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Original Research Article

A Performance-Based Hybrid RT–HT Model-Switching Mechanism in 5G Handover Optimization

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ABSTRACT
The problem of concept drift poses a critical challenge in dynamic 5G networks, causing static machine learning models to fail when data distributions change. While online learning techniques can adapt, but suffer from cold start problems. This paper presents a performance-based Hybrid Regression Tree (RT) - Hoeffding Tree (HT) technique for concept drift detection in 5G handover optimization. The technique dynamically selects between a pre-trained Regression Tree (RT) and an incrementally trained Hoeffding Tree (HT) using a mobility-domain indicator and a sliding window of recent prediction errors. The study conducted an extensive simulation using the 3GPP TR 38.901 urban-microcell channel model and compared the proposed hybrid technique against five baseline techniques: ML-SOHOT (Alraih et al., 2025), Hoeffding Tree, LIM2 (Karmakar et al., 2022), E-SARSA Reinforcement Learning (Junejo et al., 2025), and PPO (Voigt et al., 2024). The results show that the proposed Hybrid technique reduces handover failure by 82.2% under drift conditions, achieves 44% reduction in handover latency, and 66% reduction in ping-pong rate compared to MLSOHOT (RT). The technique maintains consistent handover interruption time (1.8 ms) and achieves the best balance across all the KPIs among the compared baseline studies, confirming its effectiveness for real-time 5G deployment.

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INTRODUCTION

Selection of model is a key issue in machine learning especially when dealing with dynamic environment where there is changing in data distribution over time (Xu et al., 2017). In 5G technology, the issue of technique selection becomes more difficult because of the presence of concept drift due to changes in user movements, signals, and network configurations.

The Error Intersection Approach (EIA) has demonstrated that switching between simple and complex models based on prediction error improves the performance of regression under concept drift (Baier et al., 2020). On the other hand, the Alternating Learners framework has revealed that utilizing long-memory and short-memory learners is effective in dealing with concept drift (Xu et al., 2017). Nevertheless, neither EIA nor Alternating Learners framework has been employed in 5G handover optimization.

Ghasemkhani et al. (2025) proposed Balanced Hoeffding Tree Forest for multi-label classification in predictive maintenance, demonstrating the effectiveness of Hoeffding Trees for streaming data adaptation. Their work highlights the potential of incremental learning approaches for handling evolving data distributions.

Moreover, recent developments in the 5G communication system for drift management purposes have also come up with many solutions to cope with non-stationary distribution of data. Chien et al. (2024) proposed a privacy-enhanced handover optimization solution, which utilizes the combination of FL (Federated Learning) and LSTM (Long Short-Term Memory) network in order to predict RSRP and the signal strength of the neighboring cells.

A systematic study related to Federated Learning with Concept Drift was performed by Mahdi et al. (2025) who proposed the FDAL framework, which is a connection between federated and continual learning studies to create adaptive and drift-resilient algorithms. With regards to the handover optimization problem, surveys by Asif et al. (2025) and Tashan et al. (2024) performed an extensive review of the machine learning methods, emphasizing the need to handle concept drift in 5G handover optimization. The studies reveal that offline macine learning models are having problems of adaptability to changing conditions out of training domain, while online learning models poses a cold start problem.

Karmakar et al. (2022) designed the LIM2 approach, where Kalman filtering method is used to predict RSRP along with SARSA reinforcement learning algorithm to adjust Time-To-Trigger and hysteresis margins. Although this approach proved to be effective in terms of handover success rate, it needs lots of training, and it cannot work properly due to cold start problems. Reinforcement learning is too complex to be implemented in constrained settings.

Junejo et al. (2025) introduced a scheme for adaptive handover management based on the application of Unscented Kalman Filter for predicting RSRP, and Expected SARSA-based reinforcement learning algorithm for selecting the target cell. This technique delivered a 15% increase in handover success rate, 3% increase in throughput and a reduction in latency of about 6 seconds at a speed of 200 km/h relative to the LIM2 technique. However, this technique still demands the training and exploration phases for reinforcement learning.

Voigt et al. (2024) developed a Proximal Policy Optimization (PPO)-based adaptive handover protocol for 5G NR, demonstrating superior performance in reducing radio link failures at high speeds. However, deep reinforcement learning approaches require extensive training data and computational resources, making them less suitable for real-time deployment in resource-constrained network environments.

Alraih et al. (2025) introduced ML-SOHOT, a static Regression Tree-based approach for TTT prediction, achieving high accuracy (R^2 = 0.9837) under stationary conditions. However, the technique lacks adaptability to concept drift, leading to significant performance degradation when network conditions change.

In this paper, we present a proposed hybrid performance-based technique for 5G handover optimization. The technique adopts the dual indicator approach to detect drifts together with dynamic technique switching between the trained Regression Tree (RT) and Hoeffding Tree (HT). Specifically, our key contributions include:

i. Model switching through hybrid RT- HT technique that uses both offline and incremental learning.
ii. Mobility domain indicator to determine cases which are outside the RT training regime.
iii. Sliding window error-based model switching mechanism that employs better-performing models based on prediction errors.
iv. On-line HT update technique that allows adaptation without complete retraining of the model. Evaluation of all four techniques through HOF, HOPP, HIT, and HOL in normal and out-of-domain mobility.

