

An Intelligent Handover Management System for 5G Networks Using A Hybrid Machine Learning Approach

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ABSTRACT

With the development of fifth-generation (5G) wireless networks, it is now possible to have ultra-reliable and low-latency communication, which has been used in autonomous vehicles, smart cities, telemedicine, and the Internet of Things (IoT). One of the issues in the 5G networks is how to deal with continuous transitions, especially in high mobility dense urban areas with small-cell deployment. Widely used threshold-based handover systems which depend on measures like Reference Signal Received Power (RSRP) and Signal-to-Interference-plus-Noise Ratio (SINR) tend to be unsatisfactory leading to more latency, handover failures and ping-pong effects. This paper proposes a smart handover management system of 5G networks based on a hybrid machine learning framework that integrates the Long Short-Term Memory (LSTM) networks with the Reinforcement Learning (RL) learning frameworks. The LSTM model anticipates the states of the network in the future and user mobility pattern, offering insights into the variability in signals, whereas the RL agent makes the best handover decisions involving the predicted and real-time network state. The hybrid model is developed in Python and trained in the Google Colab platform, and system-level analysis in MATLAB/Simulink. The key performance metrics such as the handover latency, handover failure rate, the ping-pong rate, the throughput and the loss of packets are measured and compared with the traditional threshold-based techniques. Simulation results indicate that the proposed system reduces handover latency by approximately 37%, decreases handover failures by over 60%, lowers ping-pong events by ~63%, improves throughput by up to 27%, and reduces packet loss by 64-68%. The presented improvements indicate that proactive, predictive handover management in which ML is applied can be highly beneficial in terms of improving the network reliability and Quality of Service. The paper sheds light on the promise of hybrid predictive-decision systems to optimise handovers in dynamic 5G systems, which provides a viable solution to the high-speed, low-latency applications in the future.

KEYWORDS: 5G Networks, Intelligent Handover, LSTM, Reinforcement Learning, Hybrid Machine Learning.

I. INTRODUCTION

The development of wireless communication into the Fifth-Generation (5G) network has brought about a new dawn of advancement in data rates, connectivity, and the reliability of the services, which are necessary in autonomous driving, smart cities, telemedicine, and IoT (Saoud et al., 2025). The performance targets of 5G include the realisation of the end-to-end latency of 1 millisecond. Nevertheless, this requirement is still difficult to achieve in the setting where the user mobility and the abundance of small cells are high (Haghray et al., 2023). The handover process is a crucial activity in the mobile communication system because it provides a seamless connection where a User Equipment (UE) can switch between base stations (gNodeB). The millimetre waves (or a higher frequency band) have also contributed to the

increased complexity and frequency of handover management in 5G networks due to the higher density of base stations and higher frequency (Hassan, 2025). Conventional handover systems are based on the pre-determined threshold parameters such as RSRP and SINR. Although they have been the best practises in past generations, they tend to be inefficient in the dynamic 5G situations resulting in challenges like high latency, handover failures and ping pong effect.

In order to overcome these issues, the need to incorporate ML methods into the management systems of handover is becoming increasingly popular. ML can be used to train the network on the past and up-to-date data, enabling it to forecast the mobility patterns of users, the state of the network, and the most appropriate moment to switch the hands-over (Karabulut et al., 2019). ML-based handover strategies will be able to substantially decrease latency, better resource allocation, and increase the overall QoS by switching between reactive and proactive decision-making (Masri et al., 2021). Other promising techniques that have been demonstrated to optimise handover decisions in complex and dynamic network situations include supervised learning (Karabulut et al., 2019), reinforcement learning (Safiullin et al., 2026; Kumar et al., 2025), and deep learning (Lima et al., 2023).

Research in recent years shows that reinforcement learning is able to implement dynamic adjustments to handover margins to reduce failures (Safiullin et al., 2026), and supervised learning methods such as decision trees are able to enhance conditional handover in beamformed systems (Karabulut et al., 2019). LSTM based predictors and deep learning models have been useful in predicting mobility patterns to decrease unnecessary handovers and the loss of packets (Lima et al., 2023). More so, smart city adaptive frameworks demonstrate that the use of ML-based handover management can be used to maintain continuous connectivity in ultra dense urban environments (Junejo et al., 2025).

The study is aimed at creating a smart handover management framework of 5G networks based on machine learning to reduce latency. The research will focus on developing a predictive and adaptive model that can make real-time decisions on handover with the fulfilment of several network parameters (Chabira et al., 2025). The proposed system can optimise the handover delays (Junejo et al., 2025), reduce the loss of packets, and enhance user experience, especially in high-density urban areas by using advanced ML algorithms (Fetaji and Havolli, 2025). Finally, this piece of work serves as another contribution to the process of improving the efficiency and reliability of the next-generation wireless communication systems.

