Adaptive Handover Optimization in LTE: Comparative Evaluation of Fuzzy Logic and DQN

K M Istiaque
Department of Electrical and Electronic Engineering
Islamic University of Technology
Gazipur, Bangladesh
istiaque20@iut-dhaka.edu

M M Sadman Shafi
Department of Electrical and Electronic Engineering
Islamic University of Technology
Gazipur, Bangladesh
sadmanshafi@iut-dhaka.edu

Shafayet Sadik Sowad
Department of Electrical and Electronic Engineering
Islamic University of Technology
Gazipur, Bangladesh
shafayetsadik@iut-dhaka.edu

Mohammad Tawhid Kawser
Department of Electrical and Electronic Engineering
Islamic University of Technology
Gazipur, Bangladesh
kawser@iut-dhaka.edu

Abstract*— This paper investigates adaptive handover optimization techniques in LTE networks using real-world mobility datasets collected through drive testing in Dhaka, Bangladesh. The dataset comprises timestamped measurements of RSRP, RSRQ, CINR, and handover events, enabling comparative evaluation of three models: an operator-defined baseline, a fuzzy logic system, and a reinforcement learning–based Deep Q-Network (DQN). The operator-defined model, based on fixed thresholds, exhibited consistently high unnecessary handovers. The fuzzy logic model improved adaptability by dynamically adjusting handover parameters, reducing both unnecessary and missed handovers. The adaptive DQN achieved the most favorable balance, lowering total handovers by 15–17%, minimizing unnecessary handovers by up to 95%, and maintaining missed handovers at baseline levels. These results highlight the importance of adaptive decision-making in mobility management, with reinforcement learning providing superior scalability and robustness over static and rule-based approaches.

Keywords*— LTE networks, fuzzy logic, Deep Q-Network (DQN), adaptive decision-making, drive test dataset.

I. Introduction

Handover (HO) management plays a critical role in ensuring seamless mobility in LTE and beyond networks. Conventional operator-defined handover strategies rely on static thresholds for parameters such as Time-to-Trigger (TTT) and Handover Margin (HOM). While simple to implement, these fixed rules often result in frequent and unnecessary handovers, especially in dense urban environments with high interference and mobility dynamics. Such inefficiencies not only degrade user experience through ping-pong effects but also increase signaling overhead for the network.

To address these challenges, adaptive approaches have been introduced. Fuzzy logic–based systems provide a rule-driven mechanism to map imprecise radio conditions into qualitative decision outputs, enabling more flexible handover control. More recently, reinforcement learning (RL) techniques, particularly Deep Q-Networks (DQNs), have emerged as powerful tools to optimize handover decisions by learning from real-time network conditions.

This study presents a comparative evaluation of operator-defined, fuzzy logic, and adaptive DQN models using LTE mobility datasets obtained through drive testing in Dhaka, Bangladesh. Performance is assessed across three datasets (Day 1–Day 3) using total handovers, unnecessary handovers, and missed handovers as key indicators. The results demonstrate that while fuzzy logic improves adaptability over static models, adaptive DQN consistently delivers superior performance, achieving fewer handovers, minimal inefficiencies, and stable reliability across diverse scenarios.

II. Literature Review

Conventional HO schemes set fixed thresholds of RSRP, TTT and HOM but these static rules do not track rapidly changing radio conditions, which leads to poor decisions and excessive handovers [1, 2]. To overcome this rigidity, Reinforcement Learning has been used to adapt parameters such as HOM and TTT on the go [3, 4]. In particular, Q-learning is attractive because it learns effective policies from experience without prior environment models, leveraging feedback tied to signal quality, user mobility, and interference levels [5]. Extensions of this approach combine Q-learning with techniques like subtractive clustering or fuzzy logic to refine decision granularity and improve HO prediction [6], offering finer control in heterogeneous settings. In HetNets, Q-learning has been employed to tune handover thresholds dynamically, curbing ping-pong events and HO failures [7]. Related work also couples RL with optimization methods to co-optimize base-station selection and beamforming, boosting throughput while keeping latency low [8].