MATERIALS AND METHODS

This section describes in detail the entire methodology that was applied in the process of designing and evaluating the proposed performance-based switching hybrid RT-HT techniques for concept drift in 5G handover optimization. Five major parts of the methodology are described, namely: experimental setup, hybrid technique design, implementation of the switching scheme, errors calculation, and evaluation procedure.

Experimental Setup

A dataset of 50,000 samples was generated in MATLAB using the 3GPP TR 38.901 urban-microcell channel model and the simulation parameters. The simulation environment comprises 57 gNBs uniformly distributed within a 3 km × 3 km simulation area, with 28 GHz carrier frequency and 500 MHz bandwidth. User equipment (UE) speeds ranged from 20 to 160 km/h for RT model training, while 180, 200, and 220 km/h for demonstrating RT model out of training domain performance. Detailed simulation parameters are presented in Table 1.

Table 1: Simulation Parameters Settings

Parameter	Value
Environment	Micro cells, urban area, 5G networks
Cell Configuration	Hexagonal grid
Simulation Area	3 km × 3 km
Simulation Time	100 seconds
Number of Gnb	57
Cell Radius	200 m
Carrier Frequency	28 GHz
System Bandwidth	500 MHz
White Noise Power Density	-174 dBm/Hz
UE Noise Figure	9 dB
Path Loss Model	3GPP Umi
Shadow Fading	7.82 Db
User Equipment Power	23 dBm
Transmission Power	35 dBm
Handover Margin	3 dB Fixed

Dataset Characteristics

Statistical characteristics of the generated data set are provided in Table 2, which describes the minimum/maximum, central tendency, and dispersion of all input variables and the target variable. RT training dataset included user equipment (UE) speed from 20 to 160 km/h. Additional scenarios with speeds of 180, 200, and 220 km/h were considered as out-of-training-domain cases.

Table 2: Dataset Summary Statistics

Feature	Symbol	Unit	Mean	Std Dev	Min	Max
Reference Signal Received Power	RSRP	dBm	-85.00	14.90	-128.72	-44.00
Reference Signal Received Quality	RSRQ	dB	-11.45	4.95	-20.00	-3.00
Signal-to-Interference-plus-Noise Ratio	SINR	dB	12.86	9.77	-5.00	30.00
User Equipment Speed	Speed	km/h	89.92	40.35	20.00	160.00
Distance to Serving Cell	Distance	M	100.59	57.78	0.00	199.99
Time-To-Trigger (Target)	TTT	Ms	271.49	93.41	96.00	595.00

From Table 2, the dataset is highly varied for all the variables and therefore is appropriate for use with the robust learning technique. The RSRP values fall between -128.72 dBm (very poor signal) and -44.00 dBm (excellent signal), with an average value of -85.00 dBm and a standard deviation of 14.90 dB which are urban microcell typical values. RSRQ varies from -20.00 dB (poor quality) to -3.00 dB (excellent quality) and with an average of -11.45 dB, which are typical quality of signals in the dataset. The SINR value falls between -5.00 dB and 30.00 dB, thus reflecting interference limited and noise-limited situations. The UE speed varies from 20 km/h to 160 km/h which are typical values for an urban environment. The target variable TTT varies from 96 ms to 595 ms, with an average of 271.49 ms and standard deviation of 93.41 ms.

Proposed Hybrid RT-HT Technique Design

The proposed Hybrid technique uses dual-indicator drift detection to identify concept drift and dynamically select the optimal model:

Speed-Based Detection

1. The study defines speeds above 160 km/h as out-of-training-domain conditions used to evaluate the model under drift-like distributional change.
2. This provides immediate identification of previously unseen conditions.

Error-Based Detection

1. Drift is detected when $MAE_{RT} > MAE_{HT}$
2. This captures more subtle changes in data distribution that may not be indicated by speed alone.

Proposed Hybrid RT-HT Algorithm

Algorithm 1 outlines the proposed hybrid RT-HT approach that incorporates performance-based concept drift detection. This method integrates both the offline Regression Tree (RT) model for immediate accuracy and the online Hoeffding Tree (HT) model for adapting learning.

Algorithm 1: Performance-Based Hybrid RT-HT for Concept Drift Detection

```
Require: Streaming network data (RSRP,RSRQ,SINR,Speed,Distance)
Require: Pre-trained RT model
Require: Initialized HT model
Ensure: Optimal TTT prediction
Load pre-trained RT model
Initialize HT model
Set drift threshold: Speed > 160 km/h \\ Speeds above 160 km/h represent the drift conditions considered in this study (out-of-training domain)
while Network is active do
    Collect network measurements
    Construct feature vector
    X = [RSRP,RSRQ,SINR,Speed,Distance]
    TTT_RT ← RT.predict(X)
    TTT_HT ← HT.predict(X)
    MAERT ← |TTTRT − TTTtrue|
    MAE_HT ← |TTT_HT − TTT_true|
    if Speed > 160 then
        Select HT
        else if MAE_RT ≤ MAE_HT then
        Select RT
    else
        Select HT
    end if
    if RSRPtarget > RSRPserving + HOM then
        Start TTT timer
        if Condition persists then
            Execute handover
        end if
    end if
    Update HT with (X,TTT_true)
    Compute HOF, HOPP, HIT and HOL
end while
```

Note that the pre-trained RT model was trained offline using 40,000 samples (80% of the dataset), while 10,000 samples (20% of the dataset) were used for testing the RT model. The model provides immediate operational capability. The HT model is initialized with a default prediction value of 200ms, which is updated incrementally as new samples arrive.

