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Predictve Handover Optimization

Master of Science in
Telecomminucation Engineering - Ingegneria Telecomunicazione

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Abstract

In the future cellular networks, there will be cell densification, in which cells are becoming smaller. For this reason, the number of handovers that a moving User Equipment (UE) faces increases significantly if a conventional handover decision scheme is used. The increased number of handovers causes more signaling overhead for the network. Furthermore, the Handover Failure (HOF)s due to the serving or target cell's low signal quality will also increase. So it is very important to decrease the number of handovers and HOFs, So the UE can transmit and receive data with more sophisticated Modulation and Coding Schemes (MCS) and achieve a higher data rate.

The advances in Machine Learning (ML) and Artificial Intelligence (AI) research open up the door for prediction techniques of channel state information. The predicted channel state information can be used to decrease the number of handovers and HOFs. This thesis focuses on a handover optimization scheme that relies on predicted channel state information to minimize the number of HOFs and unnecessary handovers while maintaining the signal quality as high as possible. The proposed scheme assigns UE to one cell at each time step by posing an Integer Programming (IP) optimization problem. The performance of solutions to the original IP problem with solutions to its Linear Programming (LP) relaxation is compared.

The proposed scheme is evaluated using the ns3-ai simulator with the help of the SUMO simulator using a map of Berlin.

Keywords: Handover procedure, Handover Failure, Too Late Handover, Too Early Handover, Wrong Cell Selection, Ping-pong Handover, Optimized Network, Convex Optimization.

Abstract in lingua italiana

Nelle reti cellulari del futuro, si avrà una densificazione delle celle, le quali diventaranno più piccole. Per questa ragione, se si utilizza uno schema di decisione di handover convenzionale, il numero di handover che un UE in movimento deve affrontare, aumenterà significativamente. L'aumentare dei handover, potrà causare un maggiore overhead di segnalazione per la rete. Inoltre, per via della scarsa qualità del segnale della cella di servizio o di destinazione, potranno aumentare anche i HOF. Pertanto, è molto importante ridurre il numero di handover e HOF, in modo tale per cui l'UE possa trasmettere e ricevere dati con MCS più sofisticati e inoltre possa raggiungere una velocità di trasmissione più elevata.
Gli sviluppi nella ricerca di ML e AI aprono la strada a tecniche di previsione delle informazioni sullo stato del canale. Le informazioni sullo stato del canale previste, possono essere utilizzate per ridurre il numero di handover e HOFs. Questa tesi si concentra su uno schema di ottimizzazione dell'handover che si basa sulle informazioni previste sullo stato del canale per ridurre al minimo il numero di HOFs e handover non necessari, mantenendo la qualità del segnale il più alta possibile. Il metodo proposto assegna l'UE ad una cella in ogni intervallo di tempo mediante la formulazione di un problema di ottimizzazione IP. Le soluzioni al problema originale IP vengono confrontate con le soluzioni alla sua relazione di rilassamento LP per valutare le prestazioni del metodo proposto.
Lo schema proposto è valutato utilizzando il simulatore ns3-ai con l'aiuto del simulatore SUMO utilizzando una mappa di Berlino.
Keywords: Procedura di handover, Handover Failure, Too Late Handover, Too Early Handover, Wrong Cell Selection, Ping-pong Handover, Rete ottimizzata, ottimizzazione convessa.

Contents

1 | Introduction

1.1. Background

In today's cellular networks, having reliable communication with a minimum amount of service disruption is crucial. As we approach five-generation (5G) and six-generation (6G), high demand in mobile applications such as video streaming, V2V, V2X, etc. requires high network capacity, so it will be necessary to adopt small cell utilization[1] [2].

While the moving UE transmits and receives data to its current cell,it measures signal power from other cells. At some point, It is necessary to get disconnected from its serving cell and switch to another due to the degradation of the current cell's signal strength. This process is called handover.

The time it takes to perform a handover from one cell to another is called Handover Interruption Time (HIT). This process usually takes between 30ms to 60ms [3]. During this period, the user cannot transmit any data since there is a signaling procedure being done between the serving and target cells.

Cells usually have overlaps in coverage. This overlap helps UE not to fall into Radio Link Failure (RLF) while the handover is being performed. If the UE moves along the border of two cells, there will be many handovers from one cell to another and vice versa. This type of handover is called ping-pong handover, and it causes unnecessary signaling for the network.

Even though the cells have coverage overlap, there might be RLF before, during, or after the handovers. This event is called HOF. HOF can be due to low signal quality in the current or target cell. If it is because of the current cell's low signal quality, the HOF is called too late handover. If it is because of the target cell's low signal quality, the HOF is called too early handover. Furthermore, the UE may do a handover to the wrong cell and fall into RLF. In this case, the HOF is categorized as the wrong cell selection. After the HOF, the UE needs to reconnect to one cell [4]. This process takes hundreds of milliseconds to a couple of seconds[5]. During this process, the UE is not able to transmit any data.

The total time that the UE cannot transmit and receive data due to performing handovers

and HOFs is called Mobility Interruption Time (MIT).
The UE faces many more handovers and HOFs by using small-cell technology. So, keeping the number of HOF and ping-pong handovers as little as possible is very important.
Nowadays, cellular networks use an event-based handover mechanism. One of the methods used in event-based handover is called A3-event handover. In A3 event handover, the handover executes if the target cells serve with an offset better than the current cell for a specific amount of time. This amount of time is called Time To Trigger (TTT).
In order to be able to minimize the number of handovers and HOFs, networks use the concept called Self Organized Network (SON). A SON is a network that can adapt and optimize itself without the involvement of humans. One of the main features of SON is Mobility Robustness Optimization (MRO)[6]. MRO tries to find the best set of offset and TTT to minimize the number of handovers and HOF. However, MRO is not the best solution to minimize the number of handovers and HOF.

1.2. Thesis Contributions

There are a lot of different handover algorithms that try to mitigate the handover and HOF at the same time. All existing methods are reactive because they only have current and past information, so it is impossible to decrease the handover and HOF simultaneously. However, if we had perfect knowledge of the future, we could avoid HOF and decrease handovers. For this reason, we are trying to use the prediction that approximates future knowledge[7].
The main contribution of this thesis is to see if it is possible to reduce the number of handovers HOF simultaneously while keeping the received signal quality as high as possible by using the predicted channel information from the future time instance and finding algorithms that perform handover.
For this purpose, the ns3-ai and SUMO simulators have been used. The SUMO simulator generates the user's mobility based on the map data. Then the channel value data, which in our case is quantized Reference Signal Received Quality (RSRQ), has collected by running ns3, and finally, the handover decision is optimized.

1.3. Thesis Outline

The main contribution of the thesis is described in this section. Chapter two defines essential concepts such as handover procedure, unwanted handovers, and RLF. Also, the current problem solution is discussed in this chapter. Chapter 3 defines the theoretical background and optimization method, the main idea to solve the problem, and an optimization algorithm. Chapter 4, simulation and numerical results, the scenario configuration of the thesis is discussed, and finally, the result with the explanation is written. Chapter 5 closes the thesis by combining the components provided in each chapter. Then describes methods for future work based on the ideas proposed in this thesis.

2 | Literature review

In this section, the handover procedure will be described in detail. Then the handover event, ping-pong handover, and different types of HOF are defined. Finally, the related works to decrease the number of handovers and HOF are expressed.

2.1. Handover Procedure

When specific requirements are met, The UE sends commands to the serving cell, and the serving cell decides to start a handover. As it is shown in fig 2.1, if the handover command is sent through the X2 interface, which connects two eNodeB (eNB) directly, the handover is called **X2 handover**. On the other hand, if the handover command is carried through the S1 interface, which connects tow eNBs through the Evolved Packet Core (EPC), the handover is called **S1 handover**. The X2 interface is initialized by neighbor identification and based on Automatic Neighboring Relation Function (ANRF) Process.[8]

As it can be seen in fig 2.2 and 2.3 the handover procedure is done in 5 phases :

- **Before Handover:** The UE is attached to the source eNB, and the Dedicated

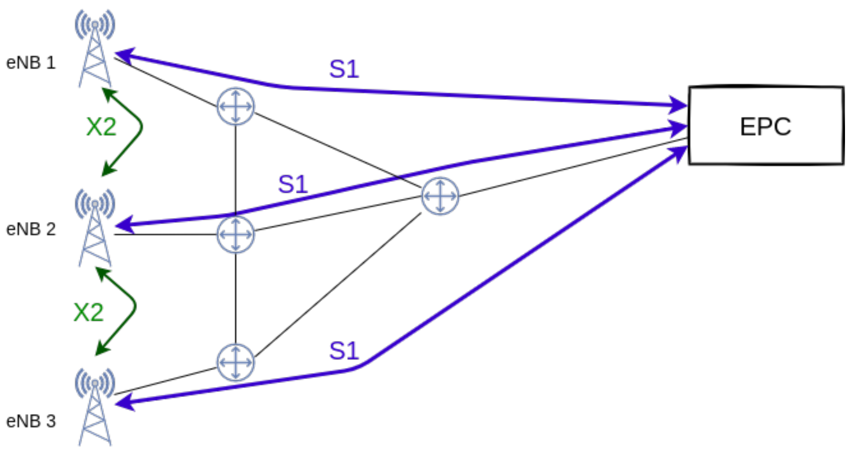


Figure 2.1: X2 and S1 interface

Radio Bearers (DBRs) and Signalling Radio Bearers (SRBs) are established, which allows a Uplink (UL)/Downlink (DL) transmission between the source eNB and the UE.

- **Handover Preparation:** The UE sends the periodic measurement report to the source eNB. This report contains information about all the neighboring cells. Based on the information, the source eNB chooses the best target cell and sends the handover request to the target cell.As it is illustrated in fig 2.2, the handover request is sent through the X2 interfaces where eNBs are directly connected while in fig 2.3 the eNBs are communicating through the S1 interface. Then the target eNB performs admission control. If it can provide the requested resources for the new UE, it sends a handover request acknowledgment (ACK) to the source eNB. Finally, the source eNB sends the handover command message, which changes the UE status to the Radio Resource Control (RRC) idle. This message contains the information needed to perform the handover.

- **Handover execution:** The source eNB sends the Sequence Number (SN) status transfer message. Then, UE is synchronized with the target based on the given parameters. Finally, the handover completion message is sent to the target cell by UE.

- **Handover Completion:** The target eNB receives the RRC Connection Reconfiguration Complete message, which changes the UE's status from idle to the RRC connected.Afterward, the source eNB UE context is released via receiving the UE release context message from the target eNB.

- **After Handover:** UE is attached to the target eNB, and UL/DL traffic is transmitted as in the initial step.

