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Original Article

Adaptive User Migration based on Deep Reinforcement Learning for Cloud Radio Access Network

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Abstract - *A proposed design for 5G and below mobile communication systems is Cloud Radio Access Networks (C-RAN), which offers consumers seamless connectivity while meeting their constantly rising demands. Baseband Units (BBUs) and Remote Radio Heads (RRHs) make up the base station functionality in C-RAN. After that, cloud computing and virtualization techniques are used to centralize and virtualize the BBUs from multiple locations. The BBU pool is where all data processing and control are carried out, and RRHs are in charge of radio functionalities. Since one of the advanced network challenges is user mobility, particularly in high-density environments, an efficient user handover is necessary to maintain high Quality of Service (QoS) and minimize packet loss. Traditional handover mechanisms rely on fixed SINR thresholds to decide when to migrate users between RRHs. Such static methods may lead to suboptimal handovers, particularly in dynamic network environments. Therefore, this paper proposes and evaluates two intelligent user migration strategies-Fuzzy Logic and Deep Reinforcement Learning (DRL)-to replace the static SINR-based approach. Both methods aim to improve the decision-making process for RRH selection during user migration. The fuzzy logic model uses expert-defined rules based on user velocity, distance, load, and SINR to make fast and interpretable decisions. In contrast, the DRL model learns an optimal migration policy through interaction with the environment using a multi-objective reward function. All three methods-traditional, fuzzy, and DRL-are implemented and tested in a Simu5G-based C-RAN environment. The results show that both AI-based methods significantly outperform the traditional approach. Notably, the DRL method achieves the highest performance gains, with a 46.4% increase in throughput, 66.7% reduction in handover failures, and 40% decrease in latency. These results highlight the advantages of integrating AI techniques for efficient and intelligent mobility management in next-generation wireless networks.*

Keywords - *Cloud Radio Access Network, DRL, Fuzzy logic, RRH failure, Simu5G, User migration.*

1. Introduction

Exponential proliferation of mobile devices and Internet of Things (IoT) devices has evoked fierce demands for increased data rates, reduced delay, and superior Quality of Service (QoS) for mobile communication networks [1]. However, traditional cellular network architectures are increasingly unable to meet these demands, particularly as there is a transition toward next-generation services such as 6G [2]. High deployment costs, inter-cell interference from dense small-cell networks, and baseband processing complexity have further intensified these limitations [3]. To address these issues, Cloud Radio Access Network (C-RAN) has emerged as a promising architecture that centralizes baseband processing through cloud computing and virtualization [4, 5]. C-RAN decouples Baseband Units (BBUs) and Remote Radio Heads (RRHs), allowing flexible resource pooling and simplified RRH deployment. Despite these advantages, user mobility and frequent handovers among densely deployed RRHs remain major challenges in maintaining service quality and reducing signaling overhead. Traditional handover mechanisms are often based on static Signal-to-Interference-plus-Noise Ratio (SINR) thresholds, which fail to adapt to dynamic environments and result in inefficient user migration and increased handover failures [6-12]. User mobility significantly impacts the Quality of Service (QoS) in dense cellular and cloud-based architectures like C-RAN. According to [13], frequent handovers in high-mobility scenarios can lead to up to a 25% increase in handover failure rates and a 30–40% increase in signaling overhead, directly affecting network stability and user experience. Moreover, poor handover decisions under mobility can result in throughput degradation of up to 20% and increased latency and packet loss, especially when centralized BBUs are overloaded or RRHs are misallocated [14, 15]. These challenges underscore the critical need for intelligent and adaptive handover strategies that can dynamically adjust to user behavior and network conditions. To fill this gap, this paper proposes two AI-driven user migration strategies-Fuzzy Logic and Deep Reinforcement Learning (DRL)-for optimizing handovers in C-RAN. The fuzzy logic model uses expert-defined rules to enable fast and interpretable decisions based on parameters like user velocity, distance, load, and SINR. In contrast, the DRL model learns optimal handover policies from environmental interaction using a multi-objective reward function. This dual-approach enhances adaptability and decision accuracy and enables a comparative analysis of rule-based and learning-based handover strategies under identical simulation conditions.

The main contributions are as follows:

1. This work identifies and addresses the inefficiencies of traditional handover mechanisms in dense C-RAN environments.
2. It develops a fuzzy logic-based user migration model that provides interpretable, low-complexity decisions.
3. Designing a DRL-based handover mechanism with a multi-objective reward function to learn optimal user association policies.
4. Finally, this work validates both models using the Simu5G simulation platform and demonstrates significant performance improvements over traditional SINR-based handover methods.

While previous research has applied fuzzy logic and reinforcement learning independently to handover and resource management, this work is novel in its comparative application of both techniques within the same C-RAN environment using a unified simulation framework. The fuzzy logic model provides a fast, interpretable baseline using expert-defined rules based on network parameters such as velocity, distance, load, and SINR. In contrast, the DRL model autonomously learns optimal handover policies through environmental interaction and a multi-objective reward structure. This side-by-side evaluation offers new insights into the trade-offs between explainability and adaptability in mobility management, which has not been comprehensively addressed in prior literature. The structure of the paper is as follows: Section 2 provides a review of relevant literature. Sections 3 and 4 outline the system assumptions and architectural framework. Sections 5 and 6 describe the proposed user migration models based on fuzzy logic and Deep Reinforcement Learning (DRL). Section 7 presents the performance evaluation, and Section 8 concludes the paper.

2. Literature Review

Handover parameter optimization has been extensively explored in the context of LTE and LTE-Advanced networks. Early efforts focused on tuning handover margins and Time-To-Trigger (TTT) values to reduce ping-pong effects and handover failures. For instance, [16] introduced optimization techniques for LTE/LTE-A in-building systems, while [17] applied fuzzy logic to minimize the ping-pong effect. More advanced methods, such as weighted fuzzy self-optimization [18] and velocity-aware handover management [19], further enhanced decision-making based on user mobility. In dense small-cell deployments, [20] demonstrated how fuzzy logic could effectively reduce handover failure rates and improve network performance. As networks evolved toward higher complexity and user density, researchers turned to learning-based approaches. In [21], a Double Deep Reinforcement Learning (DDRL) model was used for intelligent handover decisions, integrating user trajectories and signal patterns. Meanwhile, [22] proposed an optimal user association strategy in uplink C-RAN to balance the load and minimize handovers, marking the transition toward centralized and cloud-managed mobility control.

In SDN-based architectures, [23] explored handover management in ultra-dense networks, aiming to reduce latency through centralized decision-making. Reinforcement Learning (RL) strategies also gained traction; [13] proposed a smart handoff policy for mmWave heterogeneous networks, while [14] applied contextual bandit models to enhance decision-making under mobility. However, these models often lack the ability to incorporate real-time metrics such as RRH load and user speed, which are essential in the highly dynamic C-RAN environment. Fuzzy logic has continued to play a role in adaptive network decisions. For example, [24] introduced a fuzzy-based admission control scheme in federated Open RAN architectures to improve fairness and user experience.