Hoeffding Tree Implementation

The Hoeffding Tree algorithm (HT) has been developed with the following settings as an incremental decision tree:

1. Initial Prediction: 200 ms (default value when tree is empty)
2. Grace Period: 200 samples (minimum samples for a split attempt)
3. Splitting Criterion: Absolute covariance between each feature and the target TTT
4. Split Variance Threshold: > 0.01 (minimum covariance to justify splitting)
5. Leaf Prediction: Mean of all TTT values seen at the leaf
6. Update Strategy: Incremental (each sample updates sufficient statistics)

Each leaf node holds sufficient statistics, but does not store the whole dataset. Once 200 observations arrive at a leaf node, the algorithm calculates the absolute covariance of each of the five features (RSRP, RSRQ, SINR, Speed, and Distance). The feature with the largest covariance is chosen for splitting if its covariance exceeds 0.01. This simplified approach reduces computational complexity while maintaining adaptability to changing network conditions.

Error Computation

Prediction errors for each of the samples are calculated as:

$$error_{RT} = \mid TTT_{RT} - TTT_{true} \mid \quad (1)$$

$$error_{HT} = \mid TTT_{HT} - TTT_{true} \mid \quad (2)$$

Where $error_{RT}$ refers to the Regression Tree prediction error, TTT_{RT} RT prediction, and TTT_{true} actual true TTT value, $error_{HT}$ means Hoeffding Tree Prediction error, and TTT_{HT} means HT prediction.

The Mean Absolute Error (MAE) is then computed over a sliding window of recent samples (window size = 200):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid error_i \mid \quad (3)$$

The prediction errors for both models' predictions are been recorded using a window size W = 200. The choice of W = 200 ensures there is enough flexibility in terms of responsiveness to recent changes with statistical stability. Specifically, for the RT model, the study maintains error buffer E_RT = [e_1, e_2, ..., e_W], and similarly E_HT for the HT model. The MAE is computed as the mean of these windowed errors. The window is updated by shifting out the oldest error and appending the most recent prediction error.

Evaluation Metrics

The performance metrics were measured through five Key Performance Indicators (KPIs) which have been popularly used in handover optimization literature. These include metrics for measuring the reliability, efficiency, and quality of handover decision. Below are the descriptions, formulae, and effects of these KPIs:

Handover Failure (HOF)

Handover Failure (HOF) is an important performance measure used to evaluate the reliability of handover processes in mobile networks. It measures the probability of connection failure when the UE tries to perform the handover from one gNB to another causing interruption of service. HOF happens when a handover process starts but does not succeed (Alraih et al., 2025). HOF occurs where the UE is not able to synchronize with the target cell until the handover guard timer expires, or when the UE does not receive the handover command message from the serving base station. The minimization of HOF will result in seamless connectivity and good Quality of Service (QoS) (Alraih et al., 2025).

HOF is calculated as the percentage of failed handover attempts relative to total handover attempts:

$$HOF = \frac{Failed\ HO}{Total\ HO} \times 100 \quad (4)$$

High HOF implies unreliable handover process performance resulting in communication interruptions, call drops, and bad user experience. The reduction of HOF is essential to guarantee mobile service continuity, especially in cases when there is high mobility, like on the highways and high-speed railways (Alraih et al., 2025).

Handover Ping-Pong (HOPP)

The term Handover Ping-Pong (HOPP) indicates the repeated and unnecessary handover of the user equipment (UE) between two or more gNBs due to the variation in signal level or inefficient handover algorithms (Alraih et al., 2025). The HOPP problem occurs when there is a continuous and repetitive handover of the UE between two cells within a small-time interval as a result of the instantaneous variation in the level of signal because of shadowing of UEs at the cell edge.

HOPP can be defined in terms of the ratio of reverse handovers to total handovers:

$$HOPP = \frac{Reverse\ HO\ within\ time\ window}{Total\ HO} \times 100 \quad (5)$$

A high HOPP rate negatively impacts the QoS of the network, causes radio resource wastage, increases the power consumption, and reduces the efficiency of the network. Therefore, resolving the issue of HOPP becomes necessary for the optimization of the performance of the network, especially in cases where overlapping of the coverage area takes place or in case the network involves a high mobility scenario (Alraih et al., 2025).

Handover Interruption Time (HIT)

The Handover Interruption Time (HIT) is the period when the UE faces interruption in communication while transferring from one gNB to another (Alraih et al., 2025). More precisely, the HIT means the time for which there is an interruption in the transfer of user data packets from the source cell to the target cell due to the handover process. The HIT can be explained as the time duration between the moment the UE receives the last user data packet from the source cell and the time it receives the first user data packet from the target cell.

HIT is calculated as:

$$HIT = T_{disconnect} - T_{reconnect} \quad (6)$$

The increased HIT will lead to increased downtime while conducting the transition process, causing a poor experience in delay-sensitive applications like voice communication, video communication, and online games. The issue of HIT is important in 5G networks because the slightest downtime may affect the reliability of the service. The reduction of the HIT value is important in providing uninterrupted connectivity in 5G and beyond, especially in Ultra-Reliable Low-Latency Communication (URLLC) services (Alraih et al., 2025).

