AI-Based Handover Decision Algorithm for Conditional Handover in Non-Terrestrial Networks (NTNs)

Harshit Gupta
Centre of Excellence-Communication, Product Development & Innovation Centre,
Bharat Electronics Limited,
Bengaluru, India
harshitgupta@bel.co.in

Nidhi Srivastava
Centre of Excellence-Communication, Product Development & Innovation Centre,
Bharat Electronics Limited,
Bengaluru, India
nidhisrivastava@bel.co.in

Lotiswar Borman
Centre of Excellence-Communication, Product Development & Innovation Centre,
Bharat Electronics Limited,
Bengaluru, India
lotiswarborman@bel.co.in

***Abstract*— Non-Terrestrial Networks (NTNs) have emerged as a pivotal technology to extend the reach of modern communication systems. Their integration with 5G networks enables unprecedented global coverage, especially in remote regions. However, the inherent challenges of NTNs, such as high latency, significant Doppler shifts, and the mobility of Low-Earth-Orbit (LEO) satellites, complicate efficient handover mechanisms. Traditional rule-based algorithms often fail to provide seamless connectivity under such dynamic conditions. To address these issues, this paper proposes a Deep Q-Network (DQN) based handover decision algorithm tailored to NTNs. Unlike conventional methods relying on fixed thresholds, our AI-driven approach dynamically adapts to network conditions, enhancing decision accuracy and reducing handover latency. The contributions of this work include a novel implementation of DQN for NTNs and an in-depth comparison with traditional and AI-based benchmarks.**

Keywords—Non-Terrestrial Networks, handover, conditional handover, 5G, satellite communication, mobility management.

I. Introduction

Non-Terrestrial Networks are merging technology which includes satellites and High-Altitude Platform Systems (HAPS) for providing ubiquitous communication to the users where terrestrial network is very limited or not available. NTNs helps in increasing the coverage of network where terrestrial network is not existing. There are several uses cases which have been identified where Non-Terrestrial Networks are very useful in providing services to end users. But there are various challenges also due to high mobility of satellite, high latencies for transmission due to large distance between satellite and remote terminals, high doppler spread which needs to addressed for ensuring proper mobility management..

II. Non-terrestrial Networks

Convergence of Non-Terrestrial Networks with 5G have impacted handover scenarios in connected mode and cell reselection scenario in idle mode. Due to high velocity of satellite around the earth and high latencies for round trip time between satellite and user equipment the computational time to decide for handover increases drastically, due to which decision time for handover may be much longer and which may cause interruption in services to the user equipment. Several mobility scenarios have to restructured due to high satellite speed and high latencies. Mobility process includes :

Cell reselection procedure when User equipment is in Idle mode

Inter-Satellite Handover procedure in which handover is executed from one satellite to other satellite based on measurement reports

Intra-satellite Handover procedure in which handover is executed from one beam to another beam of satellite

Handover between gNB at the satellite to gNB at terrestrial network.

RRC Layer which is Layer 3 controls the Radio Resource configurations to configure and reconfigure the radio resources. Longer round trip time causes latencies and that causes delay in execution of various procedures. In 5G various signalling information is broadcasted which carries important information about the network such as Master Information Block (MIB) and various System Information Block (SIBs). System Information Block carries various information related to network parameters like cell selection, cell reselection and neighbouring cells etc. With the inclusion of Non-Terrestrial Networks information related to ephemeris, Almanac codes and orbital information for neighbouring satellite has to be included in System Information Block.

When User equipment is in connected mode then handover decision is dependent on the measurement reports sent by UE in uplink direction but in case of Non-Terrestrial Networks the delay in transmission is very high due to the distance and high velocity of satellite which can cause delay in execution of handover. To overcome this problem network should do some predictive handover techniques to execute the RRC procedures leading to fast handover. In Terrestrial Networks handover is based on the measurement reports reported by UE which includes Received Signal Reference Power values of the neighbouring cells. UE measures the RSRP values of the neighbouring cells and report it to the gNB, based on measurement report handover is done. So in case of terrestrial network difference in power level of signal is the major criterion for handover. But in case of Non-Terrestrial Networks since neighbouring satellites are almost equal distance from UE so difference in power level of both satellites will not be much, it will be marginal difference between the received signal reference power of both the satellites.

