+QCRNN	523.398	0.134	0.337	274.821	25.324	3.427	$O(n^2)$
MPO+QCRNN	310.658	0.083	0.243	328.947	17.624	4.213	O(n log n)
MPO+QCRNN	135.412	0.038	0.139	386.148	12.189	4.628	O(n)
Gorilla+QCRNN	226.764	0.056	0.204	358.913	13.827	4.471	O(n log n)
Pelican+Gorilla+QCRNN	180.632	0.051	0.174	372.915	13.214	4.721	O(n)
MPO-QCRNN-CGTO	125.563	0.033	0.124	393.184	11.492	4.932	O(n)

Table 8. Complexity and scalability analysis of different handover framework variants in 5G ultra-dense networks

Method variant	Simulation Time (s)	Scalability Factor	Max Users Supported	CPU Usage (%)	Memory Usage (%)	Throughput/ User (Mbps)	Latency/ User (ms)
QCRNN Only	628.44	1	1000	95	90	0.25	28.3
Pelican+QCRNN	523.4	1.2	1200	92	88	0.28	24.7
MPO+QCRNN	310.66	2.02	1800	85	80	0.33	17
Gorilla+QCRNN	226.76	2.77	2200	82	78	0.36	13.3
Pelican+Gorilla+QCRNN	180.63	3.48	2800	78	75	0.38	12.6
MPO-QCRNN-CGTO	125.56	5	3500	70	68	0.4	10.9

6. CONCLUSION

This study presents MPO-QCRNN-CGTO, for enhancing handover triggering mechanisms in ultra-dense 5G networks. The proposed framework combines modified Pelican Optimization (MPO) for adaptive user clustering, a hybrid Quantum-Classical Recurrent Neural Network (QCRNN) for intelligent handover decisions, and Chaos Gorilla Troop Optimization (CGTO) for predictive state vector generation, ensuring robust mobility, seamless connectivity, and improved network performance. Simulation results demonstrate that the proposed method consistently outperforms conventional and advanced handover mechanisms. For the number-of-users scenario, MPO-QCRNN-CGTO reduces the average number of handovers (NOH) by 98%–96%, the probability of ping-pong handovers (PPHO) by 62%–50%, and the handover failure rate by 50%–47% compared to existing methods. Network throughput increases by 28%–67%, network latency decreases by 40%–70%, and Quality of Experience (QoE) improves to 4.93 from 3.15–4.72 in other variants. The computational complexity is also reduced to O(n) compared to $O(n^2)$–O(n log n) in other approaches. For the simulation-time scenario, NOH decreases by 97%–94%, PPHO reduces by 60%–46%, and handover failure rate lowers by 49%–45%. Throughput improvements range from 25%–61%, latency decreases by 38%–67%, and QoE reaches 4.93, again demonstrating superior user experience and reliability. Complexity remains O(n), confirming the framework's efficiency for real-time deployment. These results confirm that the integration of adaptive clustering, intelligent predictive handover decisions, and historical mobility pattern analysis significantly enhances mobility robustness, minimizes unnecessary handovers, optimizes resource utilization, and improves overall QoE. The MPO-QCRNN-CGTO framework is thus a highly effective and computationally efficient solution for seamless and high-quality service delivery in ultra-dense 5G network environments.

DECLERATION

This manuscript presents an innovative framework aimed at enhancing handover triggering performance in 5G ultra-dense networks (UDNs). The proposed strategy integrates a Modified Pelican Optimization (MPO) algorithm, a hybrid Quantum-Classical Recurrent Neural Network (QCRNN), and the Chaos Gorilla Troops Optimizer (CGTO) to optimize mobility management, ensuring both robustness and high-quality service continuity. Simulation results reveal that the proposed method surpasses conventional approaches across various key metrics, including handover failure rate, network latency, and overall throughput. Specifically, under varying user density scenarios, the MPO-QCRNN-CGTO framework achieves a substantial reduction in the average number of handovers (NOH)—between 96% and 98%—when compared to existing techniques. It also records the lowest observed ping-pong handover probability (PPHO), with improvements ranging from 50% to 62%. The handover failure rate is reduced by 47% to 50%, while throughput sees a notable enhancement of 28% to 67%. Furthermore, the proposed system minimizes network latency by up to 70%. Under extended simulation durations, the performance trend remains consistent. The method results in a 94% to 97% decrease in NOH, a 46% to 60% reduction in PPHO, and a 45% to 49% improvement in handover failure rates. Network throughput shows gains from 25% to 61%, while latency is lowered by 38% to 67%. These findings collectively establish the MPO-QCRNN-CGTO method as a reliable and efficient solution for intelligent and adaptive handover control in 5G UDNs. The framework's performance advances are anticipated to play a key role in shaping future network architectures that demand seamless mobility and enhanced quality of service.