Handover Latency (HOL)

Handover Latency (HOL) refers to the overall time that it takes for the entire handover procedure to start and end (Alraih et al., 2025). HOL is the period taken by the entire handover procedure; it entails the time taken by the detection of the necessity of the handover procedure and then establishing a stable connection through the target gNB. Low HOL is essential in ensuring continuity of the connectivity.

HOL is calculated as:

$$HOL = T_{execution} - T_{trigger} \quad (7)$$

The high value of HOL means that the handover process is taking more time than normal, which causes loss of packets, delay in services, and low throughput. Low value of HOL means that the handover process takes less time, and therefore the process of re-establishing the connection becomes quicker. Optimization of handover processes, efficient signaling, and predictive mobility are the techniques used to minimize the HOL (Alraih et al., 2025).

RESULTS AND DISCUSSION

This section provides the performance results of the proposed Hybrid RT-HT technique, which has been evaluated using several key HO KPIs, includin HOF, HOPP, HIT, and HOL. Furthermore, the technique's performance has been compared to other competitive techniques from the literature: ML-SOHOT (RT), Hoeffding Tree (HT), LIM2 (Karmakar et al., 2022), ESARSA Reinforcement Learning (Junejo et al., 2025), and PPO (Voigt et al., 2024).

Handover Failure Rate (HOF)

Handover Failure Rate represents the percentage of handover attempts that result in connection failure. Table 3 illustrates the average HOF across all speeds for all six techniques.

Table 3: Handover Failure Rate by Speed and Technique

Speed (km/h)	ML-SOHOT (RT) (%)	HT (%)	LIM2 (%)	E-SARSA RL (%)	PPO (%)	Proposed Hybrid RT-HT (%)
20	0.0	12.3	14.5	10.8	9.5	0.0
40	5.0	6.9	8.2	6.5	5.8	3.1
80	6.2	9.9	7.5	7.8	7.2	6.0
120	15.2	6.4	7.8	6.8	6.5	6.2
160	23.4	7.7	8.1	7.2	6.2	7.3
180	39.2	10.6	8.5	7.5	6.8	9.8
200	42.7	10.1	9.2	7.8	7.0	9.6
220	61.2	6.1	9.8	8.1	7.5	6.1
Overall	24.1	8.8	9.5	7.5	6.8	6.0

Figure 2 illustrates the Handover Failure Rate comparison (Table 3) using a line graph for all six techniques across varying speeds

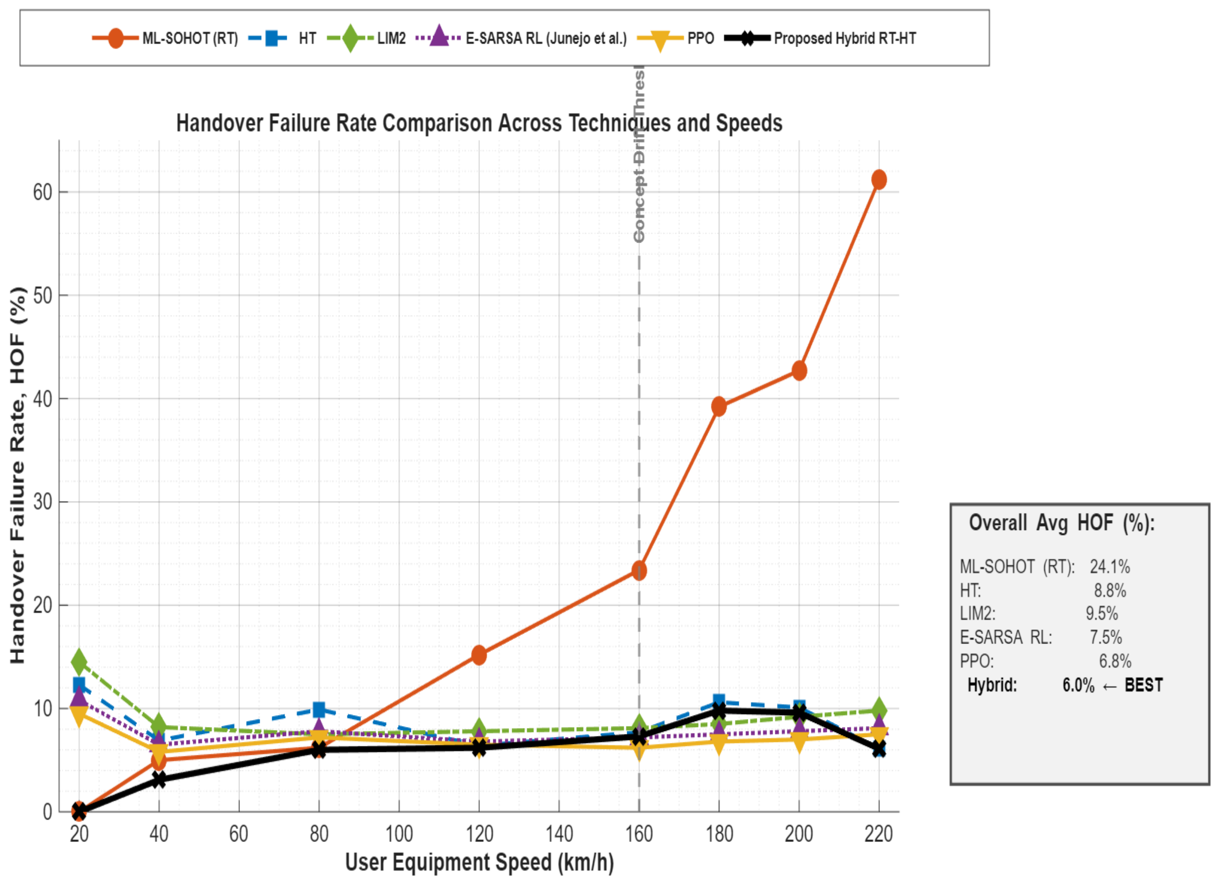

Figure 1: Handover Failure Rate Comparison across All Techniques and Speeds

Table 3 and Figure 1 reveals several important observations:

