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Transformer-Based Mobility Prediction for Seamless Vertical Handover in Beyond 5G Networks

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Abstract

The heterogeneity of Beyond 5G (B5G) networks, which include cellular, Wi-Fi, satellite, and edge computing communications, is further complicating efforts to provide seamless communication for users on the move. Traditional vertical handovers rely on instantaneous network measurements and threshold-based decision rules, leading to excessive handovers, delays, packet losses, and degraded quality of service in highly dynamic environments. This paper proposes the TBMP-SVH framework, which uses Transformer-based mobility modelling to predict future user mobility patterns accurately and then optimally process the corresponding vertical handover decision proactively. The TBMP-SVH framework integrates techniques for pre-processing user mobility trajectories, Transformer-based sequence learning, and a predictive multi-criteria method for vertical handovers that assesses received signal strength, latency, throughput, and network load. During the evaluation

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of the TBMP-SVH framework, it was tested in various mobility scenarios against traditional RNN, GRU, and LSTM methods. The TBMP-SVH framework achieved a mobility prediction accuracy of 96.8%, compared with RNN (88.2%), GRU (91.5%), and LSTM (93.1%). Further, the TBMP-SVH framework produced an average handover latency of 42 ms, handover success rate of 98.1%, packet loss of 1.9% and average network throughput of 186.4 Mbps. The TBMP-SVH framework substantially improves vertical handover performance, network reliability and service continuity through the use of Transformer-based mobility intelligence, and is therefore positioned to be a key enabler of next generation B5G mobility management systems.

Keywords: Beyond 5G Networks, Vertical Handover, Mobility Prediction, Transformer Networks, Seamless Connectivity, Network Selection, Deep Learning, Mobility Management.

1 Introduction

From today's 5G technologies to the emergence of 6G systems including Beyond 5G (B5G) and future 6G technologies, communication systems become a convergence of a highly diversified ecosystem involving terrestrial cellular, Wi-Fi 6/7 infrastructure, non-terrestrial network (NTN), satellite, unmanned aerial vehicle (UAV), near-space communication technologies (Aouedi et al., 2025; Liu et al., 2025). It provides ubiquitous connectivity to support delay-sensitive and bandwidth-intensive applications. Thus, mobility management becomes a core function that ensures continuous services to users when move across heterogeneous network domains. Future mobility schemes are also expected to exhibit an intelligent nature and possess predictive capabilities to adapt to varying network status and fast-moving trajectories (Zhang et al., 2025; Javaid et al., 2024). The proliferation of the integrated satellite-aerial-terrestrial network architecture makes handover decisions challenging with regard to varying contexts, necessitating learning-based mobility management techniques (Liu et al., 2025; Javaid et al., 2024). Future 6G will embrace intelligent network architectures with flexible antenna systems and AI-oriented frameworks that enable highly adaptable mobility management and service continuity (Memon et al., 2025). Mobile prediction is an integral approach to facilitate future service continuity with the help of user trajectory learning and self-attention mechanism to model user behavior, enabling a more accurate predictive mobility for seamless vertical handover in heterogeneous environments (Zhang et al., 2025; Javaid et al., 2024; Anas et al., 2024).

Vertical handover, where a user can move from a one type of access technology to another type, while the call is in progress (Pjanić et al., 2024). The classical method to make a handover decision relies on RSS, SINR or a threshold-based network selection rule (Pjanić et al., 2024). However, these techniques are computationally simple and ignore users' future mobility and variations of the wireless environments and usually lead to a greater number of failures, ping-pong effect, extra handover triggers and increase communication latency (Ziani et al., 2025; Pjanić et al., 2024). The use of modern prediction techniques, like those based on LSTM has shown some improvements but not enough for a long sequence mobility model or when complicated space-time relationships are presented (Helmy et al., 2025; Ziani et al., 2025). Transformers models provide a novel perspective and outcompete prior techniques in sequential data processing and can capture long-range dependencies through attention mechanism in a wide range of wireless applications, particularly in time-series forecasting and user trajectory prediction (Zhang et al., 2025; Liu et al., 2025). Nevertheless, there is a significant lack of research regarding the application of Transformer-based mobility prediction in designing proactive vertical handover optimization in B5G and beyond network environments (Ziani et al., 2025).

