PERFORMANCE EVALUATION OF MOBILITY WITH ANN IN NON-TERRESTRIAL NETWORKS

Li-Sheng Chen [1] and Shu-Han Liao [2]

[1] Department of Computer Science and Information Engineering, National Ilan University, Ilan, 260007, R.O.C.
[2] Department of Electronic and Computer Engineering, Tamkang University, New Taipei, 251301, R.O.C.

ABSTRACT

Low Earth Orbit (LEO) satellites exhibit high mobility, leading to frequent handover challenges. Addressing these handover issues is crucial for maintaining seamless and stable service connections. This paper presents a novel D1 event handover scheme that integrates Kalman filtering with artificial neural networks(ANN) to enhance handover performance in Non-Terrestrial Networks (NTN). In the proposed method, Kalman filtering provides precise UE position estimates and generates smooth trajectory predictions, which serve as inputs to a neural network. The neural network adaptively adjusts handover parameters (hysteresis and threshold) and intelligently selects the optimal target cell based on predicted positions, signal-to-interference-plus-noise ratio (SINR) and network load. Through modelling and simulation experiments, we demonstrate that the proposed scheme significantly reduces handover failure rates and ping-pong events. The results show that, compared to traditional D1 handover mechanisms and RSRP-based handover methods, the proposed scheme improves handover stability and reliability, offering an effective solution for intelligent mobility management in dynamic NTN environments.

KEYWORDS

Non-terrestrial networks (NTN), Handover, artificial neural networks(ANN), Kalman filter

1. INTRODUCTION

The evolution of mobile communication is advancing towards the sixth generation (6G), aiming to overcome the limitations of 5G, which has largely been confined to terrestrial networks. Recognizing the potential of non-terrestrial networks (NTN), both the international telecommunication union (ITU) and the 3rd generation partnership project (3GPP) are actively working on standardization. In this context, satellite communication is gaining significant attention, particularly with the increasing adoption of low earth orbit (LEO) satellites. These satellites stand out due to their lower deployment and operational costs, enabled by advancements in miniaturization and reusable launch technologies. Additionally, LEO satellites offer reduced signal propagation delays compared to their geostationary orbit (GEO) counterparts, making them an attractive alternative for communication systems[1][2]. Despite these advantages, LEO satellites pose unique challenges due to their high velocity and low altitude, leading to frequent handover events. Unlike GEO satellites, which maintain a fixed position relative to the earth, LEO satellites require continuous mobility management to maintain seamless connectivity. As a result, extensive research has been dedicated to optimizing handover mechanisms in LEO-based communication networks. For instance, previous studies [3] have

David C. Wyld et al. (Eds): SIGML, CNSA, MoWiN, CCSEIT, NIAI, AIAP – 2025
pp. 79-86, 2025. CS & IT - CSCP 2025 DOI: 10.5121/csit.2024.150205

proposed various handover strategies, including optimized satellite selection algorithms and techniques for integrating terrestrial networks (TN) with NTNs to enhance mobility management. Additionally, the research [4] has explored the impact of handover parameters such as time-to-trigger (TTT) and handover margin on system performance. A range of algorithms [5] [6] has been developed to enhance LEO handover efficiency. Some studies [7] [8] have reviewed recent trends in handover techniques, while others have focused on event-triggered mechanisms such as the A4 event for measurement reporting. A novel scheme [9] introduced a handover-independent mobility management scheme, which leverages an on-demand, cell-free coverage model to mitigate the cost inefficiencies of traditional cellular architectures. Another proposed solution [10], the area-based mobility management scheme, integrates the global positioning system (GPS) to manage handovers in LEO networks, addressing the high mobility cost and service degradation associated with satellite motion. Furthermore, NTN mobility solutions [11] have been analyzed under various scenarios, including urban macro environments and high-speed train networks. To counteract excessive handovers caused by moving satellite beams, researchers [12] have proposed a fixed-duration strategy for LEO satellites operating in earth-fixed scenarios. Additionally, machine learning techniques have been explored [13], such as an auction-based handover algorithm that considers received signal strength and service duration. Other studies [14] have introduced innovative architectural solutions, including embedding mobility management functions directly within satellites to enhance the flexibility of satellite-terrestrial integrated networks.