Also, there are approaches using fuzzy logic. A fuzzy Type-1 controller to tune LTE HO parameters against multiple classic algorithms resulting in large reductions in average HOs and ping-pong events [9]. Another fuzzy-logic LTE HO parameter optimizer explicitly positions fuzzy rules to adapt TTT/HOM against speed and radio balance [10]. Fuzzy HO in heterogeneous network shows that fuzzification mitigates ping-pong in multi-criteria HO decisions [11, 12]. An attention-enhanced rainbow-DQN-based joint traffic prediction to outperform existing methods in terms of the handover efficiency was used in [13]. An approach formalizes ping-pong HOs and shows how fuzzy decision-making suppresses them better than hard thresholds by smoothing borderline scenarios [14].

The use of Deep Q-Networks (DQN) has also been explored too. An MDP is defined over LTE SON fault actions and compares heuristic queues to a DQN agent across metrics using the Vienna LTE simulator [15]. A double deep Q-network (DDQN) deep reinforcement learning (DRL) framework was used to make blockage predictions based on past received signal data such that RLFs can be actively avoided [16]. DQN-ALrM formulates multi-metric HO and introduces an adaptive learning rate with momentum using DQN [17].An ultra-dense 5G study uses three Deep-Q models to decide when to hand over, which cell to choose, and how to tune A2/A4 thresholds [18].

III. METHODOLOGY

The methodology adopted in this study is designed to evaluate and compare different handover (HO) optimization strategies using real-world drive test data. The dataset was collected from a live LTE network and includes key radio measurements such as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Carrier to Interference-plus-Noise Ratio (CINR), along with timestamps and handover events. These parameters were preprocessed and used as input to multiple decision-making models, each representing a different approach to mobility management.

Three models were considered in this work:

- **Operator-defined model:** a fixed threshold-based baseline representing conventional handover decision-making in cellular networks.
- **Fuzzy Logic model:** an adaptive thresholding approach that maps radio conditions to handover control parameters using linguistic rules, allowing dynamic adjustment of TTT and HOM based on the observed environment.
- **Adaptive DQN:** a reinforcement learning model that dynamically adjusts TTT and HOM values in response to real-time network conditions to optimize the handover process, minimizing unnecessary HOs while maintaining network reliability.

Each model was implemented and tested on the same dataset to ensure a fair comparison. Performance was evaluated using three key indicators: total HO count, missed HO, and unnecessary HO. The comparative analysis enables assessment of each model's ability to balance efficiency and reliability in real-world LTE mobility scenarios.

A. Operator Defined Model (Drive Test based Dataset)

The first step in this study involved establishing a baseline using an operator-defined model, where mobility decisions were recorded directly from a live LTE network. For this purpose, a drive test campaign was conducted in Dhaka, Bangladesh, using professional-grade measurement tools including XCAL-M software, Samsung Exynos-based user equipment (UE), and GPS modules. This setup ensured the synchronized collection of timestamped radio measurements alongside mobility events.

The drive test route spanned approximately 13 km, from Le Meridien (Uttara) to BRAC University, and was repeated across multiple sessions during peak traffic hours. Following a Multiple Site Verification (MSV) approach, the campaign covered around 26 km in total, capturing over 100 handover events under realistic mobility and interference conditions in a densely deployed LTE urban network.

The dataset [19] includes Layer 3 radio parameters such as serving and neighbor cell RSRP, RSRQ, CINR, cell identifiers, and operator-defined handover triggers. The collected raw data was preprocessed to handle missing values, standardize timestamps into a uniform millisecond-based format, and engineer additional features, including RSRP differences, RSRQ differences, and short-term RSRP trends. These features provide meaningful inputs for the adaptive decision-making models while retaining the inherent handover behavior defined by the operator.

This drive test–based dataset thus provides a real-world baseline of operator-controlled handover performance, against which adaptive techniques such as Fuzzy Logic and Deep Q-Network (DQN) models are evaluated in subsequent sections.

B. Fuzzy Logic Model for Adaptive Handover Control

Fuzzy logic provides a rule-based decision-making framework capable of reasoning under uncertainty and imprecision. Unlike static threshold-based methods, it maps quantitative radio measurements into qualitative linguistic categories (e.g., low, medium, high) and infers decisions through a comprehensive set of rules. In this study, fuzzy logic was used to dynamically adapt Time-to-Trigger (TTT) and Handover Margin (HOM) parameters, which are critical in determining the timing and aggressiveness of handovers in LTE networks. The main objective was to minimize unnecessary handovers while maintaining reliability under real-world mobility conditions.