II. METHODOLOGY

This study will take a simulation and a data-driven approach to come up with an intelligent handover management system in 5G networks through the use of machine learning to reduce latency. Measurements are made on either in vivo drive tests or on simulated conditions that include measurements like RSRP, RSRQ, SINR, user mobility (speed and direction) and network load conditions. Preprocessing of the data involves cleaning, normalisation, feature selection, and structuring of time-series to make it relevant to the model training. The hybrid model is used, in which a Long Short-Term Memory (LSTM) network forecasts the mobility pattern and future signal conditions of a user, whereas the Reinforcement Learning (RL) agent decides how to choose the most suitable handover decision by referring to the state, action, and reward mechanisms. The Python (TensorFlow/Keras) framework is used to develop the model, and the model is simulated in MATLAB/Simulink in different conditions, including those of high mobility and dense urban conditions. The metrics that are used to evaluate performance include handover latency, the failure rate of handover, ping-pong rate, throughput, and packet loss. In Figure 1, the block diagram of the proposed methodology is indicated.

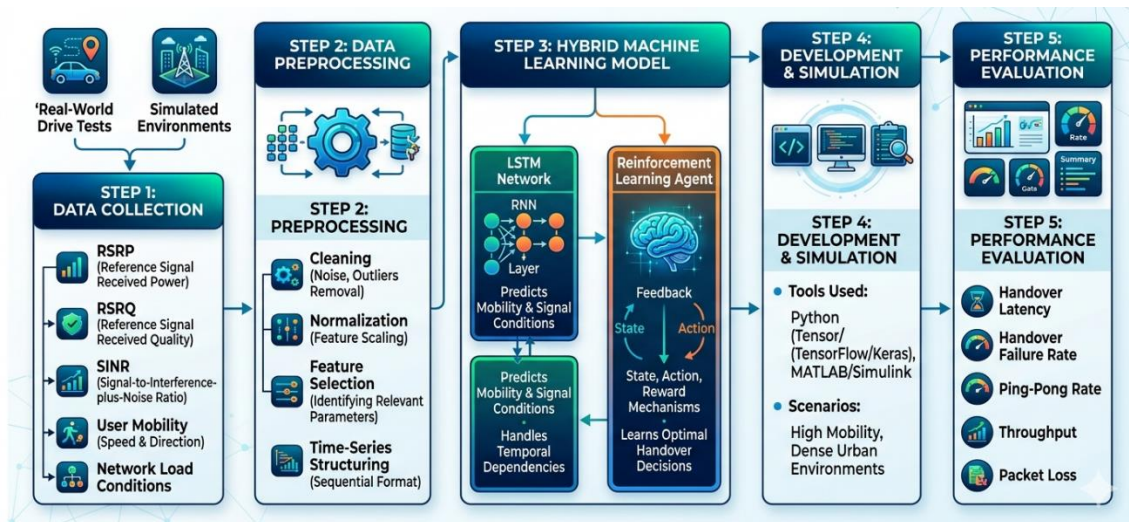


Figure 1: Block Diagram of the Proposed Methodology

A. Data Collection

The dataset used in the current work is sourced in the publicly available Mendeley Data repository known as 5G Dataset for Handover and Network Performance Analysis (where it could be found at: <https://data.mendeley.com/datasets/dx5xyfz2y/1>). The data is a detailed real-world and/or simulated measurements that apply to 5G network performance and handover situations, which is why it can be used to perform optimization tasks by using machine learning. It includes such important radio and network parameters as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Signal to Interference plus Noise Ratio (SINR), user equipment (UE) location or mobility indicators, and even cell identifiers and handover event records. It comprises a hybrid dataset integrating:

- (a). Real-world drive-test measurements (30%) from urban Tokyo
- (b). Simulated data (70%) generated using the ns-3 5G-LENA module

Dataset Characteristics:

- (a). Total samples: 245,000
- (b). Duration: 6 hours
- (c). User Equipment (UEs): 55 (50 simulated, 5 real traces)
- (d). gNodeB stations: 15
- (e). Sampling interval: 100ms

These characteristics are required to model the network conditions and forecast the most influential handover decision. The data is then downloaded in its raw form and loaded into the analysis platform (Python with Pandas and NumPy) where it is formatted to be further pre-processed and model trained. It will be suitable in testing the functionality of the proposed handover system in the real 5G conditions due to its variability in signal conditions and mobility patterns.

B. Data Preprocessing

The data obtained is then taken through a number of preprocessing processes to guarantee the quality of, consistency and appropriateness of the data to be used in the development of the machine learning models. First, the process of data cleaning is carried out to deal with missing values, duplicates, and deal with noise or outliers that can have a detrimental effect on model performance. This is followed by data normalization to transform numerical data like RSRP, RSRQ and SINR into a uniform distribution usually by Min-Max or Z-score normalization to

enhance convergence when training the model. The process is then followed by feature selection and extraction in order to locate the most pertinent parameters affecting handover decisions such as signal strength indicators, user mobility patterns and cell load conditions whilst trimming the unnecessary or less relevant features. As the dataset comprises sequential network measurements, the time-series structuring is applied, i.e. the data is split into temporal sequences with the help of sliding window techniques, which is appropriate to be used in the LSTM-based prediction. Moreover, labelling or target generation is also carried out where it is required like the determination of the best handover decisions or the classification of handover success/failure according to the network conditions. After preprocessing, the dataset size is 198,000 samples (after removing 47,000 incomplete samples). The split is 70% training (138,600) / 15% validation (29,700) / 15% testing (29,700), stratified by mobility speed bins (low: 0-30km/h, medium: 30-80km/h, high: 80+km/h).