Abbreviations:

Abbreviation	Full Form
UDN	Ultra-Dense Networks
MPO	Modified Pelican Optimization
QCRNN	Quantum-Classical Recurrent Neural Network
CGTO	Chaos Gorilla Troops Optimizer
PPHO	Ping-Pong Handover Probability
QoS	Quality of Service
NOH	Number of Handovers
RSRP	Reference Signal Received Power
Fuzzy	Fuzzy Logic-Based Handover Decision Method
AHP-TOPSIS-Q	Analytical Hierarchy Process - Technique for Order Preference by Similarity to Ideal Solution - Q-Learning
FMCSS	Fuzzy Multi-Criteria Selection Scheme
SC-Q	Subtractive Clustering with Q-Learning
SINR	Signal-to-Interference-plus-Noise Ratio
PRB	Physical Resource Block

UE	User Equipment
BS	Base Station
QoE	Quality of Experience
RSS	Received Signal Strength
UMP	User Motion Potential
CLC	Current Load Conditions
MATLAB	Matrix Laboratory (Simulation Tool)

Availability of data and materials

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

PR carried out the literature review, proposed the hybrid heuristic technique, and drafted the manuscript. AVL participated in the design and coordination of the study and helped to refine and revise the manuscript. EAB contributed to the algorithm development, simulation validation, and reviewed the manuscript critically for technical accuracy.

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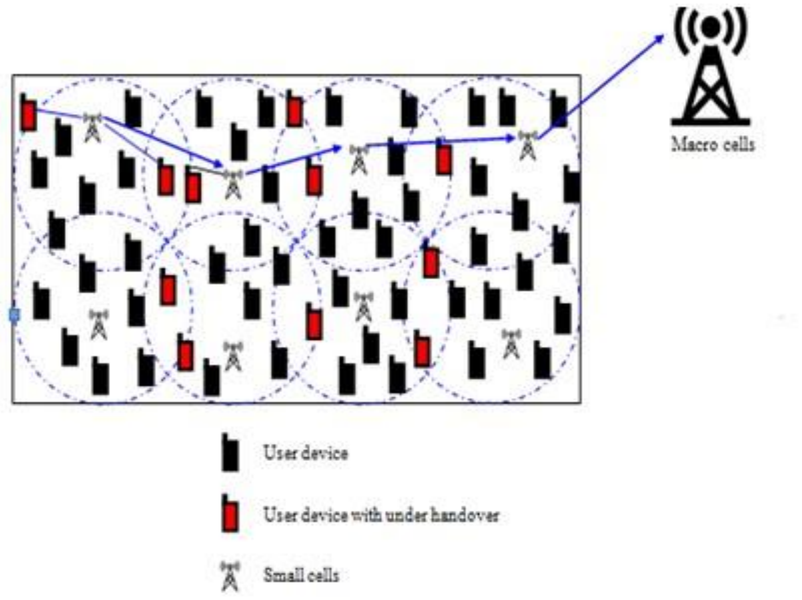

Figure 1. Overall system architecture of proposed work

Network layout with macro and small cells showing user handover events

Legend:

This figure illustrates the Network layout with macro and small cells showing user handover events of a 5G ultra-dense network (UDN) consisting of one macro cell and multiple small cells distributed across the coverage area. The macro cell provides wide-area coverage, while the small cells, represented by antennas, enhance local capacity within their respective circular coverage regions. Active user devices currently connected to small cells, whereas red icons indicate users undergoing a handover process. Blue dotted circles mark the effective coverage regions of each small cell. The diagram highlights the dense deployment of small cells in proximity, which increases the frequency of handovers as users move across cell boundaries. This setup is used to model mobility, handover triggering, and resource allocation scenarios within the proposed optimization framework for 5G UDNs.