Similarly, [25] proposed a DRL-based model for intelligent network slicing in 5G, blending adaptability with long-term optimization. In the context of virtualized environments, [26] used fuzzy logic to manage overloaded cloud data center hosts, while [27] developed a multi-objective DRL framework for reconfiguring VNFs in O-RAN to reduce operational delays. Other notable applications include [28], where fuzzy logic improved traffic load prediction for large-scale parallel systems, and [29], which surveyed 5G C-RAN design challenges and opportunities. In edge computing environments, [15] proposed a hierarchical fuzzy logic model for handover decisions, and [30] reviewed the latest tools and techniques in fuzzy systems for smart applications. Expanding on learning-based methods, Mao et al. [31] introduced a DRL approach for mobile-edge computing with energy harvesting, which demonstrated how adaptive models could optimize resource use while reducing latency-principles that closely align with the work on mobility management. In contrast, this work contributes in the following ways:

- It targets the underexplored problem of intelligent RRH selection for user migration in C-RAN.
- It integrates fuzzy logic and DRL methods, providing both a rule-based baseline and an adaptive learning mechanism.

- It designs a novel DRL reward function that balances throughput, latency, and handover failures, enabling multi-objective optimization.
- It validates these models in a realistic Simu5G environment, unlike many prior studies that rely on analytical or simplified simulation setups.

Overall, the proposed approach addresses critical limitations in previous works and establishes a practical framework for mobility management in next-generation C-RAN deployments.

3. System Model Assumption

This section discusses the assumptions about RRH, BBU pool, user connection, and their initial association. Table 1 lists the symbols and notations utilized in this investigation. Here, look at a C-RAN design with m tiny RRHs spread out widely around the network. M and N can be used to represent the set of RRHs and users, where M = {1,2,...,m} and N = {1,2,...,n}.

The fronthaul link connects each RRH to the BBU pool. The user-RRH association is managed by the BBU pool using the data that users provide at each time stamp. A circle with a radius of R can be used to represent the coverage area, and it is believed that all small RRHs have the same transmission range.

Unfortunately, an RRH's capacity determines how many users it can support at any given time [32]. All the BBU data, including the BBU controller, is encompassed under the BBU pool. It gets updated frequently based on user reports from the respective RRHs. Position coordinates and coverage area of every RRH are also known to the controller.

The BBU controller runs the association and handover decision algorithms and sends them to the RRHs. The association of user and RRH can be expressed through the association indicator $\sigma_{i,j}$, which means user i is associated with RRH j or not.

$$\sigma_{i,j} = \begin{cases} 1 \; if \; user \; i \; associated \; with \; RRH \; j; \; \forall j \in M \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \quad (1)$$

Based on proximity, the users will first be assigned to an RRH. In particular, the RRH nearest to the user will be linked to that user. The Euclidean distance formula can be used to determine the distance between RRH j and User i, represented by $D_{i,j}$, as shown below:

$$D_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (2)$$

Upon entering the network, the user may get signals from several RRHs. Therefore, it is first linked to the RRH that is closest to the user.

Table 1. List of symbols and notations

Symbol	Description
m	The quantity of RRH
N	The number of users
(x_i, y_i)	Location of user i
M	Group of RRH
(x_j, y_j)	Location of RRH j
N	Group of users
$\sigma_{i,j}$	An association between user i *and* RRH j
$D_{i,j}$	The separation between RRH j and user i
δ_i^j	SNR that user i received from RRH j
k	Index of candidate RRH
A_k	Set of candidates RRH
S_t	State at time t
a_t	Action at time t
$X_{i,j}$	Set of association features
r_t	Reward at time t
Η	The learning rate
Γ	The discount factor
α	Throughput weight
β	Handover Failures weight
γ	Latency weight

4. Simulation of CRAN using the Simu5G Platform

To create a C-RAN in the simulation platform Simu5G [33] and simulate user migration between RRHs and users, this work models the key components of a C-RAN architecture, including the User Equipment (UE), RRHs (gNodeBs), and the Central Unit (CU) or Baseband Unit (BBU). Since simu5G is a network simulator, it assumes MEC acts as a virtual BBU pool. The study is more focused on user migration from one RRH to another, considering the parameters affecting user migration rather than the resource utilization in the BBU. The following components are created for the simulation purpose:

- User Equipment (UE): The mobile devices that will move across RRHs and generate data traffic.
- gNodeBs (gNB): These represent the RRHs in the C-RAN architecture, which handle the radio communication with UEs.
- Core Network (CN): Manages the data plane and control plane functionalities.
- Central Unit (MEC): The baseband processing unit, which can be centralized in the C-RAN, reducing the complexity at the RRHs.

A simplified assumption about the C-RAN is shown in Figure 1.

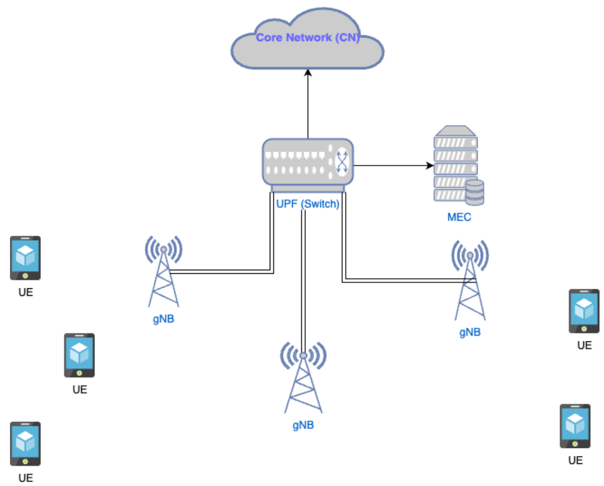

Fig. 1 General structure of the proposed C-RAN

5. Proposed User Migration Model Based on Fuzzy Logic

To enhance user handover decisions in the Cloud-RAN environment, this study proposes a fuzzy logic-based user migration model that enables real-time, rule-based selection of the most suitable Remote Radio Head (RRH). Unlike static threshold-based methods that often result in unnecessary or delayed handovers, the fuzzy logic system considers multiple contextual factors simultaneously, offering a more adaptive and interpretable solution. The fuzzy inference system utilizes four key input variables that influence handover effectiveness:

- Distance between the user and the RRH
- User mobility speed (velocity)
- Signal-to-Interference-plus-Noise Ratio (SINR)
- Current load on the candidate RRH

Each input is mapped to linguistic variables using predefined membership functions. For instance, distance is characterized as Close, Medium, or Far; velocity as Slow, Average, or Fast; SINR as Low, Medium, or High; and RRH load as Light, Moderate, or Heavy. These fuzzified inputs are then processed using a Mamdani-type fuzzy inference system. A rule base consisting of expert-defined IF–THEN statements is used to evaluate the suitability of candidate RRHs. An example rule is:

“IF Distance is Close AND Velocity is Slow AND Load is Light AND SINR is High, THEN Suitability is Very High”.