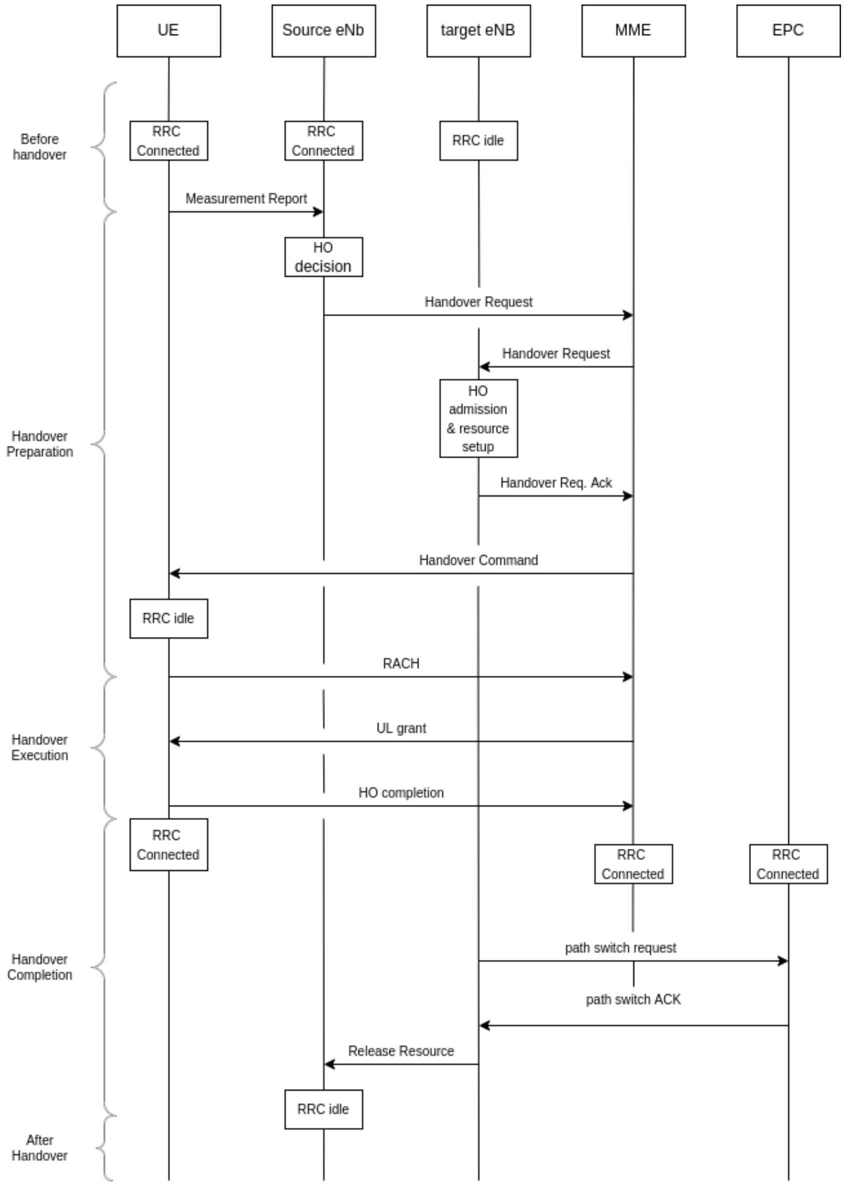


Figure 2.2: X2 Handover Procedure

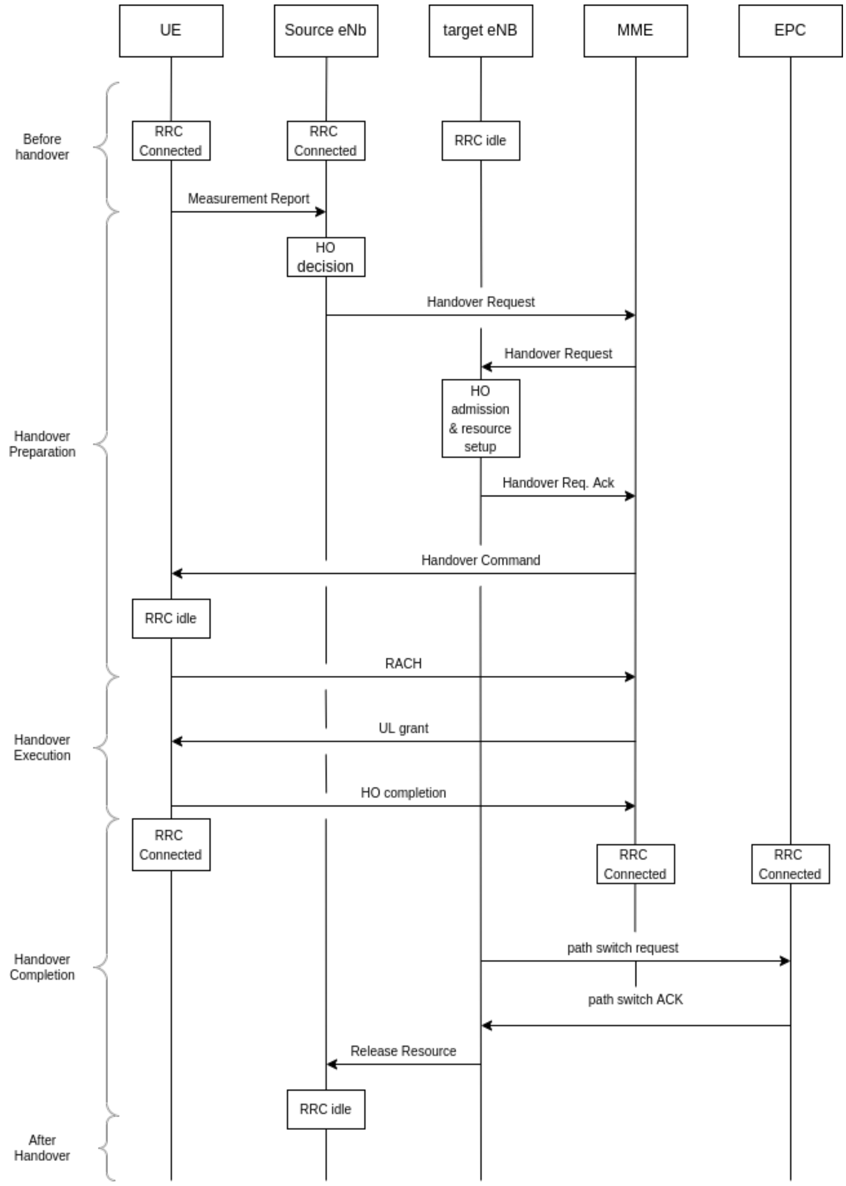


Figure 2.3: S1 Handover Procedure

2.2. Definition of Relevant Events

2.2.1. Handover Events

As it was discussed in the previous section, one of the most critical steps of the handover decision is the measurement report from UE. The eNB decides whether or not to do a handover based on the measurement report. 3rd Generation Partnership Project (3GPP) defines predefined sets of measurement report mechanisms to be performed by UE, called "Events." Each event has two conditions, one to start sending the event to eNB and one to stop. In this section, Events A1, A2, A3, A4, and A5 are going to be defined[9].

- **Event A1 :** As you can see in figure 2.4 event A1 triggers when the current serving cell becomes better than a defined threshold:

$$\mathrm{RSRQ_{serv}} - \mathrm{Hys_1} > \mathrm{Threshold_1}$$

This event stops when the following condition is satisfied :

$$\mathrm{RSRQ_{serv}} + \mathrm{Hys_1} < \mathrm{Threshold_1}$$

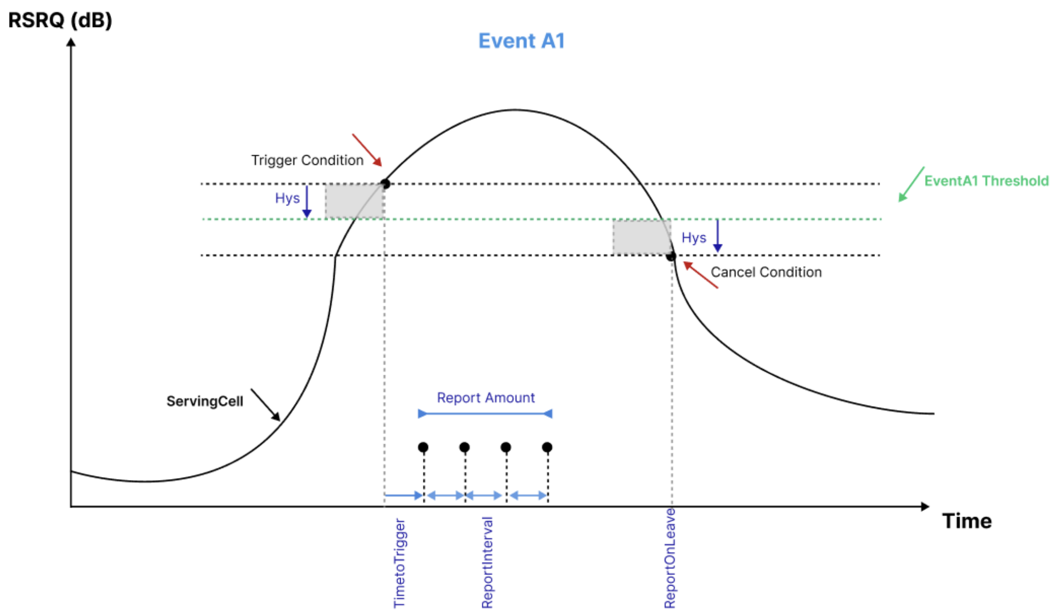


Figure 2.4: A1 Event Handover

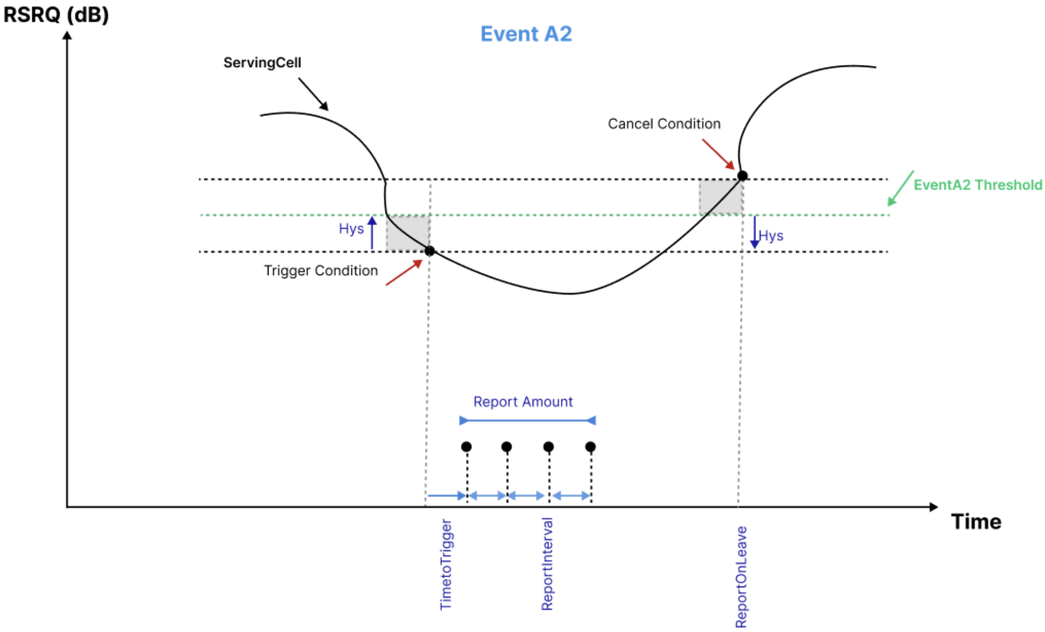


Figure 2.5: A2 Event Handover

- **Event A2 :** As you can see in figure 2.5, event A2 triggers when the current serving cell becomes worse than a threshold.

$$RSRQ_{serv} + Hys_2 < Threshold_2$$

This event stops if the serving cell becomes worst than the threshold :

$$RSRQ_{serv} - Hys_2 > Threshold_2$$

- **Event A3:** As you can see in figure 2.6, event A3 triggers when an adjacent cell becomes better than the current serving cell by an offset.

$$RSRQ_{neigh} + O_{neigh} + CIO_{neigh} + Hys > RSRQ_{serv} + O_{serv} + CIO_{serv} + Off$$

where :

  - $RSRQ_{neigh}$: measurement result of the neighbouring cell.
  - $RSRQ_{serv}$: measurement result of the serving cell.
  - O_{neigh} : Frequency-specific offset of the frequency of the neighbor cell.

- O_{serv} : Frequency-specific offset of the frequency of the serving cell.
- CIO_{neigh} : Cell individual offset of the neighbour cell.
- CIO_{serv} : Cell individual offset of the serving cell.
- Off : Specific offset for this event.
- Hys : Hysteresis parameter for this event.

This event stops if the following condition is satisfied:

$$\mathrm{RSRQ}_{\mathrm{neigh}} + \mathrm{O}_{\mathrm{neigh}} + \mathrm{CIO}_{\mathrm{neigh}} - \mathrm{Hys} < \mathrm{RSRQ}_{\mathrm{serv}} + \mathrm{O}_{\mathrm{serv}} + \mathrm{CIO}_{\mathrm{serv}} + \mathrm{Off}$$

In order to make the equation simpler, we define the following:

$$\mathrm{Hys}_3 = -\mathrm{O}_{\mathrm{neigh}} - \mathrm{CIO}_{\mathrm{neigh}} + \mathrm{O}_{\mathrm{serv}} + \mathrm{CIO}_{\mathrm{serv}} + \mathrm{Hys}$$

So the condition for the A3 event to trigger can be rewritten as:

$$\mathrm{RSRQ}_{\mathrm{neigh}} - \mathrm{Hys}_3 < \mathrm{RSRQ}_{\mathrm{serv}}$$

