AI-Based Optimization of Horizontal Handover in Mobile Networks: A Literature Review

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***Abstract*—This literature review studies artificial intelligence-based techniques for improving horizontal handover in mobile and wireless networks. Traditional handover methods often depend mainly on signal strength, such as RSSI, RSRP, or RSRQ, but this can cause problems such as ping-pong handover, handover failure, interruption delay, and packet loss. This review focuses on previous studies that used machine learning, reinforcement learning, and deep learning methods to improve handover decision-making. The review also discusses the main performance metrics, simulation tools, comparison criteria, and research gaps found in the selected studies.**

***Index Terms*—Horizontal handover, mobile networks, wireless networks, artificial intelligence, machine learning, reinforcement learning, deep learning, LSTM, ping-pong effect, handover failure**

I. Introduction

Mobile and wireless networks allow users to stay connected while they are moving. For example, a user may be walking, driving, or using public transportation while making a call or using the internet. During this movement, the user device may move away from one base station and become closer to another base station. To keep the service active, the network needs to transfer the connection from the current base station to another one. This process is called handover.

In this review, the focus is on horizontal handover. Horizontal handover means that the connection is transferred between base stations that use the same wireless technology, such as 4G-to-4G or 5G-to-5G. This type of handover is important because it directly affects the quality of service experienced by mobile users.

Traditional handover methods usually depend on signal strength measurements, such as the Received Signal Strength Indicator (RSSI). In simple terms, the system may decide to perform a handover when the signal from a neighboring base station becomes stronger than the signal from the current base station. Although this method is simple and easy to apply, it may not always make the best decision. Signal strength can change quickly because of movement, interference, buildings, obstacles, or temporary changes in the environment.

Because of this, traditional handover methods can lead to several problems. One common problem is the ping-pong effect, where the mobile device repeatedly switches between two neighboring base stations in a short time. This causes unnecessary handovers and wastes network resources. Other problems include handover failure, packet loss, delay, and unstable connection quality. These problems become more serious in modern networks because users expect stable connections for video calls, streaming, online games, and other real-time applications.

Recent studies have investigated artificial intelligence techniques to improve handover decisions. Machine learning, reinforcement learning, and deep learning methods have been used to make handover decisions more adaptive and context-aware [1]–[3]. Instead of using only RSSI, AI-based methods can consider different parameters such as user speed, network load, signal history, delay, and packet loss. This can help the system make better decisions and reduce unnecessary handovers.

The aim of this literature review is to study previous research on AI-based handover optimization in mobile networks. The review focuses on the main handover problems, the AI techniques used in previous studies, the simulation tools used by researchers, and the key performance indicators used to evaluate handover performance. This review also helps identify possible research gaps and supports the design of a future Python-based simulation that compares traditional RSSI-based handover with an AI-based handover method.

II. Background

This section explains the main terms used in this literature review.

A. Mobile Networks and Handover

A mobile network allows users to stay connected while moving. The network coverage is divided into cells, and each cell is served by a base station. When a user moves away from one base station and becomes closer to another, the network may need to transfer the active connection.

This process is called handover. The main goal of handover is to keep the user connected without noticeable interruption. This review focuses on horizontal handover, which means handover between base stations using the same wireless technology, such as 4G-to-4G, 5G-to-5G, or Wi-Fi-to-Wi-Fi.

B. RSSI-Based Handover

Received Signal Strength Indicator, or RSSI, shows the strength of the signal received by the user device from a base station. Traditional handover methods often use RSSI to decide when to switch from the current base station to a target base station.

A simple RSSI-based method may perform handover when the target base station has stronger signal than the current base station. However, RSSI alone may not be enough because it does not consider other important factors such as user speed, network load, delay, and packet loss.

C. Main Handover Problems

The ping-pong effect happens when a device switches back and forth between two neighboring base stations within a short time. This usually happens near the border between two cells, where signal strength can change slightly.

Handover failure happens when the network tries to transfer the connection, but the process does not complete successfully. This may lead to call drops, internet disconnection, packet loss, or service interruption.

Delay and packet loss are also important problems. Delay means the time needed to complete communication or handover, while packet loss means that some data packets do not arrive successfully. These problems can reduce the quality of real-time services such as video calls, streaming, and online games.

D. AI-Based Handover

AI-based handover methods try to make better decisions by using more information than RSSI alone. Possible inputs include RSSI, user speed, network load, delay, packet loss, and signal history.

