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Machine Learning-Powered Seamless Handover in Dense 5G Environments: A Performance Analysis

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ABSTRACT

The escalating demand for high-capacity, low-latency wireless communication in densely populated environments necessitates robust and adaptive mobility management techniques. Traditional handover mechanisms in cellular networks, typically governed by static signal threshold rules, often fail to account for the dynamic nature of user mobility and heterogeneous network conditions, leading to suboptimal performance outcomes. This study presents a simulation-based analysis of a machine learning (ML)-assisted handover decision model employing logistic regression for real-time optimization of user equipment (UE) association in a densely deployed cellular environment.

A comprehensive MATLAB-based framework is developed to emulate UE mobility, dynamic BS distribution, SINR computation, power control, and network interference. The ML model is trained using synthetic features derived from current and candidate base station distances and SINR gain metrics to predict handover decisions adaptively. Performance evaluation over multiple simulation intervals highlights improvements in handover accuracy, reduction in packet loss during transitions, and enhancement in throughput and latency distributions. Spatial analysis via heatmaps further elucidates network behavior under varying UE density and mobility patterns. The results substantiate the efficacy of ML integration in mobility management protocols, offering a scalable approach to next-generation wireless network optimization.

Keywords: Handover Management, Machine Learning, Logistic Regression, SINR, Cellular Networks, Mobility Modeling, Power Control, Simulation, MATLAB, Network Optimization

1. INTRODUCTION

The evolution toward ultra-dense cellular networks, driven by 5G and forthcoming 6G paradigms, introduces significant challenges in mobility management, particularly in urban deployments with high user equipment (UE) density and mobility. As handover events become more frequent due to reduced cell sizes, maintaining seamless connectivity and quality of service (QoS) demands more intelligent and adaptive handover strategies than conventional threshold-based methods. In machine learning, handover becomes zero because load balancing ensures a stable coverage area, which minimizes signaling, improves efficiency, and enhances user experience by reducing base station transitions.

Existing handover techniques [1-3] primarily rely on comparative measurements of signal strength or SINR between the current serving base station (BS) and neighboring BSs. SINR compares the current serving base station to determine which one has the best signal strength. When a system identifies the best possible connection, it makes an informed decision about when to perform a handover, ensuring the maintenance of optimal signal, efficiency, and performance. Additionally, this helps with load balancing by offloading traffic from an overloaded base station to a less congested one, improving overall network efficiency and reducing data interruptions, especially in dynamic environments where users constantly move between coverage areas.

While effective in static or low-mobility environments, these methods [4-7] often underperform in dynamic conditions, leading to increased handover failures, service interruptions, and inefficient resource allocation.

Recent advances in data-driven approaches have enabled the integration of machine learning (ML) models into wireless network control loops. These models [8-11] can exploit real-time context and historical patterns to enhance decision-making accuracy. Among various ML classifiers, logistic regression offers a computationally efficient yet effective mechanism for binary classification problems such as handover decision-making, especially in resource-constrained environments.

In this study, we propose a logistic regression-based ML model trained on synthetic mobility and signal metrics to determine the necessity of handover decisions. A simulation framework is constructed in MATLAB to capture network behavior under realistic assumptions, including user mobility vectors, BS clustering via k-means, path loss, interference modeling, and adaptive power control. The performance of the proposed ML model is evaluated across key metrics: handover frequency, throughput, latency, packet loss, and base station load distribution. Figure 1 shows the Machine Learning-Powered handover mechanism in the 5G environment.