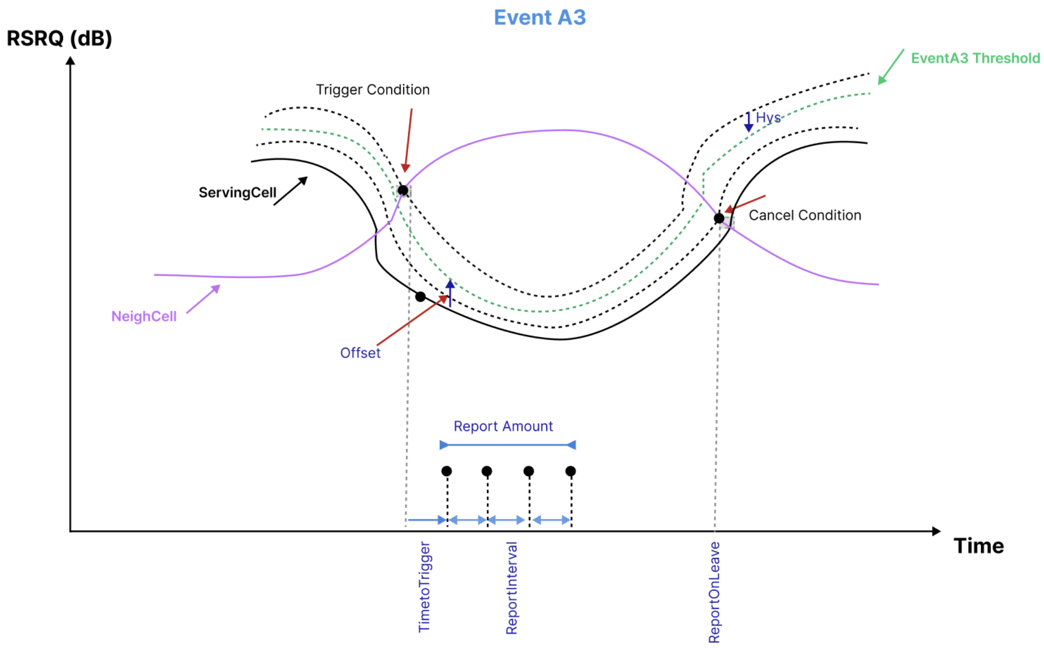


Figure 2.6: A3 Event Handover

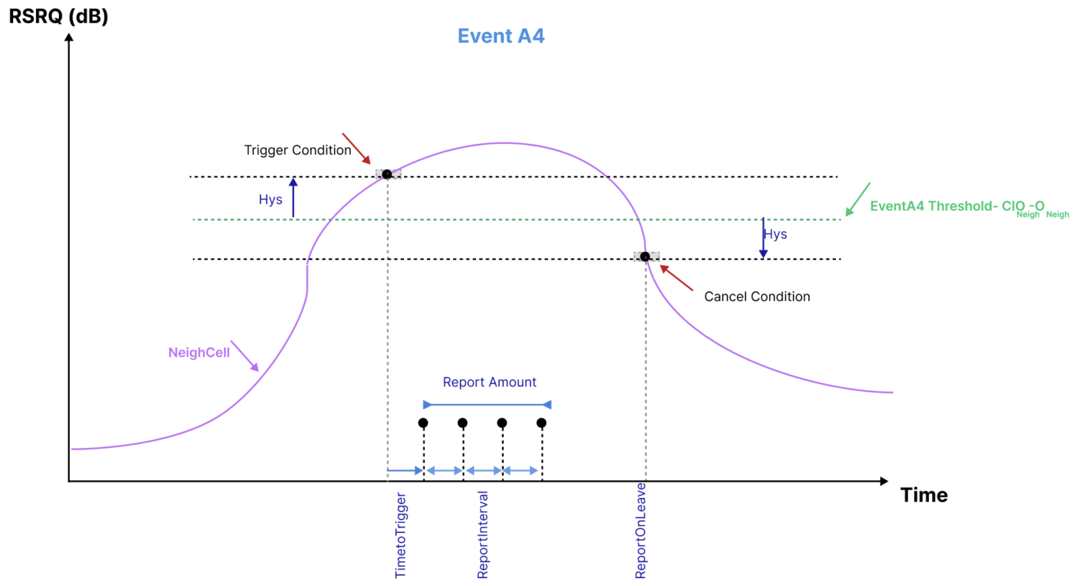


Figure 2.7: A4 Event Handover

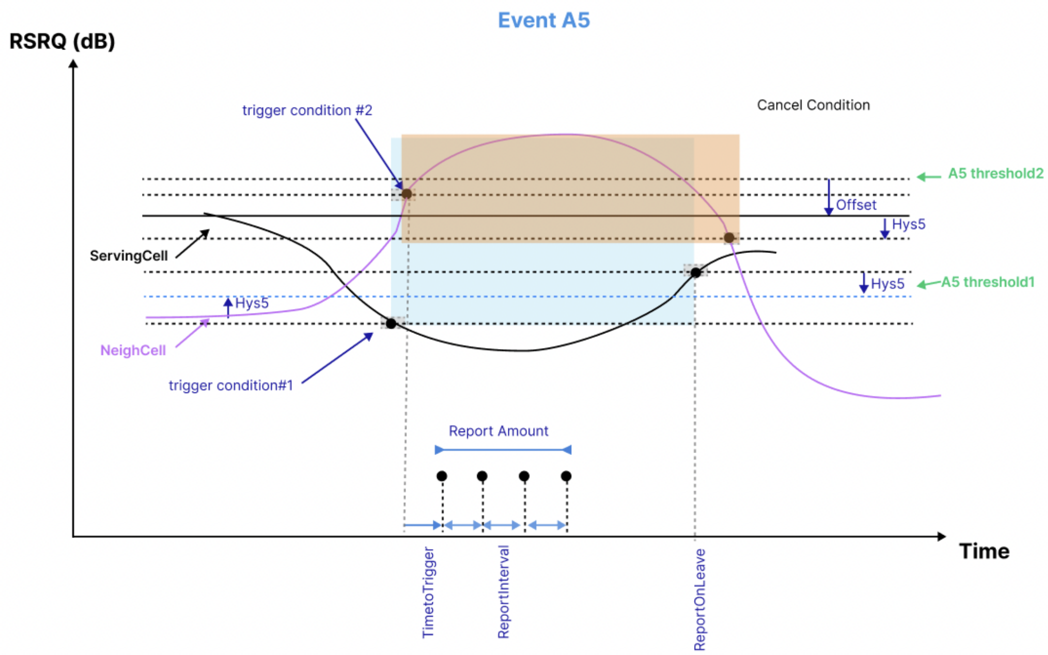


Figure 2.8: A5 Event Handover

- **Event A4 :** As you can see in figure 2.7, event A4 Triggers when a neighbor cell becomes better than a defined threshold.

$$RSRQ_{neigh} + \mathrm{O}_{\mathrm{neigh}} + \mathrm{CIO}_{\mathrm{neigh}} - \mathrm{Hys}_4 > \mathrm{Threshold}_4$$

This event stops if the following condition is satisfied:

$$RSRQ_{neigh} + \mathrm{O_{neigh}} + \mathrm{CIO_{neigh}} + \mathrm{Hys_4} < \mathrm{Threshold_4}$$

- **Event A5** : As you can see in figure 2.8 event A5 Triggers if two condition are satisfied :
  1. Current serving cell becomes worse than the first threshold
  2. Neighbor cell becomes better than the second threshold.

  $$\mathrm{RSRQ_{serv} + Hys_5 > Threshold_{51}}$$

  and

  $$\mathrm{RSRQ_{neigh} - O_{neigh} + CIO_{neigh} - Hys_5 > Threshold_{52}}$$

  This event stops if one of the following conditions is satisfied:

  $$\mathrm{RSRQ_{serv} - Hys_5 < Threshold_{51}}$$

and

$$\mathrm{RSRQ_{neigh} - O_{neigh} + CIO_{neigh} + Hys_5 < Threshold_{52}}$$

As mentioned at the beginning of this section, the network decides to do a handover based on the measurement report, which consists of a series of events. In the following subsection, two different configurations for the network will be defined, and the handover can be done based on them.

A3 event Handover:

The network can be configured to operate A3 event handover. This type of handover triggers when the neighboring cell serves better than the threshold concerning serving the cell for a specific amount of time. The threshold is defined in **measurement control**, and this amount of time is TTT[10].

$$\mathrm{RSRQ_{neigh} - Hys_3 < RSRQ_{serv} \quad for \quad t_0 - T_{TTT,A_3} < t < t_0}$$

A2 A4 event Handover:

The network can be configured to operate to start a handover while events A2 and A4 occur concurrently. When the serving cell serves less than the threshold, and the neighboring cell serves better than the threshold, the measurement report is sent to the serving cell, which sends the handover request to the best target cell with the best signal quality[10].

$$\mathrm{RSRQ_{serv}} + \mathrm{Hys_2} < \mathrm{Threshold_2}$$

and

$$RSRQ_{neigh} + \mathrm{O_{neigh}} + \mathrm{CIO_{neigh}} - \mathrm{Hys_4} > \mathrm{Threshold_4}$$

2.2.2. Undesired Handovers

Event-based handovers are based on real-time measuring, so the UE falls into many undesired handovers. There are four different undesired handovers, Too Late Handover, Too Early Handover, Wrong Cell Selection, and ping-pong handover, which will be explained in the following.

Too Late Handover :

As it is illustrated in fig 2.10, too late handover is recognized by the network if the UE stays connected to its serving cell so long that during the TTT or during the procedure of handover, it falls into RLF and then reconnects to a cell which is different than a serving cell [11].The RLF is reported by the destination cell to the originating cell through the X2 or S1 interface, and the originating cell identifies a handover that occurred too late.

Too Early Handover:

As it is illustrated in fig 2.11, too early handover happens when the UE moves into a target cell too soon. The connection is instantly lost due to low link quality after a successful handover in a target cell. The UE then reconnects to its previous cell. The serving cell identifies the too-early handover [11].

Wrong Cell Selection :

As it is illustrated in fig 2.12, a wrong cell handover is detected by the network when an RLF occurs shortly after a successful handover to the target cell, and then the UE reconnects to a cell which is neither the serving cell nor the target cell. The last connected cell informs the target cell of the first handover about the failure. The target cell can recognize that this RLF is not due to a too-late handover but to a wrong-cell handover and notifies the originating cell [11].

Ping-Pong Handover :

As it is illustrated in fig 2.9 ping-Pong handover is recognized by the network when the UE moves along the border of two cells and does a successful handover to the target cell but shortly does a handover to its previous cell [11].

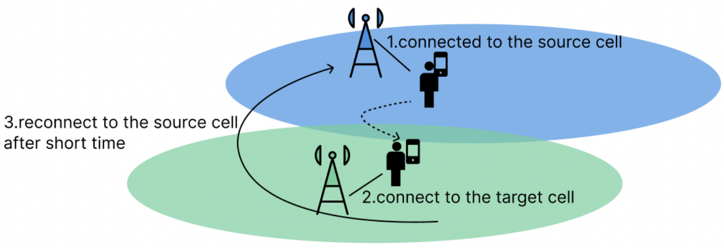


Figure 2.9: Pingpong handover.

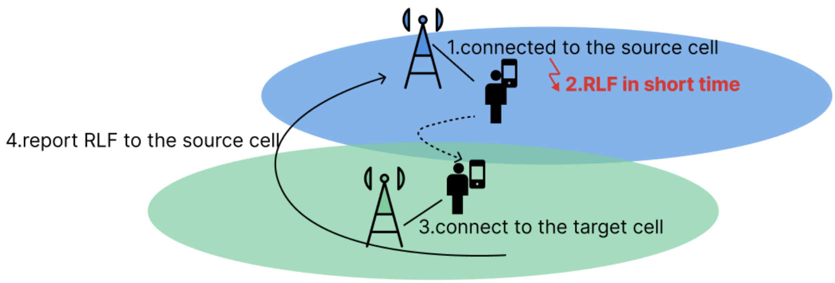


Figure 2.10: Too Late handover.

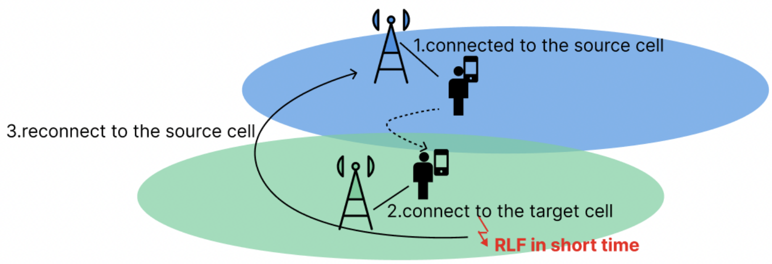


Figure 2.11: Too Early handover.

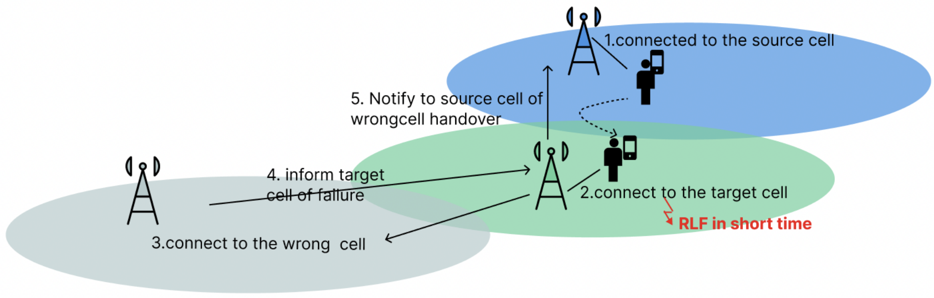


Figure 2.12: Wrong Cell handover.

Radio Link Failure :

As it is illustrated in fig 2.13, the RLF is detected as follows :
If 20 consecutive frames do not decode due having low Signal to Interference and Noise Ratio (SINR) value, an out-of-sync indication is sent to the UE RRC layer. When the number of consecutive out-of-sync indications matches the value of the N310 parameter, the T310 timer is started. During this timer, the number of frames that were able to be decoded due to having higher SINR is counted. The UE is considered back in-sync if the number of consecutive in-sync indicators matches N311. Otherwise, the RLF has happened [5].

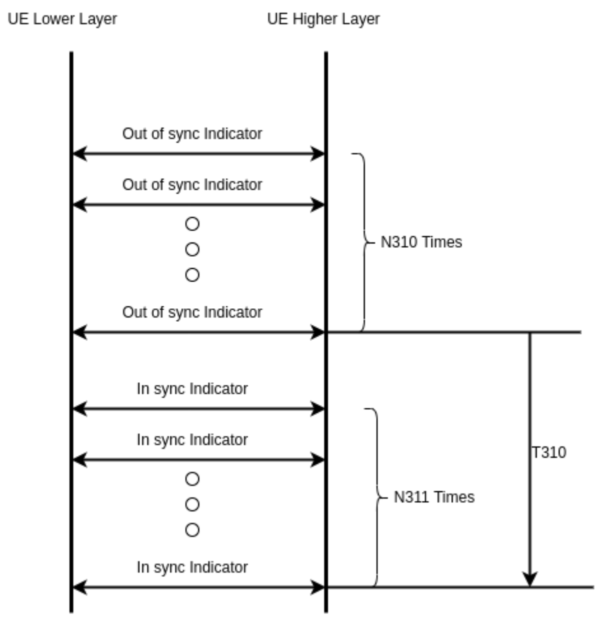


Figure 2.13: Too late handover.

2.3. Defenition of Relevant KPI

In this section, the KPIs that are used in simulation and performance evaluation are defined.