The overall fuzzy-based handover optimization process is illustrated in Fig. 1.

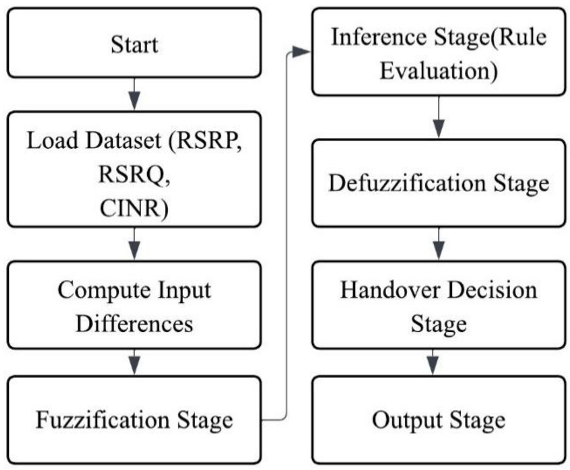

Fig. 1. Fuzzy Logic Handover Decision Process

Input Parameters

The fuzzy inference system employed three input parameters derived from the drive test dataset:

- RSRP difference (Neighbor – Serving): Indicates the relative signal strength advantage of the neighboring cell.
- RSRQ difference (Neighbor – Serving): Represents the relative signal quality difference.
- Serving Cell CINR: Captures the link quality under interference and noise conditions.

Each input variable was mapped into three linguistic categories (low, medium, high) using triangular membership functions, with adjustments made to ensure adequate coverage of realistic radio conditions.

Output Parameters

Two adaptive outputs were defined to regulate handover behavior:

- **Adaptive TTT (25–200 ms):** Categorized as short, medium, or long.
- **Adaptive HOM (0 to 2 dB):** Categorized as low, medium, or high.

Lower TTT and HOM values encourage aggressive handovers, whereas higher values enforce conservative behavior to prevent frequent switching.

Fuzzy Rule Base

The adaptive fuzzy logic system employs eight rules mapping RSRP and RSRQ differences along with serving cell CINR to adaptive TTT and HOM values, targeting reductions in missed and unnecessary handovers, as summarized in Table 1.

Table 1: Fuzzy Rule Mapping for Handover Decision Parameter

Fuzzy Rule Base	Input		Output	
Rule No.	RSRP & RSRQ diff	CINR	HOM	TTT
1	High	low	Low	Short
2	High	medium	Low	Medium
3	High	high	Medium	Medium
4	Medium	low	High	Medium
5	Medium	medium	Medium	Medium
6	Medium	high	High	Medium
7	Low	low	Medium	Medium
8	Low	medium /high	High	Long

The purposes of the rules outlined in Table 3 are as follows. Rule 1 ensures rapid handover execution to mitigate missed handovers when the neighboring cell exhibits superior strength and the serving link quality is degraded. Rule 2 achieves a balance between missed and unnecessary handovers, facilitating handover without excessive aggression. Rule 3 minimizes unnecessary handovers by introducing a delay, given the sustained quality of the serving link. Rule 4 reduces the incidence of missed handovers by enabling handover when the serving cell quality is suboptimal, despite a moderately better neighboring cell. Rule 5 maintains equilibrium between missed and unnecessary handovers under moderate operational conditions. Rule 6 decreases unnecessary handovers, prioritizing retention on a sufficiently robust serving cell. Rule 7 addresses missed handovers by supporting handover when the neighboring cell offers a slight improvement over a poor serving cell. Finally, Rule 8 diminishes unnecessary handovers, promoting retention on the current cell when the neighboring cell does not provide significant improvement and the serving cell remains adequate.

C. *Deep Q-Network*

Reinforcement Learning and Deep Q-Network (DQN) Framework

Reinforcement Learning (RL) is employed to optimize handover (HO) decision-making in LTE networks by formulating the problem as a Markov Decision Process (MDP). At each time step t, the RL agent observes the current state s_t, selects an action a_t from the action space, and receives a reward r_t from the environment based on the effectiveness of the chosen handover parameters. The objective is to maximize the expected cumulative discounted reward:

$$(\pi)^* = argmax\, \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t | \pi\right] \qquad (1)$$

where π represents the handover policy and $\gamma \in [0,1]$ is the discount factor.