All matching rules are aggregated and evaluated using fuzzy implication and fuzzy aggregation techniques. The final suitability score for each RRH is then defuzzified using the centroid method to produce a crisp output. The RRH with the highest suitability score is selected as the target for user migration.

$$\mu(z) = \begin{cases} 0 & if\ z \le a\ or\ z \ge b \\ \frac{z-a}{m-a} & if\ a < z \le m \\ \frac{b-z}{b-m} & if\ m < z < b \end{cases} \tag{3}$$

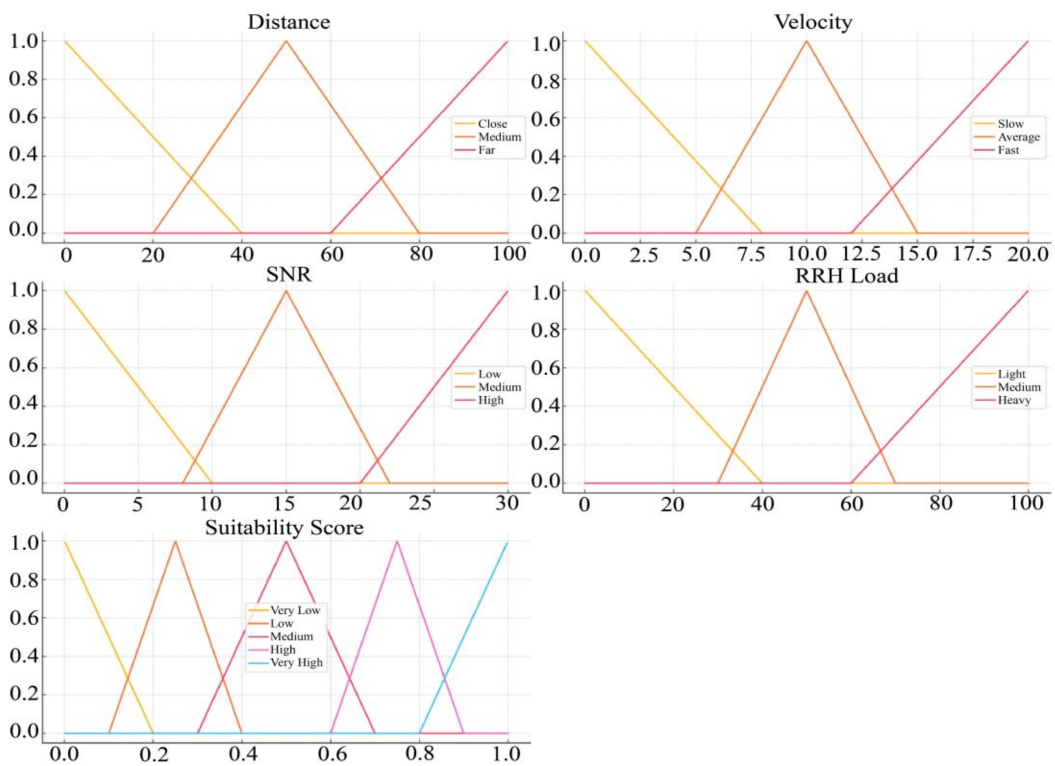

Fig. 2 Fuzzy logic-based user migration process

An upper bound b, a lower bound a, and a value m, where a < m < b, can be used to define the triangle membership function μ(z). A value between 0 and 1 is assigned to each element of input x. Using a trial-and-error method, the membership functions' core width and boundary regions are chosen. Since more crossing results in the frequent activation of numerous rules, it is important to carefully select the area where nearby linguistic variables meet. Conversely, less overlap reduces the smoothness and flexibility. The inputs and outputs of the fuzzy system are mapped using the Mamdani-type inference method [16]. All potential connections between the four input values and one output value are included in the fuzzy rules set. Because each input contains three linguistic variables, all possible combinations of the input variables result in a total of (4^3) = 64 rules. Equation (3) provides the corresponding degree of membership function for the linguistic input variables, shown in Figure 2. Algorithm 1 shows the overall fuzzy logic-based User-RRH migration process. This approach provides a transparent and efficient decision-making mechanism that does not require training or historical data. It enables fast responses to dynamic network conditions and reduces the risk of unnecessary handovers by incorporating multiple parameters beyond signal strength alone.

Algorithm 1. Fuzzy logic-based user migration procedure

Step 1:	Initialize the C-RAN network components in Simu5G.
Step 2:	For each user, collect real-time values of Distance to RRH, SINR, Velocity, and RRH Load.
Step 3:	Fuzzify the input variables using predefined membership functions (e.g., Close, Medium, Far).
Step 4:	Apply fuzzy inference rules (IF–THEN) to compute the Suitability score for each candidate RRH.
Step 5:	Aggregate all rule outputs and apply the Mamdani fuzzy inference method.
Step 6:	Defuzzify the aggregated fuzzy output using the centroid method to obtain a crisp Suitability score.
Step 7:	Select the RRH with the highest Suitability score for user migration.
Step 8:	Execute the handover and update the system state accordingly.
Step 9:	Repeat the process as users move within the network.

6. Proposed User Migration Model Based on Deep Reinforcement Learning

This section describes the deep reinforcement learning approach that was utilized for choosing the RRH for a user at handover, which was the desired user migration methodology for implementing a smarter handover to another RRH, without becoming the user-RRH mapping for a substantial period of time, thus conserving the total number of handovers. The trigger condition that was utilized for executing the handover can be expressed as:

$$Serving\ SNR < Threshold\ - HOM \qquad (4)$$

To decrease ping-pong handover, a margin for handover called HOM is integrated. It is not of concern for this work. It is assumed that it is zero for simplification. If the condition of Equation (4) holds for a predetermined time called TTT, the event of handover happens for the conventional scheme of handover. The user device tracks the received SNR of the current serving RRH when a handover event is initiated. It will report a measurement to the current serving RRH if, within the TTT time, the received SNR does not rise above the threshold SNR.

After TTT, the user needs to select a valid RRH. According to SNR values that a user gets from close RRHs, the BBU controller selects candidate RRHs for a user when they announce the measurement to the BBU pool. Therefore, only the RRHs that are selected as candidate RRHs are considered for selecting the target RRH. Let Ak be the set of RRHs that are available,

$$A_k(t) = \{k \in\ M\ |\delta_{i,k}(t) > \delta_{th}\} \qquad (5)$$

Where k is the candidate RRHs' index', δth is the minimum SNR, which must be preserved for the user-RRH link. $\delta_{i,k}$ is the received SNR by user *i* from RRH *K*, M is the RRH set. Our target is to assign user *i* to an RRH from set A_k. Therefore, the modeling of a design for an RRH selection under a Deep Reinforcement Learning (DRL) setup. In DRL algorithms, an agent gets trained through interacting with an environment.

At each instant of action t ∈ T, the agent sees a state st ∈ S, performs an action at ∈ A, then moves to a new state st+1 ∈ S and gets a reward rt as feedback. The reward is a value equivalent to the problem objective, and maximizing total reward is the agent's task. Modelling the handover problem from an MDPC, the RL agent gets trained for the optimal decision of user handovers. [34].

- State (s): A vector containing the current SINR of the UE, velocity, its distance from available RRHs, and the traffic load on each RRH.

  s_t = [$SINR_{UE}$, Velocity $_{UE}$, distanceRRH1, distance RRH2..., load RRH1, load RRH2…]

- Action (a): The decision to either remain connected to the current RRH or migrate to a different RRH.

  a_t ∈ {stay, migrate to RRH1, migrate toRRH2...}

- Reward (r): The reward function is designed to maximize throughput and minimize handover failures and latency. The reward is positive for successful handovers that improve throughput and negative for handover failures.

  This paper introduced a weighted reward that balances throughput, latency, and handover failures, which means a weighted multi-objective, while standard DRL usually targets a single objective; this paper uses

$$r_t = \alpha \times \text{Throughput} - \beta \times \text{Handover Failures} - \gamma \times \text{Latency} \quad (6)$$

The DRL agent uses the Q-learning algorithm to update its policy based on the reward received after each handover decision. The Q-value for state-action pairs is updated using the following equation:

$$Q(st, at) = Q(st, at) + \eta\,[\,rt + \Gamma * \max(Q(s_{t+1}, a_{t+1})) - Q(st, at)] \quad (7)$$

Where η is the learning rate and Γ is the discount factor. Algorithm 2 shows the overall DRL-based User-RRH selection procedure, while Figure 3 shows a flowchart of the traditional-based versus DRL-based User migration and RRH selection procedure.