Reference Signal Received Power : The term Reference Signal Received Power (RSRP) refers to the strength of the reference signal received by a mobile device from a Base Station in a wireless communication system.
The reference signal is a known signal sent by the base station that the mobile device uses to evaluate the performance of the wireless channel and decide the appropriate transmission strength for the UL channel. The RSRP for a given cell is computed by calculating the linear average of the Resource Element (RE)s power contributions that carry the cell-specific reference signal within the measurement frequency bandwidth under consideration [12].
Received Signal Strength Indicator : Received Signal Strength Indicator (RSSI) is a measurement of the overall received power detected by the UE from all sources within a certain measurement bandwidth is the Long Term Evolution (LTE) carrier RSSI. This comprises thermal noise, neighboring channel interference, the power received from the serving cell, as well as the power received from other cells (both serving and non-serving) [12].
Reference Signal Received Quality : As it was described in the section 2.2.1, the events in measurement reports are measured based on RSRQ. RSRQ is obtained based on the following formula :

$$RSRQ = \frac{N \times RSRP}{RSSI} \tag{2.1}$$

- **N** : The number of REs of the LTE carrier RSSI measurement bandwidth.

When the UE sends a measurement report to eNB, it does not send the RSRQ value. It maps the RSRQ to an integer value between 0 to 34 based on the defined table in 3GPP specification[13].In this thesis, the RSRQ value is used as a channel value.

Mobility Interruption Time : MIT is the total time that the UE is not able to transmit and receive any data to its current cell due to handover or HOF. In this thesis, the handover is assumed to take 60 ms, and HOF is assumed to be one second.

Note that the number of ping-ping handovers and HOFs such as Too Late Handover, Too early Handover, and Wong Cell Selection which was defined in 2.2.2 are used as a

KIP for performance evaluation.

2.4. Related works

2.4.1. Self organized network

Network systems are becoming more complex due to heterogeneity. The complexity challenges their management, and SON aims to address complexity through automation. SONs are Radio Access Network (RAN) that automatically configure, optimize, and heal themselves to increase efficiency, stability, and quality of service in mobile networks[6].

2.4.2. Mobility Robustness Optimization

The MRO function has been introduced by the 3GPP group as a part of the SON functions. It is an effective solution for mobility management mobile networks. MRO performs automatic adjustments for Handover Control Parameter (HCP) settings to maintain the connection quality of the UEs. The main aim of MRO is to automatically optimize HCP settings such as TTT and hysteresis. The optimization process is based on various methods depending on the designed algorithms. The designed algorithms aim to maintain the channel value between the UEs and the serving eNB above a certain value during communication [14].
Several MRO algorithms have been proposed throughout the literature to address mobility issues, and some of these methods will be explained.
In [15], the authors have proposed an algorithm for adjusting handover parameters, which is based on several influenced factors such as distance, channel condition, cell load, and user velocity. Furthermore, each function's weight is considered to estimate an accurate handover parameter.
In [16], the authors have examined undesirable handovers and RLF and calculated the optimum Cell Individual Offset based on geometry, user position, and velocity to minimize RLFs and ping-pong handovers at the same time.
In [17], the authors propose an Auto Tuning Optimization (ATO) algorithm that updates hysteresis and TTT based on user speed and received signal reference power to adapt hysteresis and TTT. The proposed algorithm reduces the frequent handovers and HOF ratio.
In [18], to reduce the number of handovers, HOF and enhance mobility management, a handover mechanism is introduced that dynamically modifies handover parameters in

response to the detection of HOF.

2.4.3. Fuzzy Logic Scheme

The authors use the fuzzy logic scheme to improve handover performance in [19] and [20]. A control system built on fuzzy logic is known as a fuzzy control system.
In [19], the authors offer a self-optimizing fuzzy logic-based approach for adapting a hysteresis for handover decisions depending on user velocity and radio channel quality. The suggested algorithm aims to decrease the number of ping-pong handovers and the HOF ratio while allowing UEs to benefit from dense small-cell deployment. In [20], The author has designed a Fuzzy Logic Controller (FLC) that inputs the Call Drop Rate and HOF. The first step translates the input into a fuzzy set with linguistic terms such as very high, high, low, and very low. In the second step, the fuzz sets are translated to the actions the FLC should execute. The output is $\Delta hysteresis$, which should be added to the hysteresis.

2.4.4. Conditional Handover

As a part of 3GPP Release 16[21], Conditional Handover (CHO) has been proposed. The idea and principle have been discussed in [22] to improve the reliability of the handover. CHO was introduced to decrease the number of handovers and RLF by dividing the handover into two steps. At first, the UE is configured with measurement control and periodically observes the current and neighbors' cell signal power. If the preparation condition which can be seen in equation 2.2 is satisfied, the UE sends a measurement report to its serving cell. Based on the measurement report, the serving cell chooses a set of target cells and sends the preparation handover command to them. Target cells configure themselves based on the commands and allocate resources to the UE. Then instead of executing the handover, the UE waits and monitors target cells until the handover execution condition 2.3 is satisfied and performs the handover. So, in this case, multiple candidates are prepared for the handover, and there is more robustness with respect to baseline handover.
CHO can be formulated as follows :

$$\mathrm{P_{serv}}(m) + \mathrm{o^{exec}_{serv,target}}(m) < \mathrm{P_{target}}(m) \quad \text{for} \quad \mathrm{m_{exec}} - \mathrm{T_{TTT,exec}} < \mathrm{m} < \mathrm{m_{exec}} \tag{2.2}$$

$$\mathrm{P_{serv}}(m) + \mathrm{o^{exec}_{serv,target}}(m) < \mathrm{P_{target}}(m) \quad \text{for} \quad \mathrm{m_{exec}} - \mathrm{T_{TTT,exec}} < \mathrm{m} < \mathrm{m_{exec}} \tag{2.3}$$

Where :

- $\mathrm{P}_{\mathrm{serv}}(m)$: serving cells power
- $\mathrm{P}_{\mathrm{target}}(m)$: target cells power
- $\mathrm{T}_{\mathrm{TTT,prep}}$: reparation time to trigger
- $\mathrm{T}_{\mathrm{TTT,exec}}$: execution time to trigger
- $\mathrm{o}_{\mathrm{serv,target}}^{\mathrm{prep}}(m)$: preparation hysteresis
- $\mathrm{o}_{\mathrm{serv,target}}^{\mathrm{exec}}(m)$: execution hysteresis

2.4.5. Machine Learning Methods

In recent years, ML methods have been used to improve handover optimization by decreasing the number of HOF and redundant handovers.
In [23], the authors developed an intelligent handover management method that improves target cell selection. In their method, the handover algorithm learns from its previous experience using machine learning techniques how the handover decision to a specific cell influences the UE's Quality of Experience (QoE). A supervised learning approach based on a neural network is used to predict the most appropriate cell for handover.
In [24], the author has presented a Data-driven Handover Optimization (DHO) strategy to mitigate mobility issues such as undesired and Ping-pong handovers. In this technique, data is collected using mobile communication measurements, and then a model is provided to predict the relationship between the HOFs and features from the obtained dataset. Based on the model, the handover parameters, such as the hysteresis and TTT, are tuned to minimize the HOFs.

2.5. Simulation tools

In this section, the simulation tools that are used in this thesis are explained.

2.5.1. ns-3

ns-3 is a discrete-event network simulator primarily intended for research and education. ns-3 is free software accessible for research, development, and use under the GNU GPLv2 license [25]. ns-3 is written in C++ and Python and supports scripting. Python wraps the ns library using the pybindgen package, which delegates the parsing of the ns C++

headers to castxml and pygccxml to build the necessary C++ binding glue automatically. Finally, these automatically generated C++ files are built into the ns Python module, allowing users to interact with the C++ ns-3 models and core via Python scripts. The ns simulator has an integrated attribute-based system for managing simulation parameter default and per-instance settings.

2.5.1.1. LTE-EPC Model

The LTE model includes the LTE Radio Protocol stack (RRC, PDCP, RLC, MAC, PHY). These entities reside entirely within the UE and the eNB nodes. The LTE model has been designed to support the evaluation of the following aspects of LTE systems:

1. Radio Resource Management
2. QoS-aware Packet Scheduling
3. Inter-cell Interference Coordination
4. Dynamic Spectrum Access

The EPC model includes core network interfaces, protocols, and entities. These entities and protocols reside within the SGW, PGW, and MME nodes and partially within the eNB nodes.
The main objective of the EPC model is to provide means for the simulation of end-to-end IP connectivity over the LTE model. To this aim, it supports the interconnection of multiple UEs to the Internet via a radio access network of multiple eNBs connected to the core network, as shown in Figure Overview of the LTE-EPC simulation model.
[26]

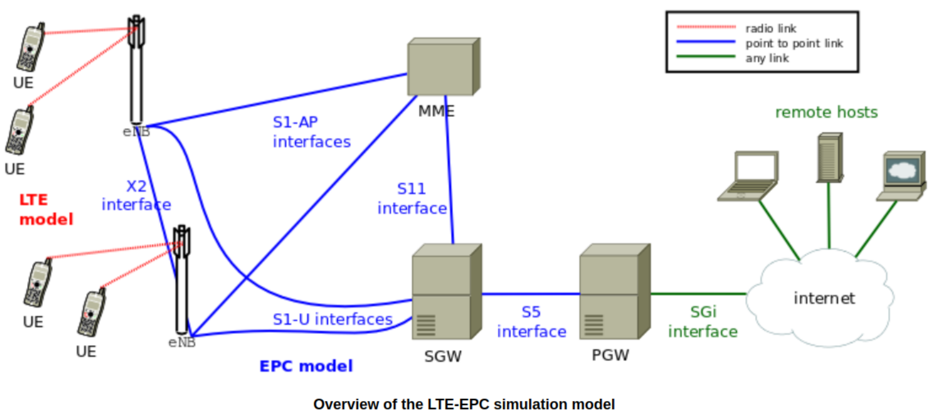


Figure 2.14: LTE EPC model

2.5.2. ns3-ai

The ns3-ai module [27] consists of two components, the ns-3 interface developed by C++ and the AI interface developed by Python. This module provides a high-level interface for the rapid development of DL/RL algorithms, as well as the core module for data transfer from one C++ application to another Python one. The main idea behind the interface between AI frameworks and ns-3 is to allow data to be transferred in numerous processes. Each process has its own user address space, and the global variables of one process cannot be accessed by the other; therefore, data interchange between processes must go through the kernel's buffer. Several methods for communicating across processes include pipe, socket (used by ns3-gym), and shared memory. The density and complexity of networks are quickly increasing in the next generation of wireless communication networks, increasing data and training time. Hence, the capacity to exchange a considerable amount of data in a short period should be prioritized, which pushes us to select shared memory as the main module for data transmission.

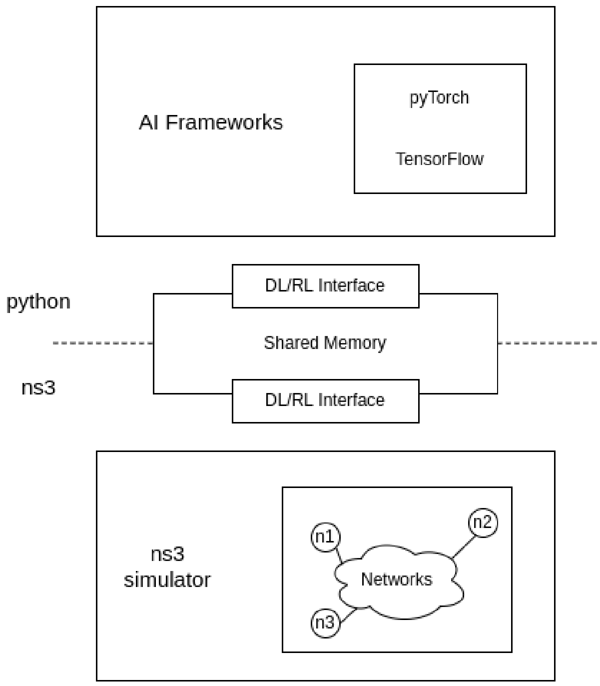


Figure 2.15: ns3-ai architecture

2.5.3. SUMO

"Simulation of Urban MObility" (SUMO) is an open-source, highly portable, microscopic, and continuous traffic simulation tool designed to manage large networks. It is primarily being developed by the German Aerospace Center's Institute of Transportation Systems personnel. It supports intermodal simulation, including pedestrians, and has a comprehensive set of scenario-creation tools. SUMO is released under the terms of EPL 2.0. With each simulation run, SUMO allows making different results. They range from simulated induction loops to single car locations written in each time step for all vehicles and to sophisticated data like trip information or aggregated measurements along a street or lane. In addition to traditional traffic metrics, SUMO now includes noise and pollution emission/fuel consumption models[28].

3 | Theoretical Background and Optimization Method

In this chapter, the optimization techniques such as constrained optimization, discrete optimization, IP, Mixed Integer Programming (MIP), Linear Relaxation (LR), and convex optimization will be explained in detail. The problem formulation of the thesis and optimization algorithm will be discussed.

3.1. Constrained Optimization

Constrained optimization is an optimization problem in which the objective function must satisfy one or more constraints to obtain an optimal solution. In other words, the purpose of constraint optimization is to find the optimum solution to an optimization problem while considering specific restrictions or limits[29]. A constraint optimization problem can be formulated as follows:

$$\arg\min \quad f(x) \tag{3.1}$$

$$\text{subject to} \quad g_i(x) \leq 0, \quad i = 1, \ldots, m \tag{3.2}$$

$$h_j(x) = 0, \quad j = 1, \ldots, p \tag{3.3}$$

Where:

- $f(x)$ is the objective function to be minimized.
- $x \in \mathbb{R}^n$ is the vector of decision variables
- $g_i(x) \leq 0$ is the inequality constraints
- $h_j(x) = 0$ is the equality constraints

The goal is to find the values of x that minimize $f(x)$ while satisfying the constraints.