To approximate the optimal action-value function Q*(s,a), a Deep Q-Network (DQN) is implemented. The DQN predicts the long-term expected reward for each possible action given the current state. Two separate neural networks are used:

- **Online Network** → Continuously updated during training.
- **Target Network** → Stabilizes learning by periodically synchronizing with the online network.

This dual-network structure mitigates oscillations and improves convergence stability.

State Space Definition

The input to the DQN agent is a 7-dimensional continuous state vector derived from LTE measurement reports.

For each time step t, the state vector is defined as:

$$s_t = [Q_{weighted}, \Delta RSRP, \Delta RSRQ, CINR_{serv}, \Delta RSRP_{t-1}, \Delta RSRP_{t-2}, RSRP_{\_trend3}] \qquad (2)$$

where:

- $Q_{weighted} = 0.6 \cdot \Delta RSRP + 0.3 \cdot \Delta RSRQ + 0.1 \cdot CINR_{serv}$
- ΔRSRP = Neighbor RSRP − Serving RSRP
- ΔRSRQ = Neighbor RSRQ − Serving RSRQ
- $CINR_{serv}$ = Serving cell CINR
- $\Delta RSRP_{t-1}$, $\Delta RSRP_{t-2}$ = Previous-step RSRP differences
- $RSRP_{\_trend3}$ = 3-step RSRP trend

Thus, the state space is:

$$S \subseteq \mathbb{R}^7$$

Action Space Design

The agent selects actions corresponding to different handover parameter configurations. The action space consists of all possible combinations of Time-to-Trigger (TTT) and Hysteresis Offset Margin (HOM) values:

$$\mathcal{A} = \{(t,h) \mid t \in \text{TTT levels},\ h \in \text{HOM levels}\} \quad (3)$$

In this work, the following discrete values were defined:

- **TTT levels** = [25, 50, 100, 150, 200] ms
- **HOM levels** = [0, 0.5, 1.0, 1.5, 2.0] dB

Total number of possible actions:

$$\mid \mathcal{A} \mid = 5\times5=25$$

Each action corresponds to a unique (TTT, HOM) pair, allowing the DQN to dynamically control handover aggressiveness based on network conditions.

Environment and Reward Design

A custom LTE handover simulation environment was developed where the agent interacts sequentially with real LTE measurement data.

For each state-action pair, the environment simulates the next state and computes a reward r_t based on the quality of the handover decision.

The reward structure is summarized in Table 2.

Table 2: Reward Structure

Scenario	Condition	Reward
Beneficial HO	RSRP gain ≥ 6 dB	+6.0
Bad HO	HO executed but RSRP gain < 6 dB	−5.0
Unnecessary HO	HO triggered when not required	−2.0
Missed HO	No HO when needed (RSRP gap ≥ margin)	−3.0
Stable Connection	No HO needed and agent stays	+2.0
Ping-Pong HO	HO within 500 ms of previous HO	−6.0

This reward design balances handover efficiency and network stability, enabling the agent to avoid unnecessary HOs while preventing radio link failures.

Deep Q-Network Architecture

The Q-function Q(s,a;θ) is approximated using a deep neural network implemented in Pytorch.
The architecture is illustrated in Fig. 2.

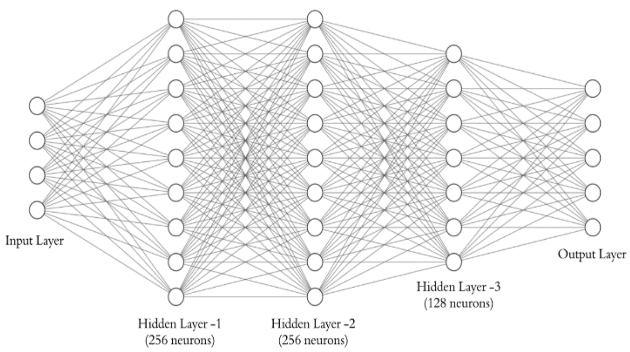

Fig. 2. Deep Q-Network Architecture

Key Components

- Input Layer: Accepts the 7-dimensional state vector.
- Hidden Layers:
  - Fully connected layers: [256, 256, 128]
  - Activation: Leaky ReLU
  - Normalization: LayerNorm
  - Regularization: Dropout = 10%
- Output Layer: Produces Q(s,a) values for all possible actions.