Ensuring seamless service continuity in NTN requires robust mobility management strategies. While prior research [15] has addressed many challenges, most existing studies have not fully accounted for multiple parameters influencing LEO satellite handovers. Notably, NTN environments do not always exhibit significant signal strength fluctuations, making traditional reference signal received power (RSRP)-based handovers less effective in certain scenarios. Consequently, location-based handovers have been proposed as a viable alternative. In this paper, we introduce a novel D1 event handover scheme that integrates Kalman filtering [16] with artificial neural networks (ANN) [17] to improve handover performance in non-terrestrial networks. The proposed method employs Kalman filtering to produce accurate UE position estimates and smooth trajectory predictions, which are then fed into a neural network. This network dynamically adjusts handover parameters, such as hysteresis and threshold values, and intelligently selects the most appropriate target cell based on predicted positions, signal quality, and network conditions. Through modelling and simulation, we demonstrate that this scheme effectively reduces handover failure rates and minimizes ping-pong events. Our results show that, compared to traditional D1 handover and RSRP-based approaches, this scheme enhances both stability and reliability, providing a robust solution for intelligent mobility management in dynamic NTN environments. The remainder of this paper is organized as follows: Section II provides an overview of the handover in NTN networks., Section III describes the proposed scheme, Section IV covers the simulation and performance evaluation, and Section V concludes the paper.

2. HANDOVER IN NTN NETWORKS

In traditional terrestrial networks (TN), handover between cells is primarily based on radio signal strength metrics such as Reference Signal Received Power (RSRP). However, as networks expand into non-terrestrial networks (NTN), RSRP-based handover mechanisms face significant challenges. Instead, location-based handover (LBH), which relies on the geographical position of the user equipment (UE), may offer a more effective solution for NTN environments.

In NTN, satellites provide much larger coverage areas than terrestrial base stations, with a single satellite beam covering hundreds or even thousands of kilometers. As a result, when a UE moves between adjacent beams or satellites, the change in RSRP is relatively small, which may lead to delayed handover triggers or frequent ping-pong effects. Low Earth Orbit (LEO) satellites in NTN move at high speeds, causing rapid fluctuations in RSRP measurements. Additionally, environmental factors such as terrain, cloud cover, and urban obstructions impact NTN signals differently than in TN, further destabilizing RSRP-based handover decisions. NTN systems, particularly those using Geostationary Earth Orbit (GEO) satellites, experience higher transmission latency. The delay in reporting RSRP measurements from the UE to the core network and executing the handover decision may cause incorrect handover timing, leading to situations where the UE has already entered a new coverage area before the handover is completed.

Given the limitations of RSRP-based handover in NTN, LBH presents a more effective approach by leveraging the UE's geographical position to predict and optimize handover timing.

LBH can utilize GPS or other satellite-based positioning systems to determine the UE's location and, in combination with NTN satellite orbit data, predict when the UE will enter a new beam or satellite coverage area. This predictive capability helps avoid reliance on unstable RSRP measurements. By analyzing the UE's movement direction and speed, LBH can determine whether a handover is truly necessary, rather than reacting to momentary fluctuations in RSRP. This approach minimizes unnecessary handovers, improving network stability and resource efficiency. LBH is applicable across various NTN topologies, including GEO, medium earth orbit (MEO), and LEO satellite systems. Since satellite orbits and beam coverage areas are predetermined, LBH can be tailored to different NTN deployment architectures, making it a more universal solution.

Event D1 is a handover trigger mechanism introduced in 3GPP Release 17 for non-terrestrial networks. Unlike traditional signal-based handover events (e.g., Event A3 used in terrestrial networks), Event D1 primarily relies on the UE's geographical position and satellite orbit information to predict when a handover is needed, ensuring seamless connectivity in NTN environments.