3.1.1. Discrete Optimization

Discrete optimization is a branch of constrained optimization that deals with problems where the set of feasible solutions is discrete. In contrast to continuous optimization, where the decision variables can take on any value in a continuous range, discrete optimization focuses on finding the best solution from a finite set of possible solutions[29].

Discrete optimization can be defined as follow :

$$\arg\min \quad f(x) \tag{3.4}$$
$$\text{subject to} \quad x \in S \tag{3.5}$$

Where:

- $f(x)$ is an objective function to be minimized or maximized.
- x is a decision variable that takes values from a discrete set S of feasible solutions.
- The constraint $x \in S$ ensures that the solution x is selected from the set of feasible solutions.

3.1.2. Integer Programming

IP is a type of constrained optimization in which the decision variables are restricted to take integer values. It solves optimization problems where the decision variables represent discrete choices. Integer programming aims to find the optimal combination of decision variables that maximizes or minimizes the objective function subject to the given constraints[29]. IP can be defined as follows :

$$\arg\min \quad c^T x \tag{3.6}$$
$$\text{subject to} \quad Ax \leq b \qquad\qquad x \in \mathbb{Z}^n \tag{3.7}$$

Where:

- c is a vector representing the objective function to be maximized or minimized.
- x is a vector of decision variables to be optimized.
- A is a matrix of coefficients representing the constraints on the decision variables.

- b is a vector of constants representing the right-hand side of the constraints.
- $\mathbb{Z}^n$ denotes the set of integer values that each element of x can take.

The above formulation represents a minimization problem where the goal is to find the values of the decision variables x that minimize the objective function $c^T x$, subject to the linear constraints represented by $Ax \leq b$. The constraint $x \in \mathbb{Z}^n$ ensures that the decision variables must take integer values.

3.1.3. Mixed Integer Programming

MIP is a constrained optimization type involving solving a linear or nonlinear optimization problem subject to continuous and integer variables. In MIP, some variables are restricted to integer values, while others can take continuous values.
MIP aims to find the optimal values for all variables that satisfy the problem's constraints and optimize the objective function, which is a linear or nonlinear function of the variables. The solution of a MIP problem is a set of values for all continuous and integer variables that maximize or minimize the objective function while satisfying all the constraints of the problem.

$$\text{minimize} \quad c^T x + d^T y \tag{3.8}$$
$$\text{subject to} \quad Ax + By \leq b \qquad x \in \mathbb{R}^n \quad y \in \mathbb{Z}^m \tag{3.9}$$

where:

- $x \in \mathbb{R}^n$ is a vector of continuous variables
- $y \in \mathbb{Z}^m$ is a vector of integer variables
- $c \in \mathbb{R}^n$ and $d \in \mathbb{R}^m$ are coefficient vectors for the objective function
- $A \in \mathbb{R}^{p\times n}$ and $B \in \mathbb{R}^{p\times m}$ are matrices of coefficients for the constraints
- $b \in \mathbb{R}^p$ is a vector of constraint bounds.

The goal is to find values of x and y that minimize the linear objective function subject to the linear constraints. The variable y is constrained to integer values.

3.1.3.1. Linear Relaxation

LR is a technique used in mathematical optimization, particularly in the context of integer programming and mixed integer programming. It involves relaxing the integer constraints of an optimization problem to obtain a problem that can be solved using linear programming.

The basic idea of LR is to remove the integer constraints from the optimization problem, allowing the variables to take on continuous values. This results in a linear programming problem that can be solved using efficient algorithms, such as the simplex or interior-point methods.

Solving the LR of an integer programming problem provides a lower bound on the optimal objective value of the original problem. The gap between the solution of the LR and the IP problem is referred to as the integrality gap[30].

However, it is essential to note that the solution of the LR may only sometimes provide a good approximation to the optimal solution of the original integer programming problem, mainly if the integrality gap is significant.

3.1.4. Convex Optimization

Convex optimization is a field of mathematical optimization that deals with the problem of minimizing a convex function subject to a set of convex constraints. In convex optimization, both the objective function and the constraint set are convex, which makes the problem well-behaved and allows for efficient optimization algorithms[29].

Here is the mathematical definition of a general convex optimization problem:

$$\text{minimize} \quad f(x) \tag{3.10}$$

$$\text{subject to} \quad g_i(x) \leq 0, \quad i = 1, 2, \ldots, m \tag{3.11}$$

where:

- x is a vector of variables
- $f(x)$ is a convex function of x
- $g_i(x)$ is convex functions of x.

The optimization problem is convex if both the objective and constraint functions are convex and if it is a minimization problem.

A function $f(x)$ is convex if for any two points x_1 and x_2 in its domain and any scalar θ between 0 and 1, the following inequality holds:

$$f(\theta x_1 + (1-\theta)x_2) \leq \theta f(x_1) + (1-\theta)f(x_2)$$

This inequality is known as the convexity condition, implying that the function lies above or equal to any of its tangents.

3.1.5. Convex Set

A set S is convex if for any two points x_1 and x_2 in the set and any scalar θ between 0 and 1, the point $\theta x_1 + (1 - \theta)x_2$ is also in the set.

3.2. Model Predictive Control

Model Predictive Control (MPC) is an advanced control approach used to maximize the performance of dynamic systems in engineering and process control systems. It is a model-based control technique that uses a predictive model of the system's behavior to identify the optimal control inputs resulting in the highest system performance while considering operational limits or limitations.MPC begins by developing a mathematical model of the system to be controlled. This model represents the system's behavior and how it reacts to various inputs. The model may be a linear or nonlinear function.MPC uses it to forecast the system's future behavior given a set of probable control inputs. Based on this prediction, MPC selects the optimum set of control inputs to achieve the highest system performance while respecting any operational constraints, which is accomplished by solving an optimization problem that aims to minimize a cost function while being constrained by a set of constraints that represent the physical restrictions or operational needs of the system. After the optimal control inputs are identified, they are applied to the system for a short period before the process is repeated. The model is updated, and the optimization problem is addressed again using the new data. This iterative process continues, with MPC continually predicting and optimizing the system's behavior across a time horizon into the future to achieve the required performance. As a consequence, a closed-loop control system, as it is illustrated in figure 3.1 is created that modifies the system's behavior in real time depending on the system's present state and expected future behavior.

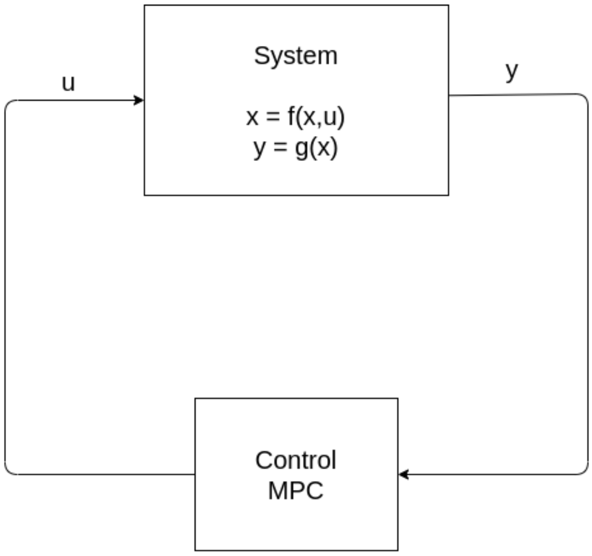


Figure 3.1: Model Predictive Control

3.3. Proposed Predictive Handover Optimization

As discussed, the event-based handover scheme falls into many handovers and HOF since it relies only on channel information from its current and past measurements. By predicting the channel's value, the performance can be improved. In order to improve the performance, the MPC scheme is used. As it is shown in fig 3.2, First of all, the UE gets connected to the strongest cell. Each time step has a time window in which the channel value is predicted. Then an optimizer computes the cell assignment from time step t to the t + window size based on the predicted data. Then, the optimizer's output value at t+1 is used to decide if the UE should stay connected to its previous cell or do a handover to another cell. If the chosen cell at t+1 falls into the RLF, the UE reconnects to the best cell and repeats the same procedure. Otherwise, it repeats the same procedure based on the current cell that it has connected.

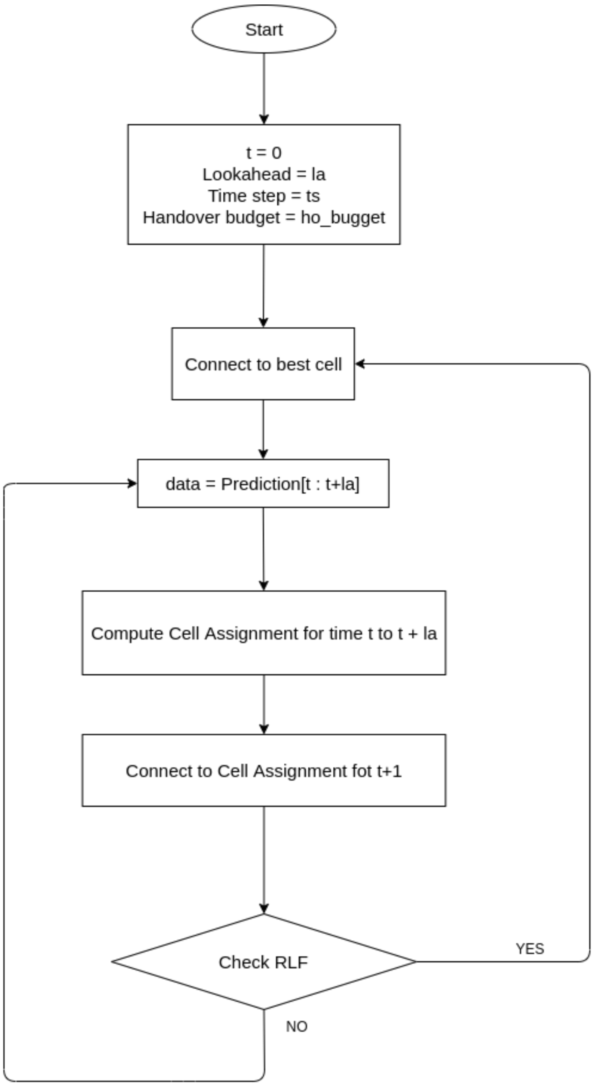


Figure 3.2: system block diagram overview

As discussed above, one optimization problem is solved at each time step. Let's focus on one of these problems:

3.3.1. Problem Formulation

The UE wants to achieve the average maximum data rate at each time step. Since it is not easy in practice and simulation to acquire this data rate, the RSRQ is taken as an approximation. So instead of maximizing over achievable data rate, the maximization is done based on the RSRQ.
As shown in the table 3.1, there is a matrix of RSRQ in which rows represent the cell and columns represent the time instance. So $\text{RSRQ}_{i,j}$ means that at time instance of j, if the UE gets connected to cell i, it will get the $\text{RSRQ}_{i,j}$. After the optimization, the second row

RSRQ_{11}	RSRQ_{12}	RSRQ_{13}	RSRQ_{14}	...	RSRQ_{1T}
RSRQ_{21}	RSRQ_{22}	RSRQ_{23}	RSRQ_{24}	...	RSRQ_{2T}
RSRQ_{M1}	RSRQ_{M2}	RSRQ_{M3}	RSRQ_{M4}	...	RSRQ_{MT}

Table 3.1: RSRQ values for optimization based on time window at each time step

is used for the handover decision since it represents the next time steps channel values.

Let us assume that there are **M** number of cells. We want to maximize the averaged received RSRQ, but We let the user have an at last **N** number of handovers. The assumptions can be represented mathematically as follows :

Handover Number : N

Set of all cells : $M = \{1, ..., M\}$

Time Sets : $T = \{1, ..., T\}$

RSRQ : $R = [r_{\text{ij}}] \in \mathbb{R}_{++}{}^{M\times T}$

Optimization Variable : $\boldsymbol{X} = [\boldsymbol{x_1, x_2, ..., x_T}] = [x_{ij}] \in \mathbb{R}_{++}^{M\times T}$

The optimization problem can be represented as follows:

$$\begin{aligned} \max_{\mathbf{X}\in\mathbb{R}^{M\times T}} \quad & \sum_{i=1}^{M}\sum_{j=1}^{T}\frac{r_{ij}x_{ij}}{T} \\ \text{subject to} \quad & x_{ij} \in \{0,1\} && \forall i \in M, \forall j \in T \\ & \sum_{i=1}^{M} x_{ij} = 1 && \forall j \in T \\ & |\{j \in T' : x_j \neq x_{j+1}\}| \leq N && T' = \{1, ..., T-1\} \end{aligned}$$

- **The objective function** of this optimization problem is the maximize the average predicted RSRQ achieved by the cell assignment according to X.
- **The first constraint** states that the decision variable $x_{i,j}$ is binary. The practical meaning of this constraint is that if $x_{i,j} = 1$, cell i at time instance j has been chosen to get connected to. and if $x_{i,j} = 0$ the corresponded cell is not selected.
- **The second constraint** states that the summation of all the rows at each time instance of the decision matrix is one. Since the decision variable is binary, the practical meaning of this constraint is that it assures that the user gets connected to one and only one cell at each time step.