Algorithms 2. DRL-based user migration procedure

Step 1:	Initialize the C-RAN Network in Simu5G function initialize_CRAN_network(): initialize Baseband Unit (BBU) initialize multiple Remote Radio Heads (RRHs) initialize User Equipment (UEs) with mobility models, connect RRHs to BBU via high-speed backhaul Set up the SINR-based handover mechanism for comparison.
Step 2:	Simulate User Migration and Data Collection function simulate_user_migration(): For each UE in the network: Assign a linear/random mobility model (UE moves between RRH coverage areas), generate data traffic (e.g., UDP application) record SINR, throughput, handover events, and latency at each step store the collected data (e.g., SINR, distance to RRHs, traffic load) for each UE
Step 3:	Define the Deep Reinforcement Learning (DRL) Model function define_DRL_model(): state = [SINR of UE, velocity, distance to nearest RRHs, traffic load on each RRH] actions = [stay connected to current RRH, migrate to another RRH]
Step 4:	Define the reward function function calculate_reward (throughput, handover_failure, latency) reward = α * throughput - β * handover_failure - γ * latency return reward initialize the Q-table or neural network to approximate Q-values set hyperparameters (learning rate η, discount factor Γ)
Step 5:	Train the DRL Agent function train_DRL_agent(): For each episode (simulation run): initialize state (current SINR, velocity, distances to RRHs, load) while UE moves across RRH boundaries: Choose action (stay or migrate) using epsilon-greedy policy Execute the action (handover if needed) observe new state (updated SINR, RRH load) calculate reward based on current throughput, handover success, and latency update Q-values using Bellman equation: Q(s, a) = Q(s, a) + η [r + Γ * max(Q(s', a')) - Q(s, a)] update state to new state (s ← s') end episode save the trained model
Step 6:	Plug in Trained DRL Model for Handover Decision Making function deploy_trained_DRL_model(): For each UE in the network: Observe current state (SINR, velocity, distances, traffic load) Use a trained DRL model to predict the optimal handover decision and execute action (stay or handover to new RRH) Continue simulation and record performance metrics.

Step 7:	Performance Comparison function compare_performance ():
	initialize two scenarios:
	- Traditional-based handover mechanism
	- DRL-based handover mechanism (trained model)
	for both scenarios: run the simulation for multiple UEs migrating between RRHs, collect metrics: throughput, handover failures, latency
	// Compare Results and calculate performance improvements:
	throughput_improvement = (DRL_throughput - traditional_throughput) / traditional_throughput
	handover_failure_reduction = (traditional_failures - DRL_failures) / traditional_failures
	latency_reduction = (traditional_latency - DRL_latency) / traditional_latency output

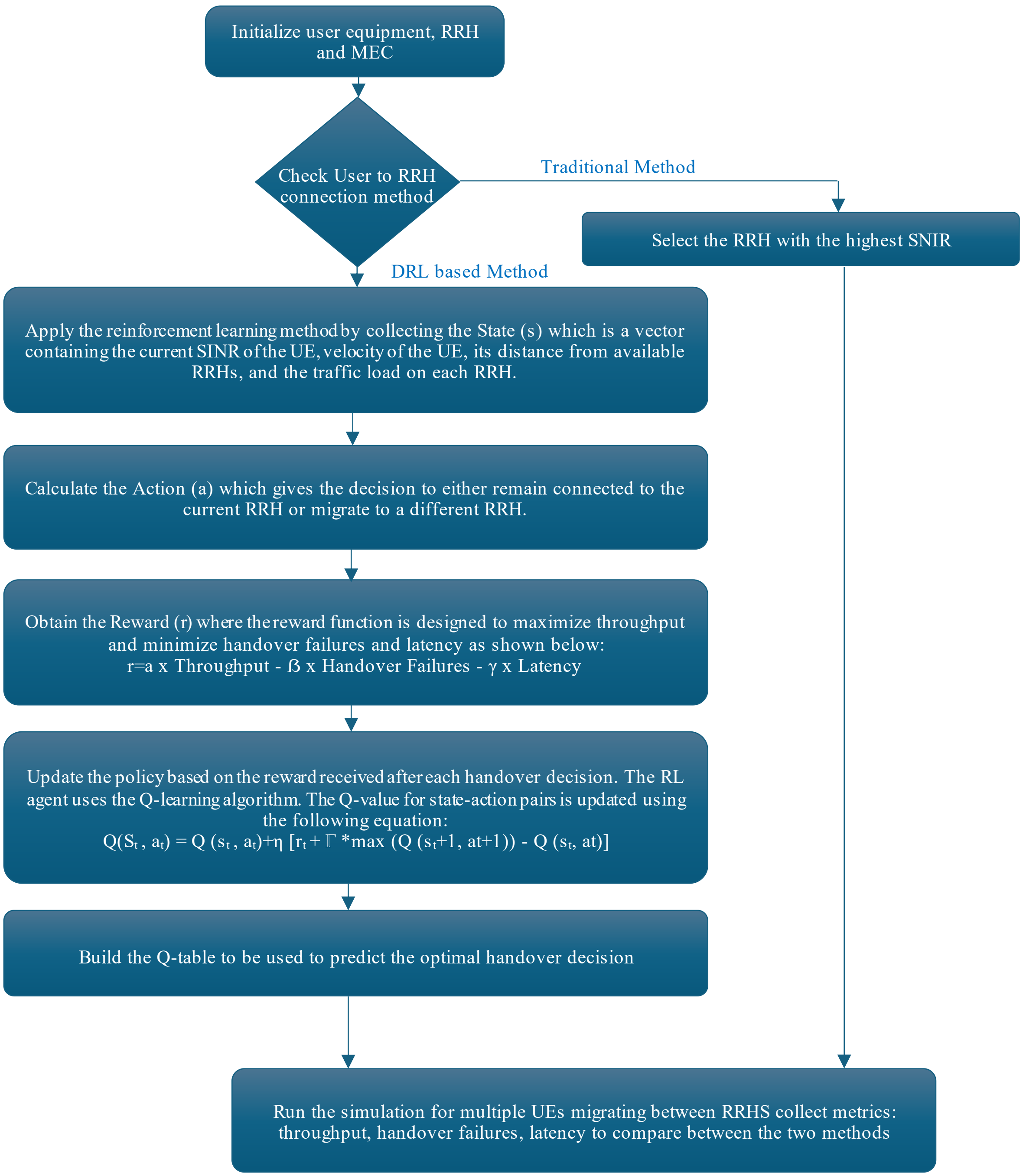

Fig. 3 Flowchart of the traditional-based versus DRL-based user migration

7. Performance Evaluation and Results

This section evaluates the proposed DRL-based user migration model for users' association with RRH. It compares the suggested scheme with the conventional SINR-based handover and fuzzy logic models to assess its performance.