Event D1 is fundamentally a type of location-based handover since it uses the UE's location (e.g., GPS data) and satellite trajectory information rather than RSRP or other radio signal strength metrics to trigger a handover. This approach addresses key NTN challenges, such as slow RSRP variations and delayed handover decisions, making the handover process more precise and efficient. The UE should trigger the measurement report event when both conditions D1-1 and D1-2 are met.

$$\text{Event D1-1:} \quad Ml1 - Hys > Thresh1 \tag{1}$$

$$\text{Event D1-2:} \quad Ml2 + Hys < Thresh2 \tag{2}$$

The UE should stop the measurement report event when either condition D1-3 or D1-4 is met.

$$\text{Event D1-3:} \ Ml1 + Hys < Thresh1 \tag{3}$$

$$\text{Event D1-4:} \ Ml2 - Hys > Thresh2 \tag{4}$$

With Event D1, the handover is triggered when the UE is predicted to leave the current coverage area and enter a new one, avoiding the drawbacks of traditional RSRP-based triggering, such as late handover initiation or instability in NTN scenarios.

3. PROPOSED SCHEME

The NTN D1 event handover scenario is characterized by rapidly changing signal conditions and frequent transitions between cells. Traditional fixed hysteresis and threshold settings often lead to suboptimal decisions, either triggering handovers too early or too late. In this work, we propose a novel scheme to dynamically determine optimal hysteresis Hys_{opt} and threshold $Thresh_{opt}$ values by leveraging real-time position estimates from Kalman filter and artificial neural networks model, as shown in Figure 1.

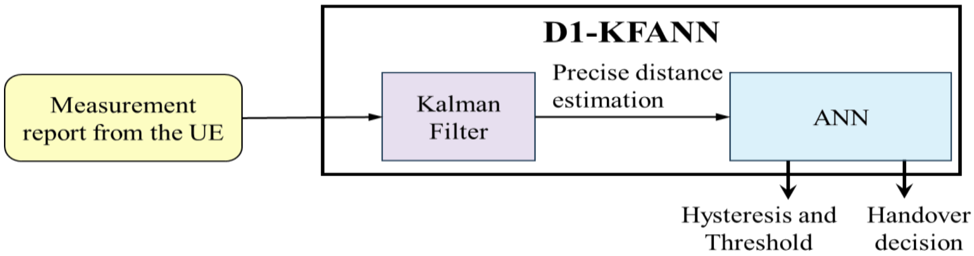

Figure 2. The architecture of the proposed scheme

The framework aims to minimize unnecessary handovers, reduce ping-pong effects, and improve overall handover success rates.

The UE's state vector at time *t* is defined as

$$\mathrm{x}(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \\ y(t) \\ \dot{y}(t) \end{bmatrix} \tag{5}$$

where

$x(t)$ and $y(t)$: The position coordinates of the UE in a two-dimensional plane, typically representing longitude and latitude.

$x^{\cdot}(t)$ and $y^{\cdot}(t)$: The velocity components in the respective axes. These terms indicate how fast the UE is moving along each direction.

State transition model using Kalman filter:

The evolution of the UE's state can be expressed as

$$x(t) = Fx(t-1)+w(t) \tag{6}$$

where

F is the state transition matrix and $w(t)$ is process noise, typically modeled as zero-mean Gaussian noise with covariance Q. For a constant velocity model:

The observation model is:

$$z(t) = Hx(t)+v(t) \tag{7}$$

where:

$z(t)$: Observation vector, typically including position estimates derived from GNSS or other sources.

H: Observation matrix, mapping the state space to the measurement space.

$v(t)$: Measurement noise,$v(t) \sim N(0,R)$

Choosing optimal values Hys_{opt} and $Thresh_{opt}$ is critical to minimizing unnecessary handovers and avoiding situations where the handover is triggered too late, causing call drops or quality degradation.