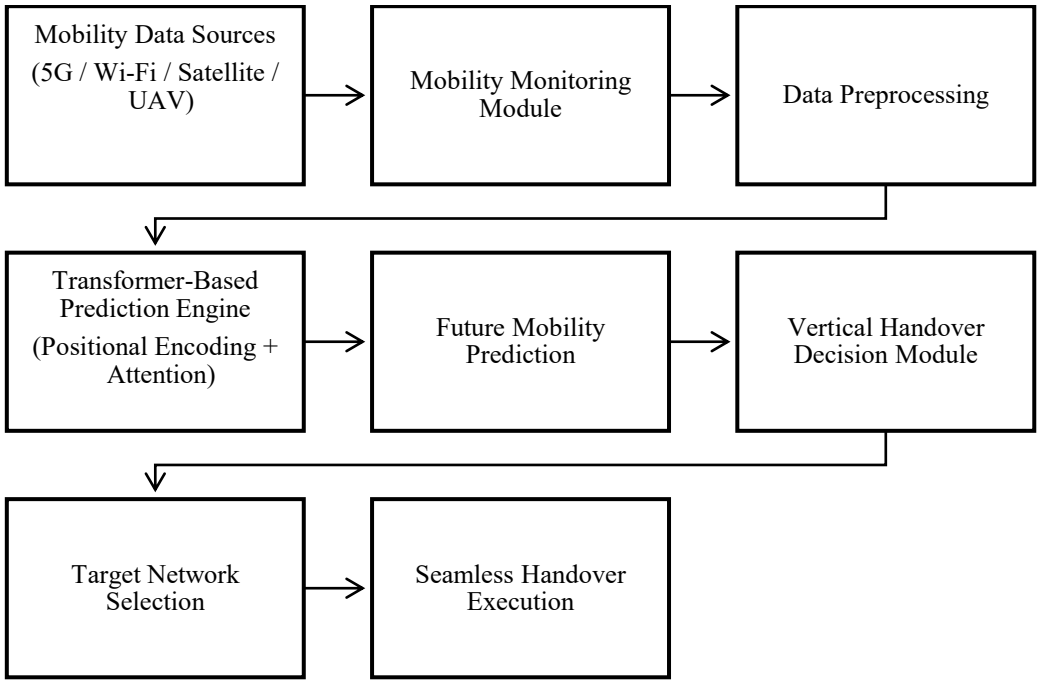


Figure 1: Conceptual architecture of the proposed TBMP-SVH framework

The overall architecture of the TBMP-SVH framework can be seen in figure 1. The first step involves mobility data collection from various sources, including 5G, Wi-Fi, satellite and UAV and other types of access technologies. The mobility data collected is then processed through a monitoring and preprocessing module. After the mobility data has been processed, it is forwarded to the Transformer-based prediction Engine, which uses positional encoding, along with the self-attention mechanism, to predict future mobility patterns for users. After predicting the mobility state, the vertical handover decision module will analyze all currently available networks and select the best target network based on the predicted state. In addition to analysing the current state of the network, the end user will be able to execute the vertical handover process seamlessly, without losing connectivity and to ensure improved continuity of service in Beyond 5G network environments.

The emerging deployment of the integrate satellite-aerial-terrestrial communication networks leads to greater demand for mobility management functions and the proactive vertical handover management scheme become a must for B5G network due to the drawback of conventional reactive handoff. In this paper, a Transformer-Based Mobility Prediction (TBMP-SVH) framework is designed for seamless vertical handover in the beyond 5G(B5G) networks. Leveraging mobility trajectory learning, including historical data with self-attention mechanisms, the TBMP-SVH predicts user movements in time and space to enable proactive network selection decisions, thereby reducing handover delays, excessive handovers, handover failures, and improving the overall service continuity in heterogeneous mobile communication systems.

This paper will be structured as follows: A review of currently studied vertical handover techniques is covered in Section II. Included with this is mobile prediction models and research on Transformer-based network intelligence. Section III describes the proposed TBMP-SVH framework including system architecture, mobility prediction model, and predictive handover algorithm. In Section IV an overview of the experimental setup, performance metrics and evaluation of results is provided. Section V then discusses findings in terms of practical deployment considerations for Beyond 5G networks. Finally, Section VI concludes with a summary of the paper and potential research areas going forward.

