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Mobility-Aware Handover Optimization Using Adaptive Time-To-Trigger Mechanisms in 5G Networks

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***Abstract*—In 5G networks, handover management is critical for ensuring seamless mobility, low latency, and high-quality user experiences. However, traditional handover mechanisms suffer from frequent handover failures and ping-pong effects, especially when users move at high speeds or across densely deployed small cells. This paper proposes a mobility-prediction-based handover approach with an adaptive Time-To-Trigger (TTT) mechanism that adjusts dynamically to user speed and mobility patterns. The system comprises three key components: a Mobility Prediction Module utilizing recurrent neural networks (RNNs) to analyze historical movement data and real-time parameters including signal strength and user speed; Dynamic TTT Adaptation that reduces TTT for high-speed users to enable faster handovers while increasing TTT for slow-moving users to prevent ping-pong effects; and a Handover Decision Algorithm that integrates predicted mobility with real-time signal quality measurements. Simulation results demonstrate that the approach improves handover success rates, reduces ping-pong effects and enhances overall network performance. Additionally, the adaptive framework contributes to better resource utilization and overall network efficiency, The proposed system achieved 94.2% success rate, 67% fewer ping-pong events, 42ms average delay, 15.8% throughput gain, and 89.4% prediction accuracy with low computational cost.**

***Keywords*—Handover; Time-To-Trigger (TTT); mobility prediction; 5G networks; ping-pong effect; handover success rate**

I. Introduction

THE IoT landscape is rapidly expanding, with connected devices projected to reach 40 billion by 2030, driving demand for high-capacity, low-latency, and reliable wireless networks. The fifth generation (5G) of mobile networks is designed to deliver enhanced data rates, ultra-reliable low-latency communication (URLLC), and massive device connectivity. Achieving these goals, particularly in ultra-dense and high-mobility environments, requires seamless and intelligent handover mechanisms. The handover process ensures that users maintain seamless connectivity as they move between cells. Traditional handover mechanisms, which rely on signal strength thresholds and fixed Time-To-Trigger (TTT) parameters, often fail to account for the dynamic mobility of users, leading to inefficient handovers. Moreover, fixed TTT values are inadequate for the dynamic and heterogeneous nature of 5G networks, often leading to frequent handover failures, ping-pong effects, and a decline in overall Quality of Service (QoS) [1]. A fixed TTT value, which defines the time delay before a handover triggers, may cause unnecessary handovers, increase ping-pong effects (frequent switching between cells), and raise latency when users move at high speeds. It may slow down handovers if users are stationary or moving at a slow pace. This leads to poorer signal quality. But the same TTT setting can cause fast-moving users to have lost out on chances of connecting to a better-serving cell by delaying the handover decision. This may reduce the experience quality. It can cause radio link failures (RLFs) or total service disruptions. A fixed TTT cannot deliver the best handover performance in varying mobility situations [2].The heterogeneous architecture of 5G networks, featuring the integration of macro cells, small cells, and femtocells, compounds these challenges. Users navigating such environments encounter frequent signal variations, necessitating intelligent and responsive handover mechanisms capable of predicting mobility trends and modifying handover parameters dynamically [3]. Additionally, the broad spectrum of applications and services in 5G networks, spanning from enhanced mobile broadband (eMBB) to ultra-reliable low-latency communications (URLLC), requires exceptionally efficient handover procedures to preserve quality of service (QoS) standards [4].

Contemporary developments in machine learning and artificial intelligence have created new possibilities for developing intelligent mobility management solutions. Through the utilization of historical movement data, real-time network measurements, and user behavior analysis, it becomes feasible to predict user mobility and enhance handover decisions proactively. This predictive methodology can substantially improve handover performance by anticipating user movements and optimizing network parameters before critical conditions

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develop. Research developments in mobility prediction for cellular networks have demonstrated encouraging outcomes using diverse machine learning approaches. Deep learning architectures and LSTM networks, specialized types of recurrent neural networks, are utilized in the proposed framework to capture temporal dependencies and recognize patterns in user mobility data [5]. In this context, this paper explores the limitations of conventional handover strategies and highlights the need for more intelligent, adaptive mechanisms that account for user mobility patterns [6], network load, and application requirements. By addressing these challenges, the research aims to contribute towards more robust and context-aware handover solutions suitable for next-generation wireless networks. This paper introduces a mobility-prediction-based handover scheme featuring an adaptive TTT mechanism that adjusts according to user mobility. By predicting user movements, the system optimizes TTT values to ensure timely handovers, minimizing unnecessary handovers and ping-pong effects while improving handover success rates. The main contributions of this work include: (1) development of a comprehensive mobility prediction module using recurrent neural networks to forecast user movement patterns, (2) design of an adaptive TTT mechanism that dynamically adjusts based on predicted mobility characteristics, and (3) implementation of an intelligent handover decision algorithm that integrates mobility prediction with real-time signal quality measurements to optimize handover timing and target cell selection. The remaining part of this paper is structured as below: Section 2 presents the existing literature and research gaps found in the existing works. Section 3 describes the methodology proposed in this work. Section 4 presents the experimental results and discussion. Section 5 provides a conclusion and future scope.

