International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 4, July-Aug-2023, ISSN (Online): 2395-566X

A Comprehensive Review on the Need for Data Driven Automated Handover Mechanisms in Future Generation Wireless Networks

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Abstract- Automated handovers are critically important for maintaining the Quality of Service (QoS) in wireless networks, typically in mobile UE scenarios.. With increasing number of users and multimedia applications, bandwidth efficiency in cellular networks has become a critical aspect for system design. Bandwidth is a vital resource shared by wireless networks. Hence its in critical to enhance bandwidth efficiency. Orthogonal Frequency Division Multiplexing (OFDM) and Non-Orthogonal Multiple access (NOMA) have been the leading contenders for modern wireless networks. NOMA is a technique in which multiple users data is separated in the power domain. A typical wireless system generally has the capability of automatic fall back or handover. In such cases, there can be a switching from one of the technologies to another parallel or co-existing technology in case of changes in system parameters such as Bit Error Rate (BER) etc. This paper presents a review on existing machine learning based approaches for handover prediction in future generation wireless networks. The salient features of each of the approaches has been highlighted along with identifying potential research gaps, rendering insights into potential search avenues in the domain.

Keywords-Wireless Networks, Handover, Quality of Service, Bit Error Rate, Outage, Channel State Information (CSI).

I. INTRODUCTION

Machine Learning applications are transforming the handover process of transferring an active call or data session from one base station (BS) or cell to another in a wireless network [1]. Effective handover is crucial for maintaining seamless connectivity and ensuring the quality of service (QoS) in mobile networks [2]. Traditionally, handover decisions were made based on simple criteria such as signal strength or threshold values. However, as wireless networks have evolved in complexity and density, these conventional methods often result in suboptimal decisions, leading to call drops, increased latency, and degraded service quality. Machine learning (ML) has emerged as a promising solution to optimize the handover process by leveraging data-driven techniques to make more intelligent, adaptive decisions.Multiplexing remains a serious challenge even today with the limited amount of available bandwidth and the increasing number of users in cellular networks.

It is estimated that with the complete onset of 5G systems globally, the number of users will increase manifold. This would require more advanced multiplexing techniques to be used for the purpose of sharing a common channel among users [3]. Off late, OFDM has been the go to multiplexing technique and has been used in several wireless technologies. However, Non-Orthogonal Multiple Access (NOMA) has gained a lot of attention as the future of multiple access techniques.The most common multiplexing techniques used thus far have been frequency division multiplexing (FDM), time division multiplexing (TDM) and orthogonal frequency division multiplexing (OFDM) [4]. However, NOMA owing to its effective spectral efficiency is sought after as the next generation multiple access technique. As in frequency division multiplexing and time division multiplexing, the signals of different users are separated in the frequency and time domains respectively, the signals in NOMA based multiple access, the signals are separated in the power domain. The major challenge however lies in the detection of the NOMA signal at the receiving end with the separation of the different user signals in the case of multipath propagation and small scale fading effects [5].

1.Challenges in Existing Systems

Conventional handover mechanisms typically rely on fixed thresholds for signal strength or signal-to-noise ratio (SNR) to trigger handover decisions. These methods do not account for the dynamic and heterogeneous nature of modern wireless networks, especially with the introduction of small cells, dense urban environments, and higher user mobility. As a result, they may lead to premature handovers (ping-pong effect) or delayed handovers, which degrade the network's overall performance. Additionally, traditional algorithms do not adapt well to varying traffic loads, interference levels, or user mobility patterns, leading to inefficient resource utilization. Machine learning offers a way to address these issues by enabling more context-aware and adaptive decision-making processes [6]