2 Literature Review

Vertical handover mechanism seeks to maintain communication continuity when a mobile user travels among diverse wireless networks. Conventional approaches primarily select the most appropriate target network based on factors such as Received Signal Strength (RSS), Signal-to-Interference-plus-Noise Ratio (SINR), available bandwidth, delay and service cost. Pre-defined thresholds are often set in the process of triggering handover decisions due to its low computational complexity. Since these approaches focus on the immediate values of measurements, produce shaky handover decisions under the context of high mobile dynamics. Multi-Attribute Decision Making (MADM) approaches, such as Analytical Hierarchical Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and weighted scoring models have then been integrated into handover selection process in order to account for multiple network measurements and refine handover quality. Despite being able to provide superior network selection quality, MADM methods still remain to be reactive as they are unable to predict upcoming movements of the user or variations of network status, which leads to potential excessive handovers and degradation of service for dense mobile users Siriwardhana et al., (2021) and Huang et al., (2024).

In order to mitigate the shortage of proactive handover strategy, researchers have employed machine learning techniques, which aim to predict future user movement through utilizing historical mobility data. In the initial stages, traditional methods including Markov models, support vector machines (SVM) and random forest have been widely applied for estimating users' locations and mobility traces based on history trajectory. However, these algorithms encounter performance degradations when user movement is highly non-linear and time-variant, although superior to threshold-based approaches. Then, deep learning networks, such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have been developed to deal with spatio-temporal dependencies in mobility data and achieved much better forecasting performance by modelling sequential user mobility behavior. However, these RNN-based networks are characterized by insufficient flexibility for longer sequential data, which results in poor scalability for large scale mobility dataset, thus is not sufficient to real-time Beyond 5G mobile networks (Abd Elaziz et al., 2024; Abdellah et al., 2025).

Transformer architectures have drawn attentions and demonstrated potentials for many applications in wireless communication domain. Different from conventional recurrent architectures, Transformer, with self-attention mechanism, can learn the dependency over longer distance of sequence effectively and has achieved great results in channel prediction, traffic forecast and intelligent routing optimisation etc Zhou et al., (2024) and Liu et al., (2025). Hybrid attention-based architectures have even achieved better performance in network traffic management applications by combining long and short-term behavioral dependencies of user or network device (Tang et al., 2025; Rahman et al., 2024). Recent studies have also explored digital twin-enabled network analytics and adaptive user association strategies to improve network awareness and mobility management in next-generation wireless environments (Navidan et al., 2025; Negassa et al., 2025). But up to now, existing work using Transformers has mostly focused on traffic analytics, channel prediction and resource allocation in general. To the best of the knowledge of Study, Transformer-based mobility prediction to enhance proactive vertical handover in Beyond 5G networks has not been addressed.

From the existing research works, observe that the vertical handover approach has gradually transformed from threshold-based handover methods and MADM-based handover methods to a data-driven based predictive handover strategy. Despite the great progress of ML-based and recurrent-based deep learning methods in mobility forecasting, there are still limitations in modeling the long-term

mobility dependency. Fortunately, Transformer architectures, by employing a self-attention mechanism for sequence learning, address these problems and have demonstrated considerable capability in various wireless networking applications. However, dedicated Transformer based framework for both accurate mobility prediction and pro-active vertical handover decision is still absent. The research is the first attempt to build a comprehensive intelligence mobility aware handover framework with the intention to enhance service continuity, minimize handovers and improve the overall network performance.

3 Methodology

3.1 System Architecture for Transformer-Assisted Vertical Handover

The proposed Transformer-Based Mobility Prediction for Seamless Vertical Handover (TBMP-SVH) framework is designed for heterogeneous Beyond 5G environments comprising 5G base stations, Wi-Fi access points, satellite gateways, and aerial communication nodes. The architecture consists of three functional layers: the mobility monitoring layer, the prediction layer, and the handover decision layer.

