Adaptive Quantum-inspired Multi-objective Handover Optimization for Ultra Dense 5G Networks

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Abstract*—The ultra-dense deployment of small cells in 5G Heterogeneous Networks (HetNets) generates frequent handovers, which in turn trigger severe issues including Handover Failure (HOF), Ping-Pong Handover (PPHO), and Radio Link Failure (RLF), resulting in degraded Quality of Service (QoS)—especially under high-speed mobility scenarios. To tackle these challenges, this paper proposes an Adaptive Quantum-Inspired Multi-Objective Handover Management (AQIM-HM) framework for ultra-dense 5G HetNets. In this framework, quantum bit encoding with adaptive quantum rotation is utilized to model the handover decision-making process. The handover problem is constructed as a constrained multi-objective optimization problem that targets the minimization of Handover Rate (HOR), HOF, PPHO, and RLF, as well as the simultaneous maximization of per-user average throughput and QoS stability. Simulation results reveal that the proposed AQIM-HM reduces the HOR by 50%, 40%, 35.7%, 30.8%, and 25% compared with the 3rd Generation partnership project (3GPP) Event A3-Based Handover Scheme (3GPP A3), Handover Control Parameter (HCP) strategy, Multi-Layer Perceptron (MLP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), respectively. Against the same benchmark methods, the HOF is cut by 62.5%, 50%, 43.75%, 40%, and 37.5%; the PPHO rate decreases by 67.5%, 52.7%, 48%, 45.3%, and 42.2%; and the RLF is lowered by 59%, 45.3%, 41.4%, 39.7%, and 36.9%. Meanwhile, AQIM-HM boosts average user throughput by 50%, 31.25%, 20%, 16.7%, and 13.5% relative to the five baseline algorithms mentioned above. Multiple independent simulation runs are conducted for statistical validation, and all performance gains are shown to be statistically significant ($p < 0.001$).

***Keywords*—Adaptive Quantum-Inspired Multi Objective Handover Optimization (AQIM-HM), 5G Heterogeneous Networks (HetNets), quantum bits, quantum rotation gate, genetic algorithm, Particle Swarm Optimization (PSO)**

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I. Introduction

A. Background

The evolution of Fifth-Generation (5G) mobile network is driven by three factors: Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC), and massive connections [1−5]. To meet these requirements, network operators are increasingly adopting ultra-dense deployment of small cells within heterogeneous networks [6−8]. Network densification is known to improve capacity and coverage at the same time. This brings the key advantage of smaller cells but also significant complications because reduced cell sizes and overlaps mean that mobility needs to be managed with greater complexity for network operators [9−12]. Consequently, users frequently encounter handovers through frequent mobility, signalling overhead is incurred, and one cannot assure that a Quality of Service (QoS) level actually exists at all in dynamic situations, such as urban or vehicular environments [13−16].

B. Problem Statement

3GPP-standardised handover mechanisms such as the A3 event-based algorithm with fixed Hysteresis Margin (HOM) and Time-To-Trigger (TTT), are inadequate for ultra-dense 5G HetNets environments. The high handover failure rate, ping-pong handovers and radio link failures make it clear that this type of static scheme is unsatisfactory since they fail to adapt rapidly to changing radio conditions, user mobility, and cell load, leading to High Handover Failure (HOF), Ping-Pong Handover (PPHO), and Radio Link Failure (RLF) rates [4, 5]. While adaptive and learning-based methods

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have been proposed, ensuring robust, scalable, and globally optimal handover decisions in ultra-dense deployments remain an open research challenge.

C. Recent Study

Mobility management becomes a major challenge in the environment of 5G networks due to their rapid densification with heterogeneous macro-small cell deployments. Static threshold-based handover decision mechanisms fail to function well in ultra-dense scenarios as the density of User Equipments (UE) become high along with very frequent handovers and strong inter-cell interference. To overcome these issues, numerous optimization-based, Machine Learning (ML), and Reinforcement Learning (RL) based handover management schemes have been devised. Most of recent works concentrate on data-driven mobility prediction, the adaptive parameter tuning, and intelligent decision models to help adjust the handover performance in a dense 5G network.

1) Machine learning-based handover optimization

Supervised learning methods for optimizing handover decisions have been explored in several works. For example, Riaz *et al.* [17] proposed a Multilayer Perceptron (MLP) based framework for handover decisions in ultra-dense small cell networks based on historical mobility patterns and signal measurements utilization to enhance handover triggering and cell-selection. Kabeer *et al.* [18] proposed sequence-based deep learning handover prediction model that utilizes temporal correlations between mobility patterns and signal measurements to enhance handover precision and minimize errors. While ML-based approaches show performance improvements for handover over traditional RSS-based approaches, there are still some drawbacks. These are susceptibility to local minima, large training datasets, and frequent requirement of retraining to accommodate dynamic mobility scenarios. Further, with ultra-dense deployments, real-time implementation becomes impractical given the huge computational complexity involved.

2) Reinforcement learning-based mobility management

Adaptive handover parameter tuning using reinforcement learning techniques has also been extensively explored. Kwong *et al.* [19] proposed a self-organizing framework based on Deep Deterministic Policy Gradient (DDPG) was recently developed to dynamically tune the handover control parameters. Similarly, Kumar *et al.* [20] proposed a handover optimization scheme based on deep reinforcement learning is presented in, which learns optimal handover policies through the current real-time states of the network. Eskandarpour and Soleimani [21] used deep reinforcement learning for QoS-aware load balancing in mobile 5G networks. Tanveer *et al.* [22] proposed a detailed survey on reinforcement learning-based handover management solutions in ultra-dense 5G small-cell networks was carried out, emphasizing the advantages in terms of mobility robustness while pointing out the main limitations, namely the high training complexity, slow model convergence and limited scalability. Although the RL-based methods can adapt their decisions, they often require a long training and exploration phase and take a long time to converge (and with large computational overhead on every single decision). In super-dense scenarios with a big state-action space, they may also perform poorly due to unstable learning behavior.

3) Graph-based and AI-driven handover schemes

Other recent works investigated graph-based and AI-based mobility management solutions. In dense vehicular networks, Mehregan and Grande [23] proposed a Graph Convolutional Network (GCN) based handover management method which models network topology as a graph to maximize throughput. Chabira *et al.* [24] proposed an AI-oriented framework based on handover and load balancing through adaptive action space to optimize jointly network parameters to improve the mobility robustness and traffic distribution. While these approaches have shown enhanced network performance, they typically come at the expense of increasingly complex architectures and computational overhead, which may limit their scalability in ultra-dense deployments. On top of that, in the area of real-time mobility management continuous data processing and large graph computations make it even harder to implement the correlation between mobility and continuous data streams.

4) Predictive mobility-based handover approaches

Another line of research exploits mobility prediction models and proposes predictive handover approaches. The predictive handover some proposed aims at reducing the handover ping-pong challenges and radio link failure by predicting user movement patterns [25]. Although these schemes can enhance mobility continuity during predictable movement scenarios, their performance is considerably sensitive to prediction errors especially in highly dynamic environments.