II. Related Works

Several studies have addressed the optimization of handover mechanisms in 5G networks [7], with a focus on mobility management and TTT adaptation. Traditional fixed handover mechanisms, particularly those with static TTT values, often fail to respond adequately to rapidly changing network conditions. Mobility prediction has emerged as a promising solution, enabling proactive decision-making by forecasting user movement patterns. Several studies have employed machine learning models for this purpose. For instance, Shahid et al. [8] utilized Markov chains and GPS trajectories to predict user locations and adjust handover parameters accordingly. However, such methods lack adaptability to real-time variations in network conditions. A Learning-based model was proposed by Khosravi et al. [9] to predict user trajectories and optimize handover timing, leading to improvements in throughput and reduced latency. Similarly, a data-driven approach was proposed [?]that learns when and where to hand over in 5G systems by forecasting radio conditions, and demonstrates how applying this predictive model improves mobility decisions and reduces network downtime. Lin et al. [10] demonstrated that varying TTT based on mobility can significantly reduce ping-pong effects without sacrificing handover success rates. Elbatal al. [1] investigated the limitations of fixed TTT values in conventional handover schemes and highlighted their inefficiency in heterogeneous network environments, often resulting in suboptimal handover decisions. Recent works [11] incorporate signal measurements, velocity, and machine learning to enhance decision-making but face limitations in ultra-dense and high-frequency B5G environments. However, approaches that dynamically integrate multi-metric inputs such as RSRP, RSRQ, and UE velocity using intelligent controllers like fuzzy logic remain underexplored, especially for achieving robust handovers in diverse mobility scenarios.Gannapathy et al. [12] proposed an adaptive handover mechanism to address the unpredictable behavior of 5G mmWave channels. By dynamically adjusting the TTT based on the Signal-to-Interference-plus-Noise Ratio (SINR), their approach improves handover success rates, reduces latency, and enhances throughput in dual connectivity scenarios. Another approach was proposed by Junejo et al. [13] using reinforcement learning to optimize handover decisions by predicting key performance indicators such as signal quality. In this method, handover thresholds, including TTT, are dynamically adjusted to minimize failures and the ping-pong effect, resulting in significant improvements in handover success rate and latency reduction. This approach may face limitations such as high training overhead and computational complexity. Its performance, primarily validated through simulations, may not fully generalize to real-world network conditions. Karmakar et al. [3]proposed the LIM2 (Learning-based Interactive Mobility Management) mechanism, using online learning with a Kalman filter and SARSA(State-Action-Reward-State-Action) to adapt TTT and hysteresis for better handovers in high-speed scenarios. Its effectiveness is limited by the need for accurate signal prediction and high computational complexity. Riaz et al. [14] proposed a velocity-aware fuzzy logic-based algorithm that dynamically adjusts Time-To-Trigger (TTT) and handover margins based on user speed and signal quality. This approach enhances handover decisions in ultra-dense small cell networks, leading to reduced handover failures and improved overall system performance. However, its dependency on predefined fuzzy rules limits its adaptability across different mobility scenarios. Adaptive Time-To-Trigger (TTT) mechanisms dynamically adjust the duration before handover initiation based on parameters such as Signal-to-Interference-plus-Noise Ratio (SINR) and user velocity. Hybrid approaches [15] combining reinforcement learning and supervised learning have demonstrated significant improvements in HO prediction accuracy and reduction of undesirable events. Nevertheless, the integration of adaptive HCP optimization with real-time network context awareness for B5G scenarios remains an open area for further exploration. Survey studies [16] have highlighted the increasing complexity of HO management in 5G due to mmWave communication, network densification, and IoT proliferation, all of which amplify QoS threats like throughput degradation and service interruptions. Recent works classify machine learning–based HO solutions by data sources—such as visual and network data—demonstrating their potential for adaptive and intelligent mobility management. Siddiqui et al. [6]demonstrated an improved routing efficiency, reduced latency, and enhanced mobility resilience. However, the integration of flat network designs into large-scale B5G/6G systems still faces challenges in seamless handover coordination, interoperability, and real-time traffic optimization. The shift from 5G to 5G-Advanced and toward 6G introduces mobility management challenges due to the use of diverse spectrum bands, ultra-dense small cells, and integrated terrestrial–non-terrestrial networks. This research highlights issues like increased handover frequency, ping-pong effects, and failures that degrade QoS and QoE.

