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Recent Developments in Machine Learning Techniques for Handover Optimization in 5G

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Abstract **-** The advent of fifth-generation (5G) technology in wireless communication systems introduced a new era of connectivity, marked by exceptional capabilities. However, the complexities introduced by heterogeneous network architectures, dynamic radio conditions, and diverse application requirements pose significant challenges to many traditional mechanisms of wireless networks, among which handover. This paper addresses these challenges by delving into the potential for machine learning techniques to optimize handover in 5G networks. We review the latest state-of-the-art machine learning methodologies, focusing on their application across various stages of the handover process. By exploring the synergy between machine learning and handover optimization, this research provides valuable insights into the novel techniques aimed at ensuring robust connectivity and enhanced quality-of-service metrics in dynamic network environments.
Keywords**:** machine learning, 5G, handover, wireless networks

1. Introduction

In the era of pervasive connectivity and massive data demands, the deployment of 5G networks and their evolution towards sixth-generation (6G) technologies marks a paradigm shift in wireless communication systems. These advancements promise unparalleled throughput, ultra-low latency, and massive device connectivity, enabling applications from the Internet of Things (IoT) to augmented reality (AR) and autonomous systems. However, the efficient management of network resources and seamless user mobility are crucial to achieving ambitious goals across heterogeneous wireless environments.

One of the critical challenges in achieving seamless connectivity and maintaining Quality-of-Service (QoS) metrics in these dynamic network landscapes is the optimization of handover procedures. Handover (HO) refers to transferring an ongoing communication session from one cell to another as a mobile user traverses the coverage area.

Traditional HO mechanisms in cellular networks rely on predefined thresholds and HO decision policies based on signal strength, received signal quality, and other network parameters. However, with the advent of 5G, conventional HO strategies face new complexities arising from heterogeneous network (HetNet) architectures, dynamic radio conditions, and different application requirements. In this context, machine learning (ML) is a promising approach to enhance HO optimization by leveraging data-driven insights, adaptive decision-making, and predictive analytics.

This paper presents the latest developments in ML techniques for HO optimization in 5G networks. We categorize and review the state-of-the-art ML methodologies employed across different stages of the HO process, including prediction of HO events, optimization of HO parameters, and intelligent HO decision-making.

The remainder of the paper is organized as follows.

In Section 2 we set the stage with an overview of the related surveys and reviews on state-of-the-art ML-based HO optimization methodologies. Then, Section 3 is dedicated to providing the reader with a concise yet comprehensive background to HO in wireless networks in general and in 5G.

Building upon this understanding, Section 4 critically examines the latest ML techniques for HO optimization. For each contribution discussed, we detail the adopted approach and present the claimed advantages. Lastly, Section 5 synthesizes our findings and contributions.

2. Related works

In recent research on 5G and wireless networks, significant attention has been devoted to optimizing HO processes and enhancing QoS using ML techniques. However, the integration of ML for HO optimization remains relatively unexplored in the existing literature. Tashan et al. (2022a) investigate various methods for Mobility Robustness Optimization (MRO), leveraging velocity awareness, received signal reference power (RSRP), and fuzzy logic controllers (FLC). Building upon this work, the same authors Tashan et al. (2022b) delve deeper into MRO, specifically exploring ML-based techniques and categorizing them into supervised, unsupervised, and reinforcement learning approaches. In a complementary study, Mollel et al. (2021) propose a novel taxonomy based on the data sources used to train ML algorithms. They distinguish between visual data, from images, videos or Lidar sensors, and network-derived data, such as received signal levels, channel states, and user locations. Then, state-of-the-art ML algorithms are presented in light of this taxonomy. Tanveer et al. (2022) shift the focus towards 5G mobility management within ultra-dense small cell networks, with an emphasis on reinforcement learning methodologies. The main contribution of this paper is to provide an up-to-date review of the main ML methods employed in optimizing HOs within 5G networks.