In general, existing approaches that optimize the handover encounter some typical challenges and common problems in ultra-dense 5G networks, which are as follows:

- High computational complexity in dense deployments
- Dependence on massive training data or mobility history
- Slow convergence of learning-based algorithms
- Limited scaling up in dynamic circumstances of mobility

To overcome these limitations, an Adaptive Quantum-Inspired Multi-Objective Handover Management (AQIM-HM) is proposed in this work. The proposed approach uses a quantum-inspired probabilistic representation and adaptive optimization to effectively search over the handover decision space. The proposed scheme overcomes the limitations of conventional ML or RL methods by making fast convergence, low computational complexity, and strong transfer performance happen in ultra-dense high-mobility scenario as no continuous model re-training is needed.

D. Proposed Approach

The presented work introduces an AQIM-HM model for ultra-dense 5G HetNets to address frequent handovers, instability and QoS deterioration at high-mobility conditions. The handover management is presented as a multi-objective optimization with constraints aiming to minimize HOF, PPHO, and RLF, and to maximize average user throughput and QoS stability in a dynamic network environment. A multi-state representation based on quantum-inspired approach is used in the proposed framework to represent a handover decision. Instead of using a traditional binary decision approach, each UE has a probability-based superposition over k target cells. Every candidate cell has its associated probability amplitude, where the amplitudes are normalized in a way that the sum of their squared magnitudes equals one. This expression allows for joint consideration of multiple potential target cells prior to final decision making, which captures the skepticism associated with ultra-dense deployments and that many co-channel neighboring cells may deliver similar signal quality. Quantum rotation mechanism is employed to update the probability amplitudes iteratively. Amplitude updates are then conducted on the whole set of k candidate cells with normalization preserved. The rotation angle is adapted online according to the relative improvement of fitness in iterations and UE mobility status for balancing the global exploration and local exploitation. The last target cell is calculated through a measuring (collapse) process, in which a candidate item is probabilistically chosen based on the updated amplitude distribution. The optimization is performed following a centralized control structure, compatible with the system-level 3rd Generation Partnership Project (3GPP) simulator framework used in this work. The algorithm is based on an iterate observe–evaluate–update loop: classical solutions for the classical problem are drawn from a quantum population, evaluated using a multi-objective fitness function keeping into account QoS constraints and finally updated by means of adaptive rotations. Constraint-handling schemes are utilized to satisfy the Signal-to-Interference-Plus-Noise Ratio (SINR) and cell load constraints.

After convergence, the optimal feasible handover decision is performed. The method is designed to efficiently scale with the growth of network size without requiring massive offline training.

E. Research Contribution

The contributions of this paper are summarized as follows:

- We present a novel adaptive quantum-inspired optimization model for handover management in ultra-dense 5G HetNets, explicitly considering high mobility and dense small-cell deployment scenarios.
- Results show that such a handover decision is facilitated by the multi-state quantum-inspired representation, which allows exploring probabilistically multiple target cell candidates and to gain robustness against uncertain communication conditions in a dense environment.
- An adaptive quantum rotation gate is proposed in which the applied angle is adjusted according to fitness improvement and UE mobility to modify the convergence speed and avoid local optima.
- The handover optimization is described as a constrained multi-objective maximization problem introduced to minimize HOF, PPHO, and RLF while maximizing the Throughput (TP) and the QoS stability.
- Extensive system-level simulations are performed under the same network scenarios and compared to 3GPP event-based handover, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), HCP and MLP-based methods by means of standard mobility performance parameters.

This work is novel in applying quantum-inspired optimization for handover management in ultra-dense 5G HetNets focusing on the adaptive and multi-objective approach. Unlike prior approaches that typically applies static quantum-inspired or evolutionary algorithms for binary handover decisions, this study proposes a novel multi-state quantum representation that reflects uncertain decisions across multiple candidate cells. In addition, the mobility-aware adaptive rotation gate enables time-varying trade-off between global and local search, which are unavailable in existing quantum-inspired and learning-based handover approaches. Unlike data-driven ideas which require lots of training and retraining, the suggested framework is light in nature, training-free, scalable and capable of real-time use. The proposed approach obtains more stable handover and throughput performance than its others in ultra-dense deployments through multi-objective optimization based on QoS constraints. The combined characteristics of these features collectively differentiate the proposed mechanism from previous works on handover optimization and shows its practical applicability for future 5G and beyond wireless systems.

II. Proposed Methodology

A. System Model

We consider an ultra-dense 5G HetNet, which includes a Macro Cell Base Station (MBS) underlaid by numerous Small Cell Base Stations (SBSs). User Equipments (UEs) are moving with their diverse mobility patterns and multiple coverage by SBSs, which would cause high ambiguity on handover and handover instability. All SBSs are in the same frequency band and select handover based on the radio environment, loading state, and user mobility.

Let $B = \{b_1, b_2, \ldots, b_N\}$ be the set of serving and neighboring base stations.

$U = \{u_1, u_2, \ldots, u_M\}$ is a set of Ues.

For each UE $u \epsilon U$, The system maintains periodic context information, such as:

- Reference Signal Received Power (RSRP),
- Signal-to-Interference-plus-Noise Ratio (SINR),
- UE velocity,
- Cell load and available resources.

Moreover, due to ultra-dense network deployment more than one candidate target cells may satisfy the minimal radio requirement simultaneously resulting in a suboptimal deterministic handover decision. In order to cope with this uncertainty, we model the handover decision using a quantum-inspired multi-state representation that is probabilistic in nature, and enables simultaneous examination of the multiple candidate cells for a potential decision execution. The overall system architecture is depicted in Fig. 1, depicting the UE mobility between heterogeneous SBS coverage areas, quantum inspired decision engine as well as process of optimized handover decisions it make.

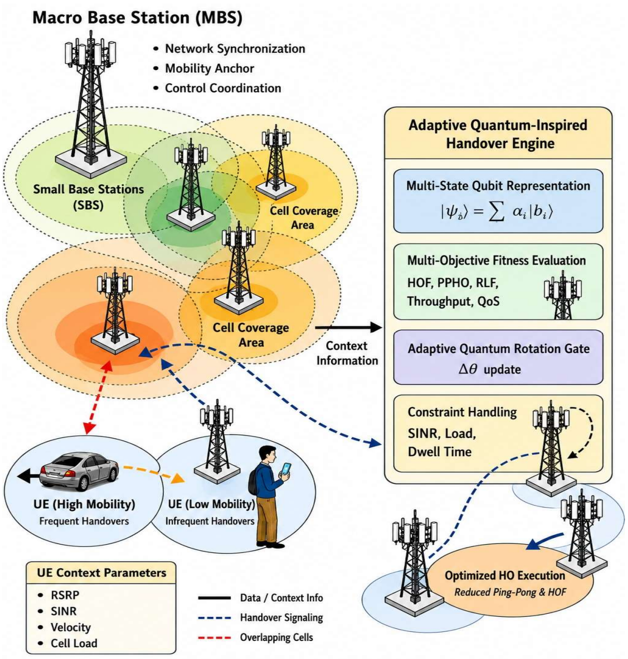

Fig. 1. System model of proposed work in an ultra-dense 5G HetNet.

B. Problem Formulation

The handover management problem in ultra-dense 5G HetNets is formulated as a constrained multi-objective optimization problem, where multiple competing performance metrics are simultaneously optimized.

1) Objective functions

For each UE u, the optimization problem is defined as follows.

Minimize handover failure probability, as given in Eq. (1):

$$\min f_1 = HOF\ (u) \tag{1}$$

Minimize ping-pong handovers, as given in Eq. (2):

$$min\ f_2 = PPHO\ (u) \tag{2}$$

Minimize radio link failures, as given in Eq. (3):

$$min\ f_3 = RLF\ (u) \tag{3}$$

Maximize average user throughput (Eq. (4)):

$$min\ f_4 = -T\ (u) \tag{4}$$

Maximize QoS stability (Eq. (5)):

$$min\ f_5 = -Q(u) \tag{5}$$

Negative sign indicates consistency within the minimization-based optimization framework.