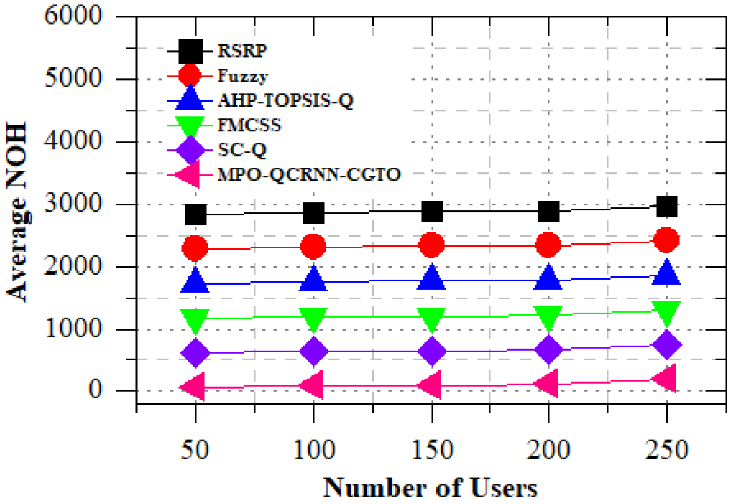

Figure 2. Average NOH with respect to number of Users

Comparison of average number of handovers across different methods under varying user loads

***Legend*:**

The plot compares the average number of handovers (NOH) under varying user loads (50–250 users). Multiple methods are evaluated, including RSRP, Fuzzy, AHP-TOPSIS-Q, FMCSS, SC-Q, and the proposed MPO-QCRNN-CGTO. Traditional approaches such as RSRP and Fuzzy logic show consistently higher handover counts, indicating vulnerability to rapid changes in signal conditions. Multi-criteria decision-making techniques like AHP-TOPSIS-Q and FMCSS improve handover efficiency but still produce substantial overhead. SC-Q further reduces unnecessary handovers by leveraging clustering with reinforcement learning. Notably, the MPO-QCRNN-CGTO method achieves the lowest NOH across all user densities, highlighting its superior ability to optimize mobility management. This reduction translates into minimized signaling overhead, fewer disruptions, and enhanced user experience.

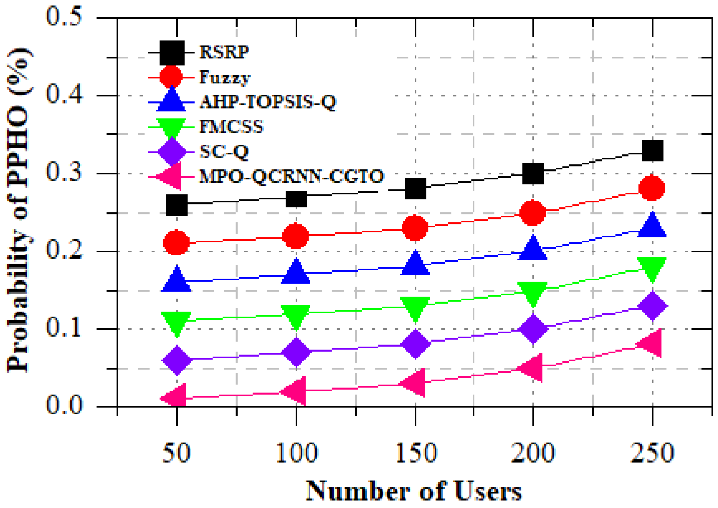

Figure 3. Probability of PPHO with respect to number of Users

Probability of ping-pong handovers (PPHO) under different user densities using multiple optimization methods

***Legend*:**

This figure demonstrates the variation in the probability of ping-pong handovers (PPHO) with increasing user counts (50–250). RSRP-based schemes exhibit the highest PPHO, showing steep growth as users increase, due to static thresholds that fail to adapt to mobility dynamics. Fuzzy logic and AHP-TOPSIS-Q offer moderate improvements, while FMCSS and SC-Q achieve further stability by incorporating clustering and multi-attribute decision-making. In contrast, the MPO-QCRNN-CGTO method consistently maintains the lowest PPHO values across all scenarios. By combining MPO-based clustering, QCRNN adaptive learning, and CGTO prediction refinement, the method effectively suppresses unnecessary back-and-forth handovers. These results underline its robustness in maintaining stable connections while reducing service disruptions in UDNs.