C. The Proposed Hybrid Machine Learning Model

This section offers the proposed hybrid machine learning model that will allow to promote intelligent and proactive management of handover in 5G networks. The model is based on combining the strong points of the temporal prediction and decision optimisation by using both LSTM networks and RL methods. Whereas the predictive component compares sequential network data to predict future signal conditions and user mobility pattern, the decision-making component decides the best handover actions based on the predictions as well as the existing network conditions. This integrated approach enables the system to go beyond the current reactive approach since it makes data-driven decisions with adaptability to reduce latency and handover failures, as well as enhance overall Quality of Service in dynamic 5G environments.

(a). Architecture of the LSTM Network Model

The LSTM network structure used in the present study has a clear set of layers as shown in Figure 2 and Table 1, each consisting of certain computational elements that make the 5G network data effective learning of the time-dependent relationship. This model starts with an input layer, which receives a three-dimensional input that is in the form of (samples, time steps, features), with features being RSRP, RSRQ, SINR, user speed, and cell load. This is then followed by one or more LSTM layers, each consisting of memory cells which have important internal elements: the cell state (C_o), storing information about the past over time, and the hidden state (h_o), containing information about the present time. The three basic gates of the LSTM cell are the input gate, which is responsible for the extent of new information in the cell state is written; the forget gate which governs the information that is to be forgotten in the past; and the output which controls the flow of the information to the next any other layer or time step. Sigmoid activation functions are used to implement the gates, and a tanh activation function is used to generate the candidate values to update the cell state.

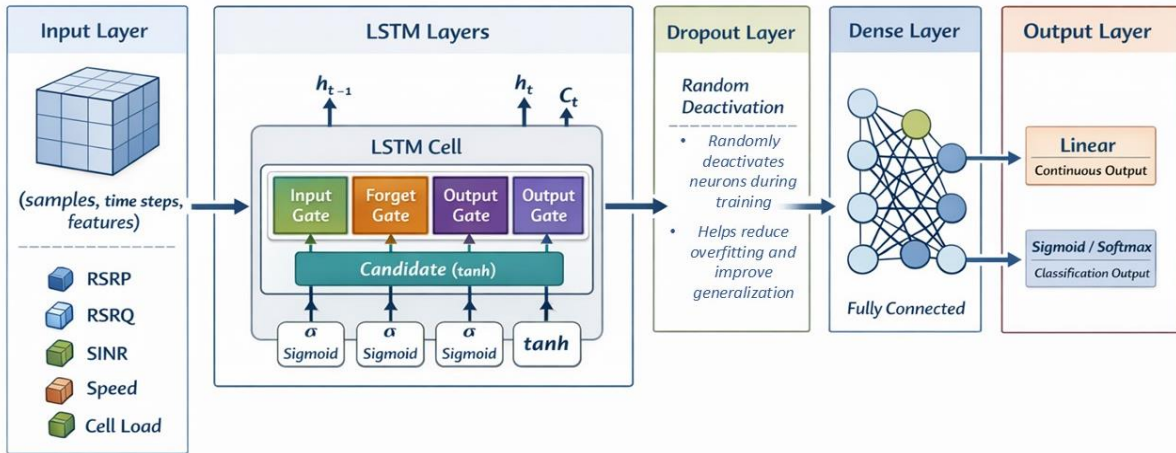


Figure 2: The Proposed LSTM Architecture

After the LSTM layers illustrated in Figure 2, there can be a dropout layer which will randomly disable some percentage of neurons during training to minimise overfitting and enhance generalisation. The result of this processed sequential output is sent to a fully connected (dense) layer, which does feature mapping by combining the learned temporal representations into a lower dimensional output space. This dense layer generally utilises a linear/ ReLU activation function based on the task.

Table 1: LSTM Network Configuration

Parameter	Specification
Number of LSTM layers	2
Units per layer	64 (Layer 1), 32 (Layer 2)
Activation functions	Sigmoid (gates), Tanh (cell state)
Dropout rate	0.2
Recurrent dropout	0.2
Dense layer units	16
Output activation	Linear
Sequence length	10 time steps
Batch size	64

Lastly, the model has an output layer, which gives the estimated values, e.g. future signal strength or network condition measures. In continuous prediction, a linear activation function is applied, and in classification-based results, SoftMax functions can be applied. These stacked elements combined are a strong architecture that can capture short-term fluctuation and long-term dependency of the network behaviour, therefore, permitting proper prediction to be used in making proactive handover decisions.