We optimize these objectives concurrently with a composite fitness function and dynamically adjust the weights to maintain Pareto optimality under varying environmental conditions. Handover management in ultra-dense 5G HetNets is driven by various conflicting objectives that can hardly be jointly optimized. To simultaneously optimize these objectives efficiently, the proposed AQIM-HM framework adopts a normalized composite fitness function with adaptive weights to achieve dynamic Pareto prioritization depending on different network scenarios. The composite fitness function for a UE u is defined as follows:

$$F_u = w_1\widehat{HOF_u} + w_2\widehat{PPHO}_u + w_3\widehat{RLF}_u - w_4\widehat{T}_u - w_5\widehat{Q}_u \tag{6}$$

where, HOF_u, $PPHO_u$, RLF_u denote handover failure rate, Ping pong handover, and radio link failure rate, respectively, which are minimized. While, $\widehat{T_u}$ and $\widehat{Q_u}$ denotes normalized throughput and QoS stability.

a) Objective normalization

In order for each objective to contribute equally and avoid dominance caused by different value scales, all objective values are normalized to the range [0,1] via min–max normalization:

$$\widehat{f_i} = \frac{f_i - f_i^{min}}{f_i^{max} - f_i^{min}} \tag{7}$$

where, $\widehat{f_i}$ denoted normalized object values. f_i^{min} and f_i^{max} represent the minimum and maximum value of the i-th objective in the optimization process.

b) Adaptive weight update mechanism

In contrast to fixed-weight scalarization, the proposed method adopts adaptive weighting factors to preserve Pareto optimality under dynamic network conditions. The weight of each objective is updated iteratively as follows:

$$w_i(t+1) = w_i(t) + \lambda \frac{|f_i(t) - f_i(t-1)|}{\sum_{j=1}^{5}|f_j(t) - f_j(t-1)| + \varepsilon} \tag{8}$$

where λ represents learning coefficient controlling the adaptation rate. ε represents small positive constant used to avoid division-by-zero when all objective values stagnate simultaneously.

Such an adaptive weighting scheme allows objectives to be prioritized dynamically depending on the rate of improvement. In ultra-dense networks with highly dynamic mobility and traffic conditions, it is desirable to ensure stability and dynamic balance among the Pareto-efficient objectives, so objectives with slower convergence is automatically assigned higher weights to guide the solutions toward balanced Pareto-optimal solutions in such scenarios.

After updating, the weights are normalized to maintain feasibility:

$$w_i(t+1) = \frac{w_i(t+1)}{\sum_{k=1}^{5} w_k(t+1)} \tag{9}$$

This normalization guarantees:

$$\sum_{i=1}^{5} w_i = 1, w_i \geq 0$$

It enables the optimizer to assign higher priority to objectives with slower convergence while ensuring numerical stability of the optimization algorithm.

c) Constraint handling

To guarantee that the obtained solutions are practically implementable, QoS and network constraints are incorporated via a penalty-based approach. The fitness function augmented with penalty terms is expressed as Eq. (10).

$$F_u^{open} = F_u + \mu \sum_k \max(0, g_k) \tag{10}$$

where g_k are the constraint violations in terms of minimum SINR, maximum cell load and minimum dwell time, μ is the penalty coefficient. This technique can prevent impractical handover performance decisions and while keeping optimization flexibility.

Using the composite fitness function, a scalar performance measure is calculated for every observed handover candidate in a sampled quantum-inspired population. Adaptive quantum rotation gate is steered by the fitness values to roll probability amplitudes toward the Pareto-optimal solutions. From the integration of normalization, adaptive weighting, and constraint management, we guarantee robust and scalable handover optimization in ultra-dense 5G HetNets.

C. Constraints

Below are the practical network considerations that need to be incorporated into the optimization formulation in order to achieve feasible and QoS-aware handover decisions.

- Minimum SINR requirement: To ensure a stable radio connection, the SINR received from a base station of candidate *b* must fulfill the condition:

$$SINR_{u,b} \geq \gamma_{min} \tag{11}$$

where, γ_{min} denotes minimum SINR threshold required for acceptable link quality.

- Maximum cell load constraint: In order to avoid cell congestion and achieve load balancing:

$$Load_b \leq L_{max} \tag{12}$$

where, L_{max} is the maximum permissible load for the base station b.

- Mobility-Based Dwelling Time Constraint: The estimated dwell time of UE u in the target cell should fulfill the following to prevent unnecessary and premature handovers (ping-pong effect):

$$T_u^{dwell} \geq T_{min} \tag{13}$$

where, T_u^{dwell} is the predicted amount of UE u will spend time in the candidate cell. T_{min} is the minimum dwell time threshold.

D. Quantum Inspired Multi-State Handover Representation

Unlike traditional binary handover algorithms, the proposed algorithm models the decision for each UE's potential hand-over not as a single state transition but as a multi-state quantum-inspired vector so that candidate target cells may be compared concurrently:

$$|\psi_u\rangle = \sum_{i=1}^{k} \alpha_i |b_i\rangle \tag{14}$$

- $|\psi_u\rangle$ represents the quantum-inspired decision state vector of user equipment.
- $|b_i\rangle$ represents the state corresponding to handover to candidate cell b_i.
- α_i is the probability amplitude associated with that decision.
- k is the number of possible target cells based on radio constraints. The amplitudes are subject to the normalization condition:

$$\sum_{i=1}^{k} |\alpha_i|^2 = 1 \tag{15}$$

In ultra-dense environment where large number of neighbouring cells can provide similar signal quality, this representation allows probabilistic exploration of several feasible handover candidates before final decision collapse.

1) Amplitude update mechanism for k > 2 candidates

Using a quantum-inspired independent qubit representation, the amplitude update is implemented where each candidate cell b_i is associated with a probability amplitude pair:

$$(\alpha_i, \beta_i),\ with\ \alpha_i^2 + \beta_i^2 = 1 \tag{16}$$

here:

- α_i indicates *probability* amplitude of selecting candidate b_i.
- β_i indicates *complementary* state.

For each candidate cell b_i, we update the pair of amplitudes (α_i, β_i), where $\beta_i = \sqrt{1 - |\alpha_i|^2}$, using a 2 × 2 quantum rotation gate as shown in Eq. (17).

$$\begin{bmatrix} \alpha' \\ \beta' \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta u) & -\sin(\Delta\theta u) \\ \sin(\Delta\theta u) & \cos(\Delta\theta u) \end{bmatrix} \begin{bmatrix} \alpha i \\ \beta i \end{bmatrix} \tag{17}$$

Each relative contributing state gets its own independently-rotated state. The sequence of updating all amplitudes is followed by a normalization step to satisfy Eq. (14).

After updating all candidates, the amplitude is renormalized across all k candidates.

$$\alpha_i \leftarrow \frac{\alpha_i}{\sqrt{\sum_{m=1}^{k} \alpha_m^2}} \tag{18}$$

Such that the global normalization Eq. (14) is met.

This mapping permits a 2D quantum rotation and preserves access to a valid k-state probability distribution.