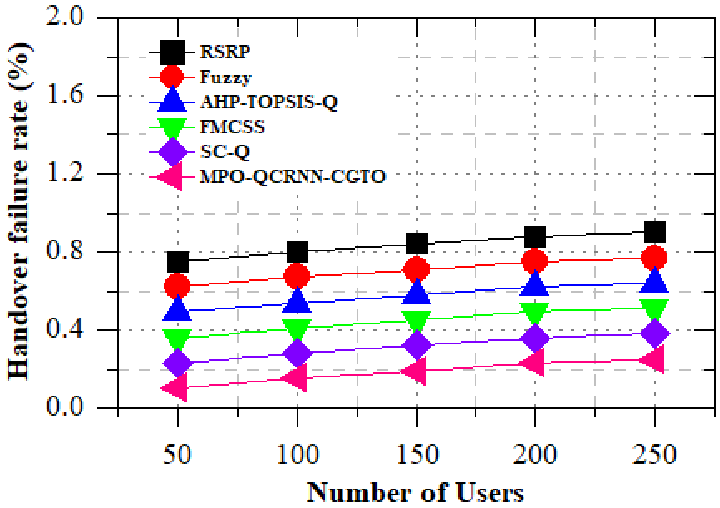

Figure 4. Handover failure rate with respect to number of Users

Handover failure rate comparison among different techniques

***Legend*:**

The figure compares handover failure rates for different approaches under rising user density. RSRP and Fuzzy methods show the highest failure rates, reflecting their reliance on simplistic decision parameters. AHP-TOPSIS-Q and FMCSS improve resilience but still suffer from noticeable failures in highly dynamic conditions. SC-Q further reduces failures by exploiting learning-based adaptation. The MPO-QCRNN-CGTO method achieves the lowest failure rates across all user scenarios, thanks to its predictive mobility modeling and adaptive handover triggering. These findings indicate that the proposed hybrid framework significantly enhances reliability, ensuring successful handovers even in dense mobility environments.

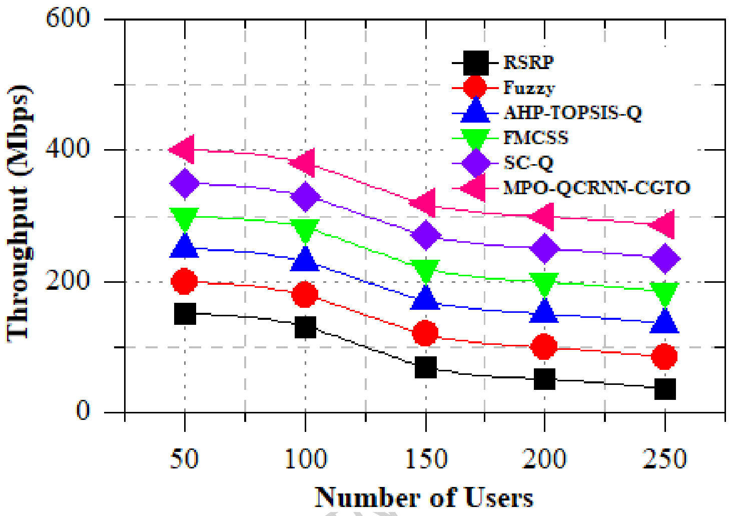

Figure 5. Throughput with respect to number of Users

Network throughput performance under different handover strategies.