7.1. Simulation Environment

This work examines a C-RAN environment with a specific number of tiny RRHs dispersed at random across a 1000(m) x 1000(m) square area. The default value for the number of RRHs is 10. RRH has its transmitted power set at 40 dBm. With a modified random walk, it is assumed that the user can only navigate through the straight paths. There are 50 users by default. The DRL model implemented in this study was based on the Deep Q-Network (DQN) algorithm. Training was conducted using TensorFlow with a learning rate of 0.001, discount factor (gamma) of 0.95, batch size of 64, and a replay memory size of 10,000. The agent was trained over 1,000 episodes, each consisting of 100 time steps. The reward function was multi-objective, incorporating handover success, latency minimization, throughput improvement, and a penalty for unnecessary handovers. The state representation included user velocity, SINR, RRH load, and distance to nearby RRHs. Table 2 illustrates the simulation parameters, and the simulation scenario is shown in Figure 4. The data set generated during the simulation is used to train the DRL agent. The agent is trained offline, where it learns the optimal handover policy by exploring different state-action combinations and receiving feedback based on the reward function.

Table 2. System model parameters

Parameters	Values
Size of network area	(1000 x 1000) m
Hyber-parameter for DRL algorithm	learning rate η=0.001
	discount factor Γ=0.9
RRH transmit power	40 dBm
User capacity of RRH	10
RRH coverage range	150 m
Parameter for reward functions in the DRL algorithm	α =0.4
	β =0.3
	γ =0.3

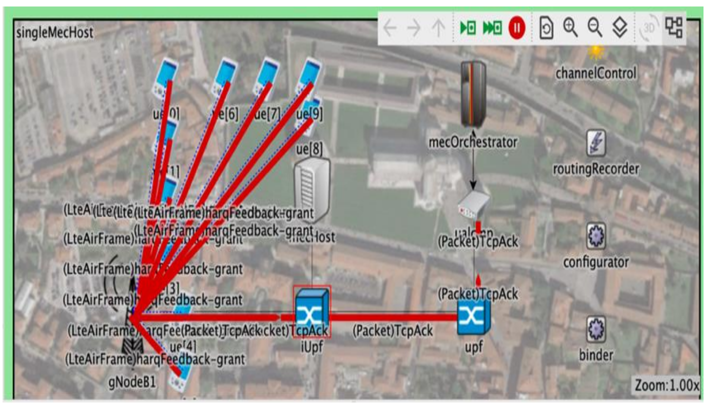

Fig. 4 The simulation scenario of the proposed model in Simu5G

7.2. Evaluated Results and Discussions

The performance of the proposed scheme is evaluated by calculating the following metrics:

- SINR: Signal-to-Interference-plus-Noise Ratio for each UE.
- Throughput: The data transmission rate achieved by each UE.
- Handover Events: The number of handovers initiated for each UE.
- Latency: End-to-end packet delay for each UE.

In the baseline simulation, handovers are triggered based on static SINR thresholds. This method leads to unnecessary handovers in some scenarios and delayed handovers in others, reducing the overall network performance. Therefore, this paper proposed a reinforcement learning-based handover mechanism that the network dynamically adapts to real-time conditions, such as user mobility, SINR, and RRH load. The DRL agent is trained to optimize handover decisions, significantly improving the performance of the network as shown in Figure 5, which presents a holistic performance comparison among the three user migration strategies: Static SINR-Based Handover (Traditional Method), Fuzzy Logic-Based User Migration and Deep Reinforcement Learning (DRL)-Based Migration. This figure integrates performance metrics-likely including throughput, handover failure rate, and latency to visualize how each method behaves under identical network conditions. Static SINR-based handover is simple but inflexible. It fails to adapt to real-time variations in user movement or network load, resulting in frequent, unnecessary, or poorly timed handovers. Fuzzy logic introduces intelligence via human-defined rules, improving decision accuracy without requiring training. However, its adaptability is limited to the quality of its rule set. DRL outperforms both by learning from interaction, optimizing not just single metrics but the overall network experience (throughput, reliability, latency) via a multi-objective reward function.

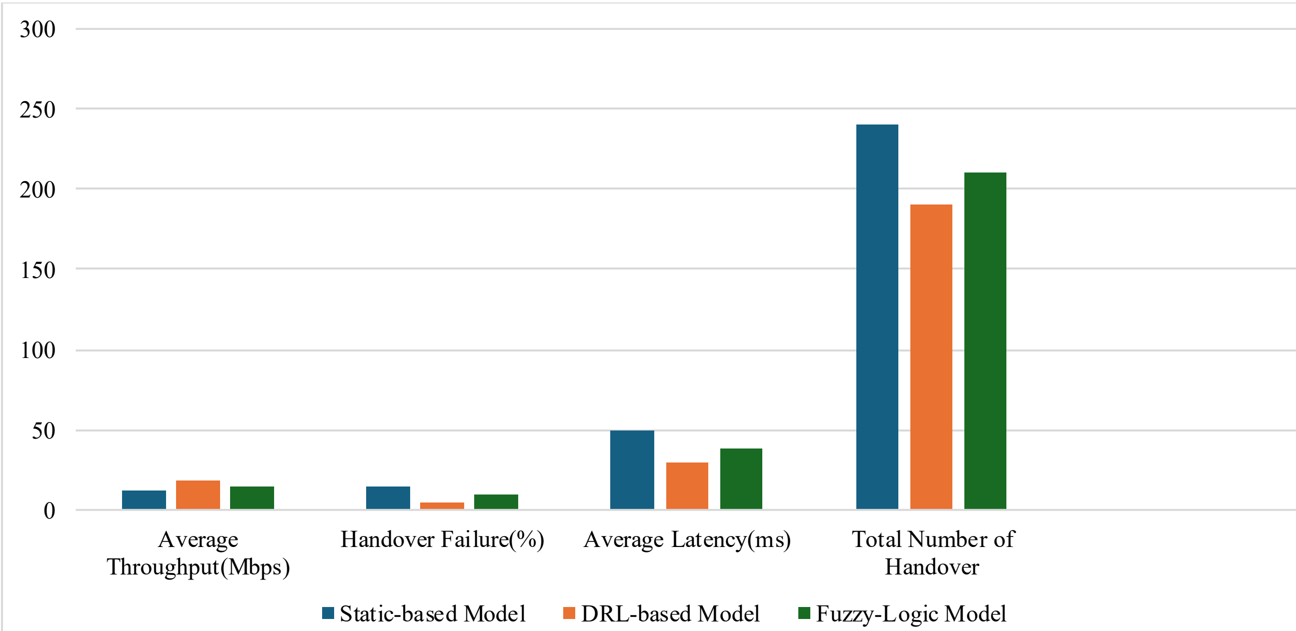

Fig. 5 An overall comparison between static, fuzzy logic and DRL-based migration models

7.3. Performance Comparison

A more detailed comparison of various performance metrics between the SINR-based and DRL-based handover mechanisms is provided below.

7.3.1. Throughput Comparison

The throughput, a key indicator of network efficiency, is significantly improved in the DRL-based model.

The DRL agent makes decisions that optimize resource allocation and handover timing, reducing the chances of network congestion or bottlenecks. Figure 6 illustrates the throughput calculation from traditional or static handover-based, fuzzy logic, and DRL or dynamic handover-based.

Figure 7 shows that the DRL-based handover mechanism increases the average throughput by 46.4%, and the maximum throughput achieved is also significantly higher compared to the SINR-based approach.

This demonstrates the efficiency of DRL in dynamically adapting to real-time network conditions.