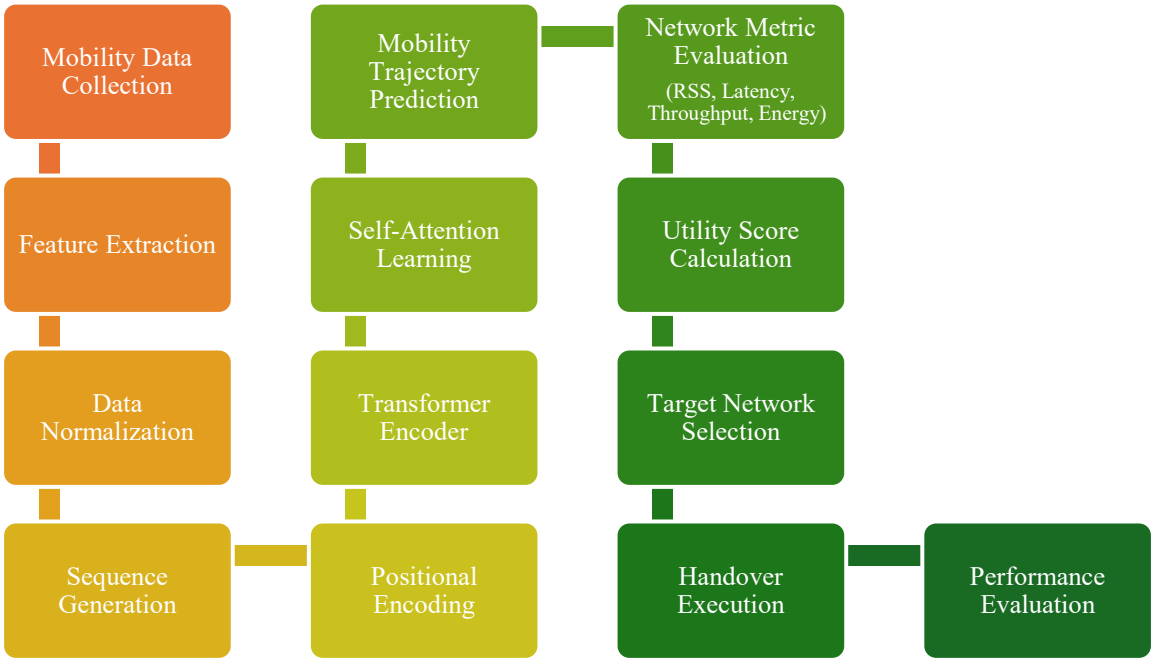


Figure 2: Workflow of the proposed transformer-based mobility prediction and vertical handover process

The seamless vertical handover between Beyond 5G networks is illustrated in figure 2 through the operational steps of the TBMP-SVH framework. Mobility data are gathered, features extracted, and normalized for analysis; After that the mobility data are sequenced and prepared for encoding and analysis. Sequence data are encoded using positional encoding, followed by analyzing using self-attention through the transformer encoder to predict future mobility trajectories. Based on the predicted user trajectories, evaluate network indicators (i.e. RSS, latency, throughput, energy use) to obtain utility measure for all networks. The target network will be the network with the highest utility score, and the network will be handed over, and then performance evaluated to provide reliable service with minimal latency and enhanced handover performance.

The mobility monitoring module continuously collects user context information, including geographical coordinates, velocity, acceleration, serving network identifier, received signal strength, latency, and throughput. These measurements are stored as sequential mobility records and forwarded to the prediction engine. To represent the mobility state of a user at time t, the input feature vector is defined as

$$X_t = [x_t, y_t, v_t, a_t, RSS_t, L_t, T_t] \qquad (1)$$

Where (x_t, y_t) denote spatial coordinates, $v_t$is velocity, $a_t$is acceleration, RSS_trepresents received signal strength, $L_t$denotes latency, and $T_t$indicates throughput. Equation (1) forms the mobility state representation used throughout the prediction process.

The handover decision framework receives predicted mobility information and evaluates candidate networks before a handover event occurs. This proactive operation minimizes service interruption and reduces unnecessary handover triggering.

3.2 Transformer-Based Mobility Prediction Model

The mobility prediction model employs a Transformer encoder to capture temporal dependencies within user movement trajectories. Raw mobility records are first normalized and segmented into fixed-length sequences. Each sequence is then transformed into embedded feature vectors suitable for attention-based learning.

Since the Transformer architecture lacks inherent sequence awareness, positional encoding is applied to preserve temporal ordering. The positional encoding for each sequence element is calculated as

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/d}}\right), PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/d}}\right) \qquad (2)$$

Where posdenotes the position index and $d$represents the embedding dimension. Equation (2) enables the model to distinguish the relative positions of mobility observations.

The core prediction mechanism is based on scaled dot-product self-attention. The attention score is computed as

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (3)$$

Where Q, K, and Vrepresent query, key, and value matrices, respectively. As defined in equation (3), the self-attention operation allows the model to identify long-range mobility dependencies and spatial-temporal correlations.

The output layer predicts the future mobility state $\hat{X}_{t+1}$, which includes anticipated location, movement direction, and network interaction characteristics. These predictions are forwarded to the handover decision engine.