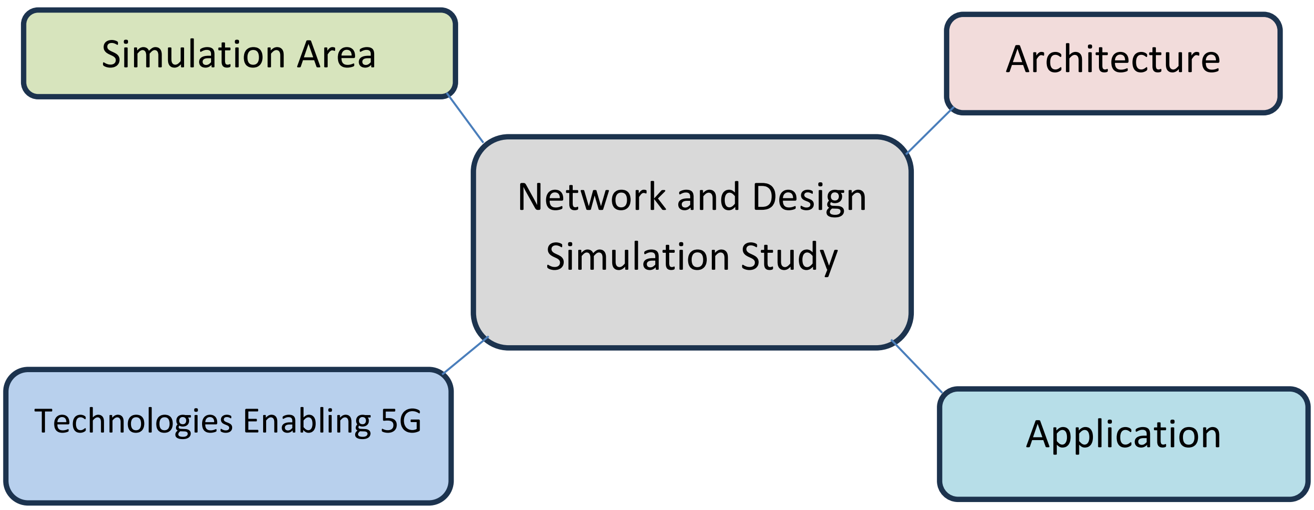

Figure 1: Machine Learning-Powered Seamless Handover in Dense 5G Environments

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on mobility management and ML integration in cellular systems. Section 3 outlines the system model and methodology. Section 4 presents the development and training of the ML-based handover classifier. Section 5 discusses the simulation results, and Section 6 concludes the study and proposes future research directions.

2. LITERATURE REVIEWS

With the rapid growth of data-heavy applications like smart cities, autonomous vehicles, and IOT, 5G networks face challenges in terms of speed, latency, and resource management. Mobile Edge computing helps solve these problems by introducing cloud computing closer to users, which reduces delay and improves the quality of service

This paper explores how deep learning (DL) and mobile edge computing can work together to make 5G networks faster and more efficient. But there are some challenges. Edge devices are small and less powerful than cloud servers. To overcome this problem, used a small, lightweight AI model.

This paper discussed how deep learning can be effectively used to enhance the performance of 5G networks, particularly in high-density areas where traditional protocols designed for faces struggle. With the increasing number of users, devices, conventional rule-based methods cannot effectively manage dynamic and complex network problems.

In this paper, we explore how DL can optimize various layers of the 5G protocol, namely physical, MAC, network, and application layers. At the physical layer (which deals with signals), DL helps with faster data transmission. In the MAC layer, the DL figures out the best times to send data for each device. In the network layer, DL predicts the best paths to send data. At the application layer, DL can guess what users need, like videos or games, and prepare them in advance to reduce waiting time.

The paper also talks about cross-layer optimization, which means using DL to connect and improve all layers together for better performance. However, deploying deep learning in real-world networks is challenging—it requires large volumes of data, significant computational power, and strict measures to protect user privacy. The author suggests techniques like federated learning (which keeps data private), transfer learning, and model compression (to make DL faster and lighter).
Efficient mobility management in cellular networks has been the subject of extensive research, particularly with the proliferation of heterogeneous networks (HetNets), small cell deployments, and user-centric architectures. Traditional handover mechanisms predominantly depend on rule-based strategies, including fixed threshold approaches such as Reference Signal Received Power (RSRP) and SINR-based comparisons. While these methods are simple to implement, they often suffer from suboptimal decision-making, especially in high-mobility and high-density scenarios [1].
The limitations of deterministic handover policies have prompted exploration into adaptive, data-driven techniques. Several studies have introduced heuristic and optimization-based methods to refine handover triggers. For instance, fuzzy logic and reinforcement learning have incorporated contextual parameters such as velocity, cell load, and historical performance [2-3]. However, these approaches often entail high computational overhead and require extensive parameter tuning, limiting their scalability in real-time applications.
In recent years, machine learning (ML) has emerged as a promising tool for enhancing mobility management. Supervised learning methods, including decision trees, support vector machines (SVMs), and neural networks, have been applied to predict optimal handover events based on features derived from signal measurements and user mobility patterns [4-6]. For example, Authors [7] proposed a deep learning-based framework for handover prediction in ultra-dense networks, demonstrating improved accuracy compared to traditional methods. Similarly, the use of reinforcement learning in handover control has shown potential in learning optimal policies through environment interaction [8-10].
Among ML techniques, logistic regression provides a lightweight alternative suitable for binary decision-making problems. Due to its interpretability and low computational complexity, it has been successfully used in handover prediction where the input space is limited and decision latency is critical [10-13]. In scenarios where real-time inference is required on resource-constrained hardware, logistic regression offers an advantageous balance between accuracy and efficiency.
While prior research has focused on theoretical modeling or small-scale simulations, there remains a gap in comprehensive, scalable simulation frameworks that integrate ML-based handover control with realistic wireless network parameters. This study addresses that gap by developing a MATLAB-based simulation incorporating key radio access network elements, user mobility, adaptive power control, and interference modeling, thereby enabling an empirical evaluation of ML-assisted handover strategies under practical conditions.