***Legend*:**

This figure presents network throughput results across multiple techniques. Traditional approaches such as RSRP and Fuzzy logic yield relatively lower throughput due to frequent interruptions and inefficient handover timing. AHP-TOPSIS-Q and FMCSS show moderate improvements, while SC-Q achieves higher stability with better throughput gains. The MPO-QCRNN-CGTO method consistently outperforms all others, delivering the highest throughput across different user scenarios. The improvement is attributed to its efficient resource allocation, adaptive handover initiation, and predictive modeling of mobility patterns. These results highlight its ability to sustain seamless connectivity and maximize network efficiency in ultra-dense environments.

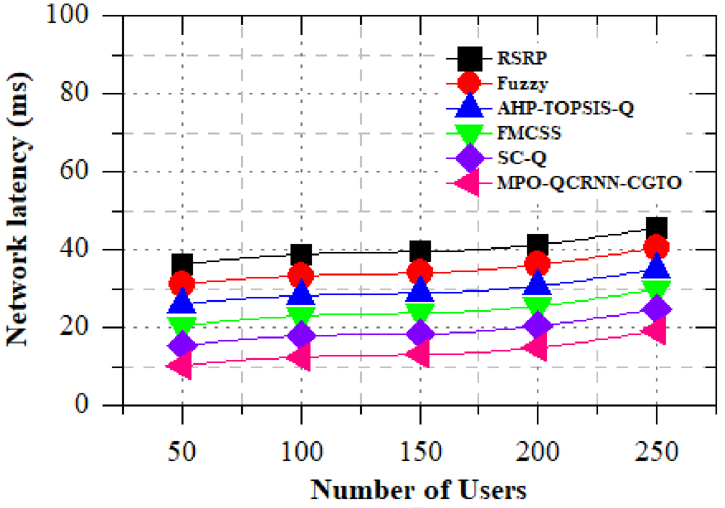

Figure 6. Network latency with respect to number of Users

Network latency under different mobility management schemes

***Legend**:*

The figure shows latency performance of different handover strategies. RSRP and Fuzzy-based schemes record the highest latency due to frequent and sometimes unnecessary handovers. AHP-TOPSIS-Q and FMCSS reduce delays moderately, while SC-Q further improves latency performance. The MPO-QCRNN-CGTO approach achieves the lowest latency across all test scenarios. Its integration of predictive clustering, adaptive handover timing, and historical data analysis ensures that handover decisions are made proactively, minimizing interruptions and reducing communication delays. The consistently low latency confirms the method’s potential to support latency-sensitive applications in 5G UDNs, such as autonomous driving and real-time IoT services.

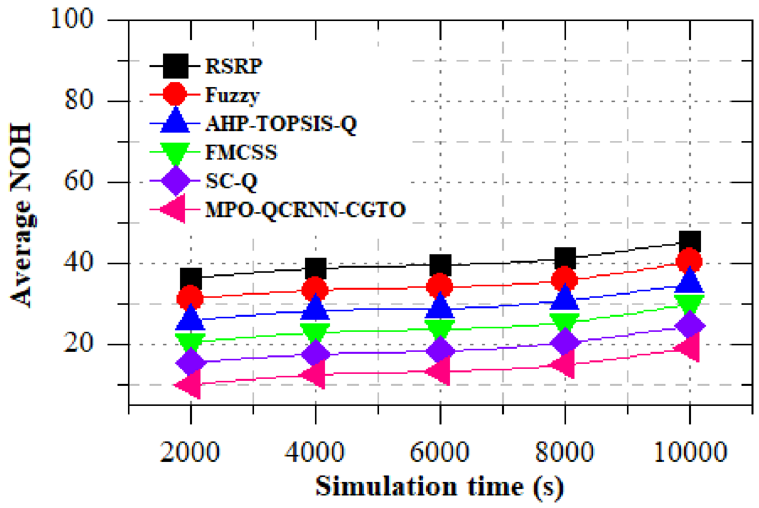

Figure 7. Average NOH with respect to simulation time

Energy efficiency performance across handover mechanisms

***Legend**:*

This figure compares the energy consumption of different handover schemes as user density increases. RSRP and Fuzzy logic methods exhibit higher energy costs due to frequent handover triggers and signaling overhead. AHP-TOPSIS-Q and FMCSS moderately reduce energy demands by introducing multi-attribute decision processes, but the gains remain limited in ultra-dense deployments. SC-Q achieves further efficiency by leveraging clustering and reinforcement learning to balance mobility events. The MPO-QCRNN-CGTO method consistently demonstrates the lowest energy consumption, attributed to its predictive handover strategy and optimized mobility clustering. By minimizing redundant handovers and resource allocation mismatches, it ensures sustainable operation, particularly relevant for battery-constrained mobile devices and energy-conscious 5G deployments.