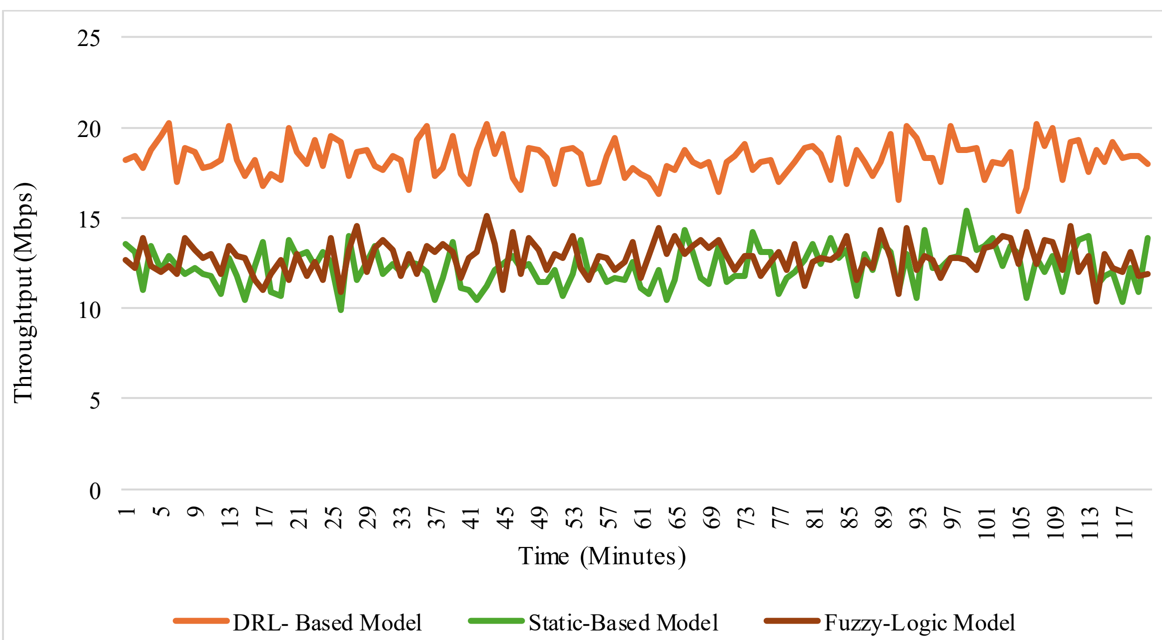

Fig. 6 Throughput calculation over two hours for the three migration models

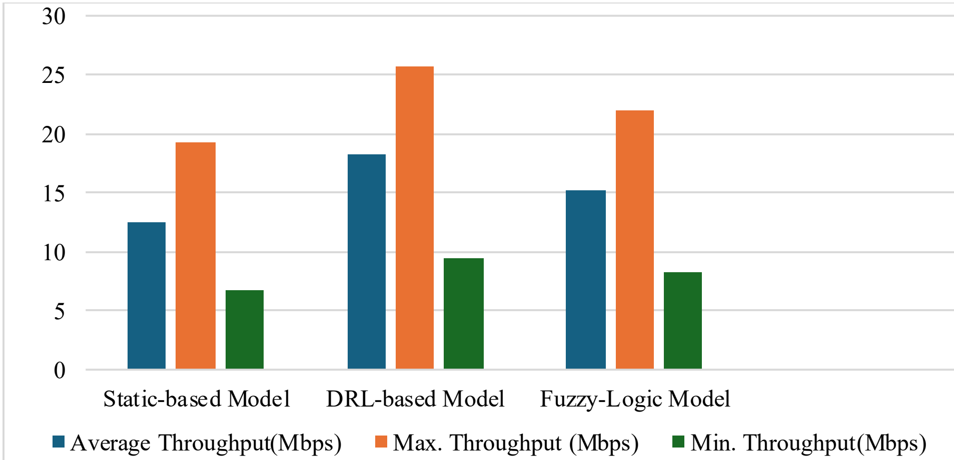

Fig. 7 Average throughput measurement for the three models

7.3.2. Handover Failures

Handover failures occur when a user is handed over to a new RRH, but the connection is lost or degraded, leading to poor performance. The DRL-based model significantly reduces handover failures, as shown in Figure 8.

Figure 9 shows that the DRL-based handover reduces the failure rate by 66.7%. This is due to the DRL model's ability to predict the optimal timing for handovers, avoiding unnecessary transitions between RRHs.

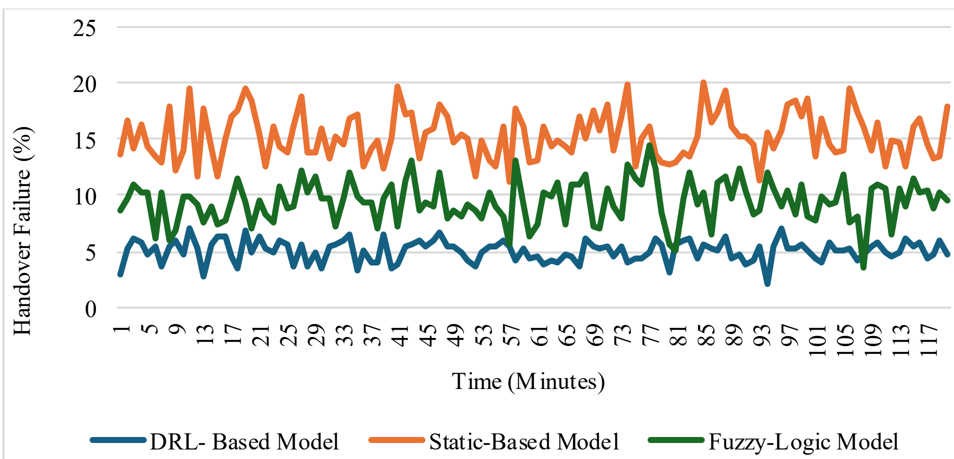

Fig. 8 Handover failures calculation for the three models for two hours

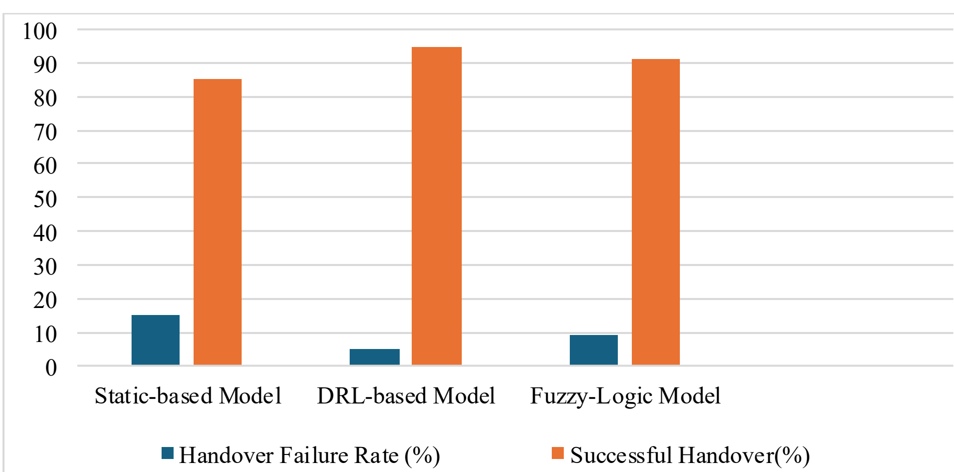

Fig. 9 Average handover failure rate for the three models

7.3.3. Latency Comparison

Latency, the delay experienced in data transmission, is a critical factor affecting users' Quality of Service (QoS). In the DRL-based model, handover decisions are optimized to reduce end-to-end delays. Figure 10 shows the latency for the three models: static, fuzzy logic and DRL-based user migration models.