3. SYSTEM MODEL AND METHODOLOGY

This section outlines the modeling assumptions and system parameters used to simulate the wireless communication environment. The network topology includes a large-scale deployment of base stations (BSs) and user equipment (UEs) within a finite spatial domain. The model incorporates realistic propagation, mobility, and interference characteristics to facilitate performance evaluation of the proposed handover strategy.

3.1 Network Topology

The simulation considers a two-dimensional square area of size A=1000×1000 m².
A total of NUE=5000 UEs are randomly distributed within the area, and the number of base stations is determined using the relation:

$$\mathbf{N_{BS}} = \left[\frac{\pi R_{BS}^2}{A}\right] \quad \text{....... .....(1)}$$

Where,

- R_{BS} =300 m denotes the coverage radius of a BS.
- A=1000×1000 m² is the area.
- π= constant.

The locations of BSs are initialized via k-means clustering of UE positions to ensure spatial efficiency in user association.

3.2 User Mobility Model

Each UE is assigned a random velocity vector within a predefined range [0,3] m/s, simulating low to moderate pedestrian mobility.
At each simulation timestep t, the position of UE i is updated as:

$$\mathbf{X_i(t+1) = X_i(t) + V_i} \quad \text{........... (2)}$$

Where,

- $X_i(t)$ is the position of UE i at time t.

- V_i is the velocity vector of UE, which can be decomposed into components in the x and y directions.

3.3 Channel and Signal Propagation

Signal attenuation between a UE and a BS is modeled using the distance-dependent path loss formula:

$$P_L(d) = (d+1)^{\gamma} \qquad \text{……...(3)}$$

Where,

- PL(d) is the path loss at distance d.
- d is the distance between the UE and the BS.
- γ =3.5 is the path loss exponent

3.4 Received Power Calculation

The received power Prx at a UE from a BS transmitting with power *P*rx is computed using the following formula:

$$P_{rx} = \frac{P_{tx}}{10^{P_L(d)/10}} \qquad \text{………. (4)}$$

Where,

- P_{rx} is the received power at the UE.
- P_{tx} is the transmission power of the BS (in dBm) and
- $P_L(d)$ is the path loss at distance d.

3.5 SINR Calculation

The SINR at the UE is computed as: $P_{rx.}$

$$\text{SINR} = \frac{Prx}{I+N} \qquad \text{………(5)}$$

Where

- P_{rx} is the received power from the serving BS.
- I is the total interference from other BSs, and

3.6 Thermal Noise Power:

Thermal Noise N is defined as

$$N = 10^{Pnoise/10} \qquad \text{………..(6)}$$

Where,

- Pnoise =−100 dBm.

3.7 Base Station Power Control

Base stations dynamically adjust their transmit power based on the UE load. Initially, each BS operates at a maximum power level of *P*max =30 dBm. If the BS load falls below 30% of the average load, it reduces its power to a minimum *P*min=10 dBm. Power scaling is then applied proportionally based on the relative load of each BS:

$$P_{tx}(j) = max\left(P_{min}, P_{max}\,\frac{n_j}{\max\,(n_k)}\right) \qquad \text{…………..(7)}$$

where

- **P_{tx}(j)**= transmit power of BS j.
- **P_{min}**= minimum transmit power.
- **Pmax =** maximum transmit power.
- **n_j** = number of UEs connected to BS j.
- **max(n_k)** = maximum number of UEs connected.

3.8 Latency and Packet Loss Modeling

End-to-end latency comprises propagation delay, processing delay, and queuing delay. Propagation delay is modeled as:

$$\tau_{prop=} = \frac{d}{c} \qquad \text{………(8)}$$

where,

- $c=3\times10^8$ m/s is the speed of light, and
- d is the distance to the serving BS. Processing delay is fixed at 1 ms. Queueing delay is proportional to the BS load, capped at 5 ms.