Role of Replay Buffer

A Replay Buffer of fixed capacity is used to store experience tuples (s_t, a_t, r_t, s_{t+1}). During training, the agent samples mini-batches uniformly, which:

- Breaks temporal correlations between sequential samples.
- Stabilizes gradient updates.
- Improves overall learning efficiency.

Deep Q-Network Agent and Learning Policy

The DQN agent is responsible for approximating the optimal action-value function Q*(s,a) and selecting handover actions. The agent employs an epsilon-greedy policy to balance exploration and exploitation:

$$a_t = \begin{cases} \quad random\ action & with\ probability\ \epsilon \\ argmax_a\ Q_{online}(s_t, a) & with\ probability\ 1-\epsilon \end{cases} \quad (3)$$

where ϵ decays linearly from an initial ϵ_{start} to a final ϵ_{end} over a fixed number of steps. This mechanism ensures sufficient exploration during early training while gradually favoring exploitation of learned policies.

Online and Target Q-Networks

In this work, two separate neural networks are maintained to stabilize the Deep Q-Learning process: the online Q-network and the target Q-network.

- Online Q-Network: Responsible for selecting actions during training. It is continuously updated via gradient descent to minimize the prediction error between the current Q-values and the expected future rewards.
- Target Q-Network: A delayed copy of the online network that is used to compute stable target Q-values. Unlike the online network, its parameters are updated less frequently by periodically copying the weights from the online network.

This dual-network architecture addresses the moving target problem in reinforcement learning, where the Q-value targets shift rapidly if the same network is used both for predicting and evaluating actions. By introducing a target network with delayed updates, the learning process becomes more stable, prevents oscillations, and improves convergence.

Furthermore, a replay buffer is employed to store past transitions (s, a, r, s′). During training, the agent samples mini-batches from this buffer to break temporal correlations and ensure more efficient and stable updates for the online network. The difference between the predicted Q-values (from the online network) and the target Q-values (computed using the target network) is minimized using the mean squared error (MSE) loss. The Adam optimizer with gradient clipping is used to ensure stable training and avoid exploding gradients.

Hyperparameters

The key hyperparameters of the DQN agent are summarized in Table 3.

Table 3: Hyperparameter Values

Parameter	Value / Range
Learning Rate	0.001
Discount Factor	0.99
Replay Buffer Size	100,000
Batch Size	64
Min Replay Size	1,000
Target Update Frequency	1,000 steps
Epsilon Start / End	1.0 → 0.05
Epsilon Decay Steps	15,000
Gradient Clipping	10.0

IV. Evaluation and Discussion

The evaluation and discussion jointly examine the effectiveness of the proposed handover optimization strategies under real-world LTE conditions. Using datasets collected from multiple drive-test sessions, the operator-defined baseline, fuzzy logic model, and adaptive DQN were compared in terms of total handover count, missed handovers, and unnecessary handovers. The results are first presented for each dataset to illustrate dataset-specific behavior, followed by a cross-day comparative analysis. The discussion then interprets these findings, explaining why the models perform differently and highlighting the advantages and limitations of each approach in dynamic mobility scenarios.

A. *Experimental Setup*

The performance of the proposed models was evaluated using real-world LTE mobility datasets collected through drive testing in Dhaka, Bangladesh. Three datasets were analyzed: Day 1 (923 samples), Day 2 (593 samples), and Day 3 (641 samples). Each dataset contains timestamped measurements of RSRP, RSRQ, CINR, and handover events.

Handover performance was assessed using three key metrics:

- **Total Handover (HO) count:** number of handover events triggered.
- **Missed HO:** instances where handover was necessary but not executed.
- **Unnecessary HO:** handovers triggered despite adequate serving cell conditions, often causing ping-pong effects.

The detailed results are summarized in Table 4, 5 & 6.