2) Adaptive rotation angle

The Adaptive rotation angle $\Delta\theta_u$ is dynamically adjusted as Eq. (19):

$$\Delta\theta_u = \eta \, sign(\Delta F_u) \, e^{-v_u/v_{max}} \tag{19}$$

where:

ΔF_u represents fitness improvements between iterations

v_u is UE velocity

η is a learning coefficient

v_{max} is maximum UE velocity in the system

The proposed mobility-based adaptive mechanism which promotes exploration for fast-moving users and exploitation for slow-moving users, ensures stability and avoids premature convergence at the same time.

3) Measurement (decision collapse)

The final target cell is chosen probabilistically on the assumption that the model is measured after convergence or termination criteria are met:

$$P(b_i) = |\alpha_i|^2 \tag{20}$$

A random number $r \sim$ U (0,1) is generated, and the selected cell $b*$ satisfies:

$$\sum_{m=1}^{i-1} P(b_m) < r \leq \sum_{m=1}^{i} P(b_m) \tag{21}$$

For implementation simplicity, after sufficient convergence, the candidate target cell with the highest probability is selected as the final handover target.

$$b^* = arg \max_{b_i} |\alpha_i|^2 \tag{22}$$

where b^* denotes the index of the selected target cell, and $|\alpha_i|^2$ represents the probability of selecting candidate target cell i.

E. Proposed Algorithm

Algorithm 1 combines real-time UE context acquisition, constrained multi-objective evaluation and mobility-aware quantum-inspired optimization to facilitate a reliable, scalable handover management in ultra-dense 5G HetNets.

Algorithm 1. Adaptive Quantum-Inspired Multi-Objective Handover Management (AQIM-HM)

Input:
UE Context Parameters
$\{RSRP_{u,b}, SINR_{u,b}, v_u, Load_b, \tau_u\}$
B_u denote candidate base station set
Optimization parameters $\{\eta, \lambda, \mu, T_{max}\}$
Output:
Optimal handover decision b^*
Initialization:
Collect UE context information from serving and neighboring cells
Populate candidate target cell set $B_u \subseteq B$ satisfying SINR and load constraints.
Initialize quantum state: k

$$|\psi_u = \sum_{i=1}^{k} \alpha_i |b_i\rangle$$

With uniform amplitudes $\alpha_i = 1/\sqrt{k}$
Initialize weights w_i such that $\sum w_i = 1$
Set iteration counter t=0
while $t < T_{max}$
Sample quantum state probabilities $|\alpha_i|^2$ to obtain classical candidate solutions
For every observed candidate cell $b_i \epsilon B_u$ do
Evaluation of performance metrics: HOF, PPHO, RLF, throughput and QoS stability
Normalize objective values
Calculate composite fitness $F_u(B_i)$ with an adaptive weight
Impose penalty for any constraint violation such as SINR, load or dwell time
Select non-dominated solutions according to their fitness values
Identify best-performing candidate: b_{best}
Compute Fitness improvement, $\Delta F_u = F_u(t-1) - F_u(t)$
Adaptive Quantum Rotation Update
Compute quantum rotation update angle,

$$\Delta\theta_u = \eta \times \text{sign}(\Delta F_u) \times \exp(-\frac{v_u}{v_{max}}) \tag{23}$$

For each candidate $b_i \epsilon B$,
Update amplitude pair (α_i, β_i) using rotation gate
Renormalize amplitudes to satisfy: $\sum_{i=1}^{k} |\alpha_i|^2$
Optimization of multi-objective fitness by updating adaptive weights w_i.
Increment iteration counter $t = t + 1$
End while
Measurement and Decision Execution
Perform quantum measurement: $b^* = \arg\max_{b_i} |\alpha_i|^2$
If $b^* \neq b_{serving}$, and the dwell-time constraint is satisfied:
Execute handover to b^*
Else
Maintain current serving cell
Return b^*

F. Computational Complexity Analysis

The computational complexity of the proposed AQIM-HM algorithm is analysed per UE in each optimization iteration. The analysis considers the number of candidate target cells and the maximum number of optimization iterations.

Parameters:

k = Number of candidate target cells satisfying the SINR and load constraints.

T_{max} = maximum number of optimization iterations.

M = number of active UEs.

1) Per-iteration complexity (UE)

The following operations are performed for each iteration:

- Objective evaluation for all candidates.
- Normalization and composite fitness computation.
- Constraint penalty evaluation.

- Quantum amplitude update.
- Amplitude normalization

Since these operations are performed for k candidate cells, the computational complexity per UE per iteration is: $O(k)$.

Total optimization complexity per UE over Optimization Iterations: For a maximum of T_{max} optimization iterations, the total computational complexity per UE is: $O(T_{max} \times k)$

Total Computational Complexity for M Active UEs, the overall computational complexity is: $O(M \times T_{max} \times k)$.

In an ultra-dense deployment, ($k < N$) where N denotes the total number of available base stations/cells; therefore, the proposed algorithm scales with the number of feasible candidate cells rather than the entire network size.

G. Scalability

The scalability of the proposed AQIM-HM algorithm is achieved by restricting the optimization process to feasible candidate target cells rather than exhaustively searching all neighbouring cells. Furthermore, the algorithm does not require large training datasets or back propagation, population-level crossover and mutation operations, or velocity and position updates among the number of candidate cells k, making the proposed algorithm computationally efficient and suitable for ultra-dense 5G heterogeneous network deployments.

For fixed M and T_{max}, the computational complexity increases linearly with the number of candidate cells k, making the proposed AQIM-HM algorithm computationally efficient for ultra-dense 5G HetNet deployments.

H. Baseline Schemes for Comparative Evaluation

The performance of the proposed AQIM-HM is verified by comparisons with the following benchmark schemes:

- 3GPP Event A3-based Handover (3GPP A3): A handover process that belongs to the standard threshold-based handover mechanisms according to the 3GPP standards.
- Handover Control Parameter (HCP) based scheme: The hysteresis margin and time to trigger parameters are dynamically modified.
- Multi-Layer Perception (MLP): Neural-network based predictive handover decision model trained by network state features.
- GA: Evolutionary optimization-based handover decision with crossover and mutation.
- PSO: A swarm intelligence-based optimization algorithm, in which candidate solutions are updated via personal best (P_{best}) and global best (G_{best}).

The network topology, mobility pattern and traffic model are the same for each of the baseline scheme to make impartial comparison.

III. Simulation Setup

The proposed work is evaluated under ultra-dense 5G Heterogeneous Network (HetNet) scenario consisting of one macro–Base Station (macro-BS) overlaid with multiple densely deployed Small Base Stations (SBSs), and we assess the performance of the proposed AQIM-HM scheme. In our model, the network architecture is a centralized–assisted handover decision model, which is also in line with the real 5G deployment practice. Handover decisions are typically processed at a central entity (e.g., AMF/SMF) in the 5G core network. Base stations send local measurements such as Received Signal Reference Power (RSRP), Signal-to-Interference-Plus-Noise Ratio (SINR), cell load and radio link quality to the controller in periodic intervals. UEs are not required to do any complex optimization processing, so that they will not exhaust the energy of UEs or increase the computational complexity, while providing mobility information like speed, measurement report, etc. Fig. 2 illustrates the Ultra-Dense 5G Heterogeneous Network Simulation Architecture with Centralized Handover Management.