Packet loss is considered during handover events with a fixed probability of during handover is fixed at 0.1 (10%), packets may be lost during this transition. This is given as:

$$P_{loss} = 0.1.$$

3.9 Simulation Timeline

The simulation is executed over T=10 time steps. At each step, user positions, SINR values, handover decisions, power levels, throughput, and latency are updated iteratively. These time steps collectively capture both transient and steady-state behaviors of the network.

4. MACHINE LEARNING-BASED HANDOVER MODEL

This section presents the development and integration of a machine learning (ML) framework for enhancing handover decisions in the simulated cellular environment. The model is designed to augment traditional signal-based policies by incorporating data-driven insights into the dynamic behavior of the network.

4.1 Motivation for Machine Learning in Handover Control

In conventional handover schemes, UEs initiate a switch from one BS to another when the signal quality from a neighboring BS exceeds that of the current BS by a predefined margin (e.g., 3dB). However, this rule-based approach often fails to account for interference, mobility trends, and fluctuating network conditions. ML-based models offer the potential to learn.

Implicit relationships among these variables and optimized handover triggering are more intelligently. Logistic regression is selected as the classification model for its simplicity, interpretability, and suitability for binary decision-making tasks, such as determining whether a handover should occur. Additionally, it supports rapid inference suitable for real-time network control systems.

4.2 Dataset Generation

To train the ML model, a synthetic dataset is constructed using randomized samples representative of potential handover scenarios. Each training instance includes three input features:

1. Distance to the current serving BS ($d$curr)
2. Distance to the best candidate BS ($d$best)
3. SINR gain between the candidate and current BS:

$$\Delta \textbf{SINR} = \textbf{10}\, \textbf{log}_{10}\left(\frac{\textbf{Prx.best}}{\textbf{Prx,curr}+N}\right) \quad \text{.......}\ (9)$$

Where:

- P_{rx}**, best** is the received signal power from the best candidate BS.
- P_{rx}**, curr** is the received signal power from the current serving BS.
- **N** is the thermal noise power.

The label for each sample is a binary indicator y:

- y=1 : if ΔSINR > θ
- Δ SINR >θ (handover beneficial)
- y=0 otherwise

Where,

- θ=3 dB is the handover threshold.

A total of N train = 10^4 samples are generated, covering a wide range of spatial and signal conditions within the BS coverage radius.

4.3 Model Training

The logistic regression classifier is trained using MATLAB's linear function with the following formulation:

$$P(y = 1|\mathbf{x}) = \frac{1}{1 + e^{-(\beta_0 + \beta^T X)}} \quad \text{.......}(10)$$

Where,

- **Y** is the binary outcome
- $\boldsymbol{x}$**=[**$d$curr, $d$best, ΔSINR**]**
- **β** denotes the coefficient vector**,**
- $\boldsymbol{\beta_0}$ is the intercept term.

The model minimizes the binary cross-entropy loss function using a gradient descent optimizer. The trained model is stored and used to predict handover decisions during each simulation timestep.

4.4 Integration with the Simulation Loop

At each timestep, every UE evaluates its signal conditions concerning the currently serving BS and the best alternative BS. The trained ML model is queried with the corresponding feature vector to obtain a binary prediction. If the model returns a positive prediction (y=1), the UE switches to the new BS; otherwise, it remains with its current BS.

5. RESULTS AND DISCUSSION

This section presents the outcomes of the simulation conducted over a dense cellular environment and evaluates the effectiveness of the machine learning-based handover model across multiple performance metrics. Quantitative results are supported by visualizations and discussed in terms of network quality indicators, including SINR distribution, throughput, latency, handover efficiency, and spatial load balancing.