Table 4: Day1 Dataset Evaluation

Key Metrics	Operator Defined model	Fuzzy Logic model	DQN (Adaptive TTT & HOM)
Total HO count	150	137	126
Missed HO	12	5	9
Unnecessary HO	26	12	3

Table 5: Day1 Dataset Evaluation

Key Metrics	Operator Defined model	Fuzzy Logic model	DQN (Adaptive TTT & HOM)
Total HO count	99	95	84
Missed HO	5	2	5
Unnecessary HO	17	7	1

Table 6: Day3 Dataset Evaluation

Key Metrics	Operator Defined model	Fuzzy Logic model	DQN (Adaptive TTT & HOM)
Total HO count	118	110	98
Missed HO	7	3	7
Unnecessary HO	21	10	2

B. *Results on Day1 Dataset*

On Day 1, the fuzzy logic model reduced unnecessary HOs by approximately 54% and missed HOs by nearly 58% compared to the operator-defined baseline, while slightly lowering the total HO count. The adaptive DQN further optimized handover performance, achieving a 16% reduction in total HOs and an 88% reduction in unnecessary HOs relative to the baseline. Missed HOs under adaptive DQN remained low, demonstrating a superior balance between network reliability and efficiency.

C. *Results on Day2 Dataset*

For Day 2, the fuzzy logic model achieved a reduction of 59% in unnecessary HOs and 60% in missed HOs, with minimal impact on the total HO count. The adaptive DQN outperformed fuzzy logic by reducing total HOs by 15% and nearly eliminating unnecessary handovers, while maintaining missed HOs comparable to the baseline. This indicates robust generalization of the adaptive learning strategy under varying mobility patterns.

D. *Results on Day3 Dataset*

On Day 3, the fuzzy logic model continued to provide balanced improvements, lowering unnecessary HOs by over 50% and missed HOs by approximately 57%. The adaptive DQN again demonstrated the most favorable trade-off: total HOs decreased by 17%, unnecessary HOs were minimized by over 90%, and missed HOs were maintained at the baseline level. These results underscore the ability of adaptive reinforcement learning to maintain network stability while optimizing handover decisions.

E. *Cross-Day Comparative Analysis*

The results across the three datasets demonstrate consistent improvements from fuzzy logic and adaptive DQN over operator-defined handover parameters. To evaluate these improvements comprehensively, the models were compared across total handover counts, missed handovers, and unnecessary handovers, as summarized in Figures 3,4 & 5.