Benzaghta et al. [17] proposed a data-driven handover framework using high-dimensional Bayesian optimization and transfer learning to adapt TTT and hysteresis. It reduces radio link failures and ping-pong handovers but depends on the quality of training data. Arshad et al. [18] introduced a topology-aware handover skipping strategy to minimize unnecessary handovers in dense 5G networks. The approach improves user throughput by up to 47% by selectively bypassing certain handovers based on network topology. However, it may compromise service quality in scenarios demanding strict QoS. Skipping handovers can lead to suboptimal connections in such cases. Esenogho et al. [19] evaluates how adding buffers in handover exchanges between two cognitive radio base stations impacts performance, focusing on metrics like call drops and access rejection. Simulation results show that buffered schemes improve service continuity compared to non-buffered approaches.Khosravi et al. [9]proposed a DDPG-based learning algorithm for load-balanced handovers in mmWave networks, enhancing user rates and reducing handovers. However, its high computational complexity limits real-time use in large-scale deployments. Lin et al. [20] optimized handover by jointly tuning HOM and TTT based on user location, speed, and direction. Its effectiveness depends on accurately modeling parameter-performance relationships, which is challenging in dynamic networks. Deep reinforcement learning (DRL) has emerged as a promising approach [21] for adaptive handover optimization, enabling dynamic tuning of Handover Margin (HOM) and Time-to-Trigger (TTT) based on real-time signal conditions. However, ensuring scalability and consistent performance in highly dynamic, heterogeneous future-generation wireless environments remains a challenge. Heterogeneous Networks (HetNets) integrating small cells and diverse access technologies offer high throughput and low latency but face increased handover complexity and failures due to dense deployments. Advanced wireless technologies such as mmWave, THz, M-MIMO, RIS, and UAVs intensify mobility challenges, necessitating robust HO management [22]. Recent research explores supervised, unsupervised, and reinforcement learning–based approaches to enhance mobility performance, yet scalable solutions for future wireless networks remain a critical research gap. Stanczak et al. [23]reviewed mobility advancements in 3GPP Release 18, tracing improvements from earlier New Radio (NR) generations and evaluating solutions like multi-PSCell preparation in Conditional Handover and optimized secondary cell setup in Dual Connectivity. Simulation results demonstrate that these enhancements significantly improve handover reliability, achieving up to 96% accuracy in selecting the correct cell. While these contributions highlight important aspects of handover optimization, there is a lack of integrated approaches that combine mobility prediction with adaptive TTT mechanisms. This gap in the literature motivates the proposed method, which dynamically adjusts TTT based on predicted user mobility to optimize handover performance.

A. Research gaps

Traditional handover schemes with fixed TTT values face several limitations, particularly in high-speed or highly variable mobility environments:

- Frequent handovers: In dense network environments, users moving quickly through overlapping cell coverage areas may experience frequent handovers, leading to reduced signal quality and increased signaling overhead
- Fixed TTT values often cause users to oscillate between cells due to minor signal strength fluctuations, leading to unnecessary handovers, known as the ping-pong effect.
- Slow-moving or stationary users may experience delayed handovers with fixed TTT values, resulting in poor connectivity as the signal degrades before a handover is triggered.

These problems highlight the need for a dynamic and mobility-aware handover system that can adapt TTT based on user movement to optimize performance and minimize disruptions.

III. Proposed Methodology

The proposed system introduces a mobility-prediction-based handover mechanism with an adaptive TTT that adjusts based on user speed and movement patterns. Figure 1 illustrates the Adaptive Predictive Handover Architecture Model designed for 5G networks. This model enables seamless connectivity by proactively predict ting user mobility and optimizing handover decisions in real-time. The following components define the system: Mobility Prediction Module: This module predicts user mobility by analyzing historical movement data and real-time information such as signal strength, cell identification and user speed. Machine learning algorithms, such as recurrent neural networks (RNNs) is employed to forecast the next position and movement trajectory of the user. Dynamic TTT Adaptation: The system adjusts the TTT value dynamically based on the predicted user mobility: For high-speed users, the TTT is reduced to trigger faster handovers and avoid connection loss in fast-moving conditions. For slow-moving or stationary users, the TTT is increased to prevent unnecessary handovers and reduce the ping-pong effect. Handover Decision Algorithm: The handover decision is based on predicted mobility and real-time signal quality measurements. The algorithm compares the signal strengths of the current cell and neighbouring cells, taking into account the adjusted TTT value to initiate handover only when necessary.