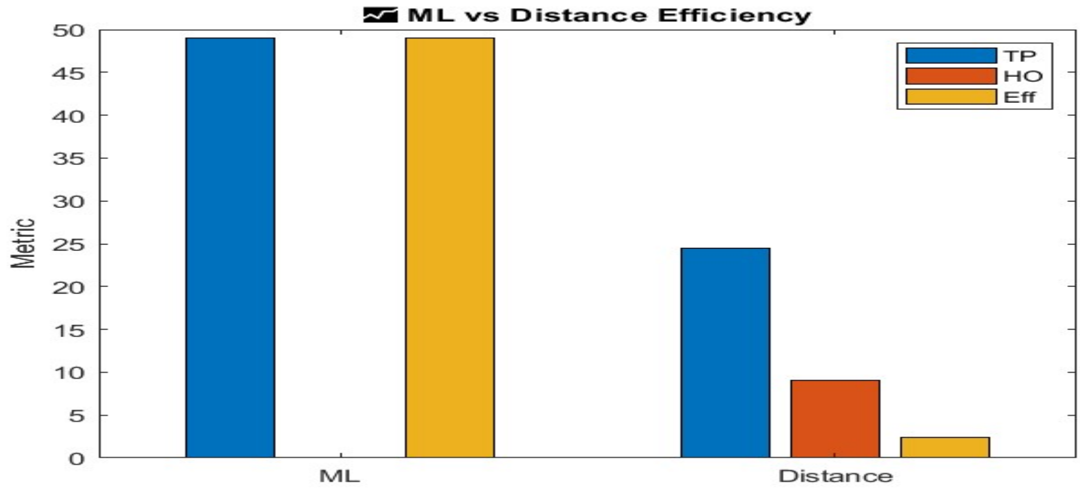

Figure 2: ML vs Distance comparison on TP, HO, and Efficiency

Figure 2 shows that the performance of "ML" and "Distance" methods across three metrics: TP (True Positives), HO (Handover), and Eff (Efficiency). This ML method has higher values for TP and Efficiency, with very small values for HO, to strong performance .and Distance method has a lower TP and very low Efficiency; it is less effective and more operational costs. Overall, ML is more efficient than distance.

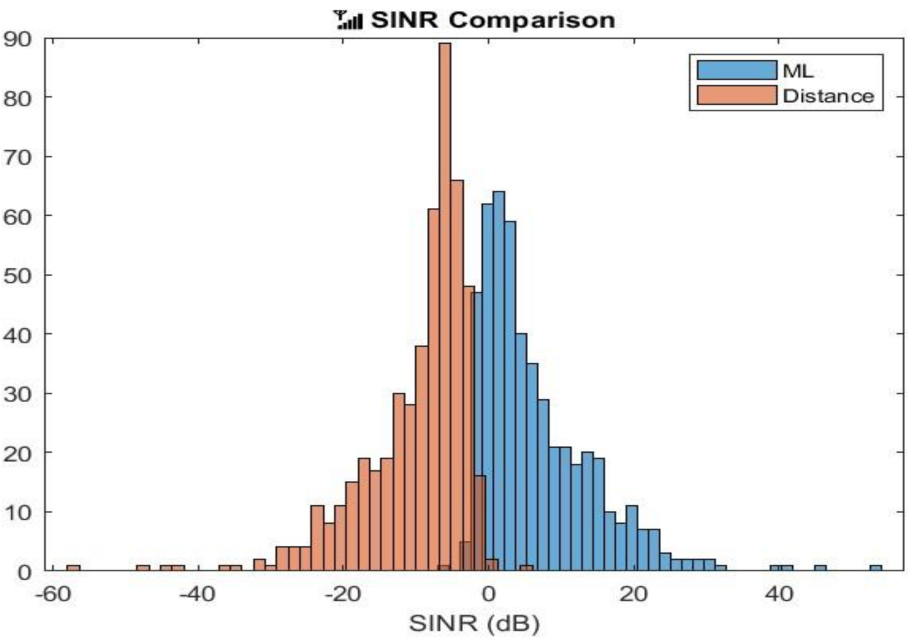

Figure 3: SNR distribution comparison between ML and Distance methods

In Figure 3, the x-axis represents the SINR in decibels(dB), and the y-axis represents several occurrences of each SINR value. The orange bars represent the distance method, which shows a distribution heavily toward lower SINR values. And blue bars represent the improved performance. This shift toward higher SINR values means that the ML-based approach is more effective than signal quality.