Figure 11 shows that the DRL-based handover reduces latency by 40% on average, with lower maximum latency values as well.

This improvement is primarily due to more efficient handover timing and reduced packet losses during handover transitions.

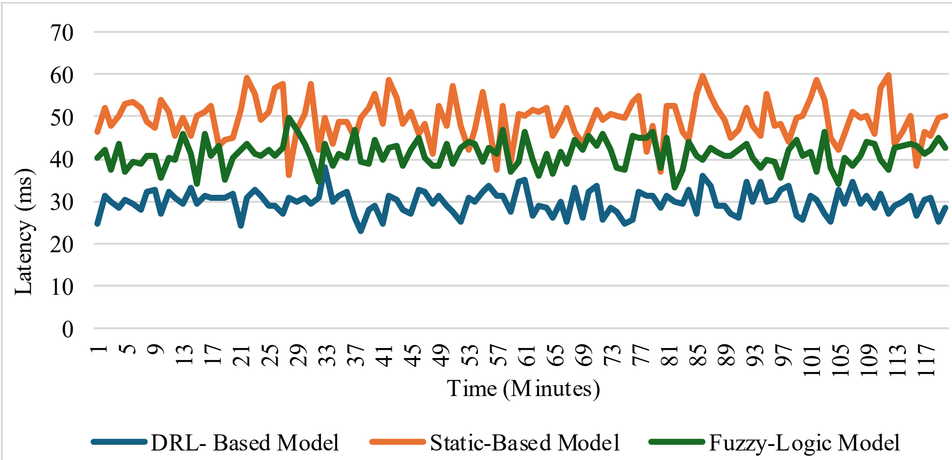

Fig. 10 Latency calculation for the three models for two hours

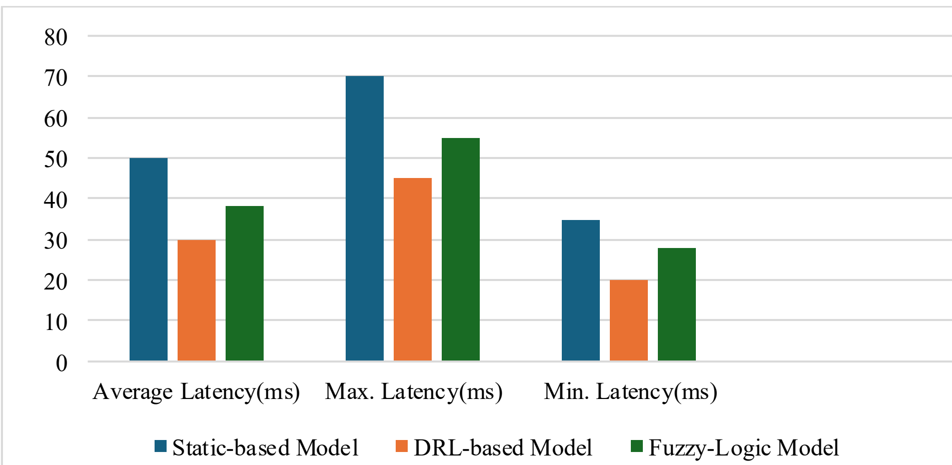

Fig. 11 Average handover failure rate for the three models

7.3.4. Impact of User Mobility

The performance of the handover mechanism was also evaluated for varying user mobility speeds. As shown in Figure 12, the DRL-based handover model performs consistently well even under higher user mobility conditions with a much lower rate of handover failures as user speed increases.

7.4. Trade-Off between Throughput and Latency

Figure 13 visualizes the trade-off relationship between throughput and latency in the context of user migration for the DR-based model in a Cloud Radio Access Network (C-RAN) environment. As expected, the figure shows an inverse correlation between throughput and latency. Higher throughput typically coincides with lower latency in the DRL-based model, highlighting the efficiency of intelligent handover decisions. The DRL-based approach achieves significantly better throughput with lower latency than the traditional model. This trade-off graph reinforces the multi-objective optimization approach taken in the DRL model's reward function, where both throughput and latency are balanced via weighted contributions (α, β, γ). The figure also visually confirms the practical performance gain of using DRL in real-time mobility management over static, threshold-based policies. It demonstrates that the DRL-based handover mechanism achieves a favorable trade-off between high throughput and low latency, unlike the traditional method, which struggles to maintain both simultaneously. This validates the superiority of AI-driven user migration strategies in future-ready C-RAN deployments.

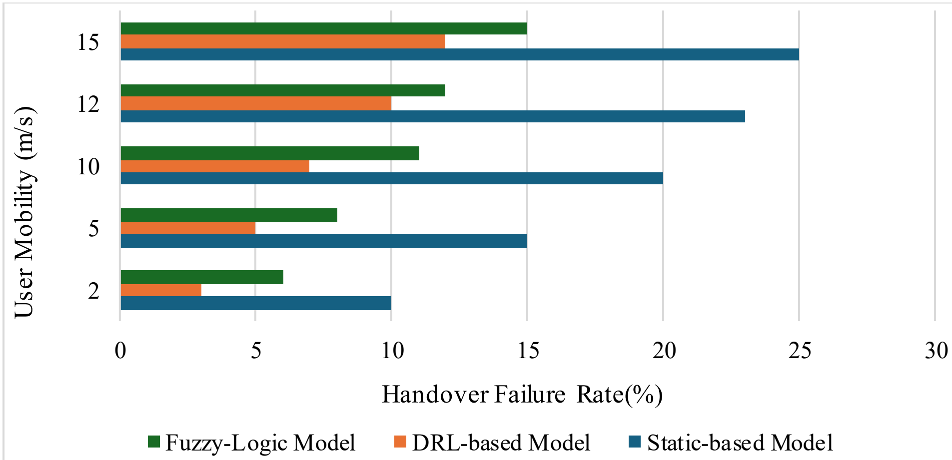

Fig. 12 Average handover failure rate for the three models by changing user mobility speed

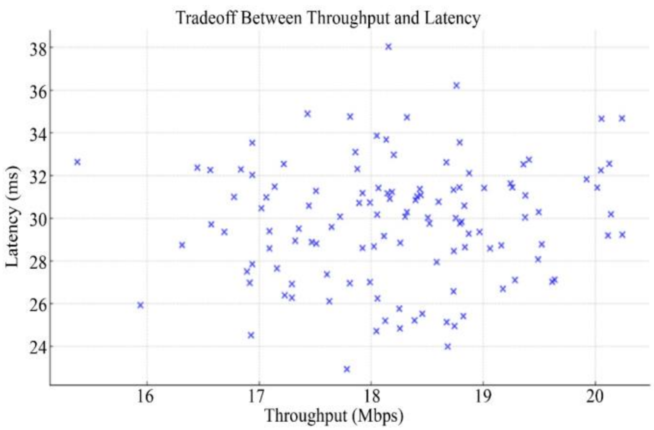

Fig. 13 Trade-off between throughput and latency

7.5. Impact of RRH Failure on Network Performance

This section focuses on evaluating how the proposed Deep Reinforcement Learning (DRL)-based handover mechanism performs in the presence of RRH (Remote Radio Head) failures. Figure 14 illustrates how the throughput changes over time in both the static SINR-based and DRL-based handover models when RRH failures occur. The DRL-based model maintains a higher throughput, even in the presence of RRH failures; in contrast, the static model exhibits significant drops in throughput following a failure.