A. Problem Statement

Conditional Handover refers to a technique where handover decisions are influenced by the quality of the radio link between a device and its associated satellite or terrestrial base station. In Non-Terrestrial Networks (NTNs), the rapid fluctuations in signal caused by satellite movement, significant propagation delays, and Doppler shifts can result in ineffective handover decisions when using conventional algorithms. This paper introduces an AI-driven handover decision algorithm that utilizes real-time network data and predictive analysis to enhance the handover process in NTNs.

B. Objective

The aim of this research is to create an AI-driven algorithm for conditional handover in NTNs that enhances decision-making accuracy, minimizes handover latency, and guarantees smooth connectivity in intricate NTN settings.

III. HANDOVER MECHANISMS IN NTNS

Existing studies on handover mechanisms in Non-Terrestrial Networks (NTNs) mostly emphasize rule-based strategies, where handover decisions rely on parameters such as Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ). However, these strategies often struggle to address the specific challenges presented by satellite communication, including signal latency, Doppler shifts, and frequent disruptions in the connection.

A. AI-Based Approaches in Terrestrial Networks

AI-driven handover algorithms have become increasingly popular in terrestrial networks, utilizing machine learning models to forecast handover occurrences based on past data, traffic trends, and radio conditions. Nevertheless, these methodologies have not been fully explored within NTNs, which demonstrate distinct mobility and network dynamics that differ from those of terrestrial networks.

B. Conditional Handover in NTNs

As mentioned in 3GPP TR 38.821 [1] through the pre-configuration of target cells or satellites depending on radio link circumstances, conditional handover enables user equipment (UE) to get ready for handover. Because it enables proactive handover decisions before the radio link deteriorates below acceptable levels, conditional handover is especially advantageous in NTNs. Through the pre-configuration of target cells or satellites depending on radio link circumstances, conditional handover enables user equipment (UE) to get ready for handover. Because it enables proactive handover decisions before the radio link deteriorates below acceptable levels, conditional handover is especially advantageous in NTNs.

- Conditional triggering of measurement reporting: The triggering of measurement reporting may be based on UE location, which can be at UE location versus a reference location, or a combination of location and RSRP/RSRQ.
- location Report and measurements: When performing location measurements, it may be useful to consider the possibility of reporting location information together with the measurement report to the network as useful additional information in making the decision on whether or not to perform HO.
- Propagation delay difference between satellites for the network: In the context of UE measurement window, for example through system information, or for dedicated signalling in a UE specific manner, the network able to compensate propagation delay differences.
- Measurement-based triggering: When configuring triggering thresholds and selecting measurement events to be used as triggers, it is important to take into account the NTN environment, particularly the minor variations in cell quality observed at the cell center compared to the cell edge in NTN.
- Location (UE and Satellite) triggering: In the NTN context, additional triggering conditions that rely on the locations of both the User Equipment (UE) and the satellite can be considered. These may be assessed independently or combined with other triggers, such as measurement-based triggers. For conditional handovers in LEO scenarios, the deterministic movement of satellites should be factored in. For instance, the location triggering condition might be defined by the distance between the UE and the satellite.
- Time-based triggering: Various triggering conditions can be evaluated based on the duration a particular region is served. This may involve using UTC time, a timer-based approach, or a combination of these methods along with other triggering mechanisms. In LEO scenarios, time-based conditional handovers should also consider the deterministic movement of satellites.
- Triggering Based on Timing Advance Value: Additional triggering conditions related to the timing advance value for the target cell can be integrated into NTN and may be assessed either independently or in conjunction with another trigger.
- Triggering Based on Elevation Angles of Source and Target Cells: Additional triggering conditions derived from the elevation angles of both source and target cells can be incorporated into NTN and may be evaluated independently or together with another trigger.