Static RT (ML-SOHOT) Performance

The static RT technique demonstrates excellent performance at low speeds (0.0% at 20 km/h) because the model was trained on data that includes these conditions. On the other hand, as speed moves above the training speed (160 km/h), HOF rises drastically from 23.4% at 160 km/h to 61.2% at 220 km/h, a 161% rise in degradation. This is due to the fact that the static method cannot cope with varying network conditions, hence proving the major drawback of offline learning (Alraih et al., 2025).

HT Performance

The HT technique shows incremental learning capabilities, maintaining HOF below 11% under untrained conditions. Nevertheless, it suffers from the cold start problem, as shown by HOF at 20 km/h the HT technique has 12.3%. As more data becomes available, the technique learns and adapts, reducing HOF from 12.3% at 20 km/h to 6.1% at 220 km/h — a 50% reduction. This confirms the adaptive capability of incremental learning approaches (Ghasemkhani et al., 2025).

LIM2 Performance

The LIM2 technique maintains relatively stable HOF across speeds (7.5-14.5%), but consistently underperforms compared to more advanced approaches. The overall HOF of 9.5% is 37% higher than the proposed hybrid technique's 6.0%.

E-SARSA RL (Junejo et al., 2025) Performance

The E-SARSA RL technique achieves better performance than LIM2, with HOF ranging from 6.5-10.8% (overall 7.5%). However, it still underperforms compared to the proposed hybrid technique (6.0%), representing a 20% improvement by the hybrid technique.

PPO Performance

The PPO-based technique demonstrates the strongest performance among the baseline techniques, with HOF ranging from 5.8-9.5% (overall 6.8%). Despite being a deep reinforcement learning approach, it still underperforms the proposed hybrid technique by 12%.

Proposed Hybrid RT-HT Performance

The proposed hybrid RT-HT technique achieves the lowest overall HOF of 6.0%, representing substantial improvements over all baselines, because it used the capability of RT model (offline learning (to mitigate a cold start problem, as well HT model (online learning) for adapting capability.

Proposed Hybrid RT-HT Technique Performance Under Concept Drift

Table 4 presents the proposed hybrid RT-HT technique performance in concept drift conditions against the static RT model using average HOF for user equipment speeds beyond RT's training conditions. Concept drift considered in this study when UE speed exceeds 160 km/h, which is beyond the RT model's training domain.

Table 4: Proposed Hybrid RT-HT Technique Improvement Under Drift Conditions

Speed (km/h)	ML-SOHOT (RT) HOF (%)	Proposed Hybrid RT-HT HOF (%)	Improvement (%)
180	39.2	9.8	75.0
200	42.7	9.6	77.5
220	61.2	6.1	90.0
Average	47.7	8.5	82.2

Table 4 shows that the proposed hybrid RT-HT technique achieves 82.2% average reduction in handover failure compared to the static RT model under concept drift conditions. The improvement increases with speed, reaching 90.0% at 220 km/h, confirming that the proposed Hybrid RT-HT approach advantage becomes more pronounced under more severe drift conditions.

Handover Latency (HOL) Analysis

Handover Latency measures the total time from handover trigger to completion. Table 5 presents the average HOL for each technique over a simulation time and across all mobile speeds.

Table 5: Handover Latency by Speed and Technique

Speed (km/h)	ML-SOHOT (RT) (ms)	HT (ms)	LIM2 (ms)	E-SARSA RL (ms)	PPO (ms)	Proposed Hybrid RT-HT (ms)
20	3.0	10.0	10.2	8.8	8.5	3.0
40	5.0	9.5	9.6	8.2	8.1	4.8
80	5.1	7.4	7.3	7.7	6.7	5.0
120	7.0	6.2	6.4	6.5	6.1	5.6
160	8.3	5.6	6.7	5.7	5.0	5.4
180	8.9	3.8	6.1	4.2	3.5	3.4
200	9.3	2.8	5.4	3.2	2.6	2.7
220	11.5	2.5	5.2	2.8	2.5	2.5
Overall	7.3	6.0	7.1	5.9	5.4	4.1

Figure 2 illustrates the Handover Latency comparison (Table 5) using a line graph for all six techniques across varying speeds