3. Background

HO in 5G networks involves the dynamic transition of User Equipment (UE) associations between base stations (BS), ensuring seamless connectivity while prioritizing optimal service quality. The 5G HO process unfolds in three distinct phases: preparation, execution and conclusion (Mollel et al. (2021)). During the preparation phase, the UE gathers information by reporting measurements from neighboring BSs to the serving BS. These measurements include parameters like RSRP and reference signal received quality (RSRQ), providing detailed insight into the network environment. Signaling exchanges occur among the serving BS, the target BS, and the network's admission controller. Here, the admission controller evaluates network-defined HO criteria and determines the need for HO initiation. Given the high data rates and low latency requirements of 5G, the admission controller's decisions are fundamental in maintaining seamless connectivity and QoS. Once the HO criteria are met, the UE releases its association with the serving BS and initiates synchronization with the target BS. Upon successful synchronization and access to the target BS, the UE sends a confirmation message to the network, signaling the conclusion of the HO execution.

Optimizing HOs in wireless networks can be challenging due to frequent unnecessary HOs, HO failures, and the ping-pong effect, which can degrade network performance. Efficient load balancing between cells, managing HO signaling overhead, minimizing power consumption, and reducing HO latency are crucial to ensure smooth connectivity and a better user experience.

Efficient HO optimization strategies, such as ML HO decision-making algorithms and adaptive network configurations, are necessary to address these challenges and enhance the performance and reliability of 5G networks.

4. Machine learning for handover optimization

The most explored ML algorithm for HO optimization in the literature is Recurrent Neural Network (RNN). In Yajnanarayana et al. (2022) a sequence-to-sequence (Seq2seq) model (a class of RNNs first presented by Google) for the optimization of intra-frequency cellular HO is proposed, where the model is trained using the trajectory information of the UE. Results show that in an environment with high UE and BS density, this approach achieves an accuracy of more than 90% for HO cell estimation.

In Zaman et al. (2022) the authors present a Long-Short Term Memory (LSTM) model, i.e. a class of RNNs designed to overcome the vanishing gradient problem. The model exploits mobility details such as location and speed to predict where the UE will be next. It also employs a fitness function to determine priority weights to choose the best edge server for task offloading, considering factors like latency, energy usage, and server load.

In Paropkari et al. (2022) radio signal conditions are continuously observed and tracked using LSTM to make a collective decision on HO. In Ali et al. (2021) the authors present a Multi-Task Learning approach for optimizing HO management and the selection of an initial Modulation and Coding Scheme (MCS) when UEs establish a new connection with a gNodeB (gNB). This approach exploits an LSTM autoencoder with a Multi-Layer Perceptron. In Shubyn et al. (2020) an RNN model based on Gated Recurrent Unit (GRU) and LSTM cells is presented. The results reveal the effectiveness of a GRU-based architecture, as it provides a faster response to environmental changes, which is often the case in wireless networks.

Another commonly used ML technique for HO optimization is Reinforcement Learning (RL). In Yajnanarayana et al. (2020) the authors propose controlling the HOs between BSs using a centralized RL agent. This agent handles the radio measurement reports from the UEs and chooses appropriate HO actions to maximize long-term utility. In this setting, the HO mechanism is solved using the Q-learning method. In Asghari et al. (2021) Q-learning and SARSA are exploited to tune the Cell Individual Offset (CIO) parameter in the HO process, which measures the willingness of a cell to accept the incoming HOs. Mollel et al. (2021) proposes a model for HO control based on the offline RL algorithm that optimizes HO decisions considering long-term user connectivity and throughput. In Tanveer et al. (2021), the authors propose and evaluate a Q-learning-based approach. The HO decision is optimized using Q-learning to provide efficient mobility support in time-sensitive applications, tactile internet, and haptics communication.

In 5G, the Open Radio Access Network (O-RAN) presents a solution to implement ML in the cellular network using the Radio Intelligent Controller (RIC), where the functionalities of the Radio Access Network (RAN) can be improved without modifying the existing RAN element. In Cao et al. (2021) a federated RL-based scheme is proposed to train the parameters of multiple Deep Q-Networks (DQN) in the O-RAN, to maximize the long-term throughput while avoiding frequent user HOs with a limited amount of signaling overheads in the O-RAN.