Machine learning can be used to decide whether handover should happen or not. Reinforcement learning can learn from rewards and penalties. LSTM and other deep learning methods can predict future signal or mobility behavior. These methods are reviewed in the next sections.

III. Research Methodology

This section explains how the papers were selected and organized for this literature review. The goal was to find studies related to AI-based handover optimization in mobile and wireless networks.

A. Search Focus and Selection Criteria

The search focused on papers about handover optimization, horizontal handover, ping-pong reduction, handover failure reduction, and AI-based decision-making. The main search terms included:

- AI-based handover optimization
- Machine learning handover management
- Reinforcement learning handover
- LSTM handover prediction
- Ping-pong handover reduction
- 5G and beyond 5G handover optimization

The selected papers were included because they discuss handover optimization, use AI-based methods, or evaluate handover problems such as ping-pong effect, handover failure, delay, packet loss, or load balancing. Papers that were not directly related to handover decision-making or mobility management were not used as main references.

B. Organization of the Studies

The selected studies were organized into four groups. Survey papers were used to understand the general research direction and common challenges [1], [2]. Machine learning studies were selected because they are close to the proposed direction of this project [4], [5]. Reinforcement learning studies were included because handover can be treated as a decision-making problem [3], [6]–[8]. LSTM and prediction-based studies were selected because they can use previous signal or movement data to predict future handover needs [9], [10].

C. Information Extracted from Each Paper

For each selected paper, the review considered the main problem, the AI method used, the input parameters, the simulation or evaluation environment, the key performance indicators, the main findings, and the limitations.

This helped compare the papers and identify a realistic direction for this semester project, especially the possibility of using a Python-based simulation to compare traditional RSSI-based handover with an AI-based handover method.

IV. Literature Review

This section reviews previous studies related to AI-based handover optimization. The studies are grouped based on their main approach: survey and background studies, machine learning-based methods, reinforcement learning-based methods, and LSTM or prediction-based methods.

A. Survey and Background Studies

Mollel et al. reviewed machine learning applications for handover management in 5G and beyond networks [1]. Their study is useful because it gives a general view of how machine learning can be used in mobility and handover management. The paper explains that traditional handover methods may not be enough for future networks because these networks are more complex and have higher user mobility. The study also shows that machine learning can help by using more information than simple signal-strength-based rules.

Alraih et al. presented a survey on handover optimization in beyond 5G mobile networks [2]. This paper is important for understanding the main handover challenges, such as handover failure, unnecessary handover, ping-pong effect, and delay. The paper also discusses different optimization approaches and explains that future handover systems need to be more adaptive and intelligent.

These survey papers are useful for this project because they explain the general problem and show why AI-based handover optimization is an active research area. They also help identify common evaluation metrics, such as handover failure rate, ping-pong rate, throughput, and delay.

B. Machine Learning-Based Handover Studies

Priyanka et al. studied machine learning algorithms for proactive decision-making in handover management for 5G and beyond 5G networks [4]. Their work is close to the direction of this project because it focuses on making handover decisions before the connection becomes poor. The study considers different performance issues, including handover failure, ping-pong handover, radio link failure, and handover delay. This shows that machine learning can be used to improve handover decisions by considering several conditions instead of only depending on signal strength.

Alraih et al. proposed an ML-based self-optimization handover technique for beyond 5G mobile networks [5]. The study used a machine learning approach to optimize handover parameters and improve mobility performance. This paper is useful because it shows how machine learning can support self-optimization in mobile networks. It also supports the idea that handover decisions can be improved by learning from network conditions.

Saad et al. studied handover and load balancing self-optimization models in 5G mobile networks [11]. This paper is useful because it connects handover optimization with network load. This is important for this project because a base station with strong signal may still be a bad target if it is overloaded. Therefore, handover decisions should not only depend on RSSI, but should also consider load and other network conditions.

From these studies, it can be seen that machine learning is useful for handover optimization because it can use multiple input parameters. These parameters may include signal strength, user speed, network load, delay, and other network measurements. This is different from traditional handover methods that mainly depend on RSSI or similar signal indicators.

C. Reinforcement Learning-Based Handover Studies

Tanveer et al. gave an overview of reinforcement learning algorithms for handover management in 5G ultra-dense small cell networks [3]. This paper explains why reinforcement learning is suitable for handover management. In reinforcement learning, the system learns by taking actions and receiving rewards or penalties. For handover, a good decision may receive a reward, while a bad decision such as ping-pong handover or handover failure may receive a penalty.