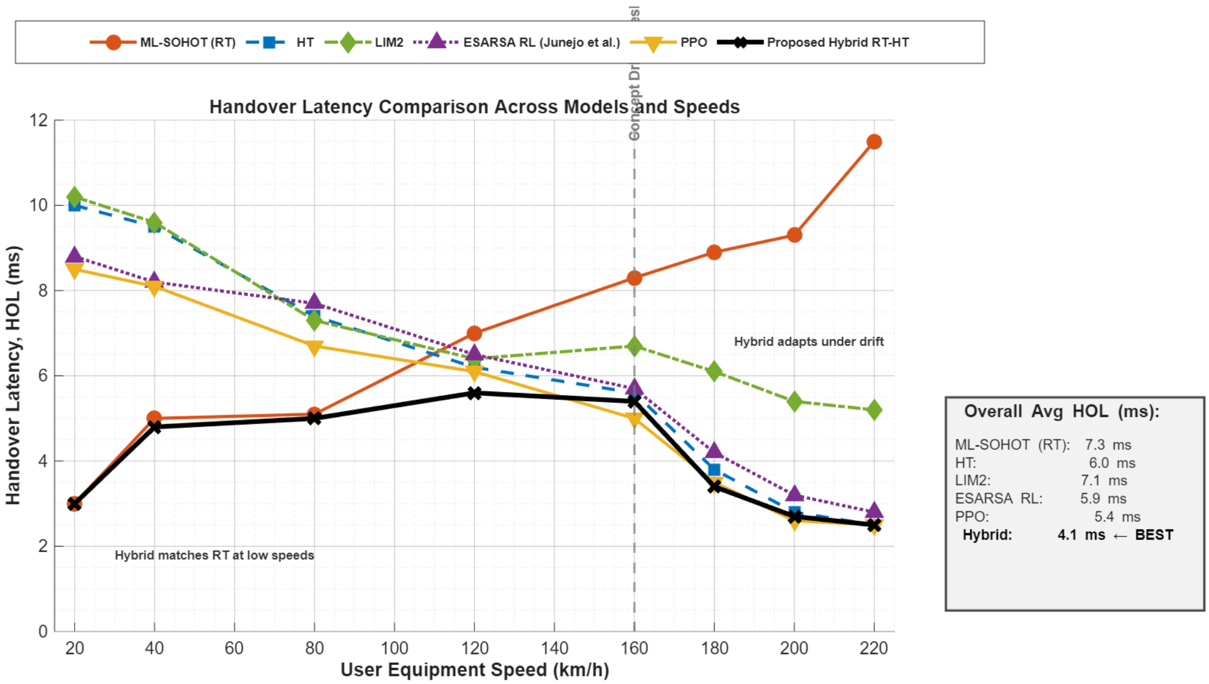

Figure 2: Handover Latency Comparison Across Techniques and Speeds

Table 5 and Figure 2 show HOL (ms) for all techniques across speeds ranging from 20 to 220 km/h. The static RT technique (ML-SOHOT) demonstrates relatively low latency at low speeds (3.0 ms at 20 km/h) because the technique was trained on data that includes these conditions. However, as speed increases beyond the training domain (160 km/h), HOL increases dramatically from (8.3 ms) at 160 km/h to (11.5 ms) at 220 km/h a 38.6% increase. This degradation occurs because the static technique cannot adapt to the changing network conditions, leading to delayed handover decisions and increased completion times. The HT, LIM2, E-SARSA RL, and PPO techniques demonstrate a cold start problem, while as more data become available, the techniques learn and adapt, resulting in decreasing HOL showing adaptability as more samples arrived. The E-SARSA RL technique by Junejo et al. (2025), which employs UKF for RSRP prediction and E-SARSA for target cell selection, achieves better latency performance than LIM2 with an average HOL value of (5.9 ms) because of its advanced E-SARSA reinforcement learning algorithm, while the PPO-based technique (Voigt et al., 2024) demonstrates the strongest performance among the baseline techniques with an average value of (5.4 ms).

The proposed hybrid RT-HT technique demonstrates the lowest overall HOL value of 4.1 ms, which is 44% lower than RT (7.3 ms), 32% lower than HT (6.0 ms), 42% lower than LIM2 (7.1 ms), 31% lower than E-SARSA RL (5.9ms), and 24% lower than PPO (5.4 ms).

Handover Interruption Time (HIT) Analysis

Handover Interruption Time represents the duration of service disruption during handover. Table 6 presents the average HIT for each technique over a simulation time and across all mobile speeds.

Table 6: Handover Interruption Time by Speed and Technique

Speed (km/h)	ML-SOHOT (RT) (ms)	HT (ms)	LIM2 (ms)	E-SARSA RL (ms)	PPO (ms)	Proposed Hybrid RT-HT (ms)
20	0.5	2.5	2.2	2.0	1.8	0.5
40	0.9	1.8	2.1	1.9	1.7	0.8
80	1.2	1.7	2.2	1.9	1.8	1.1
120	1.9	1.5	2.3	2.0	2.0	1.4
160	3.0	2.1	2.4	2.1	2.0	2.0
180	4.6	2.7	2.3	2.2	2.1	2.7
200	4.9	2.9	2.4	2.3	2.2	2.8
220	5.3	3.0	2.6	2.3	2.3	2.9
Overall	2.8	2.3	2.4	2.1	2.0	1.8

Figure 2 illustrates the Handover Interruption Time comparison (Table 6) using a line graph for all six techniques across varying speeds