The Kalman filter provides real-time, smoothed estimates of the UE's position:

Prediction step:

$$\hat{x}(t|t-1) = F\hat{x}(t-1|t-1) \tag{8}$$

$$P(t \mid t-1) = FP(t-1 \mid t-1)F^{\top} + Q \tag{9}$$

Update step:

$$K(t) = P(t|t-1)H^{\top}(HP(t|t-1)H^{\top}+R)^{-1} \tag{10}$$

$$\hat{x}(t|t) = \hat{x}(t|t-1) + K(t)(z(t) - H\hat{x}(t|t-1)) \tag{11}$$

$$P(t \mid t) = (I - K(t)H)P(t \mid t-1) \tag{12}$$

Neural network-based parameter optimization and cell Selection Input Features:

$$P(t \mid t) = (I - K(t)H)P(t \mid t-1) \tag{13}$$

$$\mathbf{z}_{\mathrm{NN}}(t) = \begin{bmatrix} \hat{\mathbf{x}}(t|t) \\ \mathrm{Ml1} \\ \mathrm{Ml2} \\ \mathrm{SINR} \\ \mathrm{Load}_{\mathrm{target}} \end{bmatrix} \tag{14}$$

These features include the filtered position estimate, signal-to-interference-plus-noise ratio (SINR) of serving and target cell, and additional network conditions.
Neural network structure:

Each layer of the neural network transforms the input feature vector $\mathbf{z}_{\mathrm{NN}}(t)$ to produce outputs representing:

The optimal hysteresis Hys_{opt}.
The optimal threshold $Thresh_{opt}$.
A preference score for each candidate cell.

Output:

The network's outputs include:
Hys_{opt} and $Thresh_{opt}$: Dynamically adjusted based on realtime conditions.
$p_{cell} = [p_1, p_2, \ldots, p_n]$: Softmax probabilities indicating the likelihood of each cell being the optimal target.

Selection Rule:
The target cell is selected as:

$$C_{\mathrm{target}} = \arg\max_i p_i \tag{15}$$

The optimization of hysteresis and threshold:
Loss Function:
To train the neural network, a loss function is designed to penalize suboptimal hysteresis and threshold values that lead to poor handover decisions. The loss includes two components:
Handover Success Loss:

Ensures the chosen Hys_{opt} and $Thresh_{opt}$ lead to a successful handover without excessive delay.

Signal Quality Loss:

Encourages thresholds that maintain good signal quality after the handover.

The total loss $\mathcal{L}$ can be written as:

$$\mathcal{L} = \mathcal{L}_{\text{success}} + \lambda \mathcal{L}_{\text{quality}} \tag{16}$$

where λ is a weighting factor balancing the two objectives.

Gradient-Based Training:

The neural network parameters are updated using gradient descent or a similar optimization algorithm. The gradients are computed with respect to both Hys_{opt} and $Thresh_{opt}$, ensuring the network converges to values that improve overall handover performance.

4. Performance Evaluation

In this section, we conducted a series of simulation experiments to evaluate the proposed D1 event handover scheme based on a combination of Kalman filtering and artificial neural networks (referred to as D1-KFANN). The D1-KFANN method was compared against two baseline approaches: (1) the traditional D1 handover mechanism with fixed hysteresis and threshold parameter values, and (2) the RSRP-based handover (RBH) approach. The simulation parameters are summarized in Table 1. For performance metrics, we employed the average ping-pong rate and the handover failure rate as the primary indicators, both of which are critical for evaluating the stability and reliability of the handover process.

Table 1. simulation parameters.

Parameter	Values
Satellite altitude	600km
Frequency reuse	FR1
Satellite Tx max Gain	35 dBi
Number of beams	11
Background traffic load	35% PRBs
Satellite beam diameter	70km
UE Tx power	28dBm
System Bandwidth	10MHz
Sub-carrier spacing	15kHz

For the traditional D1 handover mechanism, its fixed parameter settings were unable to adapt to rapidly changing signal conditions, resulting in frequent and unnecessary handovers, which led to a relatively high average ping-pong rate. The RSRP-based approach, while straightforward and easy to implement, relied solely on instantaneous signal strength comparisons. This lack of consideration for the UE's dynamic behaviour and changing cell coverage caused a notable number of ping-pong events. In contrast, the proposed method utilized Kalman filtering for position prediction and employed a neural network to dynamically adjust parameters, enabling it to adapt to signal fluctuations and significantly reduce unnecessary handovers. As shown in Figure 2, the proposed method consistently achieves lower Average ping-pongs rates across various simulation scenarios, highlighting its superior stability and reliability in handover performance. These findings demonstrate that the Kalman filter and neural network-based D1 handover scheme offers a more robust and effective solution.