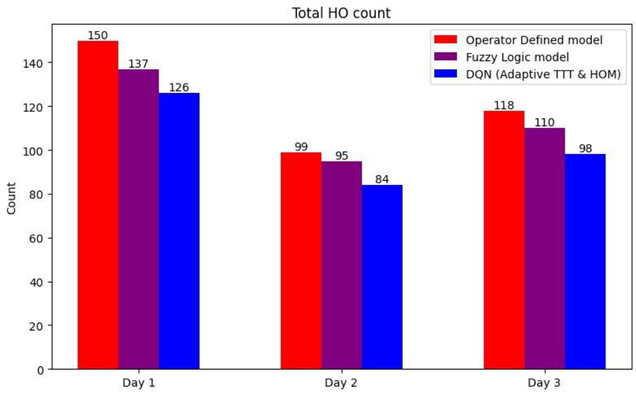

Fig. 3. Total Handover Counts Across Models

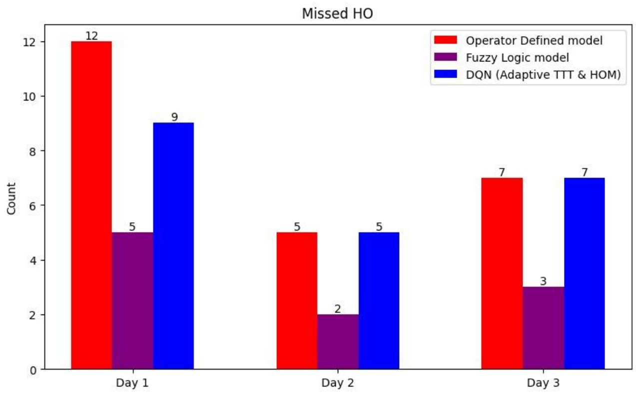

Fig. 4. Missed Handover Counts Across Models

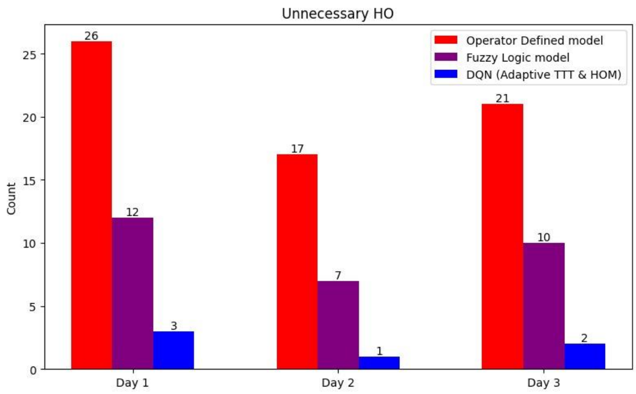

Fig. 5. Unnecessary Handover Counts Across Models

Across all three datasets, several trends are evident. The operator-defined model exhibited consistently high unnecessary handover (HO) rates, highlighting the limitations of static handover thresholds in dynamic urban environments. In contrast, fuzzy logic control provided substantial reductions in both unnecessary (52–59%) and missed HOs (57–60%), while keeping total HOs close to the baseline, reflecting moderate adaptability to varying conditions. The adaptive Deep Q-Network (DQN) consistently achieved the most favorable outcomes, with total HOs decreasing by 15–17%, unnecessary HOs reduced by 88–95% and missed HOs either maintained at or slightly below baseline levels.

F. *Discussion*

The evaluation demonstrates clear distinctions in performance among the operator-defined, fuzzy logic and adaptive DQN models.

The operator-defined model relies on fixed handover margins and timers, resulting in consistently high unnecessary HO rates across all datasets. This is due to its inability to adapt to dynamic variations in signal quality, user speed, and network load, which causes frequent handovers even when the serving cell is adequate. Missed HOs remain moderate under this approach, as conservative thresholds prevent some handover failures, but efficiency is compromised.

The fuzzy logic model provides a more balanced performance by incorporating adaptive rule-based decision-making. Its ability to handle imprecise measurements of RSRP, RSRQ, and CINR allows it to reduce both unnecessary and missed HOs substantially. The model's performance gains stem from its capability to adjust handover thresholds in response to varying radio conditions. However, total HOs remain close to the operator baseline, indicating that while fuzzy logic effectively balances reliability and efficiency, it is limited in fully optimizing the handover process under rapidly changing mobility scenarios.

The adaptive DQN consistently achieves the best trade-off across all datasets. By learning context-dependent policies through reinforcement learning, it dynamically adjusts TTT and HOM based on real-time network conditions. This adaptivity enables a reduction of total HOs by 15–17%, nearly complete elimination of unnecessary HOs (88–95% reduction), and maintenance of missed HOs at baseline levels. The model's superior performance arises from its ability to predict the optimal timing and conditions for handovers, preventing both premature and delayed HO events. This ensures robust network stability and high user experience, outperforming both static and rule-based approaches.

Overall, the results highlight that adaptivity is essential in handover optimization:

- Static thresholds (operator-defined) fail to balance efficiency and reliability, leading to high unnecessary HOs.
- Rule-based adaptivity (fuzzy logic) reduces inefficiencies while maintaining reliability, but cannot fully exploit real-time learning from the environment.
- Learning-based adaptivity (adaptive DQN) leverages continuous feedback from the network, achieving both minimal unnecessary HOs and stable missed HOs, demonstrating superior scalability and generalization for real-world LTE networks.

V. Conclusion

Adaptive handover optimization in LTE networks was evaluated using real-world drive-test datasets. The operator-defined baseline showed high unnecessary handovers, while fuzzy logic reduced both unnecessary (52–59%) and missed handovers (57–60%) through rule-based adaptability. The adaptive DQN outperformed all models, lowering total handovers by 15–17%, unnecessary handovers by 88–95%, and maintaining missed handovers at baseline levels, demonstrating superior efficiency and reliability.

A limitation of this study is its focus on a single urban environment, which may affect generalizability. Future work will extend the framework to multi-city LTE and 5G networks, incorporating heterogeneous traffic, mobility patterns, and additional contextual features to further enhance adaptive handover decisions.

In summary, reinforcement learning–based adaptivity provides the most balanced solution for mobility management, achieving an effective trade-off between efficiency and reliability compared to static and fuzzy logic approaches.

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