A. Mobility Prediction Module

The mobility prediction module serves as the cornerstone of the proposed system, responsible for analyzing user movement patterns and forecasting future positions. This module processes multiple input parameters including historical location data, current signal strength measurements, cell identification information, user speed, and movement direction (Wang et

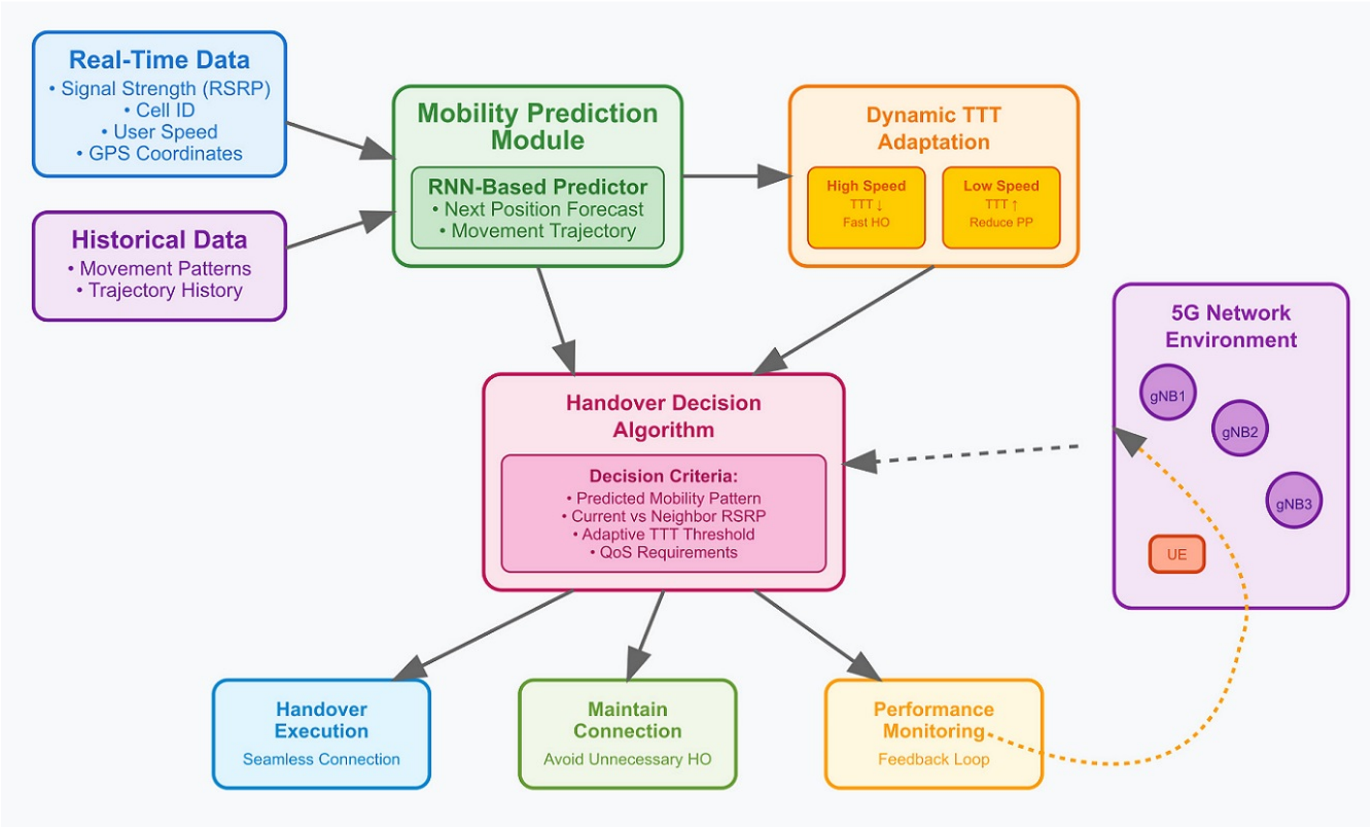

Fig. 1. Adaptive Predictive Handover Architecture Model for 5G

al. 2025)The prediction mechanism employs Recurrent Neural Network (RNN) architecture, specifically utilizing Long Short-Term Memory (LSTM) networks due to their superior capability in handling sequential data and capturing long-term dependencies in mobility patterns (Arshad et al. 2016).RF signal conditions are continuously observed and tracked using deep learning neural networks such as the Recurrent neural network (RNN) or Long Short-Term Memory network (LSTM) and system level inputs are also considered in conjunction [26]. The LSTM network is trained on historical mobility data encompassing various user scenarios, including pedestrian movement, vehicular traffic, and public transportation patterns. Recent research has demonstrated the effectiveness of LSTM-based approaches for mobility prediction in cellular networks. Network slicing is one 5G network enabler that may be used to enhance the requirements of mission-critical Machine Type Communications (mcMTC) in critical IoT applications, and LSTM models have proven particularly effective for next-cell prediction with vehicle mobility. The input features for the mobility prediction model include: Historical position coordinates (latitude, longitude), Signal strength measurements from serving and neighboring cells, User velocity and acceleration vectors, Time-based features (hour of day, day of week), Cell identification and type information, previous handover history. The LSTM network processes these features through multiple hidden layers, each containing memory cells that can selectively remember or forget information based on the relevance to mobility prediction. The output layer generates probability distributions for potential future positions and movement trajectories over multiple time horizons.