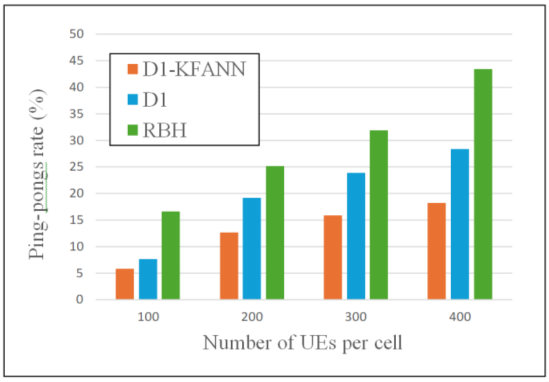

Figure 2. Average ping-pongs rate

The RSRP-based approach, while straightforward, also struggles under fluctuating signal conditions, as it relies entirely on instantaneous signal comparisons, leading to frequent handover failures. The traditional D1 approach relies on fixed parameters, making it ill-suited to handle the rapidly changing signal conditions typical of dynamic NTN environments. This lack of flexibility in handover decision-making often results in delayed or missed handovers, particularly when the UE moves quickly or when signal strength deteriorates suddenly. Consequently, the handover failure rate for this method remains relatively high. The proposed method, by incorporating Kalman filtering for precise UE position estimation and leveraging neural networks to dynamically adjust hysteresis and threshold values, achieves more accurate target cell selection and timely handover decisions. As Figure 3 shows, this method consistently delivers a lower handover failure rate across various simulation scenarios, demonstrating higher success rates and more stable performance. These results highlight the reliability and efficiency of the Kalman filter and neural network-based D1 handover scheme.

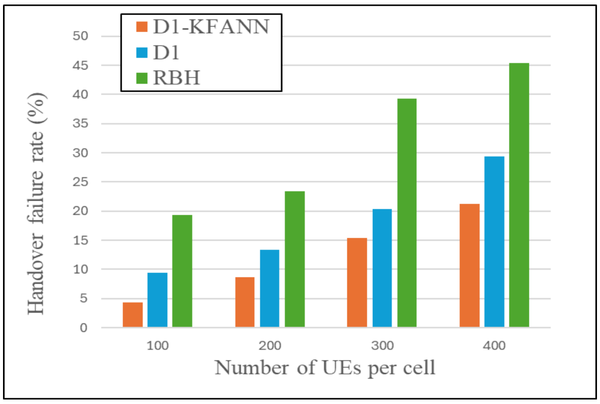

Figure 3. Handover failure rate

5. CONCLUSION

This paper introduced a novel scheme to D1 event handover in non-terrestrial networks by integrating Kalman filtering and artificial neural networks. The proposed method leverages Kalman filtering to provide precise, real-time UE position estimates and smooth trajectory predictions. These estimates feed into a neural network model that dynamically adjusts hysteresis and threshold parameters while selecting the optimal target cell. By incorporating both predictive location data and learned patterns from artificial neural networks, this scheme offers significant improvements in handover stability and reliability. Compared to traditional D1 handover mechanisms with fixed hysteresis and threshold settings, as well as RSRP-based handover methods, the Kalman-filtered neural network scheme achieved lower handover failure rates and reduced ping-pong events. These results demonstrate that the combination of predictive modeling and adaptive decision-making can effectively address the unique challenges of dynamic NTN environments, where mobility patterns and coverage conditions vary rapidly.