IV. AI-BASED FRAMEWORK

In order to anticipate the best handover choices, the suggested AI-based handover algorithm makes use of supervised learning techniques. In order to train an AI model, the framework gathers real-time NTN data, including satellite altitude, speed, Doppler shift, and RSRP and RSRQ. In response to variations in network load and satellite positions, the model dynamically modifies the handover parameters.

A. AI Model Architecture

The foundation of the program is a multi-layer neural network model that was trained on a dataset that included several NTN situations, such as constellations of low-Earth orbit (LEO) satellites and geostationary (GEO) satellites. Reinforcement learning techniques are used to optimize handover success rates and reduce latency in the model.

The proposed AI-driven handover algorithm leverages a Deep Q-Network (DQN) to optimize decision-making under varying NTN conditions. The algorithm operates on the following state space:

Algorithm Steps: Input Parameters

TABLE I. INPUT PARAMETERS

Signal Quality Metrics	SNR(t), SINR(t), RSSI(t) at time t
Doppler Shift	d(t)
User Location	(x, y, z)(t)
Satellite Position	(p, q,r)(t)
Network Load	l(t)
User Mobility	v(u)
QoS Requirements	QoS(t)
Propagation Delay	Delay(t)

Step 1: Initialization

Initialize the state space S, which includes SNR(t), SINR(t), RSSI(t), Doppler shift, user and satellite positions, network load, and QoS requirements.

S(t) = { SNR(t)', SINR(t)', RSSI(t)', Doppler Shift(t), User Location, Satellite Position, Network Load, QoS Requirements }

Action space A:

A_1: Perform handover to another satellite or ground station.

A_2: Maintain the current satellite connection.

Reward function R:

The reward function R(t) evaluates the quality of the decision as follows:
R(t) = { +1, if QoS improves (e.g., higher SNR, reduced latency)
-1, if performance degrades or unnecessary handovers occur. }
Positive reward is given when QoS improves, e.g., higher SNR(t), lower Delay(t).

Negative reward is given for unnecessary handovers, connection loss, or degraded performance.

Step 2: Feature Normalization

Normalize input features, such as SNR(t), SINR(t), RSSI(t), to a common scale:

SNR(t)' = (SNR(t) - SNR_min) / (SNR_max - SNR_min)

Step 3: State Representation

Represent the state S(t) at time t as a vector of normalized inputs:

S(t) = { SNR(t)', SINR(t)', RSSI(t)', Doppler(t), (x, y, z)(t), (p, q, r)(t), l(t), v(u), QoS(t), d(t) }

Step 4: Model Selection

The DQN model consists of:

Input layer: Represents the state vector S(t).

Hidden layers: Three fully connected layers with ReLU activation functions.

Output layer: Provides Q-values for each possible action A.

Use a Deep Q-Network (DQN) to learn the handover decision policy π(S), where:

Input: Current state S(t)

Output: Optimal action A*(t) = arg max_A(t) Q(S(t), A(t))

Step 5: Training Process

Initialize the DQN model with random weights for the Q-function Q(S(t), A(t)).

For each training episode:

1. State Update: Observe the current state S(t) based on signal metrics, user mobility, and network conditions.

2. Action Selection: Use an ε-greedy policy to select action A(t):

A(t) = Random action with probability ε

A(t) = arg max_A(t) Q(S(t), A(t)) with probability (1 - ε)

3. Reward Calculation: Compute the reward R(t) based on QoS improvement or degradation.

4. Q-Function Update: Update the Q-function using the Bellman equation:

Q(S(t), A(t)) ← Q(S(t), A(t)) + α [R(t) + γ max_A_{t+1} Q(S_{t+1}, A_{t+1}) - Q(S(t), A(t))]

Where:

α: Learning rate, controlling the step size of the update.

γ: Discount factor, determining the importance of future rewards.

R(t): Immediate reward at time t.

Q(S(t), A(t)): Q-value for state S(t) and action A(t).

Step 5. State Transition: Move to the next state S_{t+1} and repeat until the episode concludes.