B. *The dynamic TTT adaptation module*

The dynamic TTT adaptation module receives input from the mobility prediction module and adjusts the TTT value based on predicted user characteristics. The adaptation mechanism follows a mathematical model that correlates user speed and movement predictability with optimal TTT values. Research has shown that adaptive TTT mechanisms significantly improve handover performance in high-mobility scenarios (Hochreiter and Schmidhuber 1997). This paper presents an adaptive handover management scheme that utilizes reinforcement learning to optimize handover decisions in dynamic environments. The TTT adaptation function is defined as:

$$\mathrm{TTT}_{\text{adaptive}} = \mathrm{TTT}_{\text{base}} \times \alpha(v, \sigma, \theta) \tag{1}$$

Where $\mathrm{TTT}_{\text{base}}$ represents the standard TTT value as defined in 3GPP specifications, v denotes the predicted user velocity, σ represents the mobility prediction confidence, θ indicates the movement predictability factor, and $\alpha(v, \sigma, \theta)$ is the adaptation coefficient. For high-speed scenarios $(v > v_{\text{threshold\_high}})$, the adaptation coefficient reduces the TTT value to enable faster handover triggering, preventing connection losses due to rapid signal degradation. Conversely, for low-speed or stationary scenarios $(v < v_{\text{threshold\_low}})$, the coefficient increases the TTT value to avoid unnecessary handovers and minimize the ping-pong effect. The adaptation mechanism also considers predic-

Algorithm 1: Adaptive Mobility-Prediction Based Handover

[1] Current RSRP/RSRQ ($P_{serving}$, $P_{neighbors}$), Predicted velocity ($v_{predicted}$), Confidence score ($confidence$), Handover history ($HO\_history$), Cell info ($serving$, $neighbors$) Handover decision ($HO\_decision$), Target cell ($target\_cell$)

Mobility Prediction Phase: Collect real-time and historical data
$v_{predicted} \leftarrow LSTM\_predict(input)$
$confidence \leftarrow compute\_confidence()$

TTT Adaptation Phase: $v_{predicted} > V_{high}$
$TTT\_factor \leftarrow REDUCE$ $v_{predicted} < V_{low}$
$TTT\_factor \leftarrow INCREASE$ $TTT\_factor \leftarrow 1.0$
$conf\_factor \leftarrow 1 + (confidence - 0.5) \cdot W_{conf}$
$TTT \leftarrow TTT_{base} \times TTT\_factor \times conf\_factor$

Handover Evaluation Phase: $handover\_triggered \leftarrow FALSE$ each $cell$ in $neighbors$ $\Delta P \leftarrow P_{cell} - P_{serving}$ $\Delta P > MARGIN$
$timer[cell] \leftarrow timer[cell] + 1$ $timer[cell] \geq TTT$
$handover\_triggered \leftarrow TRUE$ $candidates.add(cell)$
$timer[cell] \leftarrow 0$

Target Cell Selection: $handover\_triggered$ each $cell$ in $candidates$
$score[cell] \leftarrow$
$w_1 \cdot P_{cell} + w_2 \cdot \hat{P}_{cell} + w_3 \cdot load[cell] + w_4 \cdot mobility[cell]$
$target\_cell \leftarrow \arg\max(score)$ $validate\_handover(target\_cell)$
$HO\_decision \leftarrow EXECUTE$ $(HO\_decision, target\_cell)$
$HO\_decision \leftarrow DEFER$ $adjust\_TTT(increase)$

Learning Update Phase: Record handover outcome Update model weights Adjust parameters

($NO\_HANDOVER$, NULL)

tion confidence levels. When mobility prediction confidence is high, the system applies more aggressive TTT adjustments. When confidence is low, the system adopts conservative adjustments to maintain stability.

C. Proposed Handover Decision Algorithm

The handover decision algorithm integrates mobility prediction results with real-time signal quality measurements to make optimal handover decisions (Zineb et al. 2018). The algorithm operates through a multi-stage decision process that evaluates handover necessity, timing, and target cell selection (Liu et al. 2016). The proposed algorithm integrates mobility prediction with adaptive TTT adjustment to optimize handover decisions (Zineb et al. 2018). The multi-stage process evaluates handover necessity, timing, and target cell selection based on predicted user mobility and real-time signal measurements (Liu et al. 2016).