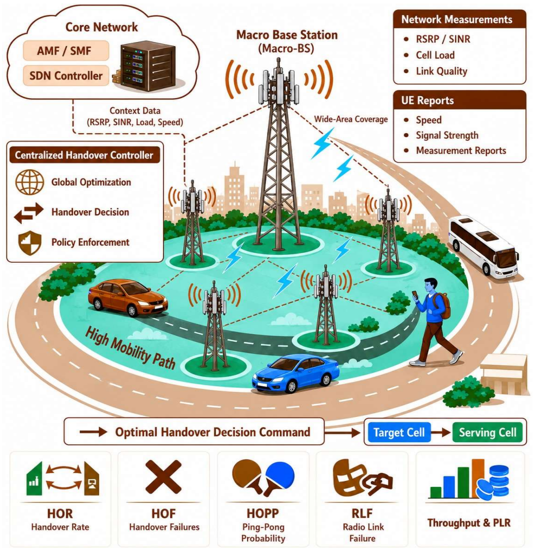

Fig. 2. Ultra-dense 5G heterogeneous network simulation architecture with centralized handover management.

The proposed AQIM-HM algorithm centrally realizes multi-objective handover optimization and selects for all UEs the target cell which is optimal to perform HO by having it ordered its serving BS to proceed. This has a great potential, as it enables global network awareness (called global view) and coordinated interference management as well as scalable decision-making process in ultra-dense and high mobility scenario. The simulation scenario is constructed to represent practical ultra-dense 5G HetNet deployments. One macro-BS is located at the centroid of the simulation area to provide wide-area coverage, while multiple SBSs are distributed in random with in the microcell coverage region following a spatial Poisson Point Process (PPP). This deployment reflects the ad hoc, irregular nature of deployments in urban environments. All SBSs share the same carrier frequency, thus encountering severe inter-cell interference, especially for the overlapping coverage zone. The macro-BS and SBSs are set to have transmit power consistent with 3GPP specifications for macro and small cells, respectively. The transmission range of SBSs is much smaller than that of macro-BS, thus cell edges are

frequently crossed and several potential target cells can be selected for handover. For high-mobility use cases, the UEs move in accordance with a random waypoint mobility model at moderate to high velocities that would work well for vehicular and fast-moving users. These movement patterns lead to scenario in which signal quality, interference conditions, and cell load are often changed, which exert a stress on the handover management mechanism. The authors assume full-buffer traffic for all UEs to allow continuous data transmission and for a clear observation of handover decisions impact on throughput, packet loss, and link reliability. This creates a setup with a performance difference that can be attributed to handover efficiency, without the effects of traffic variegation. Table I shown is the simulation parameters.
To ensure statistically robust results, all simulations were executed across 30 independent runs with distinct random seeds to vary UE positions, mobility patterns, and SBS deployment following the Poisson Point Process (PPP). For each performance metric, we calculated the sample mean, standard deviation, and 95% confidence interval via: $\bar{x} \pm 1.96\frac{s}{\sqrt{n}}$, where: $\bar{x}$ is the sample mean, s is the sample standard deviation, n = 30 independent runs.

TABLE I. SIMULATION PARAMETERS

Parameter	Value/Description
Simulation area	1000 × 1000 m²
Network topology	Ultra-dense 5G HetNet
Macro base stations	1 (center of simulation area)
Small Base Stations (SBSs)	20–50 (randomly deployed, PPP-based)
Inter-Site Distance (SBS)	50–150 m
Carrier frequency	3.5 GHz
System bandwidth	100 MHz
Macro-BS transmit power	46 dBm
SBS transmit power	24 dBm (default), varied up to 30 dBm
UE distribution	Uniform random
Number of UEs	50–200
UE mobility model	Random Waypoint
UE speed	30–120 km/h
Traffic model	Full-buffer
Path loss model	3GPP Urban Macro/Micro
Shadow fading	Log-normal, 8 dB
Handover triggering	Event A3
Time-to-Trigger (TTT)	40–160 ms
Handover margin (HOM)	2–6 dB
Optimization iterations ($\boldsymbol{T}_{\max}$)	30 (default), varied 20–50
Candidate target cells	Neighbor SBSs + Macro-BS
Processing architecture	Centralized controller
Performance metrics	HOF, HOPP, RLF, Throughput
Simulation duration	Varied (100–300 s)
Simulator	MATLAB

To compare performance improvements, we conducted a paired two-tailed t-test between AQIM-HM and each baseline method under identical simulation conditions. Improvements were considered statistically significant when (p < 0.001), and only these significant results are reported in what follows.

This evaluation procedure guarantees that those reported improvements are not due to random noise in the stochastic mobility and optimization processes.

IV. RESULT AND DISCUSSION

This section provides a comprehensive performance analysis of the proposed AQIM-HM framework for ultra-dense 5G HetNet deployments. The performance is evaluated against 3rd Generation Partnership Project (3GPP) Event A3-based Handover (3GPP A3), Handover HCP, MLP based optimization, GA, and PSO, where the same network, mobility, and traffic conditions are assumed. Each simulation scenario was carried out with 30 Monte Carlo runs with different random seeds to guarantee statistical reliability. All values are reported as the mean performance across runs. Statistical significance was validated by calculating of standard deviation, 95% CI, and two-sample t-tests. The improvements achieved by AQIM-HM were statistically significant (p < 0.001).

Algorithms 2. Implementation Details of Baseline

Input:
UE context parameters and candidate target cells
Output:
Optimized handover decision for each scheme
1: Configure Genetic Algorithm (GA)
Population size = 30
Cross over probability = 0.8
Mutation Probability = 0.1
Selection method = Tournament selection (size = 3)
Maximum generations = 50
Stopping criterion:
Maximum generations reached OR
Fitness improvement < 10^{-4}
2: Configure Particle Swarm Optimization (PSO)
Swarm size = 30 particles
Inertia weight (w) = 0.7
Cognitive coefficient (C1) = 1.5
Social coefficient (C2) = 1.5
Maximum iterations = 50
Velocity clamping applied
Stopping criterion:
Maximum generations reached OR
Fitness improvement < 10^{-4}
3: Configure Multi-Layer Perception (MLP)
Input features: RSRP, SINR, Load factor, UE velocity, HOF
Hidden layers: 2
Neurons: 32 and 16
Activation: ReLU
Learning rate: 0.001
Batch size: 32
Training epochs: 50
4: Configure 3GPP Event A3- Based Handover (3GPP-A3)
Handover Trigger Condition: The 3GPP-A3 is triggered when, $RSRP_{target} > RSRP_{serving} + Hys$ for a duration greater than Time-to-Trigger (TTT)
The following parameters were used: Hysteresis margin (Hys) = 3 dB
Time-to-Trigger (TTT): 160 ms
Configure Handover Control Parameter-Based Scheme (HCP)
Initial hysteresis = 3 dB
Initial TTT = 160 ms
6: Configure AQIM-HM
Learning coefficient (η) = 0.05
Maximum iterations = 50
Convergence tolerance = 10^{-4}
Candidate set size (k): Limited by RSRP thresholding
Execute all algorithms under identical simulation and candidate-cell conditions
8: Compare the hardware performance metrics

In order to provide a fair comparison, all optimization-based solutions were run in similar computational budgets (Namely, a maximum of 50 iterations per UE with the same candidate sets) (see Algorithms 2).