The problem with wireless communication is the random nature of wireless channel and the mobility of users. While the random nature of wireless channel creates distortions in the received signal, the mobility of users results in fading effects and signal degradation. Typically these two effect act in conjugation and result in degradation in the Quality of Service (QoS) of the system, which can be evaluated in terms of the latency, interference and bit error rate of the system.. Practical channels do not follow the conditions for distortion less transmission given by [7]:

$$mod(H(f) = k \quad (1)$$

Here,

H(f) is the channel frequency response

K is constant

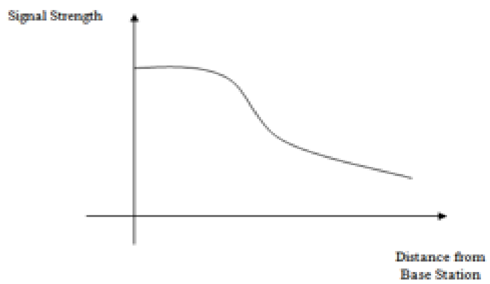

Fig.1 Signal Strength Variation in Multi-User Situations.

After considering the multipath effects, it is convenient to understand the concept of successive signal detection and equalization.Practical wireless channels generally depict multi path propagation from different interacting objects (IOs) and hence show a discrete non-singular channel response [8]

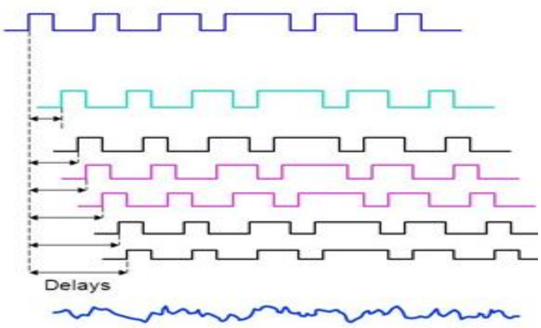

Fig.2 Inter Symbol Interference (ISI) caused due to multipath propagation

The impulse response of such a channel can be modeled as [9]:

$$h(t) = \sum_{i=1}^{k} \delta_i(t) \quad (2)$$

Here,

H(t) is the impulse response of the channel

δ represents the impulse function

The frequency domain counterpart of the channel impulse response is the channel frequency response H(f) given by [10]:

$$H(f) = \int_{-\infty}^{\infty} h(t) e^{-j\omega t}\, dt \quad (3)$$

Here,

The operator represents the Fourier Transform

$H(f)$ is the channel in frequency domain

h(t) is the impulse response of the channel

ω represents angular frequency

t is the time variable

II.PREVIOUS WORK IN THE DOMAIN

This section presents a short summary of the existing contemporary work in the domain.

Lima et al. (2023), [11] evaluates through simulations and real network data a new Deep Learning approach to support the handover triggering decision toward a data-driven procedure for next-generation networks. The solution relies on predicting future samples of standard Reference Signals using Long Short-Term Memory Networks (LSTM) in the first stage. After, the predicted power samples are sent to a binary classification algorithm to identify if the time series will lead or not to a handover triggering. The results show a mean absolute error of around 0.6 dB predicting power signal samples and over 97% of accuracy, indicating the future handover trigger moment.

Mahmod et al. (2023), [12] proposed that leveraging Artificial Intelligence (AI) algorithms with MRO techniques, this approach offers an improved solution to optimize handover decisions in a self-optimizing manner, thereby enhancing the overall network performance. To achieve this goal, it is necessary to analyze previous MRO and AI-integrated solutions and make comparisons between them. Additionally, the advantages and disadvantages of these solutions are considered. The contribution of this work lies in identifying the directions for HO self-optimization in 6G deployment. It demonstrates that deploying an AI-based solution would benefit future MRO deployments. This survey will aid in the analysis of mobility management challenges, particularly for the future mobile MRO self-optimization implementation in future technologies.

Pranato et al. (2023), [13] showed that without a reliable handover process, the high-mobility users may experience problems like a high bit error rate (BER) or even call-drop. The traditional handover algorithm is proven reliable in ideal conditions but may not work correctly in a non-ideal condition such as the presence of a coverage hole. Machine learning can be implemented to improve the handover performance in those conditions. Open Radio Access Network (O-RAN) presents a solution to implement machine learning in the cellular network using a Radio Intelligent Controller (RIC), where we can improve a lot of functionalities in the Radio Access Network (RAN) modularly without modifying the existing RAN network element. The RIC original software is using vector auto regression to determine the target cell by predicting the throughput of each neighboring cell. In this paper, we performed two modifications to the original software: improve the vector autoregression method to consider the User Equipment (UE) movement and replace the vector autoregression method with a neural network. We also prove that these modifications present easier and better target cell determination for the environment with a coverage hole that will be useful for frequent handover in high-mobility users.