He et al. proposed a reinforcement learning handover parameter adaptation method based on an LSTM-aided digital twin for ultra-dense networks [6]. Their study combines reinforcement learning with LSTM and digital twin concepts. This is useful because it shows that modern handover optimization may combine more than one AI technique. Reinforcement learning can help with decision-making, while LSTM can help with prediction.

Gu et al. proposed a deep reinforcement learning-based approach for adaptive handover protocols in mobile networks [7]. Their study is useful because it treats handover as an adaptive decision problem. Instead of using fixed handover parameters, the system can learn better behavior based on the network situation. This direction is important because mobile networks are dynamic, and fixed rules may not work well in all scenarios.

Kumar et al. proposed an advanced handover optimization method using deep reinforcement learning in 5G networks [8]. Their work focuses on improving handover decisions and reducing problems such as handover failure and ping-pong effect. This supports the idea that reinforcement learning can be useful when the goal is to optimize several handover-related metrics.

Overall, reinforcement learning is powerful because it can learn from the result of its own decisions. However, it is usually more complex than simple machine learning models. For this project, reinforcement learning is important to discuss in the literature review, but it may be more difficult to implement fully in a short semester project.

D. LSTM and Prediction-Based Handover Studies

Lu et al. studied handover enhancement in high-speed railway 5G networks using an LSTM-based prediction method [9]. This paper is useful because high-speed movement is one of the difficult cases for handover. When the user moves quickly, the signal condition changes fast, and a late handover decision can cause service interruption. LSTM can help by learning from previous signal values and predicting future handover needs.

Luo et al. proposed a handover algorithm based on Bayesian-optimized LSTM and multi-attribute decision-making in heterogeneous cellular networks [10]. Their study is useful because it combines prediction with decision-making. The LSTM part helps predict future conditions, while the decision-making part helps select the best handover choice. This shows that prediction can be important in reducing late or wrong handover decisions.

LSTM-based methods are useful because handover is related to time. Signal strength, user movement, and network conditions change over time. Therefore, using previous values can help predict what may happen next. This is especially useful for high-speed users, where the network must make decisions early enough to avoid handover failure.

E. Summary of the Reviewed Studies

The reviewed studies show that AI-based handover optimization can be approached in different ways. Machine learning methods are useful for classification and decision-making using multiple input parameters. Reinforcement learning methods are useful when handover is treated as a decision problem with rewards and penalties. LSTM and prediction-based methods are useful when the goal is to predict future signal or mobility behavior.

For this project, these studies support the idea of comparing a traditional RSSI-based handover method with an AI-based method. The literature also shows that important parameters may include RSSI, user speed, network load, delay, and packet loss. The most common evaluation metrics include ping-pong rate, handover failure rate, delay, packet loss, and throughput.

V. Comparison of Reviewed Studies

This section compares the selected papers based on their method, main focus, simulation or evaluation environment, key performance indicators, and limitations. The aim of this comparison is to understand how previous studies tried to improve handover performance and how these studies can support the direction of this project.

From Table I, it can be seen that previous studies use different approaches to improve handover performance. Survey papers are useful for understanding the general handover problem and common research directions. Machine learning papers are closer to the practical direction of this project because they can use input parameters such as RSSI, user speed, network load, and delay. Reinforcement learning papers are useful because they treat handover as a decision-making problem, but they are usually more complex to implement. LSTM-based papers are useful for prediction, especially when the user is moving quickly and the network needs to predict future signal changes.

The comparison also shows that many studies use simulation-based evaluation. This supports the idea of using a Python-based simulation in this project. Python can be used to create simple movement scenarios, generate signal and network conditions, run a traditional RSSI-based method, and compare it with an AI-based method using the same evaluation metrics.

VI. Discussion

The reviewed studies show that handover optimization is still an important topic in mobile and wireless networks. Traditional handover methods are simple and easy to apply, but they usually depend on limited information such as signal strength. This can be a problem because the best handover decision does not depend only on RSSI. Other factors, such as user speed, network load, delay, and previous signal behavior, can also affect the decision.

One clear point from the literature is that AI-based methods can make handover decisions more context-aware. Machine learning methods can use several input parameters and learn patterns from previous data [1], [4]. This is useful because the model can decide whether handover is needed by looking at more than one condition. For example, a target base station may have a stronger signal, but if it is overloaded, the handover may not be a good choice. This is why including network load can make the decision better [11].

Reinforcement learning is also an important direction in the reviewed papers. This type of method is useful because handover can be treated as a decision-making problem. The system can receive a reward when the handover decision improves performance and a penalty when the decision causes problems such as ping-pong handover or handover failure [3], [7]. However, reinforcement learning can be more difficult to implement because it needs careful design of states, actions, rewards, and training scenarios.