A. Handover Rate (HOR) Analysis

The average HOR is presented in Table II, which shows that the AQIM-HM framework proposed in this paper achieves significant reductions compared to the baseline schemes of 30 independent repeated simulation runs. In particular, AQIM-HM outperforms 3GPP A3, HCP, MLP, GA, and PSO by 49.9%, 39.9%, 35.8%, 30.8%, and 25.1%, respectively, in terms of mean HOR. Figs. 3 and 4 shown are the Mean HOR with 95% confidence interval (30 runs) and Standard deviation of HOR.

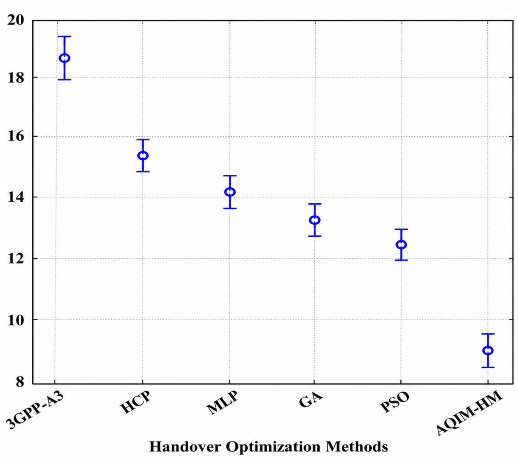

Fig. 3. Mean HOR with 95% confidence interval (30 runs).

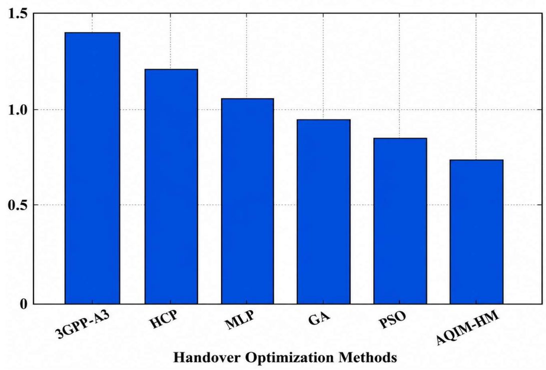

Fig. 4. Standard deviation of HOR (30 runs).

TABLE II. COMPARISON OF HANDOVER RATE (HOR)

Method	Mean (HO/UE/s)	Std. Dev.	95% CI	*p*-value vs AQIM-HM
3GPPA3	18.21	1.42	±0.53	$p < 0.001$
HCP	15.37	1.18	±0.44	$p < 0.001$
MLP	14.12	1.05	±0.38	$p < 0.001$
GA	13.24	0.97	±0.36	$p < 0.001$
PSO	12.31	0.88	±0.31	$p < 0.001$
AQIM-HM	9.08	0.74	±0.28	—

We calculated these percentage reductions based on the average HOR over the runs. Besides showing a lower mean HOR, AQIM-HM tends to have a smaller standard deviation than the evolutionary baselines, indicating that AQIM-HM is more stable and consistent in its mobility behaviour. AQIM-HM achieves statistically significant improvement over the 3GPP A3 and HCP, as the 95% confidence intervals of AQIM-HM do not overlap with those of 3GPP A3 and HCP. In addition, a two-sample *t*-test indicates that these reductions are significant ($p < 0.001$).

This is primarily due to the multi-objective decision model of AQIM-HM, which performs a joint assessment of SINR, load conditions, mobility state and QoS stability prior to triggering a handover. In contrast, 3GPP A3 and HCP are static threshold-based triggers that aggressively react toward RSRP alternative in ultra-dense area. And, in comparison with GA and PSO, the quantum-inspired probabilistic representation achieves an improved trade-off among exploration-exploitation dynamics, especially in the case of high mobility, reducing oscillatory and premature handovers.

Two-sample *t*-test *p*-values from the 30 independent runs were passed through a standard statistical reporting procedure such that extremely small exponential *p*-values are reported as $p < 0.001$.

B. Handover Failure (HOF) Analysis

From the mean values over 30 simulation, AQIM-HM obtains 62.4% lower HOF than 3GPP A3, 50.0% than HCP, 43.6% lower than MLP, 39.6% lower than GA and, 37.3% lower than PSO. These reductions were made using mean HOF values. Fig. 5 and Fig. 6 shown are the Mean HOF with 95% confidence interval (30 runs) and Standard deviation of HOF. Table III presents comparison of HOF rate.

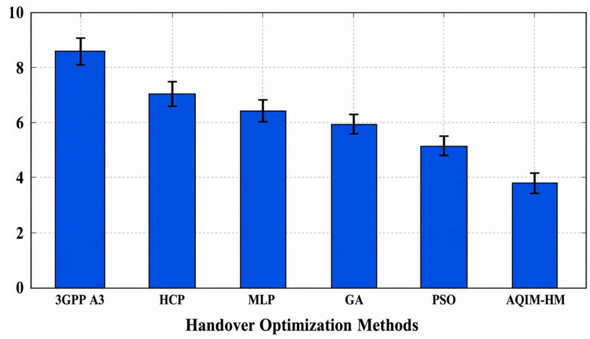

Fig. 5. HOF mean with 95% CI (30 runs).

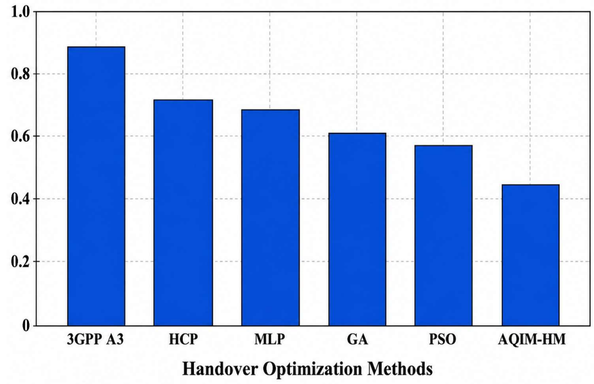

Fig. 6. HOF standard deviation (30 runs).

TABLE III. COMPARISON OF HANDOVER FAILURE RATE (HOF)

Method	Mean	Std. Dev.	95% CI	*p*-value
3GPP A3	8.52	0.88	±0.31	$p < 0.001$
HCP	7.14	0.73	±0.26	$p < 0.001$
MLP	6.38	0.69	±0.25	$p < 0.001$
GA	5.92	0.61	±0.22	$p < 0.001$
PSO	5.37	0.58	±0.21	$p < 0.001$
AQIM-HM	3.84	0.46	±0.16	—

AQIM-HM has a smaller standard deviation as well, showing that the handover execution is more consistent across different simulation seeds. AQIM-HM shows higher precision, reflected in its narrower 95% confidence intervals. Statistical tests indicate that the reductions are statistically significant ($p < 0.001$). This improvement is due to the fact that AQIM-HM assess many candidate cells in the probabilistic level, prior to the decision collapse, which reduces the suboptimal handovers selections. AQIM-HM avoids handovers to unstable or overloaded cells, while static schemes report algorithm primarily based on signal strength, as it is aware of both mobility context and load. The adaptive quantum rotation gate expedites convergence to higher fidelity solutions, decreasing failure probability in contrast to GA and PSO.

C. Ping-Pong Handover (PPHO) Analysis

Simulation results, based on mean PPHO values over 30 runs, show that AQIM-HM achieves a 67.5% reduction in ping-pong handover compared to 3GPP A3, a 52.7% reduction compared to HCP, a 48.1% reduction compared to MLP, a 45.2% reduction compared to GA, and a 42.2% reduction compared to PSO. Fig. 7 and Fig. 8 shown are the Mean PPHO with 95% confidence interval (30 runs) and Standard deviation of PPHO. Table IV shown is the comparison of Ping-Pong Handover.