3.3 Predictive Vertical Handover Decision Algorithm

The proposed handover strategy performs network selection using predicted mobility information rather than instantaneous measurements alone. Candidate networks are evaluated through a weighted utility function incorporating signal quality, latency, throughput, and energy consumption.

$$U_n = w_1 RSS_n + w_2 T_n - w_3 L_n - w_4 E_n \qquad (4)$$

Where $U_n$denotes the utility score of networks n, RSS_nrepresents signal strength, $T_n$indicates throughput, $L_n$denotes latency, $E_n$represents energy consumption, and $w_1, w_2, w_3, w_4$are weighting coefficients. According to equation (4), the network with the highest utility value is selected as the target access network.

Algorithm 1: Predictive Vertical Handover

Input:

Mobility sequence S

Available network set N

Output:

Optimal target network

1. Collect mobility observations
2. Construct feature vector using Equation (1)
3. Normalize and segment mobility data
4. Apply positional encoding using Equation (2)
5. Generate mobility prediction through self-attention mechanism defined in Equation (3)
6. Predict future user location and trajectory
7. For each candidate network n ∈ N do
8. Calculate utility score using Equation (4)
9. End For
10. Select network with maximum utility score
11. If selected network ≠ current network then
12. Initiate proactive handover
13. Else
14. Maintain current connection
15. End If
16. Return selected network

The algorithmic process of the designed TBMP-SVH framework is illustrated in Algorithm 1. Mobility data is gathered and pre-processed at the beginning of the process, mobility feature vectors are then created and encoded via positional encodings. Afterwards, user mobility is predicted utilizing a Transformer self-attention model to produce trajectory estimations in the future. Subsequently, this estimated trajectory of the users' mobility is utilized to score various networks by means of a utility function composed of RSS, throughput, latency and energy cost, and a network yielding the best utility score is chosen as the destination network, then an anticipatory handover will be triggered when needed, which reduces handovers delay, avoids redundant handovers and ensures persistent connectivity in heterogeneous Beyond 5G networks.

The handover execution phase reserves network resources in advance and performs authentication, context transfer, and link establishment before signal degradation occurs. By combining Transformer-based mobility forecasting with utility-driven network selection, the proposed framework reduces handover latency, improves service continuity, and enhances mobility management performance in heterogeneous Beyond 5G environments.

4 Results

4.1 Experimental Setup and Evaluation Metrics

The proposed TBMP-SVH framework was evaluated in a heterogeneous Beyond 5G environment consisting of 5G base stations, Wi-Fi access points, and satellite-assisted communication nodes. The simulation environment was implemented using Python 3.11, TensorFlow 2.16, NumPy, Pandas, and Scikit-learn. Model training and performance analysis were conducted on a workstation equipped with an Intel Core i7 processor, 32 GB RAM, and NVIDIA RTX-series GPU acceleration.

4.1.1 Dataset Details

A mobility dataset containing 50,000 mobility records was utilized for experimentation. The dataset includes user coordinates, velocity, acceleration, serving network type, RSS, latency, throughput, and handover status. Data were divided into 70% training, 15% validation, and 15% testing subsets. Each mobility sequence contained 20 consecutive observations to capture spatial-temporal movement behavior.

4.1.2 Parameter Initialization

Table 1: Experimental parameter settings

Parameter	Value
Sequence Length	20
Embedding Dimension	128
Attention Heads	8
Encoder Layers	4
Batch Size	64
Learning Rate	0.001
Training Epochs	100
Dropout Rate	0.2
Optimizer	Adam
Train-Test Split	70:15:15

The TBMP-SVH model parameters that are used during training and the assessment process of this article are given in table 1. The specific value used for parameters including sequence length, embedding dimension, attention heads, learning rate, batch size, and training epochs, can be selected properly to achieve convergence and ensure the effectiveness of TBMP-SVH to achieve adequate feature learning with promising mobility prediction quality and stability for different beyond 5G networking scenarios.

Performance assessment employed prediction and handover evaluation metrics. Prediction accuracy was calculated in equation (5):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

Where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. The Root Mean Square Error (RMSE) was computed in equation (6):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (6)$$

Where $y_i$and $\hat{y}_i$denote actual and predicted mobility values. The Mean Absolute Error (MAE) was determined in equation (7):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \qquad (7)$$

Equations (5) – (7) were used to quantify mobility prediction performance.

4.2 Mobility Prediction Performance Analysis

The Transformer architecture demonstrated strong capability in learning long-term mobility dependencies and future trajectory patterns. Performance was compared against conventional RNN, GRU, and LSTM models using identical training conditions.