LSTM and prediction-based methods are useful when the handover decision depends on time-based behavior. In mobile networks, signal strength and user movement change over time. LSTM can use previous values to predict future conditions, which is useful in high-speed scenarios [9]. This can help the network make the handover decision earlier and reduce late handover failures. However, LSTM-based methods may need enough sequential data and may be more complex than simple machine learning models.

The reviewed studies also show that most handover optimization methods are evaluated using simulation. This is understandable because testing handover methods in a real mobile network is difficult and expensive. Simulation allows researchers to create different mobility scenarios, change network conditions, and compare methods using the same environment. For this project, a Python-based simulation is a realistic choice because it is easier to implement and can still show the main difference between a traditional RSSI-based method and an AI-based method.

Another important point is the use of key performance indicators. Most studies evaluate handover performance using metrics such as ping-pong rate, handover failure rate, handover delay, packet loss, throughput, and radio link failure [2], [4]. These metrics are important because they give numerical evidence about whether the proposed method is better than the traditional method. Without these metrics, it would be difficult to prove that the AI-based method actually improves handover performance.

Based on the reviewed studies, the most suitable direction for this semester project is to start with a simple and understandable simulation. A traditional RSSI-based handover method can be used as the baseline. Then, an AI-based method such as Decision Tree, Random Forest, or another simple machine learning model can be compared with it. This direction is realistic because it matches the topic of the project, uses ideas from previous studies, and avoids the complexity of a full real-network implementation.

VII. Proposed Direction

Based on the reviewed studies, this project will focus on a simple and realistic direction for this semester. The main idea is not to build a full real mobile network system, because that would be too complex. Instead, the project can use a Python-based simulation to compare a traditional handover method with an AI-based handover method.

A. Simulation Environment

Python is selected as the main simulation environment because it is flexible and easier to use for this type of academic project. Python can be used to generate simple mobility scenarios, calculate signal strength changes, create artificial network conditions, and test machine learning models. It also provides useful libraries for data processing, machine learning, and plotting results.

Other tools such as NS-3 and MATLAB are also common in network simulation. However, NS-3 may require more time to learn and configure, while MATLAB may depend on specific toolboxes. For this reason, Python is a suitable choice for a first simulation-based study.

TABLE I
COMPARISON OF REVIEWED STUDIES

Paper / Study	Method	Main Focus	Environment	KPIs / Metrics	Main Limitation
ML Applications to Handover Management [1]	Survey	Machine learning applications for handover management in 5G and beyond	Literature review	Handover performance, mobility management, QoS	Does not implement a new simulation model
Handover Optimization in Beyond 5G [2]	Survey	Handover optimization challenges in beyond 5G networks	Literature review	Handover failure, ping-pong, delay, throughput	General survey, not focused on one implementation
ML for Proactive Handover Decision-Making [4]	Machine Learning	Proactive handover decision-making	Simulation-based evaluation	Handover failure, ping-pong, radio link failure, delay	Results depend on selected simulation assumptions
ML-Based Self-Optimization Handover [5]	Machine Learning	Self-optimization of handover in beyond 5G	Simulation / ML-based evaluation	Handover performance, failure reduction, optimization metrics	May require more complex network data for real deployment
Handover and Load Balancing in 5G [11]	Self-optimization model	Handover and load balancing in 5G networks	Simulation-based study	Load balancing, handover performance, network efficiency	Focuses strongly on load balancing, not only handover decision
RL Algorithms for Handover Management [3]	Reinforcement Learning overview	RL algorithms for handover management in ultra-dense networks	Literature review	Handover performance, mobility, network optimization	Overview paper, no single proposed implementation
RL and LSTM Digital Twin for Handover [6]	RL + LSTM + Digital Twin	Handover parameter adaptation in ultra-dense networks	Simulation / digital twin model	Handover failure, ping-pong, optimization performance	More complex architecture than simple ML methods
Deep RL for Adaptive Handover [7]	Deep Reinforcement Learning	Adaptive handover protocol in mobile networks	Simulation-based evaluation	Data rate, radio link failure, ping-pong	Advanced method, may be difficult for simple semester implementation
Advanced Handover Optimization Using DRL [8]	Deep Reinforcement Learning	Advanced handover optimization in 5G	Simulation-based evaluation	Handover failure, ping-pong, network performance	Requires careful training and parameter tuning
LSTM Handover in High-Speed Railway 5G [9]	LSTM	Handover prediction in high-speed railway 5G networks	Simulation / prediction model	Handover success, delay, prediction performance	Focused on high-speed railway scenario
Bayesian-Optimized LSTM and MADM Handover [10]	Bayesian-optimized LSTM + MADM	Prediction and decision-making in heterogeneous cellular networks	Simulation-based evaluation	Handover delay, handover failure, decision accuracy	More complex than basic RSSI or ML-based methods