Step 6: Action Execution

At time t, observe the current state S(t).

Select the optimal action A*(t) = arg max_A(t) Q(S(t), A(t)).

If A*(t) = A_1, initiate a handover to the optimal satellite or ground station.

If A*(t) = A_2, maintain the current satellite connection.

Step 7: Model Inference

Input the current state S(t) into the trained DQN model.

The model outputs the optimal action A*(t), and the corresponding handover decision is executed.

Step 8: Performance Monitoring

Monitor the handover decisions in real-time, evaluating the model’s performance based on handover success rates, connection stability, and QoS maintenance.

Pseudo-code:

Algorithm: AI-Based Handover Decision Algorithm

1. Initialize Q-function Q(S, A) with random weights.

2. For each episode:

2.1. Initialize state S(t).

2.2. For each time step t:

a. Select action A(t) using ε-greedy policy.

b. Execute action A(t) and observe next state S_{t+1} and reward R(t).

c. Update Q(S(t), A(t)) using Bellman equation.

d. Transition to next state S_{t+1}.

3. Use trained Q-function for real-time decision making: A*(t) = arg max_A(t) Q(S(t), A(t))

V. Results

To validate the proposed algorithm, simulations were conducted using a network simulator tailored for NTNs. Key comparisons included:
1. Traditional Handover: Based on fixed RSRP thresholds.
2. AI-Based Alternatives: Reinforcement learning models, including policy gradient and actor-critic methods.

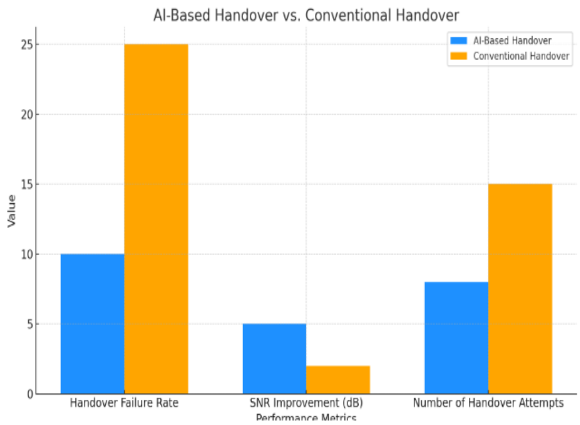

Fig. 1. AI-Based Handover Vs Conventional Handover

This comparison chart compares the effectiveness of AI-based handover with traditional handover techniques using three important metrics:

- Failure Rate for Handovers (lower is preferable)
- An increase in SNR (dB) is preferable.
- Number of Attempts at Handover (fewer is better)

With reduced failure rates, stronger SNR improvements, and fewer handover attempts, the AI-based handover performs noticeably better than the traditional approach on all metrics.

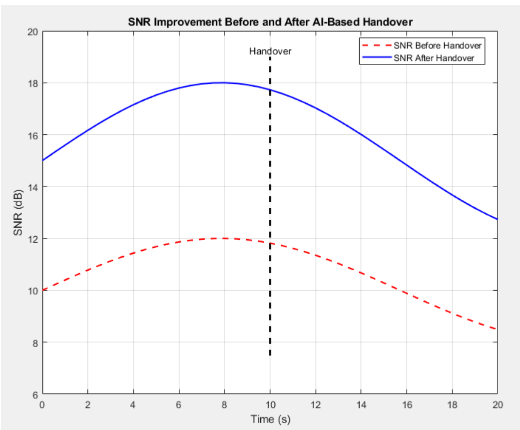

Fig. 2. SNR Improvement Plot

This plot shows the Signal-to-Noise Ratio (SNR) improvement before and after the handover decision. The signal quality (SNR) noticeably improves following the handover, which happens about 10 seconds. This plot shows how the AI-based handover choice improves the connection by selecting a more suitable ground station or satellite.