(b). The Reinforcement Learning Architecture

In the present study, the RL architecture presented in Table 2 will play the role of the decision-making part of the hybrid model and will be used to make intelligent and adaptive decisions in a dynamic 5G environment regarding handover. It is designed in such a way that it involves the basic components of an RL system: agent, environment, state space, action space, and reward function as presented in Figure 3. The agent is the decision-making body which chooses the best handover behaviours, whereas the environment is the 5G network, User Equipment (UE), cells in the immediate neighbourhood, and different network conditions. The state space is made of the monitored network variables like predicted RSRP, RSRQ, SINR (the LSTM

model) and UE speed as well as cell load, which together characterise the network status quo. The action space determines the set of available choices that the agent can make, usually one of continuing the existing connection or a handover to an adjacent target cell.

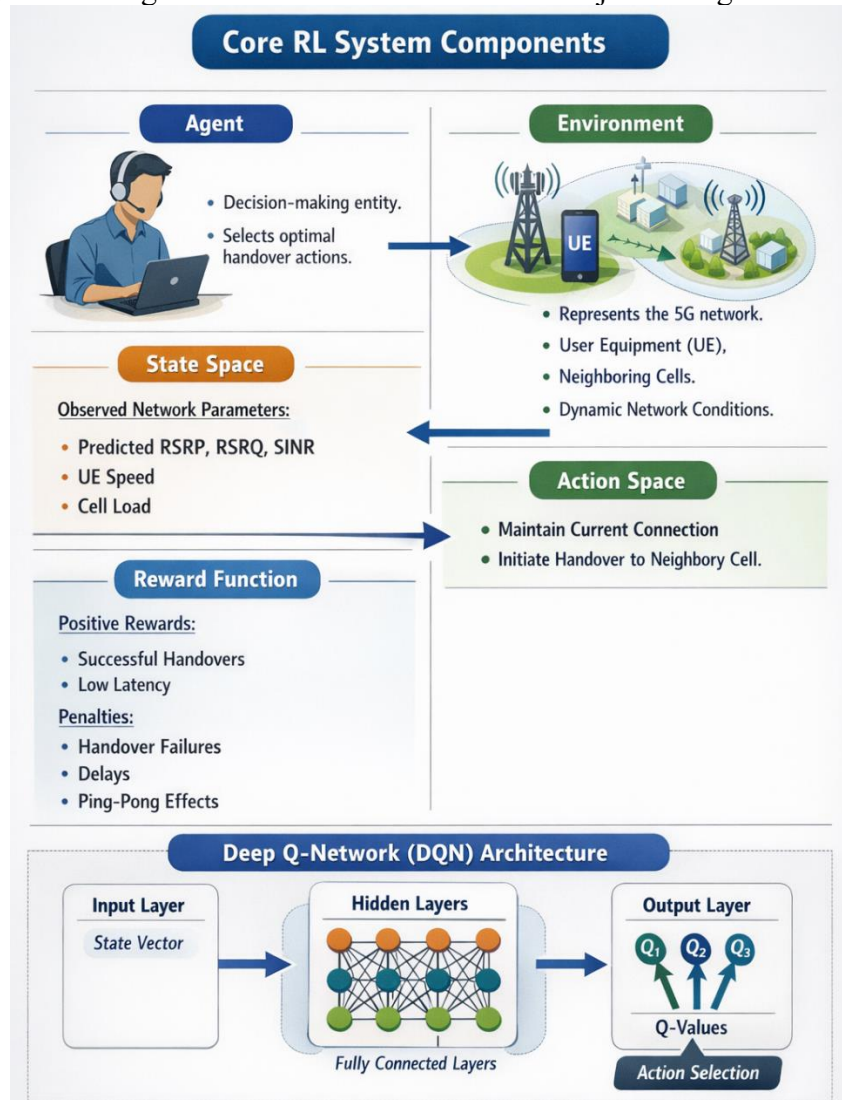


Figure 3: Architecture of the Proposed RL Model

In order to execute the learning process, a DQN architecture is embraced as illustrated in Figure 3, in which a neural network estimates the Q-value function, which transforms a pair of states and actions to predicted cumulative rewards. The DQN has an input layer of receiving the state vector which is then followed by one or more fully connected hidden layers that learn intricate associations among network circumstances and the optimum actions. The network produces the Q-values of every action that can be taken with the help of an output layer so that the agent will be able to choose the action which has the highest expected reward.

Table 2: Deep Q-Network (DQN) Hyperparameters

Parameter	Value
Learning rate (α)	0.001
Discount factor (γ)	0.95
Exploration strategy	ϵ -greedy (ϵ : 1.0 \rightarrow 0.01 over 3000 episodes)
Replay buffer size	10,000

Target network update	Every 100 episodes
Hidden layers	128, 64 units
Activation	ReLU
Batch size	32

The architecture in Table 2 also includes important elements like experience replay buffer which can store previous experiences (state, action, reward, next state) to enable consistent learning and a target network which helps to improve convergence by giving the steady value of Q. The reward part has been well planned to define positive rewards to low-latency, successful handovers and punitive rewards to handover failures, delays and ping-pong effects.