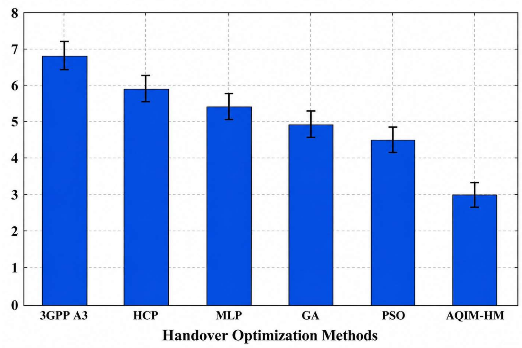

Fig. 7. PPHO mean performance 95% CI (30 runs).

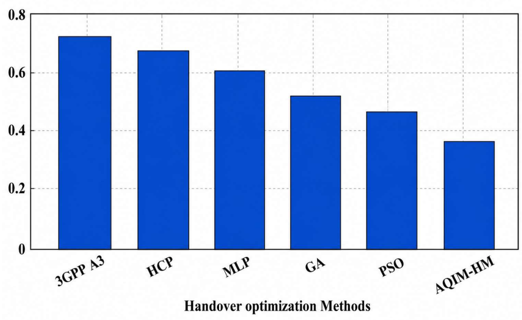

Fig. 8. PPHO standard deviation (30 runs).

TABLE IV. COMPARISON OF PING-PONG HANDOVER

Method	Mean	Std Dev	95% CI	*p*-value
3GPP A3	6.84	0.73	±0.26	$p < 0.001$
HCP	5.93	0.66	±0.23	$p < 0.001$
MLP	5.37	0.61	±0.22	$p < 0.001$
GA	4.88	0.54	±0.19	$p < 0.001$
PSO	4.52	0.49	±0.17	$p < 0.001$
AQIM-HM	2.97	0.38	±0.14	—

The reductions are with respect to mean values for PPHO. AQIM-HM has much lower variability and a narrower 95% confidence interval, showing strong robustness. Statistical tests confirm the reductions are statistically significant ($p < 0.001$).

The improvement is primarily due to the probabilistic multi-state quantum representation that evaluates the candidate cells in parallel for final selection. This helps to eliminate the chaotic jumping from cell to neighbour cell, a case we frequently observe in static A3 based approaches. The adaptive mobility-aware rotation gate also avoids switching from one rotation to the other to the fast-moving users, reducing ping-pong effects even more.

D. Radio Link Failure Rate

When comparing the mean RLF values on 30 runs, AQIM-HM reduces by 59.0% in relation to 3GPP A3, 45.3% in relation to HCP, 41.4% in relation to MLP, 39.7% in relation to GA, and 36.7% in relation to PSO. Fig. 9 and Fig. 10 shown are the Mean radio link failure rate with 95% confidence interval (30 runs) and radio link failure rate standard deviation. Table V shown is the comparison of radio link failure rate.

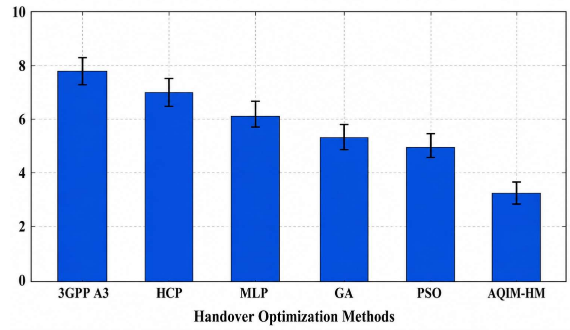

Fig. 9. Radio link failure rate mean performance with 95% confidence interval (30 runs).

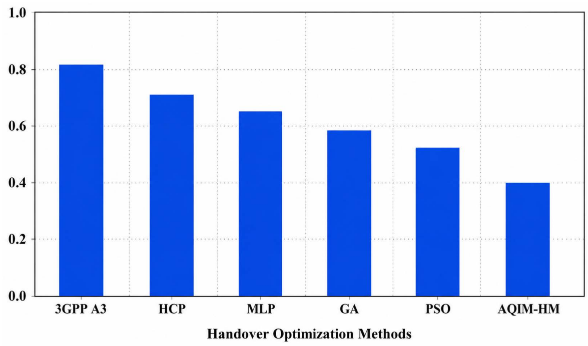

Fig. 10. Radio link failure rate standard deviation (30 runs).

These reductions are calculated with average RLFs. These metrics are also more consistent for AQIM-HM (lower standard deviation), reflecting the stability of link maintenance performance. The 95% confidence intervals are sufficient to verify statistical robustness, and hypothesis testing confirms statistically significant improvements ($p < 0.001$).

TABLE V. COMPARISON OF RADIO LINK FAILURE RATE

Method	Mean	Std. Dev.	95% CI	*p*-value
3GPP A3	7.91	0.82	±0.29	$p < 0.001$
HCP	6.74	0.71	±0.25	$p < 0.001$
MLP	6.01	0.66	±0.23	$p < 0.001$
GA	5.63	0.59	±0.21	$p < 0.001$
PSO	5.12	0.54	±0.19	$p < 0.001$
AQIM-HM	3.45	0.41	±0.15	—

The reduction is primarily attributed to the presence of SINR constraints and the constraint of dwell-time in the multi-objective fitness function. AQIM-HM helps avoid arbitrary disconnections by disabling unnecessary and premature handovers, and setting a minimum quality of the link. In contrast, traditional threshold-based techniques do not have this optimization capability in conjunction, and evolutionary algorithms may still be subject to slower adaptation, especially in highly dynamic scenarios.

E. Mean Throughput

Mean throughput denotes the mean data rate successfully transmitted to User Equipment (UE) throughout the simulation duration. This is computed by taking mean of the instantaneous throughput values for all users and for each independent run of the simulation. Fig. 11 and Fig. 12 shown are the mean throughput with 95% confidence intervals and standard deviation of throughput. Table VI shown is the comparison of average throughput.

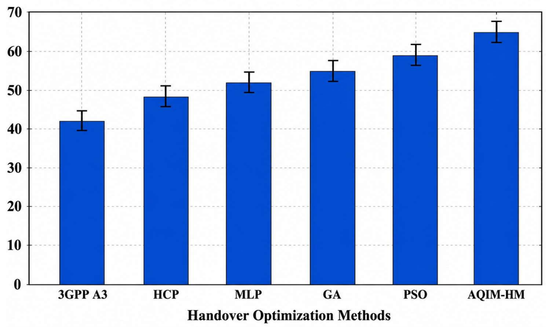

Fig. 11. Mean throughput with 95% confidence intervals (30 runs).

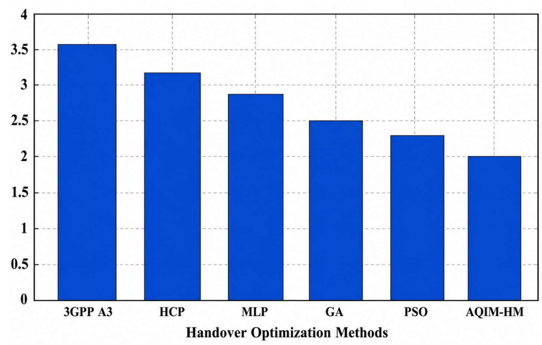

Fig. 12. Standard deviation of throughput (30 runs).