Paropkari et al. (2022), [14] proposed a a 'Deep-Mobility' model by implementing a deep learning neural network (DLNN) to manage network mobility, utilizing in-network deep learning and prediction. We use network key performance indicators (KPIs) to train our model to analyze network traffic and handover requirements. In this method, (i) 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 (ii) system level inputs are also considered in conjunction, to take a collective decision for a handover. We can study multiple parameters and interactions between system events along with the user mobility, which would then trigger a handoff in any given scenario. Here, we show the fundamental modeling approach and demonstrate usefulness of our model while investigating impacts and sensitivities of certain KPIs from the user equipment (UE) and network side.

Yang et al. (2022), [15] showed that in the 5th generation mobile network (5G), microcells are densely deployed for spatial multiplexing, working in concert with traditional macrocells. 5G network uses not only the sub-6GHz band, but also the millimeter wave (mm-Wave) band, while other radio access technology (RAT) such as long-term evolution (LTE) and LTE advanced (LTE-A), collectively referred to as LTE from now on, will continue to use the sub-6GHz band. Therefore, there is a measurement gap before performing handover (HO) from LTE to 5G. A measurement gap is the duration for which user equipment (UE) suspends communication with the serving base station (BS) and then measures adjacent frequencies or other adjacent RATs.

Hussain et al. [16] proposed that Non-orthogonal multiple access (NOMA) is one of the capable contenders to achieve the vision of 5G wireless communications. Supporting a higher number of users than available orthogonal resources is the key feather of NOMA. In this article, the basic principle of NOMA has been reviewed and compared with other orthogonal multiple access (OMA). A comprehensive survey is presented in the latest NOMA scheme. The distinguished NOMA schemes design principle features, and recent deployments are discussed. Furthermore, the performance is compared in terms of the bit error rate, system capacity, and energy efficiency. The performance results show that NOMA can achieve the required goals, in terms of the user data rate, system capacity, interference cancellation scheme, and reception complexity.

Tusha et al. [17] proposed a a hybrid power domain non-orthogonal multiple accessing (NOMA) scheme by the superposition of orthogonal frequency division multiple accessing (OFDM) and index modulated OFDM (OFDM-IM) technologies is presented and named IM-NOMA. It is shown via both computer-based simulations and mathematical analysis that IM-NOMA outperforms the classical OFDM-NOMA in terms of bit error rate (BER) under a total power constraint and achievable sum rate. The system performance of IM-NOMA not only depends on the power difference between the overlapping users but also on features of the OFDM-IM signal. Hence, this scheme is robust against possible catastrophic error performance in case similar power is assigned to the users.

III.MACHINE LEARNING ASSISTED HANDOVER

Machine learning models can be trained using vast amounts of network data, such as user mobility patterns, historical handover events, and network conditions. By analyzing this data, ML algorithms can learn to predict when a handover is necessary and which target cell would provide the best service quality. Supervised learning techniques, such as decision trees, random forests, and neural networks, can be employed to classify the optimal handover timing and target base station. Reinforcement learning, on the other hand, can be used to develop intelligent agents that make handover decisions based on real-time network conditions, optimizing long-term network performance [18].