Table 2: Mobility prediction performance comparison

Model	Accuracy (%)	RMSE	MAE
RNN	88.2	0.128	0.094
GRU	91.5	0.101	0.073
LSTM	93.1	0.087	0.061
Proposed TBMP-SVH	96.8	0.049	0.031

Table 2 evaluates the mobility prediction ability between TBMP-SVH and RNN, GRU, and LSTM through a different set of the evaluation metrics including Accuracy, RMSE, and MAE for the predictive capability. The result implies that the Transformer based solution performs significantly higher prediction accuracy, as well as much lower prediction error measurements (RMSE, MAE), which validates its capability of capturing long-range spatial-temporal dependencies.

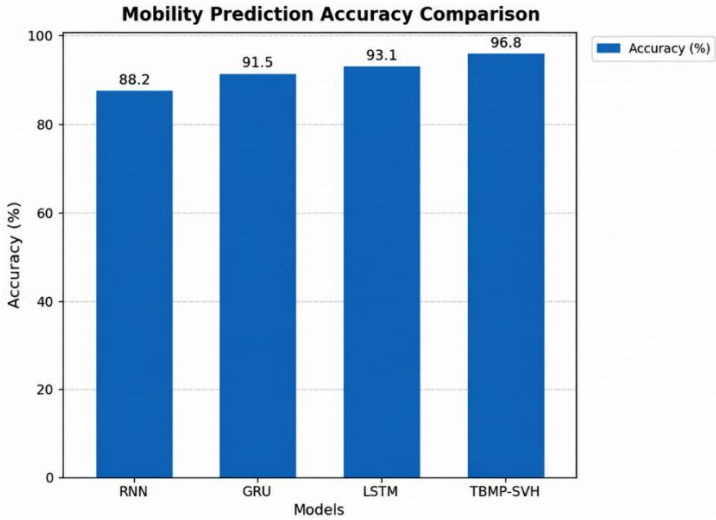


Figure 3: Mobility prediction accuracy comparison

The prediction accuracy of different mobility prediction models is illustrated in figure 3. The TBMP-SVH framework has the highest level of accuracy, 96.8%, and surpasses traditional recurring models in terms of performance on predicted performance levels.

The proposed framework achieved the highest prediction accuracy of 96.8**%**, representing improvements of 8.6%, 5.3%, and 3.7% over RNN, GRU, and LSTM models, respectively. Lower RMSE and MAE values further indicate superior trajectory estimation capability and reduced prediction error.

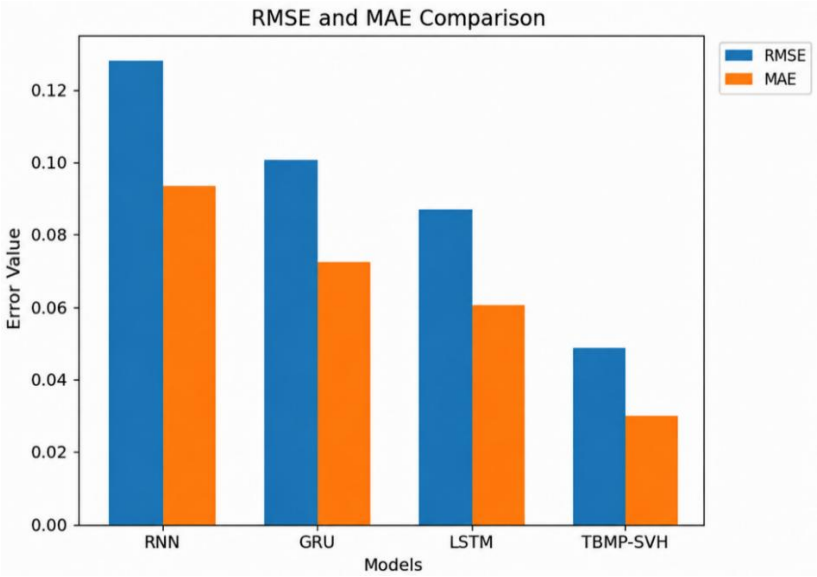


Figure 4: RMSE and MAE performance comparison

Figure 4 compares RMSE and MAE values across different models. Lower error values obtained by TBMP-SVH indicate more accurate mobility trajectory prediction.

4.2.1 Ablation Study

To assess the contribution of individual components, an ablation analysis was performed.

Table 3: Ablation study results

Configuration	Accuracy (%)
Without Positional Encoding	91.7
Without Multi-Head Attention	93.2
Without Predictive Handover Module	94.1
Full TBMP-SVH Framework	96.8

The performance assessment for different ablation of the developed framework is illustrated in table 3. By removing the positions Encoding, multiple attention head and predictive handover module of TBMP-SVH framework individually, notice that the predictive accuracy will degrade. The complete TBMP-SVH configuration achieved the highest performance.