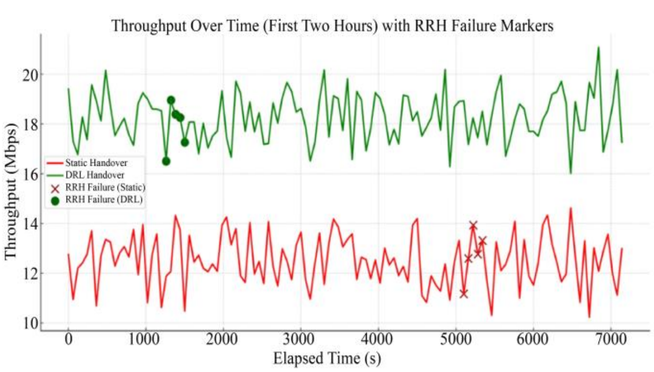

Fig. 14 Impact of RRH failure on throughput

Figure 15 compares the latency response of both handover schemes when RRH failures disrupt the network. DRL-based handover consistently keeps latency lower and more stable, showing quick adaptation to new RRH associations after a failure. The static method experiences latency spikes, especially immediately after RRH disruptions. Finally, Figure 16 focuses on how handover failures accumulate in both models when RRHs fail during operation. The static method suffers from a sharp increase in handover failures when RRHs become unavailable, due to rigid, threshold-based handover logic. In contrast, the DRL-based method significantly reduces failure rate growth, even under RRH disruptions.

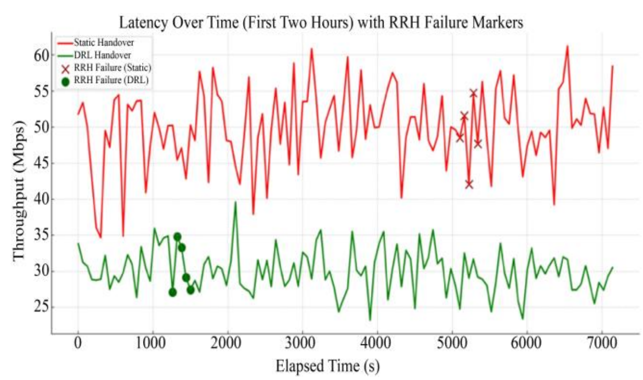

Fig. 15 Impact of RRH failure on latency

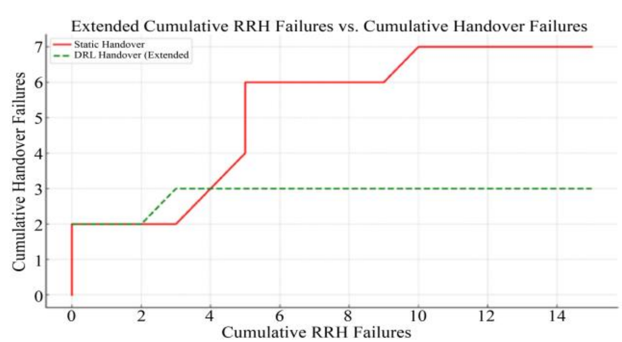

Fig. 16 Impact of RRH failure on handover failure rate

7.6. Summary of Performance Improvements

Table 3 shows that using the DRL-based handover mechanism results in significant improvements across key performance metrics when compared to the Fuzzy-logic and traditional SINR-based approach. The results clearly demonstrate the advantages of integrating AI-based decision-making into C-RAN systems. Throughput Improvement by 46.4%, the DRL-based method optimises resource allocation and handover timing, leading to more stable connections, handover failure reduction by 66.7% since traditional SINR-based handovers lead to premature or unnecessary migrations, causing increased failure rates, while the DRL-based approach learns from past handover experiences, selecting only optimal RRHs for user association. Finally, latency reduction by 40% because the traditional handover model leads to delays in decision-making, increasing end-to-end latency, while the DRL-based approach predicts the best migration times, reducing handover-induced delays. The result from the proposed model shows the superiority of DRL-based handover mechanisms over traditional SINR-based approaches, proving that AI-driven solutions can revolutionize handover management in next-generation networks.

Table 3. An overall improvement rate with DRL-based and fuzzy logic handover method

Metric	Improvement with Fuzzy-based Handover Method	Improvement with DRL-based Handover Method
Throughput Improvement (%)	21.6%	46.4%
Handover Failure Reduction (%)	40%	66.7%
Latency Reduction (%)	24%	40%

The DRL-based model is the most effective in optimizing user migration decisions in C-RAN, offering substantial improvements in throughput, handover reliability, and latency. Fuzzy logic serves as a lightweight yet beneficial alternative to static approaches, while static SINR-based methods are clearly less adaptable to the complexities of modern mobile networks.

8. Conclusion

This study demonstrates the effectiveness of using reinforcement learning to optimize handover decisions in Cloud Radio Access Networks (C-RAN). By simulating a C-RAN in Simu5G, data on user migrations between RRHs was collected, and this data was used to train a DRL agent. By leveraging a multi-objective reward function and a context-aware state representation, the proposed DRL model dynamically learns optimal migration decisions that significantly enhance network performance in terms of throughput, latency, and handover reliability. Extensive simulation results demonstrated that the DRL-based approach achieves a 46.4% increase in throughput, 66.7% reduction in handover failures, and 40% decrease in latency compared to the static method. Furthermore, the model proved to be resilient to RRH failures, adapting quickly to disruptions and maintaining stable service quality-something static methods failed to achieve. Unlike existing works that typically apply DRL or rule-based methods in isolation, this study presents a comparative framework that evaluates both fuzzy logic and DRL approaches side by side, highlighting their strengths and limitations under identical simulation conditions. This novel comparative perspective provides deeper insights into the trade-offs between interpretability and adaptability in mobility management. Moreover, the DRL model's ability to learn from real-time network feedback and adapt to changing user behavior positions it as a practical solution for real-world deployment. It is especially well-suited for integration into software-defined networks and Open RAN (O-RAN) environments, where centralized control and automation are key. By minimizing manual configuration and enabling autonomous decision-making, the DRL approach enhances network scalability, fault tolerance, and user experience in dynamic and heterogeneous wireless scenarios. This work provides a foundation for future research into scalable, intelligent mobility management in next-generation 6G wireless networks. However, several limitations must be acknowledged. The simulation relied on synthetic user mobility patterns and idealized channel models, which may not capture all real-world variances such as unpredictable interference, hardware constraints, or diverse service demands. The current setup also focuses on single-user mobility and fixed RRH layouts, which may limit its generalizability to large-scale or multi-tenant networks.

Future research could expand this framework by incorporating real mobility traces, exploring multi-user scenarios, and integrating energy consumption, cost-efficiency, and Quality of Service metrics into the reward structure. Additionally, deploying the models in physical testbeds or leveraging federated learning may enhance scalability and applicability to real-world 5G and 6G network environments. As C-RAN and AI-based mobility management become more integrated into communication infrastructures, user privacy and data protection must be prioritized. When trained on real user data, DRL models may raise concerns regarding the collection and handling of sensitive mobility or behavioral patterns. Ensuring compliance with data protection regulations (such as GDPR) and implementing anonymization techniques are essential for ethical deployment. Moreover, large-scale C-RAN systems could inadvertently widen the digital divide if access to intelligent infrastructure is limited to urban or well-funded areas. Future implementations should aim to balance technological advancement with inclusivity, transparency, and accountability.

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