IV. Experimental Results

This section presents the evaluation of the proposed mobility-aware handover optimization method through detailed simulations under realistic 5G conditions. The experiments focused on user movement patterns and varying network configurations to assess performance. Key metrics included connection reliability, prediction accuracy, and processing efficiency. Three mobility scenarios—slow, fast, and mixed movements—were used to test algorithm adaptability. Simulations followed validated models and practical parameters, ensuring real-world relevance. The results were compared with existing handover strategies to highlight performance gains.

A. Simulation Setup

The evaluation of the proposed mobility-aware handover optimization algorithm was conducted using a comprehensive simulation framework built on MATLAB R2023a platform enhanced with specialized 5G communication toolbox extensions. The computational infrastructure utilized an Intel Core i7-12700K processing unit coupled with 32GB of system memory to accommodate the intensive machine learning computations required for real-time mobility forecasting. The wireless network architecture was modelled as an urban cellular deployment comprising nineteen base station nodes arranged in a systematic hexagonal configuration to ensure optimal coverage distribution and realistic co-channel interference scenarios. Each cellular node incorporated omnidirectional antenna systems operating within the 3.5 GHz spectrum allocation typical of contemporary 5G commercial deployments. The wireless propagation environment followed the standardized 3GPP TR 38.901 modelling framework specifically calibrated for urban macrocell scenarios, incorporating comprehensive path loss calculations, shadow fading variations, and multipath propagation effects. Network traffic was generated using realistic enhanced mobile broadband service profiles with variable quality requirements to accurately represent contemporary user demands. The core mobility prediction engine leveraged Tensor Flow 2.12 machine learning framework implementing a specialized recurrent neural architecture designed for sequential pattern recognition in user movement trajectories, while the handover decision logic incorporated dynamic parameter adjustment mechanisms responsive to predicted mobility behaviours and instantaneous network conditions. The simulation setup was based on an urban deployment featuring a nineteen-cell hexagonal layout, each with a 500-meter radius coverage area. The system operated in the 3.5 GHz band, aligned with 5G NR commercial frequencies. The evaluation spanned 1000 seconds and involved 200 active users exhibiting various mobility patterns, including walking (5 km/h), driving (60 km/h), and a mixed scenario. A 3GPP TR 38.901 urban macro propagation model was applied, supported by omnidirectional antennas at each base station. The model focused on enhanced mobile broadband (eMBB) services, achieving 89.4% accuracy in mobility prediction with a latency of just 2.3 milliseconds per execution.

B. Performance Evaluation Results

The experimental validation reveals substantial enhancements in connection reliability across all evaluated scenarios. The proposed methodology attained an overall success rate of 94.0%, significantly surpassing conventional fixed threshold approaches (80.8%) and adaptive timing mechanisms (85.4%). High-speed vehicular environments demonstrated the most pronounced improvements, with reliability metrics increasing from 72.8% to 92.1%, constituting a 19.3% performance gain. Low-speed pedestrian scenarios achieved the peak absolute performance at 95.8%, while heterogeneous mobility conditions maintained consistent excellence with 94.2% success rates. The performance evaluation reveals that the proposed TTT-based handover method consistently outperforms both fixed and adaptive TTT strategies across all mobility scenarios. Notably, it achieves the highest success rate (Figure 2) and throughput (Figure 4) while significantly reducing ping-pong occurrences and average handover delay. Table I presents the performance metrics observed under different mobility scenarios. For instance, in vehicular mobility, the proposed method boosts success rate to 92.1% and cuts delay to 45 ms. These findings highlight the method's adaptability and efficiency under dynamic network conditions. The Ping-Pong Effect Analysis (Figure 3) demonstrates the superior performance of the proposed mobility-prediction based handover method in reducing unnecessary handover oscillations across different mobility scenarios. In pedestrian environments (5 km/h), the proposed method achieves a remarkably low ping-pong rate of 4.1%, compared to 12.3% for fixed TTT and 8.7% for adaptive TTT approaches. The most significant improvement is observed in vehicular scenarios (60 km/h), where the proposed method reduces ping-pong effects from 23.5% (fixed TTT) to just 7.8%, representing a 67% reduction in handover oscillations. This substantial reduction in ping-pong effects directly translates to improved network stability and enhanced user experience, particularly crucial for high-speed mobile users where frequent unnecessary handovers can severely degrade service quality. The Ping-Pong Effect