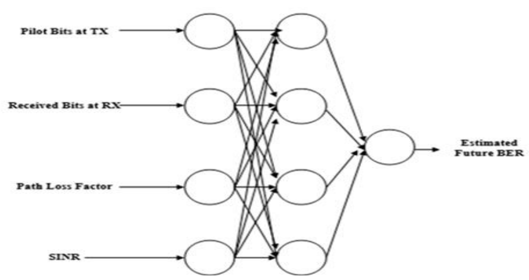

Fig.3 Machine Learning Assisted Model for Handover

However, the choice of candidates to implement handover should satisfy the conditions of co-existence. Showing that an identical SNR-BER curve can be achieved using OFDM and NOMA, thereby can justify co-existence of NOMA-OFDM for a cellular network which can lead to a possible vertical handover in case of system requirements [18]. Non-identical BER performance in the SNR range would mean different characteristics for NOMA and OFDM thereby hindering handover. Based on the Automatic Fallback approach, choose the system BER as the metric to decide upon handover [19].

Several types of machine learning techniques have been applied to optimize handover in wireless networks. Supervised learning methods such as support vector machines (SVMs) and decision trees are commonly used to predict the optimal handover time based on labeled training data. Unsupervised learning techniques, such as clustering algorithms, help in identifying patterns in user mobility and network usage, enabling more efficient handover decisions [20]. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can process more complex datasets, including time-series data, and improve handover prediction accuracy in rapidly changing environments. Additionally, reinforcement learning has gained attention for its ability to optimize handover strategies by learning from real-time interactions with the network environment [21].

To estimate the channel,

Compute the error in time domain as:

$e(t) = y(t) - d(t)$ at the receiving end.

Obtain h(t) as [22]:

$$h(t) = y(t = e(t) \quad (4)$$

This process can be applied iteratively for samples over a period 'T'. Thus the samples of the equalizer (to be designed as a filter) can be given by [23]:

$$h(t) = \sum_{i=1}^{N} h_i(t) \quad (5)$$

Finally, convert h(t) in the frequency domain by evaluation of:

$$H(f) = \int_{-\infty}^{+\infty} h(t) e^{-j2\pi ft} dt (6)$$

For reception of the signal, evaluate the following [20]:

$$S_i = sign\{real[S_{composite}(t)]\} (7)$$

$$S_q = sign\{real[S_{composite}(t)]\} \quad (8)$$

Here,

I represents the in-phase component

To, estimate the BER of the system for NOMA and OFDM,

$if\ (BER_{NOMA} < BER_{OFDM})$

{

Choose NOMA as the transmission technique

$else$

{

Fall back to OFDM

}

It has been discussed that a major challenge of NOMA based multiple access technique is the fact that small scale fading effects and multipath propagation make the amplitude of the power variable at the receiving end [24]. This results in difficulty of separating the signals of different users with equal reliability. The metric for obtaining equal reliability and quality of service (QoS) is the bit error rate (BER) of the system which is mathematically defined as [25]:

$$BER = \frac{Number\ of\ Error\ Bits}{Total\ Number\ of\ Bits} \quad (9)$$

Moreover, the BER depends on the SNR of the system mathematically which is given by:

$$P_{err} = f\ \{Q\left[\sqrt{\frac{S}{N}}\right]\} (10)$$

Here,

Q represents the Q function

S represents signal power

N represents noise power

Existing Challenges

Despite its potential, implementing machine learning for handover in wireless networks presents several challenges. One major issue is the need for large amounts of labeled data to train supervised learning models, which may not always be available. Additionally, real-time decision-making requires fast, efficient models that can operate within the constraints of limited computational resources and latency requirements. There are also concerns regarding the scalability of ML models, particularly in large, heterogeneous networks. Future research in this area will likely focus on developing more efficient algorithms, improving the interpretability of ML models, and exploring hybrid approaches that combine traditional methods with machine learning techniques.

IV.CONCLUSION

It can be concluded from previous discussions that machine learning offers a transformative approach to optimizing handover processes in wireless networks. By enabling more intelligent, data-driven decisions, ML-based handover mechanisms can significantly improve network performance, enhance user experience, and ensure the efficient use of network resources. As wireless networks continue to evolve with the deployment future generation technologies, machine learning will play an increasingly critical role in managing the complexities of modern communication systems, paving the way for more adaptive and resilient handover strategies. This paper presents a holistic review of the existing work in the domain, existing challenges and future directions of research.

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