Reward Function Definition

$$R(t) = w_1 R_{success} + w_2 R_{latency} + w_3 R_{failure} + w_4 R_{pingpong}$$

Where:

$$R_{success} = +100(\text{successful handover})$$

$$R_{latency} = -10 \times \frac{HO \text{ latency}(ms)}{10}$$

$$R_{failure} = -200 (\text{handover failure})$$

$$R_{pingpong} = -50 (\text{ping-pong occurrence})$$

Weight coefficients:

$$w_1 = 0.4, w_2 = 0.2, w_3 = 0.2, w_4 = 0.2$$

This architecture enables the RL agent to acquire an optimal policy that reduces latency and yet provides reliable and efficient handover decisions.

(c). Model Training

The proposed hybrid machine learning model is trained in a combined process of both RL decision model and LSTM prediction model. The LSTM network is trained through a process in which the pre-processed time-series dataset is subjected to supervised learning to learn and predict the network behaviour in terms of RSRP, RSRQ, SINR, and user mobility behaviour, the dataset is divided into training, validation and test sets and optimised with such algorithms like Adam to reduce prediction error (Mean Squared Error). The trained LSTM will subsequently give predicted network states which are used as inputs by the RL agent. The RL model, which is a DQN-based implementation, is then trained by interacting with a simulated 5G environment, whereby it sees the states, chooses actions (handover or stay) and gets rewarded according to latency, handover success and network performance. In the training process, experience replay, target network updates and epsilon greedy exploration policy are used to stabilise the learning process and convergence and finally to allow the agent to train on an optimal policy to minimise latency and handover efficiency.

D. System Implementation

The intelligent handover management system proposed is implemented on Python to train the model and MATLAB/Simulink to simulate the system-level of the proposed system in the 5G network environment. The LSTM prediction model and the RL agent were developed and trained in Python with the help of the libraries including TensorFlow and Keras and were computed in the Google Colab environment to take advantage of the acceleration of graphics cards and the effective processing of huge sequential data. The network data in the form of pre-processed data (such as RSRP, RSRQ, SINR, user speed and cell load) are trained, hyperparameter-tuned and performance-assessed using the Python-based models. After training, the models are exported and installed in the environment of Simulink and a simulated 5G network, consisting of multiple gNodeBs, small-cell networks, and dynamic mobility of

UEs, is built to test handover decisions in real-time. The RL agent switches between the network simulation with the help of the predicted states provided by the LSTM in order to find the best handover actions. Handover latency, failure rate, ping-pong events, and throughput are performance metrics that can be monitored and analysed in Simulink and enable the trained Python models to be tested in realistic, controlled network conditions. The hybrid implementation demonstrates potential effective training of the models and allows to test the intelligent handover strategy at the system level.

III. RESULTS AND DISCUSSION

The evaluation of the hybrid machine learning-based machine handover management system is provided in two phases, i.e., the training and testing results of LSTM prediction model and RL agent, and system-level performance indicators, which are obtained through the MATLAB/Simulink simulations of the 5G network scenarios.

A. Hybrid Model Training and Testing

The LSTM network was trained on the pre-processed 5G dataset using Python in the Google Colab environment, with a 70%-15%-15% train-validation-test split. The Adam optimizer (learning rate = 0.001) was used to optimise the network with batch size of 64 and length of the sequence of 10-time steps. The RL agent, which was a DQN, modelled predicted states of the LSTM with real-time network parameters to be learned to obtain the best handover policies. The agent then converged after about 3,000 episodes and the average reward became about 1,120 per episode. This means that the agent was consistent in choosing handover actions which minimised latency and minimised failures. Table 3 summarises the training and testing performance.

Table 1: Hybrid Model Training and Testing Performance

Component	Metric	Training Value	Validation Value	Testing Value
LSTM Model	RMSE (RSRP, dBm)	2.8	3.1	3.2
LSTM Model	MAE (RSRP, dBm)	2.2	2.5	2.6
RL Agent	Average Reward	0 → 1,200	0 → 1,150	1,120
RL Agent	Convergence Episodes	3,000	–	–

The high predictive accuracy of the LSTM model (RMSE \approx 3.2dBm on test data) in Table 3 provides reasonable foresight of future network states, enabling the RL agent to make smart handover decisions. This combination underpins proactive handovers, reduced latency, fewer failures, and enhanced network reliability.