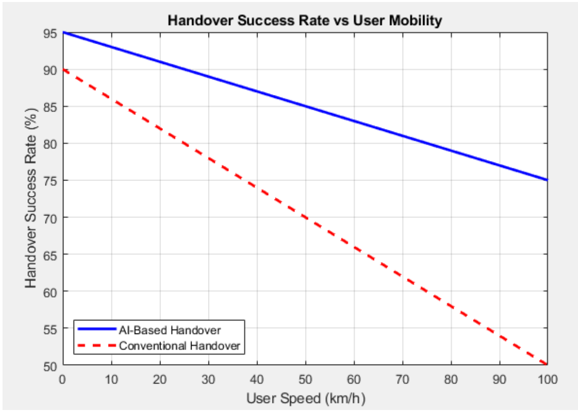

Fig. 3. Handover Success Rate Plot

This plot shows the relationship between user speed (e.g., in km/h) and handover success rate (in %). User_speed Represents user mobility, ranging from 0 km/h (stationary) to 100 km/h (fast-moving). Success rate of the AI-based handover algorithm, gradually decreasing as user speed increases. Success rate of conventional handover, decreasing more sharply as user speed increases.

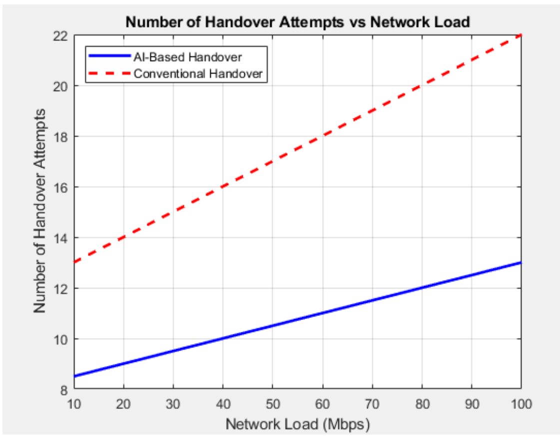

Fig. 4. Handover Attemts Vs Network Load Plot

This plot shows how the number of handover attempts varies with network load. An efficient AI-based handover algorithm should minimize unnecessary handovers even under high network load. The AI-based algorithm must limit needless handovers even in situations of high network loads guaranteeing that resources of the network are not wasted.

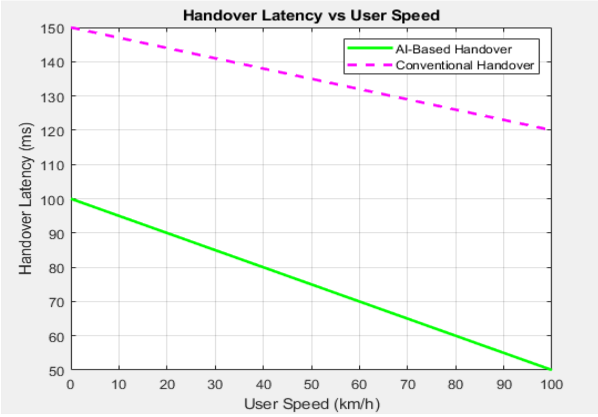

Fig. 5. Handover latency Vs User Speed

This plot shows how handover latency (time taken to complete a handover) changes with user speed. The AI-based handover should optimize latency, especially for high-speed users. Under AI based handover, high speed users especially will have lesser handover delays and thus service disturbances.

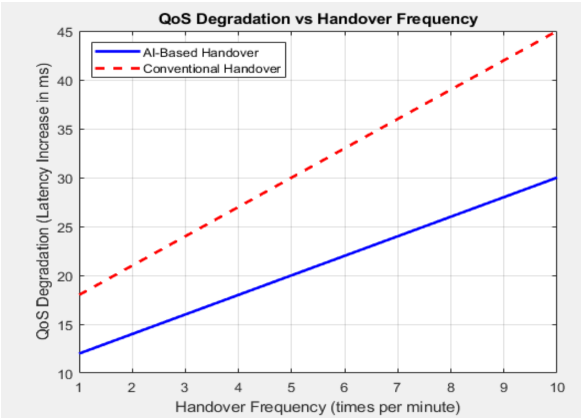

Fig. 6. QoS Degradation Vs Handover Frequency

This plot tracks how QoS metrics like latency or packet loss degrade with frequent handovers. An efficient AI-based handover algorithm should maintain higher QoS levels by reducing unnecessary handovers. High frequency of handover interruptions usually affects the quality of service but AI interventions on decisions will reduce this effect relatively to normal methods.