Although many ML-based HO optimization techniques rely on RNN and RL, there are valuable works that leverage other approaches in the literature. The solution proposed in Dahouda et al. (2023) exploits the K-means algorithm to divide UEs of non-terrestrial networks into an optimal number of clusters based on their position and then compares different ML classification models to decide whether a UE is ready to HO based on the distance from its cell center. The comparison shows that the random forest outperforms all the other models. A similar approach is employed by the authors of Raeisi et al. (2023) who propose a new Vehicular Frequency Reuse (VFR) scheme that improves cellular network performance for high-speed 5G users. To separate high-speed and low-speed users, a simple metric called Velocity-Threshold (VT) is introduced. The value of this metric is adaptively calculated by a K-Means approach according to the road condition inferred from reported velocities.

In Alablani et al. (2021) a software-defined networking (SDN)-based algorithm called adaptive two-tier is presented based on the classification algorithm K-nearest neighbor (A2T-kNN). It is designed to adapt to the movement of vehicles and the characteristics of BSs.

In Alablani et al. (2023) the same authors present a similar strategy to the one introduced in Alablani et al. (2021), called adaptive two-tier based on adaptive boosting (A2T-Boost). In a real-world case study located in downtown Los Angeles, their results show that adaptive boosting outperforms many other classification algorithms.

Farooq et al. (2022) proposes a mobility management solution that concurrently optimizes inter-frequency and intra-frequency related parameters. The final aim is to jointly maximize three critical key performance indicators (KPIs): RSRP, HO success rate (HOSR) and load between frequency bands. In this setting, an XGBoost-based model performs best for edge RSRP and HOSR while random forest outperforms the other models for load prediction.

In Prananto et al. (2023), following the same approach as Cao et al. (2021), the authors adjusted the original O-RAN RIC software by replacing the vector autoregression method with a neural network to adapt to the UE movement.

Nyangaresi et al. (2022) proposes a ML protocol that not only facilitates optimal selection of target cells but also improves security and privacy during HOs exploiting a simple Feed-Forward Neural Network (FFNN). In Alablani et al. (2021a) the authors propose a machine-learning and Internet of Vehicles (IoV)-based cell selection scheme called Artificial Neural Network Cell Selection (ANN-CS) which aims to select the small cell that has the longest dwell time exploiting an FFNN trained on moving vehicle data.

Table 1: Summary of ML algorithms and related papers.

Learning category	Task	Algorithms	Paper
Supervised	Classification	RNN, FFNN, XGBOOST, kNN, random forest	[5], [6], [7], [8], [9], [15], [17], [18], [19], [20], [21], [22]
Unsupervised	Clustering	k-means	[15], [16]
Reinforcement	Decision making	Q-learning, SARSA, DQN	[10], [11], [12], [13], [14]

Table 1 provides a summary of the ML approaches for HO optimization considered in this work, classified by learning category.

The table shows that algorithms from the three categories have different purposes. In particular, while supervised and reinforcement learning algorithms can be used as a standalone solution, unsupervised learning approaches are usually exploited as a preliminary step to cluster UEs and coupled with other techniques to perform the actual HO decision.

5. Conclusion

In this work we presented the latest developments in ML techniques for HO optimization in 5G networks. Our research highlights how RNN (and in particular LSTM) and RL are the two most exploited techniques in this field. The reason behind this trend is that in HO optimization, historical information such as signal strength, network congestion, and user mobility patterns is crucial for making informed decisions about when and where to initiate HOs. LSTM's ability to retain and utilize this temporal information makes it well-suited to predicting future HO events accurately. As regards RL, its iterative nature enables it to navigate complex decision spaces and adapt to dynamic network scenarios. This adaptability and ability to learn from experience make RL well-suited for the dynamic and evolving nature of 5G networks.

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