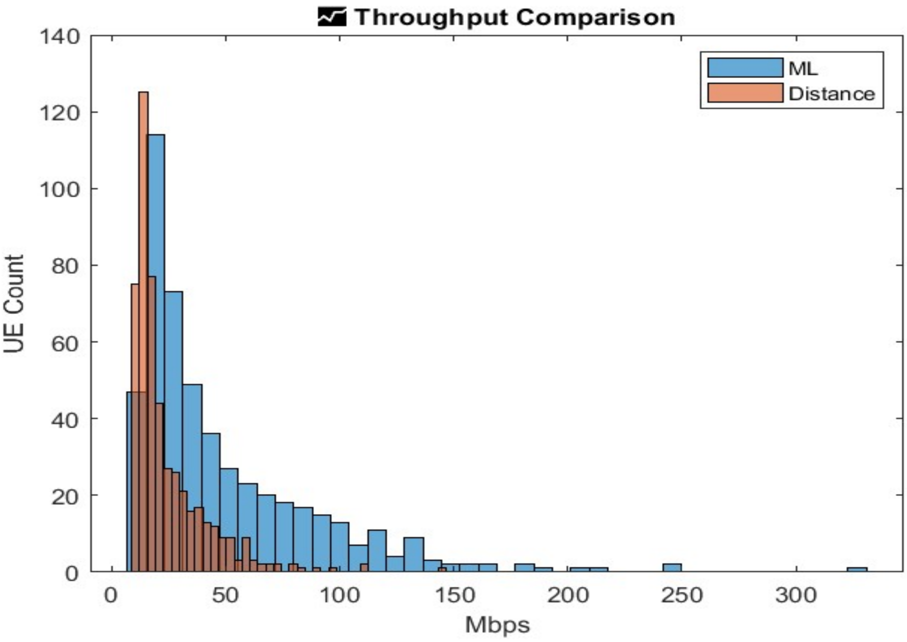

Figure 4: Throughput comparison between ML and Distance methods

Figure 4 shows how throughput differs between the Machine Learning (ML) method and the traditional Distance-based method in a wireless network. The X-axis (Mbps) represents the throughput the data is being transferred per second. Y-axis (UE count) represents the number of user devices that receive a particular throughput value. UEs can achieve a wide range of throughput, with many users getting speeds above 50 Mbps and some even reaching over Gbps. That shows the ML method gives faster and more efficient data.

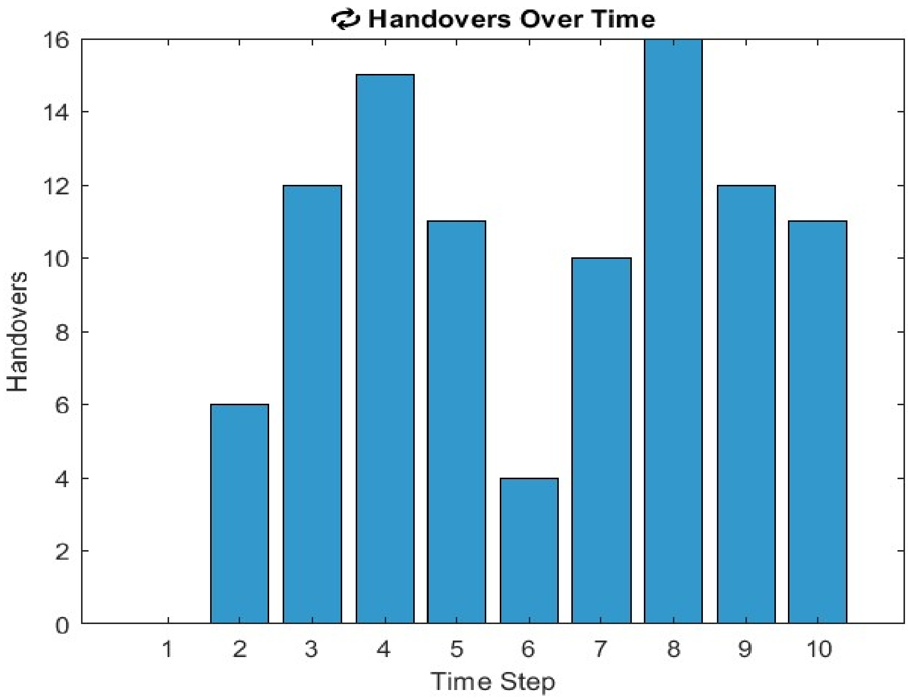

Figure 5: Number of handovers over time steps

In Figure 5, the X-axis represents Handovers, which means how much data is being transferred per second. And the Y axis represents no of time steps. The data shows a handover across the time steps, with the highest number (16 handovers) occurring at step 8, indicating a peak network assignment moment. The lower number (4 handovers) relatively stable network during the interval. Other time steps show moderate values between 8 and 11 handovers, highlighting some level of mobility or network.