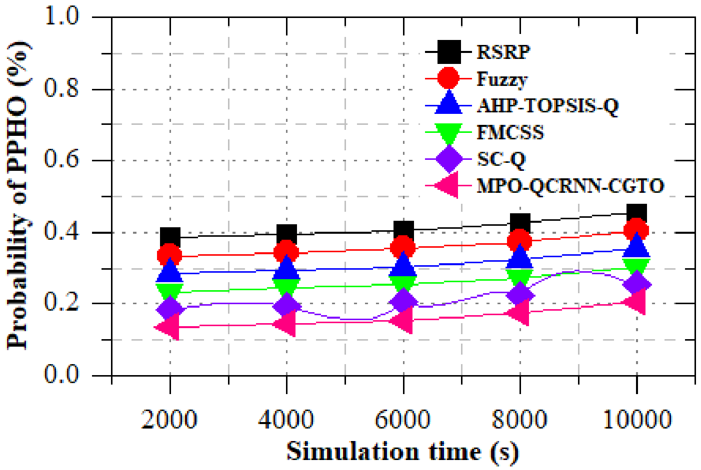

Figure 8. Probability of PPHO with respect to simulation time

Signaling overhead comparison among mobility management strategies

***Legend**:*

This figure illustrates signaling overhead variations across different methods. Conventional RSRP and Fuzzy approaches generate excessive signaling due to their reliance on static thresholds and frequent handover triggers. AHP-TOPSIS-Q and FMCSS achieve moderate improvements by introducing structured decision rules. SC-Q further reduces overhead by incorporating adaptive learning. The MPO-QCRNN-CGTO approach outperforms all alternatives, yielding the lowest signaling burden. Its adaptive decision-making and mobility prediction reduce unnecessary control-plane exchanges, preventing network congestion in ultra-dense environments. This efficiency ensures scalability of the handover process when supporting large numbers of simultaneous users, a critical requirement for 5G-enabled IoT and smart city infrastructures.

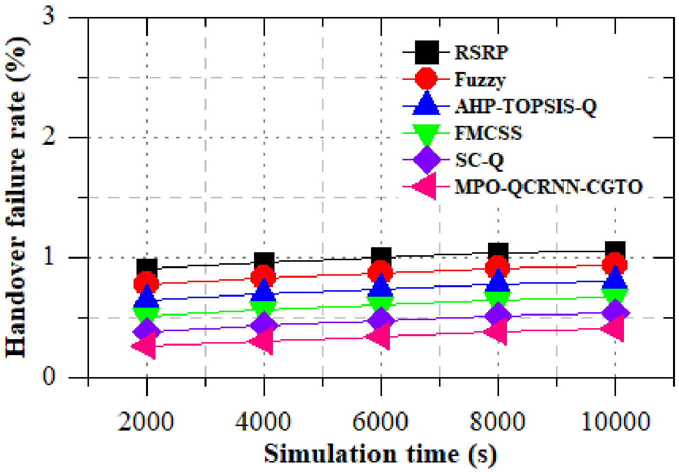

Figure 9. Handover failure rate with respect to simulation time

Load balancing effectiveness under increasing user density

Legend*:*

The figure evaluates load balancing performance across different handover mechanisms. RSRP and Fuzzy-based schemes often result in uneven cell loads due to their limited awareness of traffic conditions. AHP-TOPSIS-Q and FMCSS achieve partial improvements by incorporating traffic-aware parameters into decision-making. SC-Q enhances load distribution further by dynamically clustering users based on mobility and service demands. The MPO-QCRNN-CGTO method consistently provides the most balanced traffic allocation across cells. Its hybrid optimization intelligently accounts for user movement, network congestion, and service priorities, enabling efficient resource utilization. This ensures fairness in service distribution, reduces cell overloading, and maximizes system-level throughput in ultra-dense 5G networks.