- **The third constraint** states that the number of consecutive columns that are not equal should be less or equal to the constant N. In practice, this constraint ensures that the number of handovers should be less or equal to N. Because if the UE connects to the cell i at time j, the vector x_j is one in the i-th row and zero on the rest of the vector. If it stays connected to cell i at time j+1, the vector x_{j+1} has the same value as vector $\boldsymbol{x_j}$. However, if it does handover to cell $k \neq i$, the vector $\boldsymbol{x}_{j+1}$ does not equal $\boldsymbol{x}_j$. The $\mathbf{X}$ is a plan for UE, which will be updated at each time step.

At each time step, the handover occurs if and only if $\boldsymbol{x}_0 \neq \boldsymbol{x}_1$. If $\boldsymbol{x}_j \neq \boldsymbol{x}_{j+1}$, it does not mean that there will be a handover from time step j to j+1 since at each time step, the RSRQ matrix is being updated every time step, so in order to see if there is a handover from time step j to j+1, we should consider the matrix of RSRQ while its first column represents the time step j, then optimize it based on the given constraint and see if $\boldsymbol{x}_0 = \boldsymbol{x}_1$ or not.

Note that whenever there is a handovers in matrix $\mathbf{X}$, we have the following condition : $\sum_{j=1}^{T-1} \sum_{i=1}^{M} |x_{ij+1} - x_{ij}| \leqq 2$
So, the optimization problem can be written as follows :

$$
\begin{aligned}
\max_{\mathbf{X} \in \mathbb{R}^{M \times T}} \quad & \sum_{i=1}^{M} \sum_{j=1}^{T} \frac{r_{ij} x_{ij}}{T} \\
\text{subject to} \quad & x_{ij} \in \{0,1\} && \forall i \in M, \forall j \in T \\
& \sum_{i=1}^{M} x_{ij} = 1 && \forall j \in T \\
& \sum_{j=1}^{T-1} \sum_{i=1}^{M} |x_{ij+1} - x_{ij}| \leq 2N
\end{aligned}
$$

This is an IP optimization problem. Solving an IP problem could be computationally complex for large problems. To solve this problem, we use LR and let x be any value between 0 and 1.
The original optimization problem will be relaxed to the following :

$$
\begin{aligned}
& \underset{\mathbf{X}\in\mathbb{R}^{M\times T}}{max} && \sum_{i=1}^{M}\sum_{j=1}^{T}\frac{r_{ij}x_{ij}}{T} && (3.12)\\
& \text{subject to} && x_{ij} \in [0,1] && \forall i \in M, \forall j \in T\\
& && \sum_{i=1}^{M} x_{ij} = 1 && \forall j \in T\\
& && \sum_{j=1}^{T-1}\sum_{i=1}^{M} |x_{ij+1} - x_{ij}| \leq 2N &&
\end{aligned}
$$

Note that $\sum_{j=1}^{T-1}\sum_{i=1}^{M} |x_{ij+1} - x_{ij}| \leq 2N$ can be rewritten as :
$\sum_{j=1}^{T-1} ||\boldsymbol{X}(:,j) - \boldsymbol{X}(:,j+1)||_1$
The obtained problem is convex. Here is the proof :
To prove that the optimization problem is convex, we need to show that its objective function and constraints are convex.
The objective function is:

$$\underset{\mathbf{X}\in\mathbb{R}^{M\times T}}{\arg\max} \sum_{i=1}^{M}\sum_{j=1}^{T}\frac{r_{ij}x_{ij}}{\tau} \tag{3.13}$$

This is a linear function of x, and linear functions are both convex and concave.
First, constrain :

$$x_{ij} \in [0,1] \quad \forall i \in M \tag{3.14}$$

we need to show that the set of points that satisfy these constraints is a convex set.
A set is convex if, for any two points x and y in the set, the line segment between x and y is also in the set. In other words, if $0 \leq x_{i,j} \leq 1$ and $0 \leq y_{i,j} \leq 1$ for all i and j, then $0 \leq (1-\theta) * x_{i,j} + \theta * y_{i,j} \leq 1$ for all t between 0 and 1.
To see why this is true, consider the expression $(1-\theta) * x_{i,j} + \theta * y_{i,j}$. This is a weighted average of $x_{i,j}$ and $y_{i,j}$, with weights $(1-\theta)$ and θ, respectively. Since both $x_{i,j}$ and $y_{i,j}$ are between 0 and 1, the weighted average is also between 0 and 1, which means that $(1-\theta) * x_{i,j} + \theta * y_{i,j}$ satisfies the constraint $0 \leq (1-\theta) * x_{i,j} + \theta * y_{i,j} \leq 1$.
Therefore, the set of points that satisfy $0 \leq x_{i,j} \leq 1$, for all i,j is a convex set, and the constraint is convex.

The second constraint

$$\sum_{i=1}^{M} x_{ij} = 1 \qquad\qquad \forall j \in T \tag{3.15}$$

is a linear equality constraint, and linear constraints are always convex.
To prove this, let $x^{(1)}$ and $x^{(2)}$ be two feasible solutions, i.e., $\sum_i x^{(1)}ij = 1$ and $\sum_i x^{(2)}ij = 1$ for all j. Let $\theta \in [0, 1]$ be a scalar. Then the convex combination $x^{(3)} = \theta x^{(1)} + (1-\theta)x^{(2)}$ satisfies:

$$\sum_i x^{(3)}ij = \sum_i (\theta x^{(1)}ij + (1-\theta)x^{(2)}ij) = \theta \sum_i x^{(1)}ij + (1-\theta)\sum_i x^{(2)}_{ij} = \theta \cdot 1 + (1-\theta) \cdot 1 = 1,$$

for all j. Therefore, $x^{(3)}$ is also a feasible solution.
Since any convex combination of two feasible solutions is also a feasible solution, the constraint $\sum_i x_{ij} = 1$ for all j is a convex constraint.

The third constrain is convex :
Let X and Y be two feasible points to the main problem, and let $Z = \theta X + (1-\theta)Y$ be their convex combination, where $\theta \in [0, 1]$. We want to show that Z also satisfies the constraint:
$\sum_{j=1}^{T-1} ||\boldsymbol{Z}(:, j) - \boldsymbol{Z}(:, j+1)||_1 \leq 2N$
Expanding the 1-norm, we have:

$$\sum_{j=1}^{T-1} ||\boldsymbol{Z}(:, j) - \boldsymbol{Z}(:, j+1)||_1 = \sum_{j=1}^{T-1} \sum_{i=1}^{N} |\boldsymbol{Z}(i, j) - \boldsymbol{Z}(i, j+1)|$$

Substituting the definition of Z, we obtain:

$$\sum_{j=1}^{T-1} ||\boldsymbol{Z}(:,j) - \boldsymbol{Z}(:,j+1)||_1 =$$
$$\sum_{j=1}^{T-1}\sum_{i=1}^{N} |\theta \boldsymbol{X}(i,j) + (1-\theta)\boldsymbol{Y}(i,j) - \theta \boldsymbol{X}(i,j+1) - (1-\theta)\boldsymbol{Y}(i,j+1)| =$$
$$\sum_{j=1}^{T-1}\sum_{i=1}^{N} |\theta(\boldsymbol{X}(i,j) - \boldsymbol{X}(i,j+1)) + (1-\theta)(\boldsymbol{Y}(i,j) - \boldsymbol{Y}(i,j+1))| \leq$$
$$\sum_{j=1}^{T-1}\sum_{i=1}^{N} \theta|\boldsymbol{X}(i,j) - \boldsymbol{X}(i,j+1)| + (1-\theta)|\boldsymbol{Y}(i,j) - \boldsymbol{Y}(i,j+1)| =$$
$$\theta \sum_{j=1}^{T-1} ||\boldsymbol{X}(:,j) - \boldsymbol{X}(:,j+1)||_1 + (1-\theta)\sum_{j=1}^{T-1} ||\boldsymbol{Y}(:,j) - \boldsymbol{Y}(:,j+1)||_1$$

The last inequality follows the triangle inequality and the fact that $\theta \in [0,1]$. Since X and Y are feasible solutions to the main problem, we have:
$\sum_{j=1}^{T-1} ||\boldsymbol{X}(:,j) - \boldsymbol{X}(:,j+1)||1 \leq 2N$
$\sum j = 1^{M-1}||\boldsymbol{Y}(:,j) - \boldsymbol{Y}(:,j+1)||_1 \leq 2N$
Thus, we have:
$\sum_{j=1}^{T-1} ||\boldsymbol{Z}(:,j) - \boldsymbol{Z}(:,j+1)||_1 \leq \theta \cdot 2N + (1-\theta)\cdot 2N \;\; = 2N$ Therefore, Z is a feasible solution to the main problem, and the constraint is convex.

After solving this convex optimization problem, the obtained decision matrix $\mathbf{X}$ has a continuous value between 0 and 1, while in order to do a cell assignment, the value should be binary, and at each time step, one cell should be chosen. To achieve this property, we use the following heuristics:
We define a function ϕ that maps any vector to one-hot vector: $\phi : \mathbb{R}^M \mapsto \{0,1\}^M$. The function maps the vector $\mathbf{x}$ to one-hot vector based on the following equation:
$$\forall i \in M,\;\; \phi(x)|_i = \begin{cases} 1 & \text{if } i = i^* \\ 0 & \text{otherwise} \end{cases}$$
where i^* is : $min\{i \in M | x_i = max\{x_1, ..., x_M\}\}$
This mapping function is performed on the vector of each time step of $\mathbf{X}$ and converts $\mathbf{X}$ to $\hat{\mathbf{X}}$, which consists of a series of one-hot vector columns. Cell assignment will be done based on the second column of $\hat{\mathbf{X}}$

3.4. Optimization Algorithm

Algorithm 3.1 shows how the system works. The algorithm works as follows:
First, lookahead, which is the time frame in which the channel value is predicted, and a handover budget, which is a constraint on the number of handovers allowed for a UE, is determined. Once the UE is allocated to a cell, the channel values of all the cells from the current time step t to the t + T are predicted. Using the channel value matrix, and the handover budget, an optimization problem is formed. This optimization problem is solved using LR to determine the best handover decision. The output of this optimization problem is a matrix $\mathbf{X}$, which contains elements that may not be binary. Instead, each element of the vector has a continuous value between 0 and 1. To convert the output matrix to a matrix $\hat{\mathbf{X}}$ consisting of a series of one-hot vectors at each time step, the following heuristic is used :
$\phi : \mathbb{R}^M \mapsto \{0,1\}^M$ to map $\mathbf{X}$ to $\hat{\mathbf{X}}$ that is made of series of one-hot vectors at each time step. The second column of $\hat{\mathbf{X}}$ which represents the cell assignment at t+1 is used to decide whether a handover is needed. No handover is required if the chosen cell in this column is the same as the cell to which the UE is currently connected. Otherwise, the UE is handed over to the next cell. The process then repeats for the next time step. If, at any time instance, the UE falls into RLF, it is connected to the cell with the best RSRQ value at the current time, and the entire process restarts from the beginning.

Algorithm 3.1 Preditive Handover Optimization Algorithm

```
1: t = 0
2: Lookahead = T
3: Handover Budget = N
4: Connect to the strongest cell
5: while t < τ do
6:     t = t + 1
7:     if UE in RLF then
8:         go to step 5
9:     end if
10:    data = Prediction[t : t+T]
11:    pose the optimization problem with linear relaxation
12:    X = optimize(data,N)
13:    X̂ = φ : ℝ^M ↦ {0, 1}^M
14:    potential next cell = argmax(X̂[:,1])
15:    if potential next cell == current cell then
16:        go to step 7
17:    else
18:        handover to next cell
19:        go to step 7
20:    end if
21: end while
```

4 | Simulation and Numerical results

4.1. Scenario and Configuration

This section explains the scenario and configuration of the thesis, such as cell configuration and street map data.

4.1.1. mobility Configuration

The simulation is performed using berlin's map data. The map data was collected using OpenStreetMap, shown in fig 4.1. Then the data is exported to SUMO simulation, and the UE mobility is obtained.