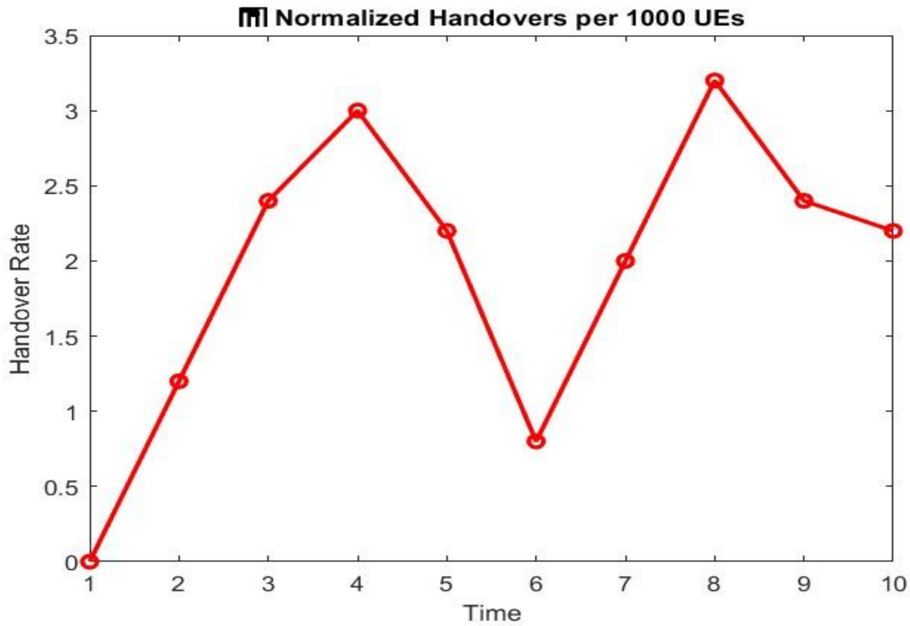

Figure 6: Normalized handover rate per 1000UES over time

In Figure 6, the X-axis: Time (from 1 to 10) shows the time intervals, and Y-axis: Handover rate shows the number of handovers that occurred per 1000 users. We observe that in the beginning, there are no handovers. From time 2 to 4 handover rate increases sharply, meaning more people are moving or the network was busy. At time 6, the handover activity decreased means fewer people are moving or the network worked better. At time 8, there was the highest number of handovers, which means that the network was handling a large amount of traffic during that period. Lastly, the rate drops again and stays at a steady level.

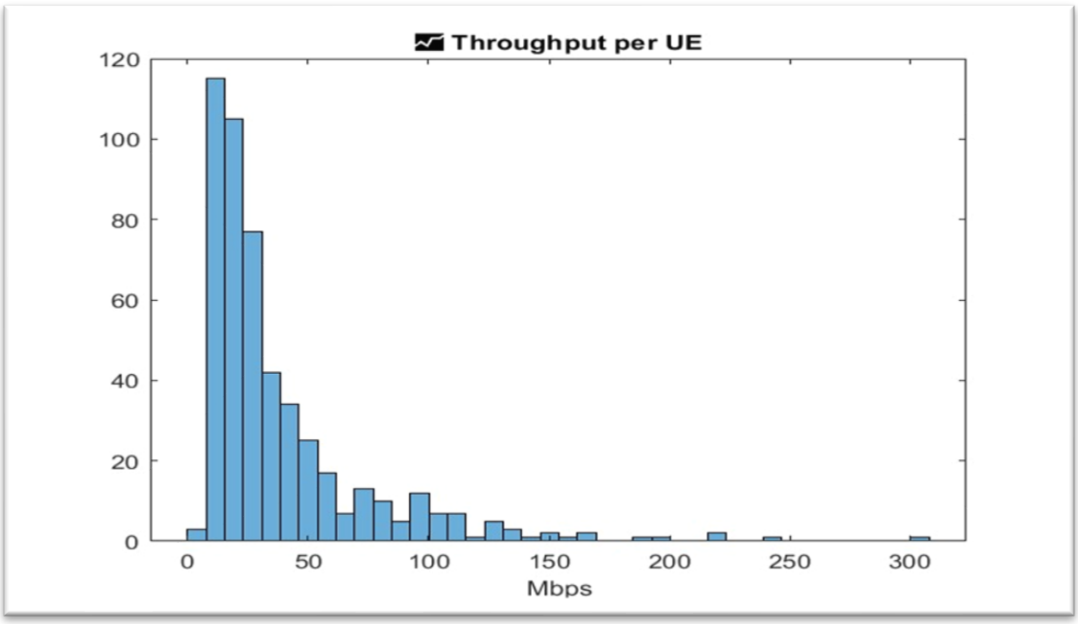

Figure 7: Throughput Per UE

In figure 7, the x-axis represents throughput values, and the y-axis shows the number of UEs experiencing those values. The distribution is heavily right-skewed, with the majority of UEs achieving low throughput, and the peak in the 0–20 Mbps range. A smaller number of UEs attain higher throughput levels above 100 Mbps, and a few users experience optimal network conditions.