Results demonstrate that positional encoding and multi-head attention significantly contribute to mobility prediction accuracy. The complete architecture consistently provides the best performance.

The contribution of each component in the framework is illustrated in figure 5. Prediction precision degraded significantly when removing some crucial module, verifying their importance.

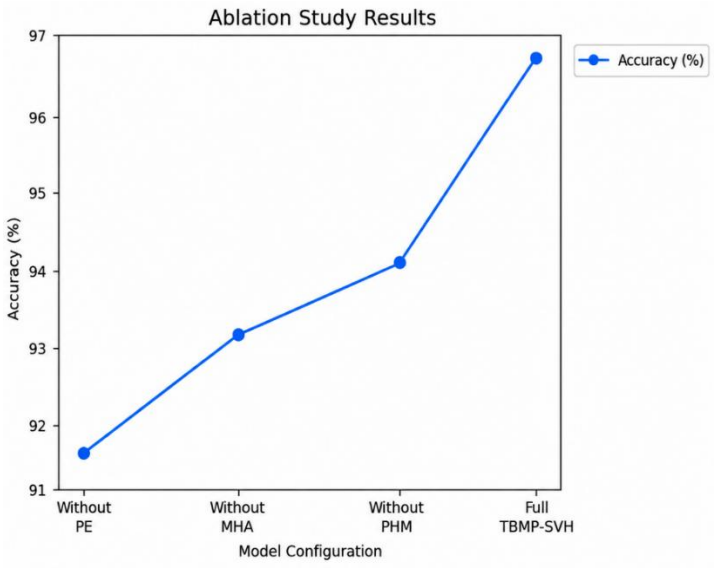


Figure 5: Impact of architectural components on prediction accuracy

4.3 Vertical Handover Performance Evaluation

The predicted mobility information was integrated into the vertical handover decision module to evaluate network selection performance. Handover Success Rate (HSR) was computed as

$$HSR = \frac{N_{successful}}{N_{attempted}} \times 100 \qquad (8)$$

Equation (8) represent $N_{successful}$ denotes successful handovers and $N_{attempted}$ represents total handover attempts.

Table 4: Vertical handover performance comparison

Method	Success Rate (%)	Latency (ms)	Packet Loss (%)	Throughput (Mbps)
RNN-Based	90.6	86	5.8	142.3
GRU-Based	93.4	71	4.2	158.9
LSTM-Based	95.2	58	3.1	171.5
Proposed TBMP-SVH	98.1	42	1.9	186.4

Table 4 displays the vertical handover efficiency in terms of handover success rate, latency, packet loss and throughput for various models. Compared to the other predictive models, TBMP-SVH achieve significantly better vertical handover performances, which confirms that accurate mobility forecasting will help prepare to the handover sufficiently for proactive handover and effective network selection in heterogeneous Beyond 5G networks.

Figure 6 is showing vertical handover performance comparison between proposed TBMP-SVH framework and best baseline model (LSTM). The proposed TBMP-SVH has best performance over all metrics.

The proposed framework achieved a handover success rate of 98.1% while maintaining the lowest latency of 42 ms. Packet loss decreased to 1.9%, and average throughput increased to 186.4 Mbps. These results indicate that proactive mobility forecasting enables earlier handover preparation and more effective target network selection.