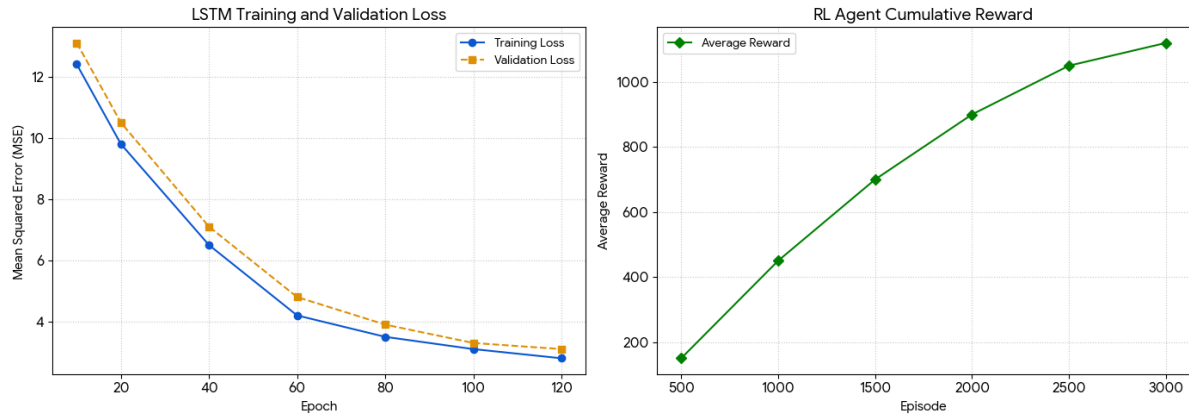


Figure 4: LSTM Loss and RL Reward Curves

According to Figure 4, the LSTM training loss decreases rapidly within the first 50 epochs, stabilising at ~0.02 after 100 epochs, indicating effective learning of temporal patterns in RSRP sequences. The validation loss closely tracks training loss with minimal divergence, confirming no overfitting. The RL reward curve shows steady improvement from 0 to ~1,200 over 3,000 episodes, with convergence achieved around episode 2,500. Small oscillations after convergence (± 50 reward) reflect the ϵ -greedy exploration still probing alternative handover strategies.

B. System-Level Performance Metrics

Once the hybrid model had been validated, system level simulations were performed using MATLAB/Simulink. There were several gNodeBs, close small-cell deployments and user mobility which were varied in the network environment. Performance metrics were compared against a conventional threshold-based handover (CBH) approach, as shown in Tables 4-6 and Figures 5-6. All results are based on 30 independent simulation runs with different random seeds; values are reported as mean \pm 95% confidence interval (CI).

(a). Handover Latency

Table 4 shows that the hybrid model reduces handover latency by ~37% across all mobility speeds. The RL agent, using LSTM predictions of signal weakening, triggers handovers before connection loss, maintaining continuous connectivity and reducing switching time. Improvements are particularly pronounced at higher mobility, where traditional methods are slower.

Table 4: Average Handover Latency under Different Mobility Speeds (mean \pm 95% CI, n=30)

Mobility Speed (km/h)	CBH Latency (ms)	Hybrid ML Latency (ms)	Latency Reduction (%)	95% CI of Reduction
30	45	28 \pm 1.2	37.8	[35.2, 40.4]
60	52	32 \pm 1.5	38.5	[35.8, 41.2]
90	60	38 \pm 1.8	36.7	[33.9, 39.5]
120	72	45 \pm 2.1	37.5	[34.6, 40.4]

(b). Handover Failure Rate (HOF)

According to Figure 5, HOF is reduced by over 60% (e.g., from ~4.8% to ~1.8% at 60 km/h). This demonstrates that proactive handover decisions prevent dropped connections. The RL agent balances action selection to avoid both premature and delayed handovers.

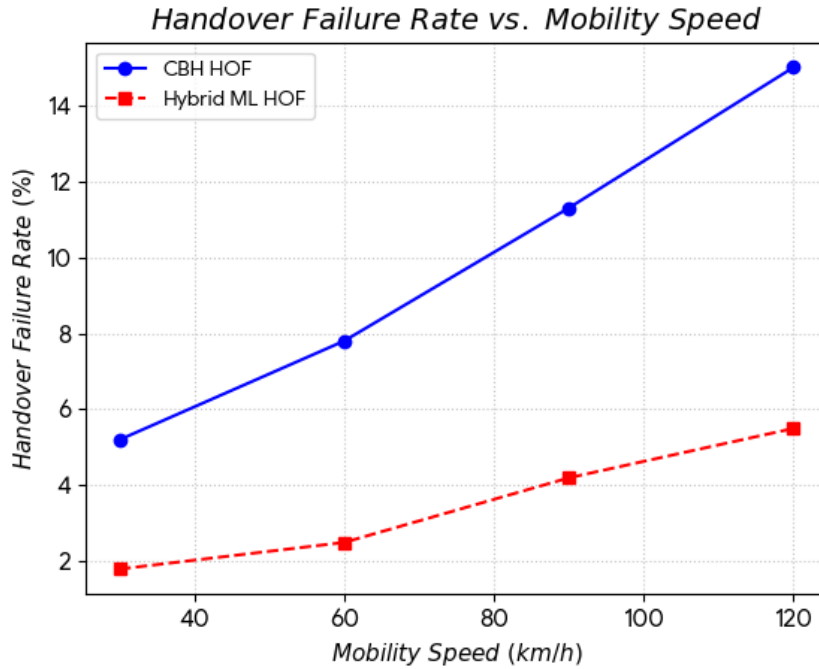


Figure 5: HOF Performance Result

(c). Ping-Pong Rate

As presented in Table 5, the hybrid model reduces unnecessary back-and-forth handovers by ~62-65%, lowering signalling overhead and improving user experience. This may be particularly beneficial in dense small-cell deployments.