REFERENCES

[1] E. A. Shao, J. Koltz, J. R. Wertz, (2016) "Quantifying the Cost Reduction Potential for Earth Observation Satellites," in Proc. 12th Reinventing Space Conference. Springer, Cham, pp. 199-210

[2] J. R. Wertz, N. Sarzi-Amade, E. A. Shao, C. Taylor, R. Van Allen, (2012) "Moderately Elliptical Very Low Orbits (MEVLOs) as a Long-Term Solution to Orbital Debris", 26th Annual AIAA/USU Conference on Small Satellites, Logan, UT.

[3] Miao, P. Wang, H. Yin, N. Chen and X. Wang, (2019) "A multi-attribute decision handover scheme for LEO mobile satellite networks," in Proc. IEEE 5th International Conference on Computer and Communications (ICCC), Chengdu, China, pp. 938-942.

[4] E. Juan, M. Lauridsen, J. Wigard, and P. E. Mogensen, (2020) "5G new radio mobility performance in LEO-based non-terrestrial networks," in Proc. IEEE Globecom Workshops (GC Wkshps), Taipei, Taiwan, pp. 1–6.

[5] C. Q. Dai, Y. Liu, S. Fu, J. Wu, and Q. Chen, (2019) "Dynamic handover in satellite-terrestrial integrated networks," in Proc. IEEE Globecom Workshops (GC Wkshps), Waikoloa, USA, pp. 1–6.

[6] K. Li, Y. Li, Z. Qiu, Q. Wang, J. Lu, and W. Zhou, (2019) "Handover procedure design and performance optimization strategy in LEO-HAP system," in Proc. 11th International Conference on Wireless Communications and Signal Processing (WCSP), Xian, China, pp. 1-7.

[7] S. Park and J. Kim, (2021) "Trends in LEO satellite handover algorithms," in Proc. 12th International Conference on Ubiquitous and Future Networks (ICUFN), Jeju Island, Korea, pp. 422-425.

[8] J. Yu, W. Lee, and J. H. Kim, (2022) "Performance evaluation of handover using A4 Event in LEO satellites network," in Proc. IEEE VTS Asia Pacific Wireless Communications Symposium (APWCS), Seoul, Korea.

[9] C. Liu, W. Feng, Y. Chen, C.-X. Wang, and N. Ge, (2021) "Cell-free Satellite UAV Networks for 6G Wide-area Internet of Things," IEEE Journal on Selected Areas in Communications, vol. 39, no. 4, pp. 1116–1131.

[10] D. Ganguly, S. Chakraborty, K. Hui, M. K. Naskar, (2012) "Area based Mobility Management by using GPS in LEO Satellite Networks," International Journal of Computer Applications, vol. 42, no. 13, pp. 41-43.

[11] E. Juan, M. Lauridsen, J. Wigard and P. E. Mogensen, (2020) "5G New Radio Mobility Performance in LEO-based Non-Terrestrial Networks," in Proc. 2020 IEEE Globecom Workshops (GC Wkshps), pp. 1-6.

[12] J. S. Baik and J. H. Kim, (2021) "Analysis of the Earth Fixed Beam Duration in the LEO," in Proc. IEEE International Conference on Information Networking (ICOIN), pp. 477–479.

[13] S. Jung, M. S. Lee, J. Kim, M. Y. Yun, J. Kim, and J. H. Kim, (2021) "Trustworthy handover in LEO satellite mobile networks," ICT Express.

[14] Z. Han, C. Xu, K. Liu, L. Yu, G. Zhao and S. Yu, (2021) "A Novel Mobile Core Network Architecture for Satellite-Terrestrial Integrated Network," in Proc. 2021 IEEE Global Communications Conference (GLOBECOM), pp. 01-06.

[15] 3GPP, (2021), "R2-2100346 TSG-RAN WG2 Meeting 113 electronic,"emeeting, pp.1-18.

[16] Kim, Y., & Bang, H. (2018). Introduction to Kalman filter and its applications. Introduction and Implementations of the Kalman Filter, 1, 1-16.

[17] Agatonovic-Kustrin, S., & Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. Journal of pharmaceutical and biomedical analysis, 22(5), 717-727.