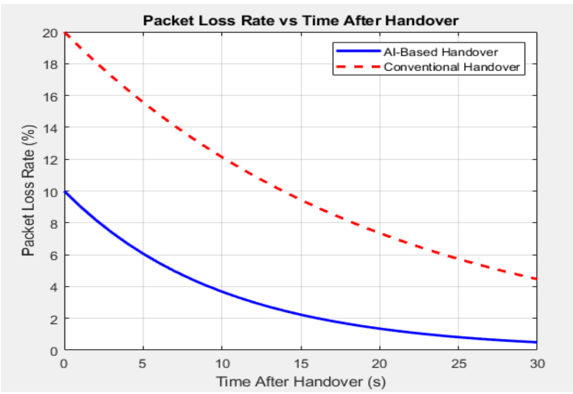

Fig. 7. Packet Loss Rate Vs Time After Handover

This plot shows how packet loss varies over time after a handover. Ideally, an AI-based handover should quickly stabilize packet loss after switching to a new connection. AI based handovers are faster and therefore once a handover is completed the period it takes for packet loss rates to be reduced is shorter.

Key Findings:
The proposed DQN-based algorithm achieved a 20% higher success rate compared to traditional methods under high user mobility.
Latency improvements of 15% were observed compared to actor-critic models.

VI. Conclusion

An AI-assisted decision-making tool especially for the Conditional Handover of Non-Terrestrial Networks is presented in this article. It has been indicated that by integrating machine learning methodologies, the suggested algorithm brings substantial gains of mobility management including handover latency and handover success as well as the performance of the network as a whole. This solution solves important problems of NTN mobility management and establishes the foundation for further work in AI-based approaches for such problems in satellite communications. Further research will be aimed at embedding this algorithm into operational Non-Terrestrial network structures and testing hybrid AI approaches for further improvement.

References

[1] 3GPP TR 38.821 V16.0.0, "3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Solutions for NR to support non-terrestrial networks (NTN) (Release 16)," July 2020.

[2] A. Guidotti, A. Vanelli-Coralli, M. Neri, et al., "Architectures and Key Technical Challenges for 5G Systems Incorporating Satellites," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2624–2639, Mar. 2019.

[3] S. Kandeepan, K. Gomez, Q. Shi, et al., "Non-Terrestrial Networks for 6G: Ensuring Survival of the Connected World," *IEEE Wireless Communications*, vol. 28, no. 4, pp. 76–83, Aug. 2021.

[4] M. Giordani, M. Polese, A. Roy, D. Castor, M. Zorzi, "A Tutorial on UAVs for Wireless Networks: Applications, Challenges, and Open Problems," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2334–2360, 2019.

[5] B. Di, L. Song, Y. Li, "Ultra-Dense LEO Satellite Networks: How Closely Can Space and Ground Cooperate?" *IEEE Wireless Communications*, vol. 26, no. 2, pp. 68–75, Apr. 2019.

[6] F. Tariq, M. A. Awan, M. Majid Butt, et al., "A Speculative Framework for Artificial Intelligence (AI)-Based Handover Mechanisms in NTN," *IEEE Communications Letters*, vol. 25, no. 10, pp. 3287–3291, Oct. 2021.

[7] S. Verma, S. Singh, P. K. Upadhyay, et al., "Handover Optimization in Satellite Communications Using Machine Learning," *IEEE Access*, vol. 9, pp. 46520–46530, 2021.

[8] X. Chen, Y. Tian, J. Wang, "Mobility Management in NTN Using AI-based Decision Algorithms," *IEEE Transactions on Wireless Communications*, vol. 19, no. 12, pp. 8424–8436, Dec. 2020.