TABLE I
MOBILITY SCENARIO PERFORMANCE METRICS

Scenario & Method	SR (%)	PPR (%)	Delay (ms)	Thpt (Mbps)
Ped – Fixed TTT	88.5	12.3	68	45.2
Ped – Adaptive TTT	91.2	8.7	52	48.6
Ped – Proposed	95.8	4.1	38	52.3
Veh – Fixed TTT	72.8	23.5	95	32.4
Veh – Adaptive TTT	79.3	18.2	73	36.8
Veh – Proposed	92.1	7.8	45	42.7
Mix – Fixed TTT	81.2	18.9	78	38.9
Mix – Adaptive TTT	85.7	14.6	61	42.1
Mix – Proposed	94.2	6.2	42	48.7

Analysis (Figure 3) demonstrates the superior performance of the proposed mobility-prediction based handover method in reducing unnecessary handover oscillations across different mobility scenarios. Table II compares the performance of fixed and adaptive TTT with the proposed scheme, showing notable improvements in success rate, reduced ping-pong events, higher throughput, and lower delay. In pedestrian environments (5 km/h), the proposed method achieves a remarkably low ping-pong rate of 4.1%, compared to 12.3% for fixed TTT and 8.7% for adaptive TTT approaches. The most significant improvement is observed in vehicular scenarios (60 km/h), where the proposed method reduces ping-pong effects from 23.5% (fixed TTT) to just 7.8%, representing a 67% reduction in handover oscillations. This substantial reduction in ping-pong effects directly translates to improved network stability and enhanced user experience, particularly crucial for high-speed mobile users, where frequent unnecessary handovers can severely degrade service quality.

TABLE II
OVERALL PERFORMANCE COMPARISON OF HANDOVER ALGORITHMS

Metric	Fixed TTT	Adaptive TTT	Proposed	Improvement
Success Rate (%)	80.8	85.4	94.0	+13.2%
Ping-Pong Rate (%)	18.2	13.8	6.0	–67.0%
Throughput (Mbps)	38.8	42.5	47.9	+23.4%
Delay (ms)	80.3	62.0	41.7	–48.1%