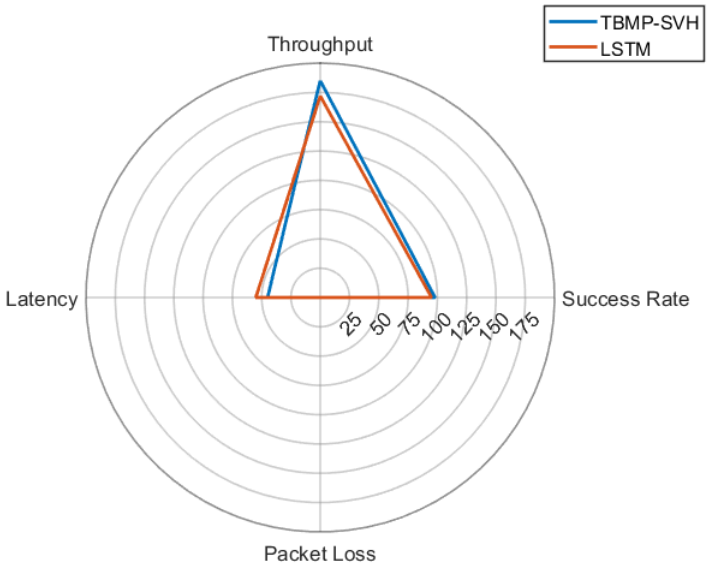


Figure 6: Vertical handover performance evaluation

4.3.1 Performance Evaluation

Experimental findings confirm that Transformer-assisted mobility prediction substantially enhances both prediction accuracy and handover efficiency. Accurate trajectory forecasting enables timely network selection decisions before significant signal degradation occurs. Reduced latency, lower packet loss, and higher throughput collectively demonstrate the effectiveness of the TBMP-SVH framework for seamless mobility management in heterogeneous Beyond 5G communication environments.

5 Discussion

The findings indicate that a Transformer-based approach to predicting user movement enhances vertical handover efficiency across heterogeneous Beyond 5G networks. The ability to predict user movement and prepare target resources prior to the degradation of the current network signal. This has resulted in a handover success rate of 98.1%, latency of 42 ms and a lower than 1.9% packet loss rate in a given period. Additionally, the self-attention mechanism used in the proposed method has effectively captured long-distance spatial and temporal dependencies in mobility data resulting in improved accuracy of prediction and substantial reduction of unnecessary handovers and ping-pong effects. The TBMP-SVH Framework outperforms conventional approaches based on RNNs, GRUs, and LSTMs regarding prediction accuracy, RMSE, MAE, throughput, and reliability during handovers. The proposed transformer model processes whole sequences of user mobility patterns simultaneously rather than sequentially, as is the case for recurrent architectures; thus, providing improved efficiency and accuracy when learning to make accurate predictions. The proposed multi-criteria network selection strategy further enhances handover decision making by jointly considering multiple parameters (i.e., signal strength, latency, throughput and energy consumption) when making handover decisions instead of relying on only one network parameter. When considering practical applications of the proposed framework, it is appropriate for large-scale Beyond 5G infrastructure (terrestrial, aerial, and satellite communication systems) deployment, as well as real-time prediction via edge computing platforms to assist with reducing processing delays, and can reduce the impact of rapidly growing user population density and increased complexity of networks. Although some challenges exist, including increased

computational requirements, dynamic behaviour of mobile users, and interoperability of heterogeneous access technologies; the improvements in mobility prediction and handover performance achieved through the implementation of Transformers for assisting with mobility intelligence represent a promising building block for reliable, scalable and service-aware mobility management of future wireless communication networks.

6 Conclusion

This research put forward the TBMP-SVH (Transformer-Based Mobility Prediction for Seamless Vertical Handover) framework to approach problems associated with the interaction of network mobility in heterogeneous Beyond 5G (B5G) networks. This introduced a new methodology into how to combine Transformer-based mobility prediction with a predictive vertical handover process to achieve both a seamless service continuum and more proactive network selection. The experimentation performed with TBMP-SVH resulted in the model predicting mobility conditions with a sequential data set at a 96.8% accuracy as compared to the predictive accuracy of RNN, GRU, and LSTM models at 88.2%, 91.5%, and 93.1%, respectively, under otherwise identical experimental conditions. The TBMP-SVH also produced the least prediction errors (RMSE = 0.049 and MAE = 0.031), indicating an exceptional ability to model complex spatio-temporal mobility patterns. The effectiveness of the prediction accuracy is illustrated by the handover results of the TBMP-SVH with a handover success rate of 98.1%, a handover latency of 42ms, less than 1.9% packet loss, and an average throughput greater than 186.4 Mbps, as such demonstrating that predictive awareness of mobility provides enhanced network reliability and user experience in highly dynamic wireless environments. This work demonstrates that self-attention sequence learning has merit in mobility management theory, and confirms the superior benefits of self-attention sequence learning over conventional learning methods such as signal threshold and recurrent learning methods. The TBMP framework will facilitate further development of intelligent B5G handover processes by enabling context-aware and proactive decision-making based on data across heterogenous access technologies. Future research could include evaluation of utilizing federated learning methods to support distributed model training while maintaining end user privacy, expanding the TBMP framework to consider intelligent 6G mobility ecosystems, and developing digital twin applications to create real-time replicas of physical networks to enhance the accuracy of predicting future mobility, dynamic resources allocation and self-administered autonomous handovers in future communication systems.

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