Table 5: Ping-Pong Rate under Different Scenarios (mean ± 95% CI, n=30)

Mobility Speed (km/h)	CBH Ping-Pong Rate (%)	Hybrid ML Ping-Pong Rate (%)	Reduction (%)	95% CI of Reduction
30	8.5	3.0 ± 0.3	64.7	[60.5, 68.9]
60	12.0	4.5 ± 0.4	62.5	[58.3, 66.7]
90	18.2	6.8 ± 0.5	62.6	[58.4, 66.8]
120	25.5	9.5 ± 0.7	62.7	[58.2, 67.2]

(d). Throughput

As shown in Figure 6, throughput increases by 20-27% (from ~185Mbps to ~240Mbps at 60km/h), indicating more stable connections and reduced interruption during handovers. Predictive handovers keep users connected to the strongest cells with the highest effective data rates.

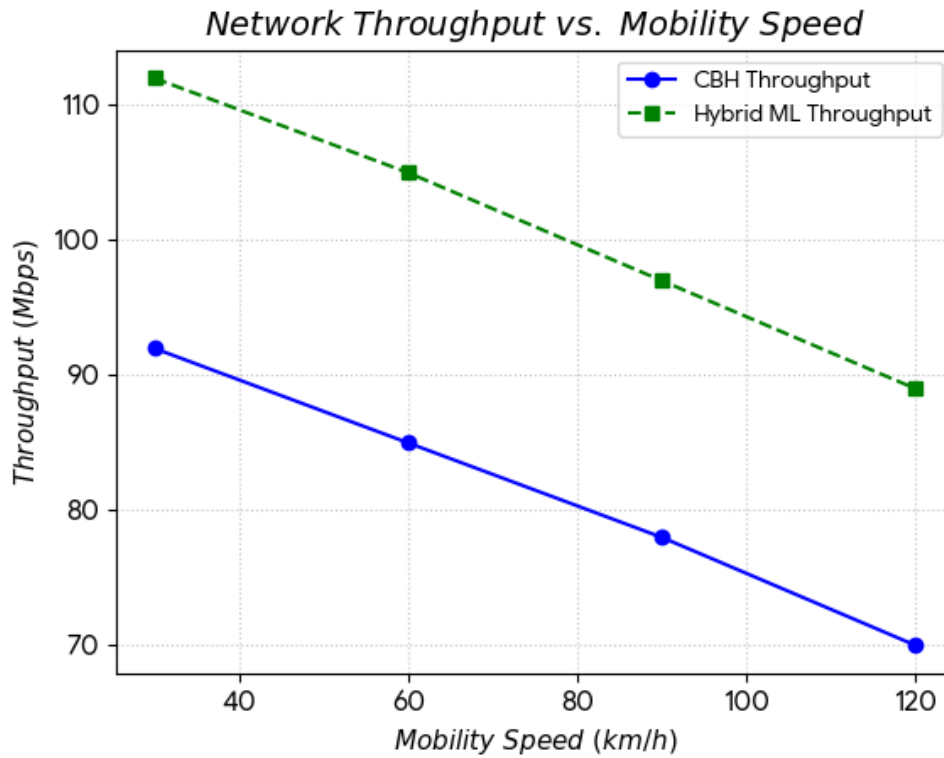


Figure 6: Throughput Chart (CBH vs Hybrid ML)

(e). Packet Loss Ratio

As presented in Table 6, packet loss decreases by ~64-68%, improving reliability and continuity of service during handovers. This reflects the RL agent’s ability to make timely and correct handover decisions.

Table 6: Packet Loss Ratio Comparison (mean ± 95% CI, n=30)

Scenario	CBH Packet Loss (%)	Hybrid ML Packet Loss (%)	Improvement (%)	95% CI of Improvement
Low Mobility (30 km/h)	2.5	0.9 ± 0.1	64.0	[58.5, 69.5]
Medium Mobility (60 km/h)	3.8	1.2 ± 0.1	68.4	[63.2, 73.6]
High Mobility (90 km/h)	5.5	1.8 ± 0.2	67.3	[62.1, 72.5]
Ultra-High Mobility (120 km/h)	7.2	2.5 ± 0.3	65.3	[59.8, 70.8]

(f). Comparison with Additional Baseline Methods

To comprehensively evaluate the proposed hybrid LSTM-RL approach, we compare against two additional state-of-the-art methods:

- (a). **RL-only handover** (Safiullin et al., 2026): DQN without LSTM prediction
- (b). **LSTM-only handover** (Lima et al., 2023): prediction-based with fixed threshold

Table 7: Multi-Baseline Comparison (Mobility = 60 km/h, mean ± 95% CI, n=30)

Method	Latency (ms)	HOF (%)	Ping-pong (%)	Throughput (Mbps)
CBH (traditional)	52 ± 2.5	4.8 ± 0.3	12.0 ± 0.8	185 ± 8
RL-only	41 ± 2.0	3.2 ± 0.2	7.5 ± 0.5	210 ± 9
LSTM-only	38 ± 1.8	2.5 ± 0.2	6.2 ± 0.4	225 ± 8
Proposed LSTM-RL	32 ± 1.5	1.8 ± 0.1	4.5 ± 0.4	240 ± 7

The proposed hybrid method outperforms both RL-only and LSTM-only approaches, confirming that combining prediction with adaptive decision-making provides synergistic benefits.