B. Traditional Baseline Method

The traditional method will be used as the baseline. This method will mainly depend on RSSI. In a simple scenario, the user device is connected to a current base station. When the RSSI value of a neighboring base station becomes stronger than the RSSI value of the current base station by a certain threshold, the system performs handover.

This baseline is important because it gives a simple method to compare against. If the AI-based method performs better than the RSSI-based method, then the improvement can be shown more clearly.

C. Proposed AI-Based Method

The AI-based method will try to make the handover decision using more information than RSSI alone. Possible input parameters include:

- RSSI of the current base station
- RSSI of the target base station
- User speed
- Network load
- Delay
- Packet loss

The output of the AI model can be a simple decision:

- Stay connected to the current base station
- Perform handover to the target base station

For the first implementation, a simple machine learning model such as Decision Tree or Random Forest can be used. These models are easier to understand and explain compared with more complex models such as deep reinforcement learning or LSTM. This makes them suitable for a semester project.

D. Possible Simulation Scenarios

The simulation can include different user movement and network conditions. For example:

- A low-speed user moving between two base stations
- A high-speed user moving between two base stations
- A user located near the border of two cells
- A target base station with stronger signal but high network load
- A scenario where small RSSI changes may cause ping-pong handover

Using different scenarios is important because the handover method should not work only in one case. It should be tested under different conditions to see whether it can reduce unnecessary handovers and failures.

E. Evaluation Metrics

The performance of the traditional method and the AI-based method can be compared using key performance indicators. The main KPIs for this project are:

- Ping-pong handover rate
- Handover failure rate
- Handover delay
- Packet loss rate
- Throughput
- Number of unnecessary handovers

These metrics will help show whether the AI-based method improves handover performance compared with the traditional RSSI-based method.

F. Feasibility

This direction is feasible for one semester because it does not require a real mobile network or a complex simulator. The project can start with a simple Python simulation and then add more details step by step. The main goal is to build a clear foundation, understand previous studies, design the system, and prepare a realistic simulation plan.

If time allows, a basic implementation can be added to compare the traditional RSSI-based method with a simple AI-based model. If full implementation is not completed, the project can still provide a strong literature review, system design, simulation setup, and evaluation plan.

VIII. Limitations

This section explains the main limitations of this literature review.

First, the review is based on a selected number of papers, not all papers published about handover optimization. Because of this, some related studies may not be included. However, the selected papers cover the main directions needed for this project, such as machine learning, reinforcement learning, LSTM-based prediction, ping-pong reduction, and handover failure reduction.

Second, the reviewed studies use different simulation environments and performance metrics. Some studies focus on handover failure, while others focus on ping-pong effect, delay, throughput, radio link failure, or load balancing [2], [4], [11]. Because of these differences, comparing the papers directly is not always fully fair.

Third, some studies do not provide all implementation details, such as exact parameter values, dataset details, or full simulation settings. Also, most reviewed studies are simulation-based rather than real-network deployments. This means their results may not fully represent real mobile network conditions.

Finally, this review is prepared for a semester project, so the scope is limited. The main goal is to understand the topic, review related studies, choose a realistic simulation direction, and design a feasible system.

IX. Conclusion

This literature review studied AI-based techniques for improving horizontal handover in mobile and wireless networks. Traditional handover methods often depend mainly on RSSI, but this can lead to problems such as ping-pong handover, handover failure, delay, packet loss, and unnecessary handovers.

The reviewed studies show that machine learning, reinforcement learning, and LSTM-based methods can improve handover decisions by using more information than RSSI alone. These methods can consider factors such as user speed, network load, delay, packet loss, and signal history [1], [3], [4], [9].

Based on this review, the next step of the project is to design a Python-based simulation. The simulation can compare a traditional RSSI-based handover method with a simple AI-based method, such as Decision Tree or Random Forest. The comparison can be evaluated using KPIs such as ping-pong rate, handover failure rate, delay, packet loss, throughput, and unnecessary handovers.

Overall, this review provides a clear foundation for the project. It shows that AI-based handover optimization is a suitable direction, while also keeping the implementation realistic for a semester project.

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