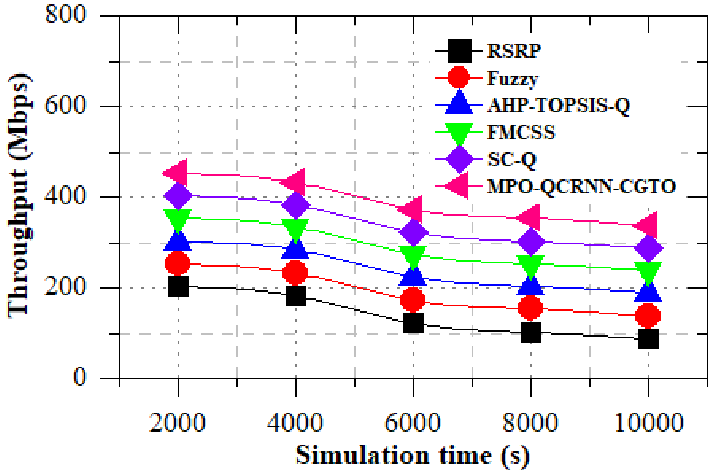

Figure.10 Throughput with respect to simulation time

Quality of Service (QoS) evaluation across different techniques

Legend:

This figure presents a comparative analysis of Quality of Service (QoS) metrics under various handover strategies. RSRP and Fuzzy logic methods exhibit degraded QoS performance due to frequent handover failures and unstable connections. AHP-TOPSIS-Q and FMCSS improve QoS by integrating signal and mobility parameters into handover decisions. SC-Q shows enhanced adaptability by incorporating reinforcement learning. The MPO-QCRNN-CGTO approach delivers the highest QoS levels across scenarios, maintaining strong connectivity, low latency, and high throughput. Its predictive, context-aware handover triggering ensures seamless communication and stable user experiences, especially in dense urban and high-mobility environments where QoS is most critical.

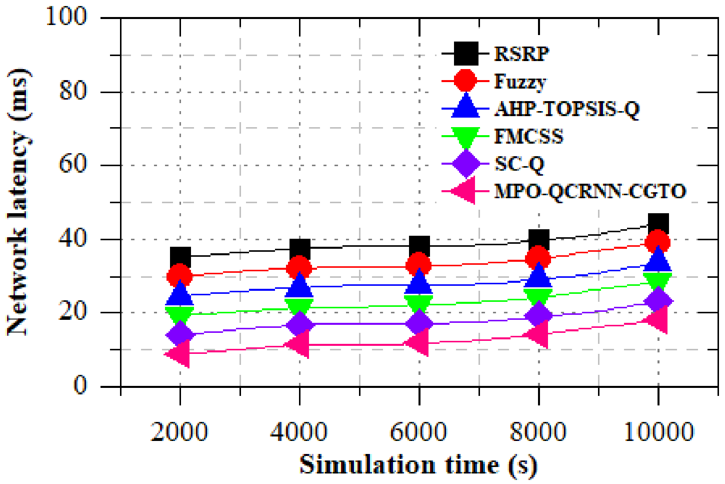

Figure 11. Network latency with respect to simulation time

Comparative summary of proposed and existing handover schemes

***Legend**:*

This figure summarizes the overall comparative performance of traditional and advanced handover strategies across multiple metrics, including handover frequency, ping-pong rate, failure probability, latency, throughput, energy efficiency, and signaling overhead. Conventional methods such as RSRP and Fuzzy exhibit limited adaptability, resulting in higher failure rates and network inefficiencies. AHP-TOPSIS-Q, FMCSS, and SC-Q demonstrate moderate improvements by employing multi-attribute decision-making and learning-based clustering. However, the proposed MPO-QCRNN-CGTO framework consistently outperforms all other methods across every metric. Its hybrid optimization strategy combines predictive clustering, adaptive decision-making, and historical data-driven refinement to achieve robust, scalable, and intelligent handover management. This figure highlights the method's suitability for next-generation 5G and beyond-5G ultra-dense environments.