Figure 4.1: map

4.1.2. Cell Configuration

In our scenario, one three-sector Macrocell with 18 microcells is used. The distance between each microcell is 300 meters, and the Macro cell is located in the center of the map. The following table shows the configuration of the Macro and microcells :

	Macrocell	**Microcell**
Tx Power(dBm)	15	40
Bandwidth(MHz)	20	20
sceduler	RrFfMacScheduler	RrFfMacScheduler
Height(m)	30	30
Horizontal Beamwidth	100	–

Table 4.1: Cell Transceiver Configuration.

figure 4.2 shows the position of cells on the map :

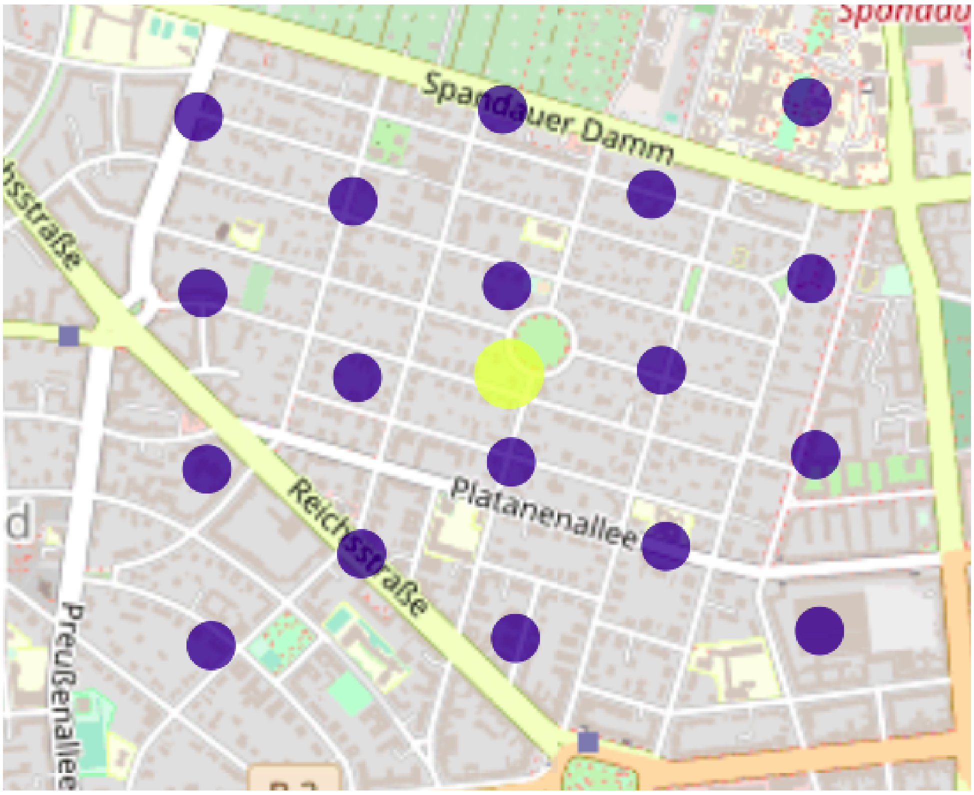


Figure 4.2: Cell Polistions of simulation

The Radio Map of the environment based on the location of the cell can be seen in the figure 4.3 :

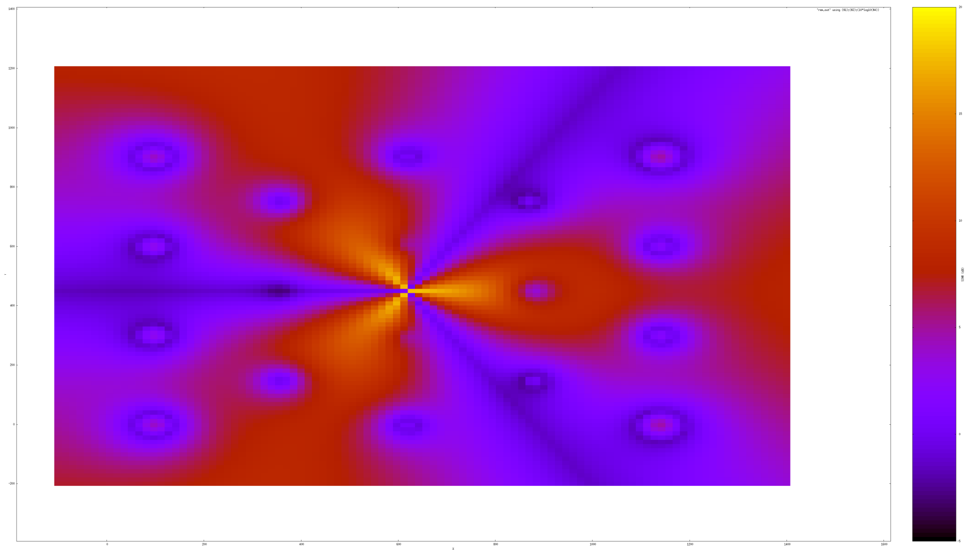


Figure 4.3: Radio Map of the enviroment

4.2. Data Collection

In this thesis the quantized RSRQ is used for the handover decision. The reason is that the UE sends quantized RSRQ to the eNB instead of RSRQ value. Furthermore, since the RSRQ is obtained based on RSRP and RSSI, It also takes into account the interference caused by neighbors' cells while RSRP only takes into account the power from the cell that the being measured.
First of all, user mobility has been obtained using the SUMO simulator. Then this mobility is fed to ns3, and the simulation is run for this specific mobility.
While the simulation is running, The UEs quantized RSRQ from all the cells in the environment can be collected at each time step. In our case, the duration of each time step is 200 ms.
The quantized RSRQ at each time step is saved and reused while the ns3-ai is running. The optimizer uses the RSRQ value of the user of all the cells from the current time of simulation to the time obtained by the time window.
The simulation was done for 100 users with varying mobility to confirm the results. The simulation takes 400 seconds to complete. The outcome was then averaged.

4.3. Handover Failure and Ping-Pong Handover Detection

In this thesis, the threshold to detect handover failure and ping-pong handover is set to 2 seconds.

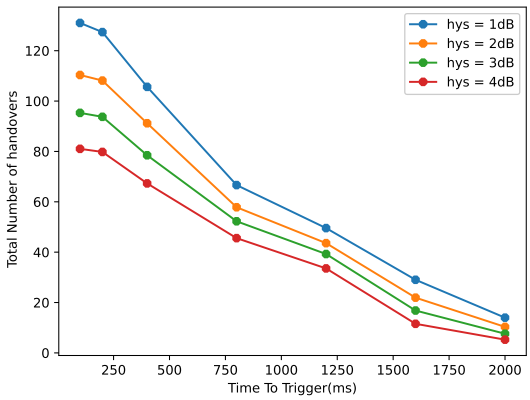
- If the UE does a successful handover, a timer starts to count. If it falls into RLF and reconnects to the previous cell before the threshold, The HOF marked As **Too Early Handover**
- If the UE does a successful handover, the timer starts to count. If it falls into RLF and reconnects to neither the previous cell nor the current cell before the threshold, The HOF marked as **Wrong Cell Selection**
- If the UE falls into RLF, the timer starts to count. if it reconnects to a cell different than its previous cell, the HOF is marked As **Too Late Handover**
- If the UE does a successful handover, the timer starts to count. If it does another handover to its previous cell, the handover is marked as **Ping-Pong Handover**

Note that since in too early handover and wrong cell selection, the handover fails duo do target cell's signal quality, in this thesis, they are both considered as **Too Early Handover**.

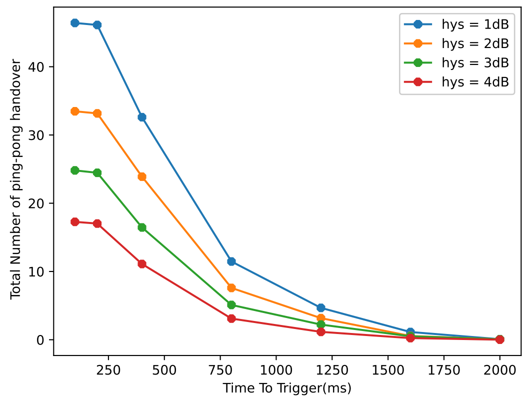
4.4. Results

4.4.1. Conventional method

In existing systems, the handovers are performed using A3-event-handover scheme described in section 2.2.1. The simulation was run for TTT starting from 100 ms to 2000ms and hysteresis starting from 1 to 4 dB:



(a) Average number of handovers for 100 simulations for conventional method



(b) Average number of ping-pong handovers for 100 simulations for conventional method

As it is shown in figure 4.4a, the number of handovers decreases as the TTT increases. This is because the UE should observe the neighboring cells for more periods to send the measurement report to the serving eNB. Furthermore, the number of handovers decreases as we increase the hysteresis. This is because the next cell should serve stronger on the specific period to send the measurement report to the eNB.
As a result, since the total number of handovers is decreasing, The number of ping-pong handovers is also decreasing. this effect can be seen in figure 4.4b.The total number of ping-pong handovers goes to zero as we reach the TTT of 2000ms since we define this value as a distinguish of Ping Pong handovers.

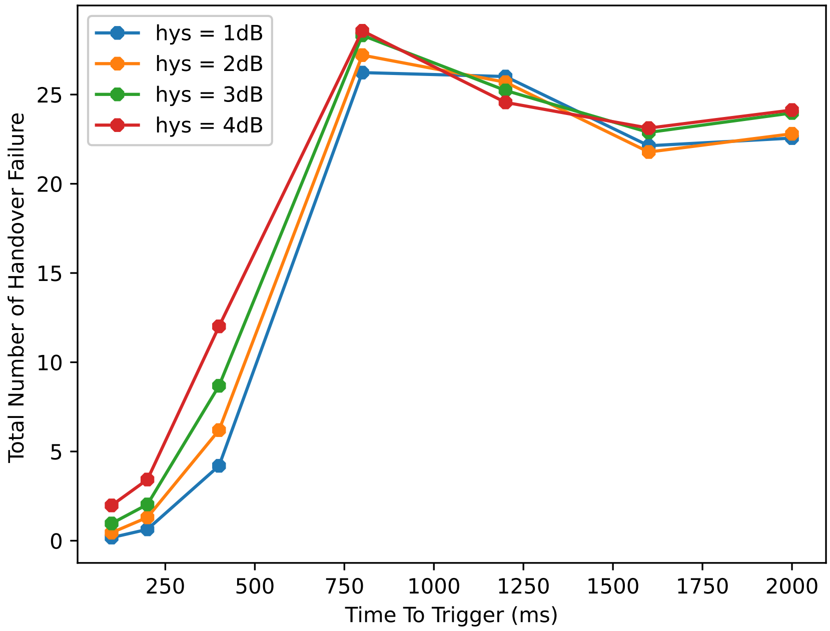


Figure 4.4: Average number of Handover Failures handovers for 100 simulations for conventional method

As it is shown in the figure 4.4, by increasing the TTT, The HOF increases. This is because, based on the loss model used in the simulation, The UE falls into many Non Line of Sight (NLOS). The NLOS effect leads to an increasing number of HOF. However, as we increase the TTT more and more, the number of HOF decreases slightly. This does not mean that the target cell is being chosen more efficiently. It is because the UE is observing for a more extended period and does not do a handover. And some times it is not necessary to do a handover while the UE is in NLOS since either it might cause a Too Early Handover or the UE still can be served by the current cell. As a result, the HOF on target cells decreases, but the number of HOFs remains large.
Furthermore, there is no pattern in increasing the hysteresis while kipping the TTT on the same value. This is because, at some point, the UE may fall into a too early handover; then, by increasing the hysteresis, the HOF goes away. However, if it increases the hysteresis more, it falls into too-late handovers, and in HOFs increase.

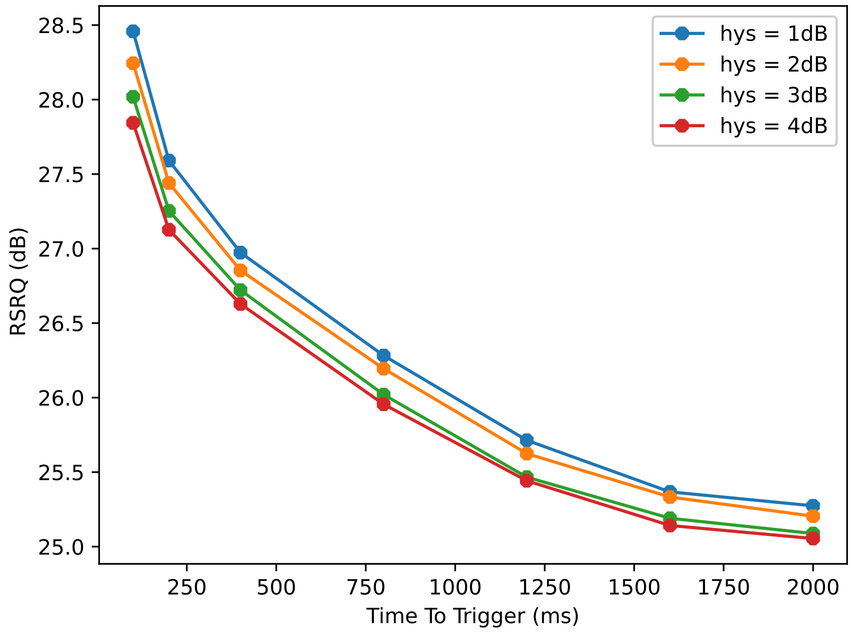


Figure 4.5: Average RSRQ for 100 simulations for conventional method

As it is shown in the figure 4.5, by increasing TTT and keeping hysteresis constant, The received RSRQ in decreased because the number of handovers is decreased, and the UE is connected to its serving cell for a more extended period rather than doing handover and connect to the cell with better signal quality. This effect also can be seen while the hysteresis is increased and TTT is kept constant because the UE searches for a stronger cell to do a handover and eventually stays connected to its serving cell for more period of time.