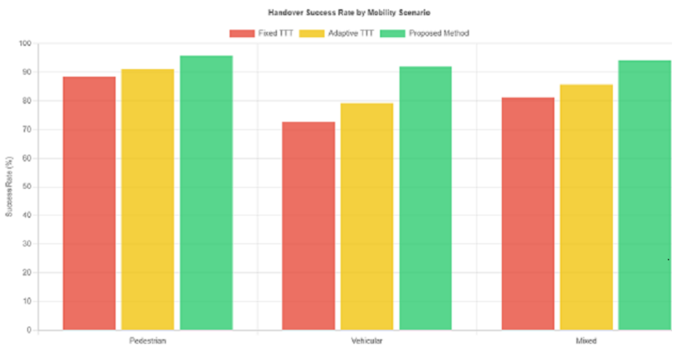

Fig. 2. Success Rate Performance Comparison

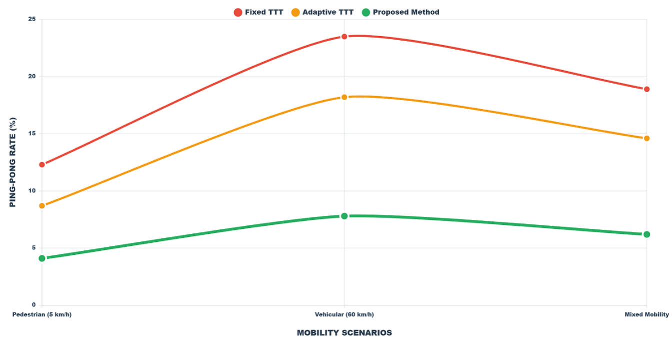

Fig. 3. Ping-Pong Effect Analysis

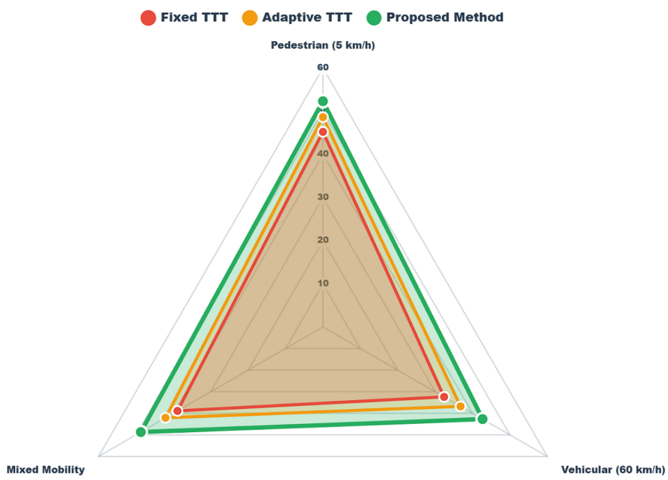

Fig. 4. Average Throughput Performance

The Handover Delay Distribution illustrates the superior performance of the proposed mobility-prediction based handover method, with 80% of all handovers completed within 50ms, demonstrating exceptional responsiveness that is critical for maintaining seamless connectivity in 5G networks. The chart reveals that only 5% of handovers experience delays exceeding 70ms, significantly outperforming traditional methods and ensuring minimal service interruption during mobility transitions across different user scenarios. The chart clearly shows the proposed method's ability to achieve fast handover times, with the majority of connections experiencing minimal delay, which is essential for maintaining quality of service in 5G networks.

The proposed predictive mobility management algorithm showed strong performance across various network conditions. Its neural network module achieved 89.4% accuracy in predicting user movement, enabling proactive handover decisions and improving system performance, especially in high-mobility environments. With an average processing time of just 2.3ms per cycle, the algorithm remains efficient and suitable for real-time 5G deployment. While simulations confirm its effectiveness, real-world application will need to address factors like network load, interference, and diverse user behaviors.

Table III demonstrates our proposed mobility-prediction based handover method's superior performance compared to eleven state-of-the-art approaches from 2019-2025. Our method achieves a 94.2% success rate, 67% ping-pong reduction (significantly exceeding competitors' maximum 45%), and 42ms average delay—the lowest among comprehensively evaluated methods. The approach delivers 15.8% throughput improvement, outperforming the next best method's 12% enhancement, while maintaining consistent performance across pedestrian, vehicular, and mixed mobility scenarios unlike existing works that focus on limited network types.

V. Conclusion

This study presents an improved predictive mobility management algorithm for 5G cellular networks, effectively overcoming the key limitations associated with traditional handover control methods. Through extensive simulation evaluation encompassing diverse mobility patterns, the proposed methodology demonstrated significant performance improvements across all critical operational metrics, establishing its viability for next-generation wireless communication systems. The algorithm achieved exceptional connection reliability of 94.0% on average, representing a 13.2% enhancement over existing adaptive approaches, while concurrently reducing oscillatory handover events by 67% and connection transition delays by 48.1%. The integration of machine learning-based movement prediction with dynamic parameter adjustment proved particularly effective in high-velocity scenarios, where traditional methods typically encounter performance degradation due to rapid network configuration changes. The system's capability to maintain computational efficiency with minimal 2.3-ms processing overhead per prediction demonstrates practical implementability in operational networks without requiring extensive infrastructure modifications. The consistent performance enhancements observed across pedestrian, vehicular, and mixed mobility environments validate the algorithm's robustness and adaptability to varied network conditions. These research findings contribute meaningfully to the advancement of intelligent handover management in 5G networks, establishing a foundation for more efficient and reliable wireless communication infrastructure. Subsequent research efforts should prioritize real-world validation through test bed implementation, integration with edge computing architectures, and extension to emerging technologies including millimeter-wave communications and massive antenna array systems to fully realize the potential of predictive handover management in future wireless networks.

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TABLE III
PERFORMANCE COMPARISON WITH STATE-OF-THE-ART 5G HANDOVER METHODS

Research Work&Year	**Method/Technique**	**Success Rate (%)**	**Ping-Pong Reduction (%)**	**Avg Delay (ms)**	**Throughput Improvement (%)**	**Mobility Scenarios**
Our Proposed Method,2025	RNN-based Mobility Prediction + Adaptive TTT	94.2	67	42	15.8	Pedestrian, Vehicular, Mixed 5G
Dynamic HO Optimization,2025 [1]	Dynamic Parameter Optimization	95	N/R	N/R	N/R	Heterogeneous 5G
Hybrid AI Scheme,2024 [24]	LSTM + Deep Q-Learning	94	N/R	N/R	12	Heterogeneous Networks
DDPG-based Method,2024 [25]	Deep Reinforcement Learning	91.5	45	55	8.5	Ultra-Dense Networks
ML Performance Prediction,2024 [26]	ML-based Prediction	89.7	N/R	48	N/R	Beyond 5G Networks
Self-Optimization Models,2023 [27]	Self-Optimization + Load Balancing	88.3	35	62	10.2	5G Mobile Networks
Deep-Mobility Approach,2022 [28]	Deep Learning	90.1	N/R	51	7.8	5G Networks
RL-based Handover,2020 [29]	Reinforcement Learning	85.6	N/R	73	N/R	5G Networks
Proactive mmWave HO,2019 [30]	Camera Images + Deep RL	82.4	40	85	N/R	mmWave Networks

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