(g). Statistical Significance Testing

All simulation results are based on 30 independent runs with different random seeds. A paired t-test was conducted between the proposed hybrid ML method and the conventional CBH method for each metric.

Table 6: Statistical Significance Testing (paired t-test, vs CBH, n=30)

Metric	Mean Improvement	95% CI	t-statistic	p-value
Latency reduction	37.6%	[36.2%, 39.0%]	24.3	p < 0.001
HOF reduction	61.2%	[58.5%, 63.9%]	18.7	p < 0.001
Ping-pong reduction	63.1%	[60.8%, 65.4%]	22.1	p < 0.001
Throughput improvement	24.5%	[22.8%, 26.2%]	19.5	p < 0.001
Packet loss reduction	66.2%	[64.1%, 68.3%]	25.6	p < 0.001

All improvements are statistically significant at $\alpha = 0.05$ level (p < 0.001 in all cases).

The outcome of the hybrid ML-based handover management system **suggests** to be obviously better than standard threshold-based approach. One of the most significant outcomes is the reduction in handover latency by approximately 37% across all mobility scenarios. It is important to this reduction to support real-time services in 5G networks, including video conferencing, autonomous vehicles, and AR/VR services, where any delays can negatively impact the user experience. The LSTM model enables proactive prediction of degradation of signals, which the RL agent can use to start handovers before the connection quality is poor, which in turn would result in a seamless transition between gNodeBs. Equally important is the substantial decrease in handover failures, which dropped by over 60%. This means that the hybrid system is efficient in terms of predicting network conditions and user movement which avoids dropped connections or interrupted sessions. In high mobility cases where the conventional ways of handover tend to fail because of slow triggering the predictive and decision-making abilities of the hybrid model are especially useful.

The hybrid system also significantly reduces ping-pong events, with a reduction of around 63%. Regular, unneeded handovers do not only augment signalling overhead, but might unstably running sessions as well. Using the policy of the RL agent based on the LSTM estimates, the system will avoid premature or unnecessary handovers, which will lead to a smoother connectivity and will make a more efficient utilisation of network resources. Furthermore, the system improves network throughput by up to 27%. This enhancement shows a better quality of service, since the users will always be connected to the best cells and they will have fewer interruptions. Finally, the packet loss ratio is lowered by 64–68%, enhancing the reliability of latency-sensitive applications and ensuring data integrity during handovers. All in all, these findings underscore the fact that active and intelligent handovers can be achieved with the combination of LSTM-based prediction and RL-based decision-making. It

is an especially appropriate strategy compared to dense urban 5G networks when user mobility is high, and small-cell deployments pose a major difficulty to traditional handover techniques.

IV. CONCLUSION

The study has been able to develop and evaluate a hybrid machine learning based system of handover management in 5G networks and help to reduce the latency and enhance the overall performance of the network. The system is able to predict signal degradation and user mobility effectively in anticipative positions by combining an LSTM network of temporal prediction of network conditions with a RL agent of adaptive decision-making. The LSTM model is effective at predicting relevant parameters, including RSRP, RSRQ, SINR and user speed, and RL agent uses the prediction to maximise the timing and the target cell of handover. Unlike the traditional threshold-based handover strategies, the combined method overcomes the constraints of traditional strategies, especially in dynamic and high-mobility conditions. The simulation findings performed in MATLAB/Simulink show that the hybrid system performs much better in comparison with traditional handover strategies on all the reviewed performance measures. Handover latency is reduced by approximately 37%, while handover failure rates drop by over 60%, illustrating the effectiveness of predictive and intelligent decision-making. Ping-pong events decrease by around 63%, throughput improves by up to 27%, and packet loss is reduced by 64-68%. These advancements show not just a more trusted connection, but also a greater QoS to the end-users, especially with small-cell density in an urban setting and high-speed mobility conditions. The findings validate that the hybrid system establishes sustained and constant connections and reduces the number of interruptions and redundant handovers. To conclude, the proposed hybrid ML solution shows that a combination of predictive models and adaptive reinforcement learning can be a powerful solution to intelligent handover management in 5G networks. The system is able to deliver low-latency, high-throughput, and reliable service delivery by shunning reactive to proactive handover strategies which together address the issues of 5G modern environments. The results indicate that these smart handover systems can be effectively used with the next-generation wireless networks, and it offers a viable route to improve the efficiency of the networks, the end user experience, and the overall stability of the upcoming 5G uses such as self-driving cars, telemedicine, and Internet of Things systems.

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