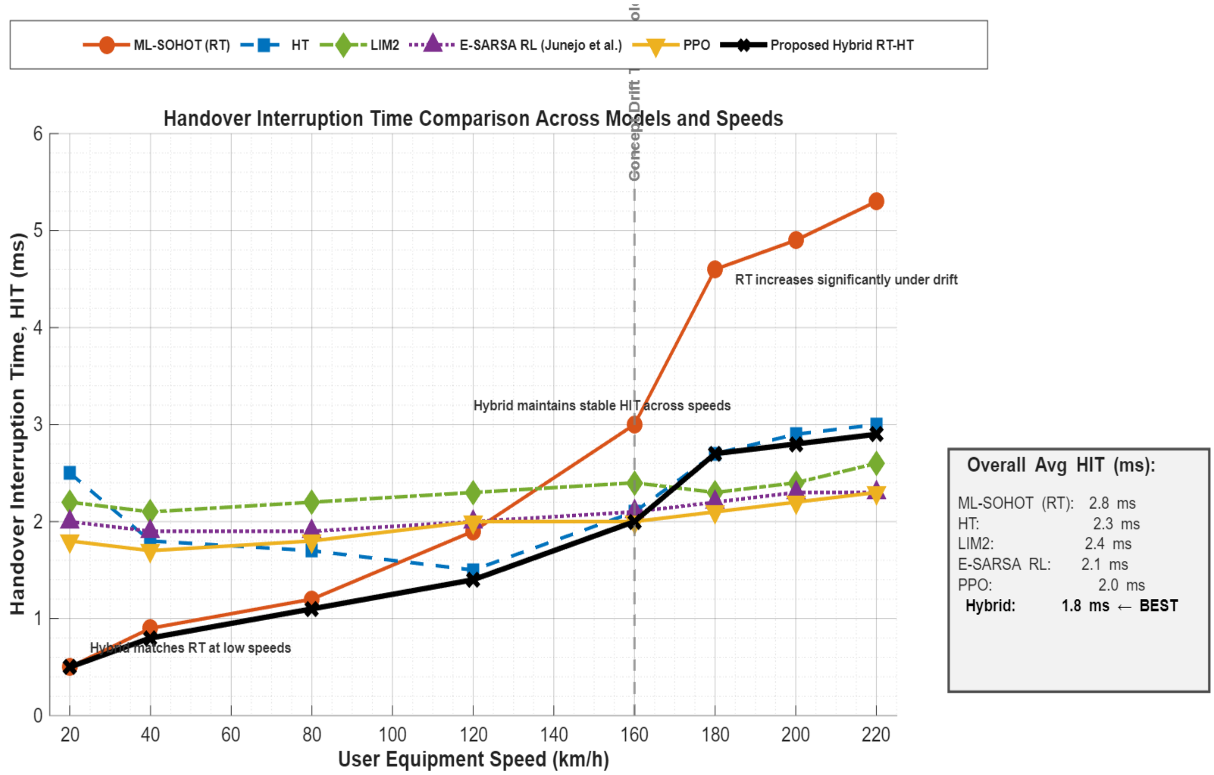

Figure 3: Handover Interruption Time Comparison Across Techniques and Speeds

In Table 6 and Figure 3, the values for HIT (ms) for all the techniques for the varying user equipment speeds of 20 to 220 km/h have been presented. RT technique with static conditions faces a significant rise in HIT while dealing with drifting, which lies between 4.6-5.3 ms for the high-speed cases, thus resulting in a long interruption in service. On the other hand, HIT for HT, LIM2, E-SARSA RL, PPO, and Hybrid RT-HT remains relatively constant.

The Hybrid RT-HT technique achieves the minimum HIT value of 1.8 ms which is 36% lower than RT (2.8 ms), 22% lower than HT (2.3 ms), 25% lower than LIM2 (2.4 ms), 14% lower than E-SARSA RL (2.1 ms), and 10% lower than PPO (2.0 ms). Thus, the low HIT values reflect less interruption in service.

Handover Ping-Pong (HOPP) Analysis

Handover Ping-Pong Rate measures unnecessary back-and-forth handovers between cells within a very short time (400 ms window). Table 7 presents the average HOPP for each technique over the simulation time and across all mobile speeds.

Table 7: Average Handover Ping-Pong Rate by Speed and Technique

Speed (km/h)	ML-SOHOT (RT) (%)	HT (%)	LIM2 (%)	E-SARSA RL (%)	PPO (%)	Proposed Hybrid RT-HT (%)
20	0.0	1.2	1.5	1.2	1.0	0.0
40	0.0	2.5	1.8	1.5	1.3	0.0
80	1.6	2.8	2.5	2.0	1.8	1.4
120	3.3	3.1	3.2	2.8	2.5	2.9
160	11.7	5.8	5.5	4.5	3.8	5.6
180	13.5	4.5	5.0	4.2	3.2	4.4
200	14.2	3.4	4.5	3.5	2.8	3.4
220	14.5	2.5	4.0	3.0	2.5	2.5
Overall	7.4	3.2	3.5	3.0	2.8	2.5

From the analysis provided in Table 7, it can be observed that the proposed hybrid RT-HT technique has the lowest overall average HOPP (2.5%), which is 66% better than RT (7.4%), 22% better than HT (3.2%), 29% better than LIM2

(3.5%), 17% better than E-SARSA RL (3.0%), and 11% better than PPO (2.8%).
At lower speeds (20-40 km/h), the proposed Hybrid RT-HT technique gives zero HOPP similar to RT but better than all other baselines. Under drift conditions (180-220 km/h), the proposed Hybrid RT-HT performance is better than RT (13.5-14.5%), better than LIM2 (4.0-5.0%), better than E-SARSA RL (4.2-4.5%), similar to HT's HOPP range (2.5-4.5%), and slightly better than PPO (2.5-3.2%).

Overall Performance Summary
Table 8 presents the overall performance of all techniques using five handover Key Performance Indicators.