TABLE VI. COMPARISON OF AVERAGE THROUGHPUT (MBPS)

Method	Mean (Mbps)	Std Dev	95% CI	*p*-value
3GPP A3	42.8	3.6	±1.29	$p < 0.001$
HCP	48.5	3.2	±1.14	$p < 0.001$
MLP	52.1	2.9	±1.03	$p < 0.001$
GA	55.4	2.5	±0.89	$p < 0.001$
PSO	58.7	2.3	±0.82	$p < 0.001$
AQIM-HM	65.2	2.0	±0.71	—

The average throughput of the proposed AQIM-HM scheme is 49.9%, 31.4%, 20.1%, 16.8% and 13.6% higher than 3GPP A3, HCP, MLP, GA and PSO respectively based on the mean throughput values obtained from 30 independent simulation runs.

Such improvements prove the competency of AQIM-HM in increasing throughput performance at the network level. AQIM-HM not only has a higher mean throughput, but also a lower standard deviation, which reflects more stable and consistent performance in a scenario of multiple simulation runs. The statistical reliability of the results is also supported by their 95% confidence intervals and $p < 0.001$ indicating that the throughput improvement is statistically significant.

The increase in throughput can be attributed to AQIM-HM's minimization of unnecessary handovers and radio link failures, which often lead to packet loss and service interruption. As a result, the network link becomes more stable, thus enhancing overall system performance.

To further enhance the spectral efficiency at the network level since improved laser-aware cell selection and better stable cell association. Experimental results show that proposed quantum-inspired adaptive rotation mechanism converges more rapidly than GA and PSO as well as targeting cells selection is more stable against dynamic mobility of nodes.

The obtained results show that AQIM-HM always outperform classical, evolutionary and learning based handover schemes with statistically significant gains confirming its suitability for ultra-dense and high-mobility 5G HetNet's deployments.

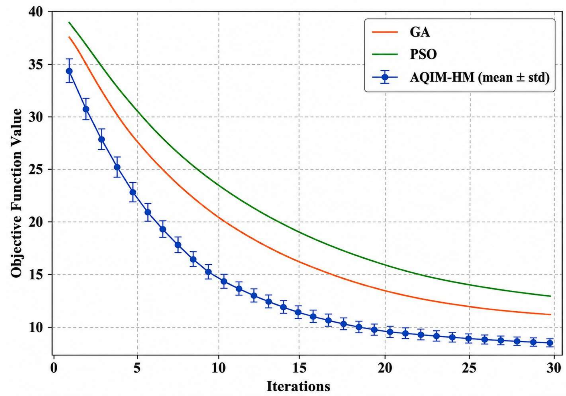

Fig 13. Convergence behavior of the proposed AQIM-HM algorithm along with conventional Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for 30 optimization iterations.

F. Convergence Analysis

The convergence analysis of the developed AQIM-HM algorithm is performed to check the stability of the optimization process with respect to iterations. Fig. 13 shows the convergence plot of AQIM-HM versus traditional optimization algorithms like Genetic Algorithm, and Particle Swarm Optimization with 30 optimizing iterations. The results show that the proposed AQIM-HM converges in about 15–20 iterations and the proposed approach yield lower objective values and faster convergence than GA and PSO, due to the probabilistic global exploration ability with quantum-inspired optimization mechanism.

G. Sensitivity Analysis

1) Impact of optimization iterations

T_{max}, the maximum number of optimization iterations was changed from 10 to 50. As shown in Fig. 14, if we increase the T_{max} from 10 to 30, the performance is significantly improved. Improvements are limited beyond 30 iterations, proving that $T_{max} = 30$ provides a good trade-off between gain and cost.

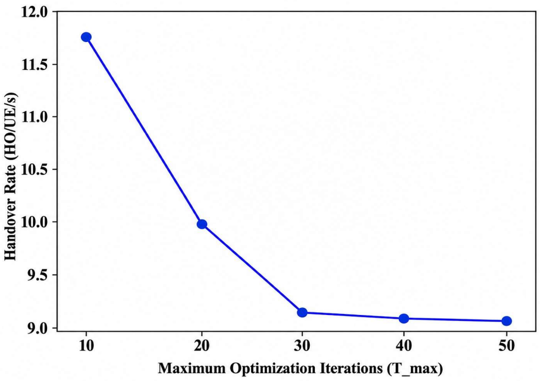

Fig. 14. Impact of optimization iterations on HOR.

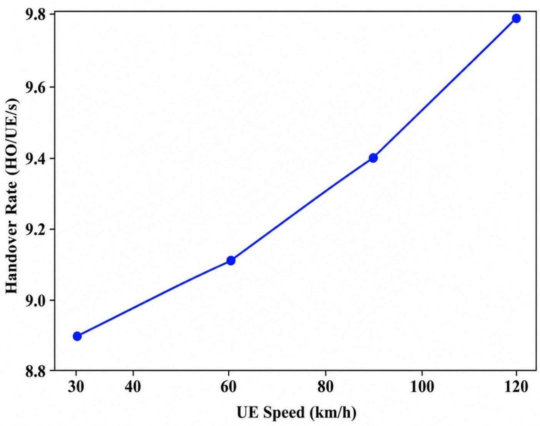

Fig. 15. Impact of UE mobility on HOR (AQIM-HM).

2) Impact of UE mobility

The mobility condition is evaluated by varying the UE speed varying from 30 km/h to 120 km/h. As illustrated in Fig. 15, there is a small increase of handover rate at higher mobility because signal varies quickly, and users are crossing cell boundaries more frequently. However, the increase is still limited and shows the robustness of the proposed AQIM-HM framework in dynamic conditions.

V. CONCLUSION

In this work, we proposed a quantum-inspired handover decision representation that allows probabilistic modeling over all candidate cells. This contrasts with deterministic RSS-based schemes and data-driven MLP approaches that rely on single-point estimates. Unlike MLP-based or reinforcement learning supervised methods, the proposed algorithm does not require offline training or online retraining, hence making it more robust in dynamic mobility conditions and scalable in ultra-dense deployments. The proposed method also overcomes a well-known drawback of MLP-based handover schemes by avoiding local optima using quantum rotation gates, and attains quicker convergence in comparison to both classical metaheuristics and learning-based methods. We evaluate the proposed framework using the same system configurations, performance metrics, and baseline schemes as the data-driven MLP-based handover optimization method in order to enable a fair and transparent comparison. Extensive simulation results show its performance advantages both under static and dynamic scenarios, as evidenced by significantly lower HOF, PPHO, and RLF, as well as higher throughput gains, even as network density and mobility increase. Furthermore, the proposed framework is lightweight and scalable for ultra-dense 5G and beyond (e.g., even 6G) mobility management scenarios, where the computational and training overheads are prohibitive for classical AI-based solutions.

CONFLICT OF INTEREST

The authors declare no conflict of interest

AUTHOR CONTRIBUTIONS

Shaik Mazhar Hussain conducted the research and wrote the paper; Shafiq Ul Rehman conducted the research; Winny Elizabeth Philip performed the simulation experiments and analyzed the results; Appala Raju Uppala performed the simulation experiments and analyzed the results; Gummula Ravi performed the simulation experiments and analyzed the results; Debashis Das reviewed the manuscript for formatting, grammatical, and typographical errors; all authors have approved the final version.

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