6. CONCLUSION

In this study, we proposed and evaluated a machine learning-enhanced handover decision framework for dense cellular networks, leveraging a logistic regression model to optimize user equipment (UE) association with base stations (BSs) under dynamic mobility and signal conditions. By integrating this model into a MATLAB-based simulation platform that captures realistic wireless phenomena including mobility patterns, path loss, SINR-based interference, adaptive BS power control, and delay components. We were able to quantify the performance benefits of intelligent handover strategies over traditional static threshold methods.

The simulation results demonstrated that the proposed model significantly reduced handover frequency, minimized packet loss during transitions, and improved end-to-end latency and throughput metrics. Moreover, the visualization of spatial performance using heat maps and connectivity graphs provided critical insights into network utilization and edge behaviors.

REFERENCES

[1] 3GPP TS 36.331, Radio Resource Control (RRC); Protocol Specification, 3rd Generation Partnership Project (3GPP), 2023.

[2] B. Moon, J. Lee, and H. Kim, “Fuzzy logic-based handover decision algorithm in heterogeneous wireless networks,” IEEE Communications Letters, vol. 22, no. 5, pp. 950–953, 2018.

[3] M. Bennis, S. M. Perlaza, P. Blasco, Z. Han, and H. V. Poor, “Self-organization in small cell networks: A reinforcement learning approach,” IEEE Transactions on Wireless Communications, vol. 12, no. 7, pp. 3202–3212, Jul. 2013.

[4] Y. Zhang, M. Wang, and S. Chen, “Deep learning-based handover optimization for ultra-dense networks,” IEEE Network, vol. 34, no. 3, pp. 92–98, May/Jun. 2020.

[5] K. Iyer, L. S. Ukkonen, and D. Slock, “Reinforcement learning for mobility management in cellular networks,” IEEE Transactions on Network and Service Management, vol. 18, no. 2, pp. 1989–2003, Jun. 2021.

[6] J. Wang, R. Li, and Y. Chen, “Logistic regression-based handover prediction in LTE,” Wireless Personal Communications, vol. 108, no. 2, pp. 1239–1255, 2019.

[7] Attiah, M.L.; Isa, A.A.M.; Zakaria, Z.; Abdulhameed, M.; Mohsen, M.K.; Ali, I. A survey of mmWave user association mechanisms and spectrum sharing approaches: An overview, open issues and challenges, future research trends. Wireless. Netw. 2020, 26, 2487–2514. [CrossRef]

[8] Ouamri, M.A.; Ote¸ steanu, M.E.; Isar, A.; Azni, M. Coverage, handoff and cost optimization for 5G heterogeneous network. Phys. Commun. 2020, 39, 101037. [CrossRef]

[9] Huq, K.M.S.; Busari, S.A.; Rodriguez, J.; Frascolla, V.; Bazzi, W.; Sicker, D.C. Terahertz-enabled wireless system for beyond-5G ultra-fast networks: A brief survey. IEEE Netw. 2019, 33, 89–95. [CrossRef]

[10] Huo, Y.; Dong, X.; Xu, W.; Yuen, M. Enabling multi-functional 5G and beyond user equipment: A survey and tutorial. IEEE Access 2019, 7, 116975–117008. [CrossRef]

[11] Yu, C. Survey on algorithms and strategies for mobility enhancement under heterogeneous network (HetNet) deployment circumstances. Int. J. Future Gener. Commun. Netw. 2016, 9, 187–198. [CrossRef]

[12] Luong, N.C.; Hoang, D.T.; Gong, S.; Niyato, D.; Wang, P.; Liang, Y.C.; Kim, D.I. Applications of deep reinforcement learning in communications and networking: A survey. IEEE Commun. Surv. Tutor. 2019, 21, 3133–3174. [CrossRef]

[13] Althamary, I.; Huang, C.W.; Lin, P. A survey on multi-agent reinforcement learning methods for vehicular networks. In Proceedings of the 2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC), Tangier, Morocco, 24–28 June 2019; pp. 1154–1159.

[14] Jiang, C.; Zhang, H.; Ren, Y.; Han, Z.; Chen, K.C.; Hanzo, L. Machine learning paradigms for next-generation wireless networks. IEEE Wireless. Commun. 2016, 24, 98–105. [CrossRef]

[15] 15. Adedoyin, M.A.; Falowo, O.E. Combination of ultra-dense networks and other 5G enabling technologies: A survey. IEEE Access 2020, 8, 22893–22932. [CrossRef]