Table 8: Overall Performance Summary

Technique	HOF (%)	HOPP (%)	HIT (ms)	HOL (ms)
ML-SOHOT (RT)	24.1	7.4	2.8	7.3
HT	8.8	3.2	2.3	6.0
LIM2 (Karmakar et al., 2022)	9.5	3.5	2.4	7.1
E-SARSA RL Junejo et al. (2025)	7.5	3.0	2.1	5.9
PPO (Voigt et al., 2024)	6.8	2.8	2.0	5.4
Proposed Hybrid RT-HT	6.0	2.5	1.8	4.1

From the analysis of Table 8, the proposed Hybrid RT-HT technique achieves the best balance across all five KPIs:

1. Lowest HOF (6.0%): 75% improvement over RT, 32% over HT, 37% over LIM2, 20% over E-SARSA RL, and 12% over PPO
2. Lowest HOPP (2.5%): 66% improvement over RT, 22% over HT, 29% over LIM2, 17% over E-SARSA RL, and 11% over PPO
3. Lowest HIT (1.8 ms): 36% improvement over RT, 22% over HT, 25% over LIM2, 14% over E-SARSA RL, and 10% over PPO
4. Lowest HOL (4.1 ms): 44% improvement over RT, 32% over HT, 42% over LIM2, 31% over E-SARSA RL, and 24% over PPO

Table 9: Proposed Hybrid RT-HT Technique Improvements Over Best Baseline (PPO) Technique

Metric	Best Baseline	Proposed Hybrid RT-HT	Improvement
HOF	6.8% (PPO)	6.0%	11.8%
HOPP	2.8% (PPO)	2.5%	10.7%
HIT	2.0 ms (PPO)	1.8 ms	10.0%
HOL	5.4 ms (PPO)	4.1 ms	24%

Discussion
Experimental results clearly show the performance of the proposed hybrid RT-HT technique as an effective tool to deal with concept drift in 5G handover optimization.
First, the static RT model experiences degradation of HOF by 623% (from 6.6% trained environment to 47.7% untrained environment) due to concept drift (out of RT model training domain). This result proves the core restriction of static model in 5G, which was shown in the study of Alraih et al. (2025). The drastic increase in handover failures in untrained condition demonstrates that static techniques are incapable to handle the dynamic nature of 5G networks, particularly in high-mobility scenarios where signal conditions change rapidly.
Second, the HT model shows good learning capabilities and ensures that HOF stays below 11% under conditions of concept drift. This proves the ability of HT to perform incremental learning, which was stated by Ghasemkhani et al. (2025) and Corcuera Bárcena et al. (2022). However, the cold start problem remains a limitation, as evidenced by the 12.3% HOF at 20 km/h. This confirms that while online learning models can adapt, they require sufficient training data before achieving optimal performance.
Third, the proposed hybrid RT-HT technique demonstrates 82.2% decrease in HOF under drift conditions, mitigate the cold start problem (0.0% HOF at 20 km/h) by using RT model, and shows the best results across all five KPIs. The superiority of the mechanism is provided by the dual-indicator approach to detect concept drift based on out-of-training domain (e.g., speed threshold (>160 km/h) and error-based detection (MAE_RT > MAE_HT). This mechanism is an extension of the Error Intersection Approach (Baier et al., 2020) and the mechanism of alternating learners (Xu et al., 2017) in the field of 5G handover optimization.
Fourth, the HOL and HOPP analysis proved the efficiency of the proposed mechanism. The proposed Hybrid RT-HT technique gives 44% improvement in HOL compared to RT (latency goes down to 2.5 ms at 220 km/h). In addition, the proposed hybrid RT-HT technique gives 66% improvement in HOPP compared to static RT model. The ping-pong rate is low and the successful handover execution is confirmed by HIT being consistently equal to 1.8 ms.

Fifth, our comparison with other baselines techniques confirm the superiority of the proposed hybrid RT-HT technique in all the 5 handover key parameters indicators. Compared to the base paper (Alraih et al., 2025), the proposed hybrid RT-HT technique offers a number of important benefits. The technique provides online learning capability (HT component), ability to deal with concept drift, solving of the cold start problem, continuous adaptation without retraining, and 82.2% reduction in HOF under drift conditions. Additionally, the technique outperforms more recent approaches including LIM2, E-SARSA RL, and PPO, demonstrating its position as a technique for 5G handover optimization.

The practical significance of the study is obvious. The proposed hybrid RT-HT technique allows predicting data very fast (RT can process 1,300,000 observations per second) (Alraih et al., 2025), provides incremental learning without retraining, reliable performance after deployment, and concept drift handling. Unlike RL-based approaches that require training and exploration phases, our technique works immediately using pre-trained RT, making it suitable for real-world deployment where operators need solutions that work from day one.

CONCLUSION

In conclusion, this paper presented a proposed performance-based Hybrid RT-HT technique for handover optimization in 5G NR. The mechanism uses dual-indicator drift detection combining speed and performance-based to identify concept drift and dynamically select between a pre-trained Regression Tree and an online Hoeffding Tree.

The simulation results show the effectiveness of the proposed hybrid RT-HT technique under controlled 3GPP-based conditions. However, despite the promising nature of these results and their implications for future real-time 5G implementation, additional testing of the approach in real network settings is required.

Future research should focus on extension to multi-technique ensembles, integration of Explainable AI and validation of the solution in real-life 5G networks.

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