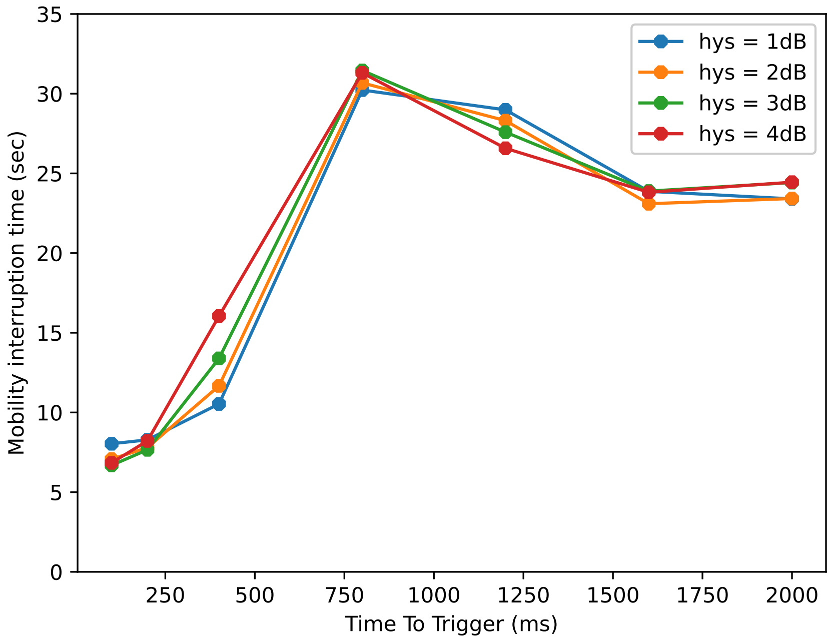


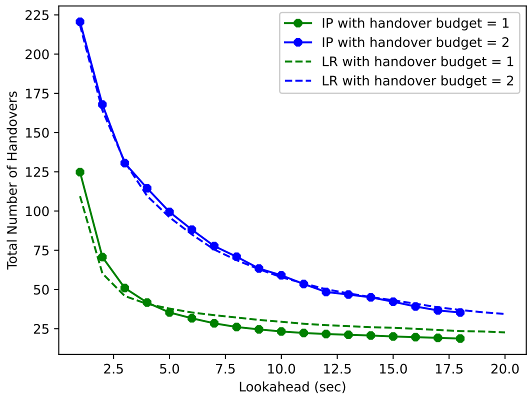
Figure 4.6: Average MIT for 100 simulations for conventional method

As discussed before, MIT is the most important KPI that the best option will be chosen based on. It brings the handover number and HOF together. MIT is the time that the UE is not able to transmit data due to performing handover and HOF. As it is shown in the 4.6, By using the conventional scheme, the UE experiences high MIT, and this is because they rely on current and previous measurements.

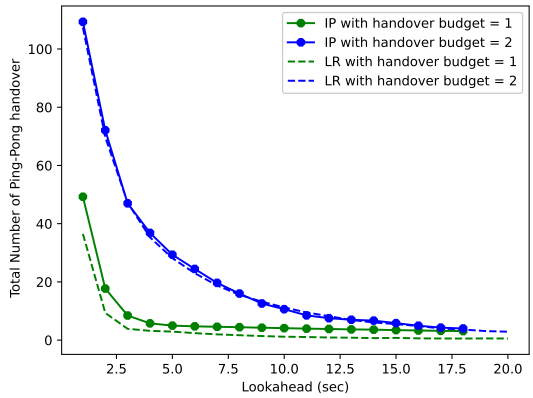
Based on MIT, the best configuration is TTT of 100 ms with Hysteresis of 3dB. However, this setting falls into the number of ping-pong handovers leading to huge signaling for the network

4.4.2. Integer Programming vs. Linear relaxation

As it was discussed in section 3.3.1, the original problem that needs to be solved every time step is IP, and linear relaxation is used in order to solve it. In this subsection, the result based on solving the problem using linear relaxation and IP is being compared.



(a) Average number of handovers for 100 simulations for IP vs LR



(b) Average number of ping-pong handovers for 100 simulations for IP vs LR

As it can be seen in fig 4.10a, increasing the time window, known as lookahead in figures, results in fewer handovers. Additionally, the number of handovers while employing linear relaxation differs slightly from the IP approach. This is because the heuristic used to convert the optimized linear relaxation matrix, which is a continuous value between 0 and 1, to the matrix made of a series of one-hot vectors would violate the handover constraint and result in a different number of handovers than the IP method, which guaranteed that the number of handovers at each step would not exceed the defined handover budge. This effect can also be seen in the number of ping-ping handovers, which is shown figure 4.10b. In conclusion, the proposed method, which is not as high computational hard for large-scale problems as IP solving, works almost the same as IP method.

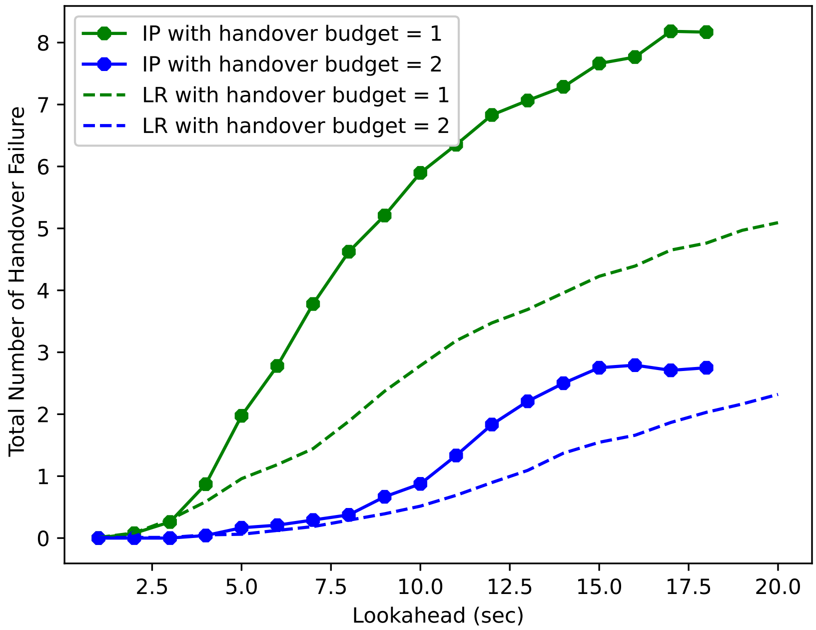


Figure 4.7: Average number of Handover Failures handovers for 100 simulations for IP vs LR

As shown in figure 4.7, increasing the lookahead leads to experiencing more number of HOFs. However, the number of HOFs is much less than the conventional method. Furthermore, the linear relaxation method leads to having less HOF than the IP, and this is because of violation in a number of handovers of the heuristic that is used in order to obtain a matrix of one-hot vectors.

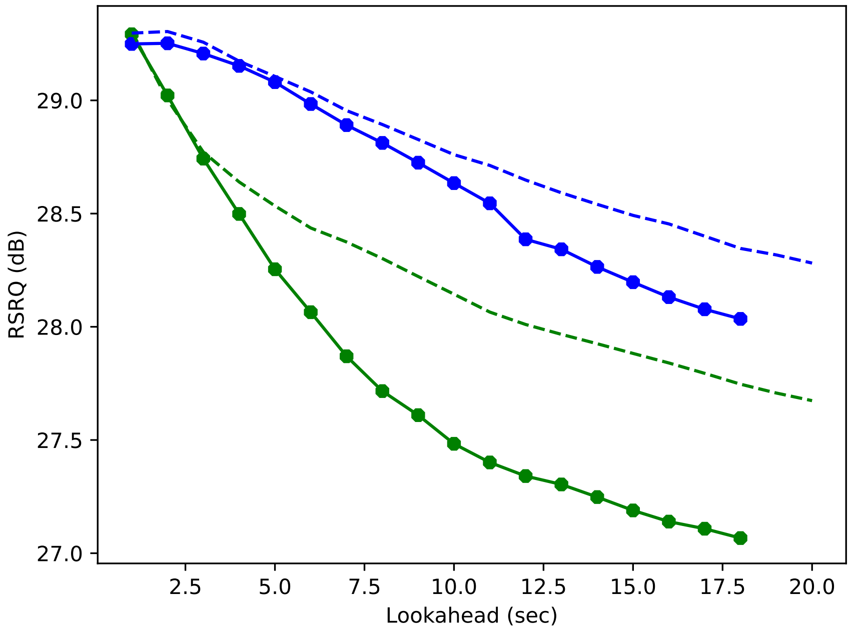


Figure 4.8: Average RSRQ for 100 simulations for IP vs LR

Figure 4.8 shows that increasing the lookahead leads to having less quantized RSRQ because the UE tends to connect to one cell than doing the handover. However, the linear relaxation method leads to having more quantized RSRQ, compared to the optimized value, and this is due to the fact that the UE falls into more number of handovers and less number of HOF.

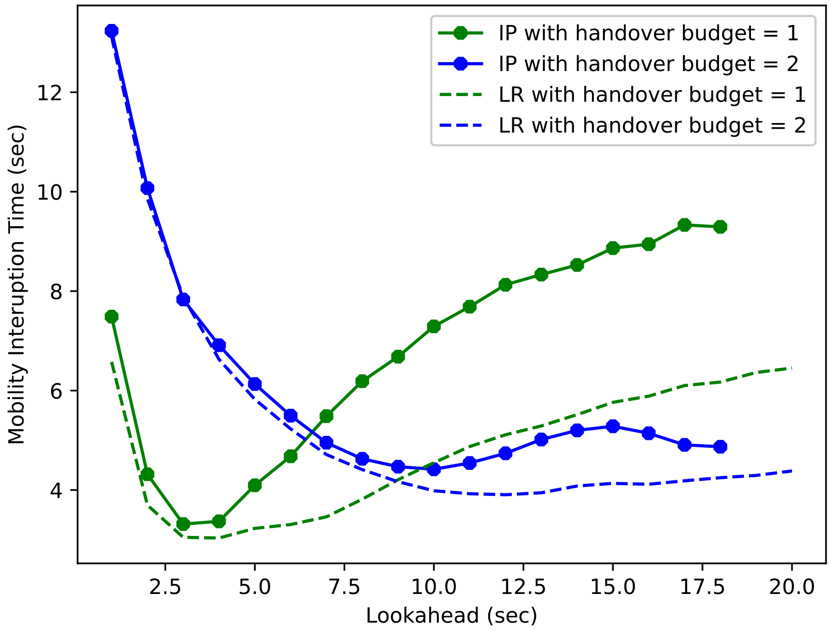
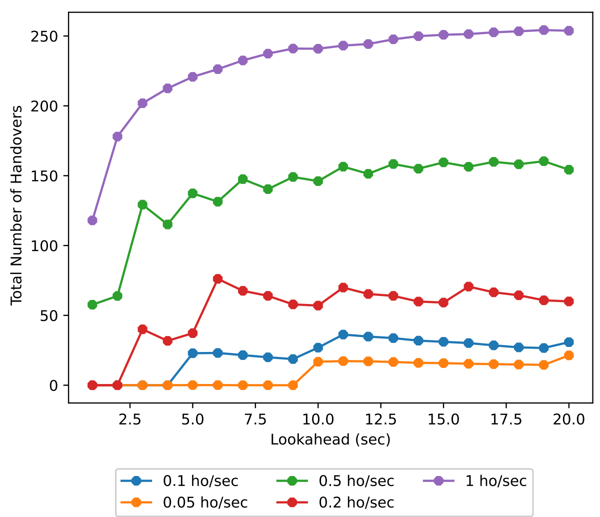


Figure 4.9: Average MIT for 100 simulations for IP vs LR

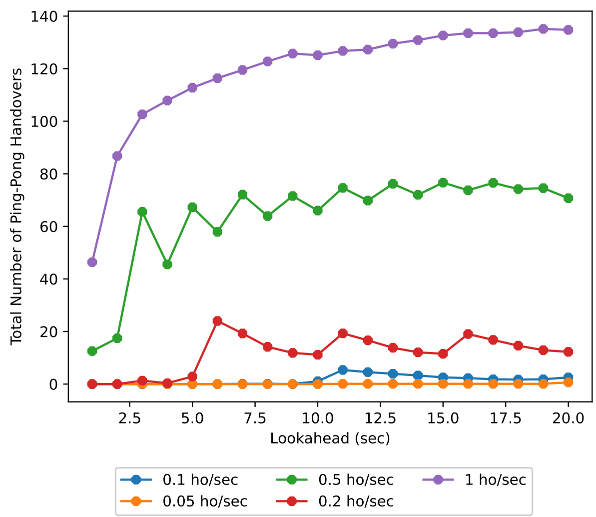
Figure 4.9 shows how lookahead affects the MIT. As it is shown, staring from lookahead 1, by increasing the lookahead, the MIT decreases at first and it is because of the fact that we face less number of handovers while keeping the HOF low, but as we increase the lookahead more and more, we face more number of HOF which leads to increasing the MIT. Furthermore, for each specific value if lookahead and handover budget, The MIT of LR method is less than IP method, and this is due to the fact that for each configuration, the number of handovers HOF in IP value is more than relaxation method.

4.4.3. Optimization for Continuous Values

As stated in section 3.3.1, the optimization problem is changed to convex after the relaxation. So, the handover budget can be a fractional value instead of an integer. Even though fractional handover does not have physical meaning, it can be used for cell assignment after using the heuristic and mapping it to the matrix made of one hot vector.



(a) Average number of handovers for 100 simulations for decimal handover values



(b) Average number of ping-pong handovers for 100 simulations for decimal handover values

Each point on this chapter's figures is the value obtained by multiplying the corresponding lookahead that can be seen on the x-axis along with the handover budget. For example, if you look at lookahead of 10 and 0.2 ho per second, the corresponding point in fig 4.10a is the number of handovers obtained by choosing a handover budget of $0.2 * 10 = 2$.
As it is written in subsection 3.3.1, the handover constraint is $\sum_{j=1}^{T-1} \sum_{i=1}^{M} |x_{ij+1} - x_{ij}| \leq 2N$. So, as long as $2N < 1$, the optimizer gives zero handovers as an output. In contrast, the number of handovers changes from 0 to a higher value after the $2N > 1$.
As can be seen in all the figure 4.10a, if by increasing the lookahead, the handover budget changes from a fractional value to an integer, there is an increase in the number of handovers while between each two integer values, the number of handovers decreases slightly. This effect can be seen in figure 4.10b.
As a result, the optimizer between each two integer values of the handover number decreases the number of handover and ping-ping handovers.

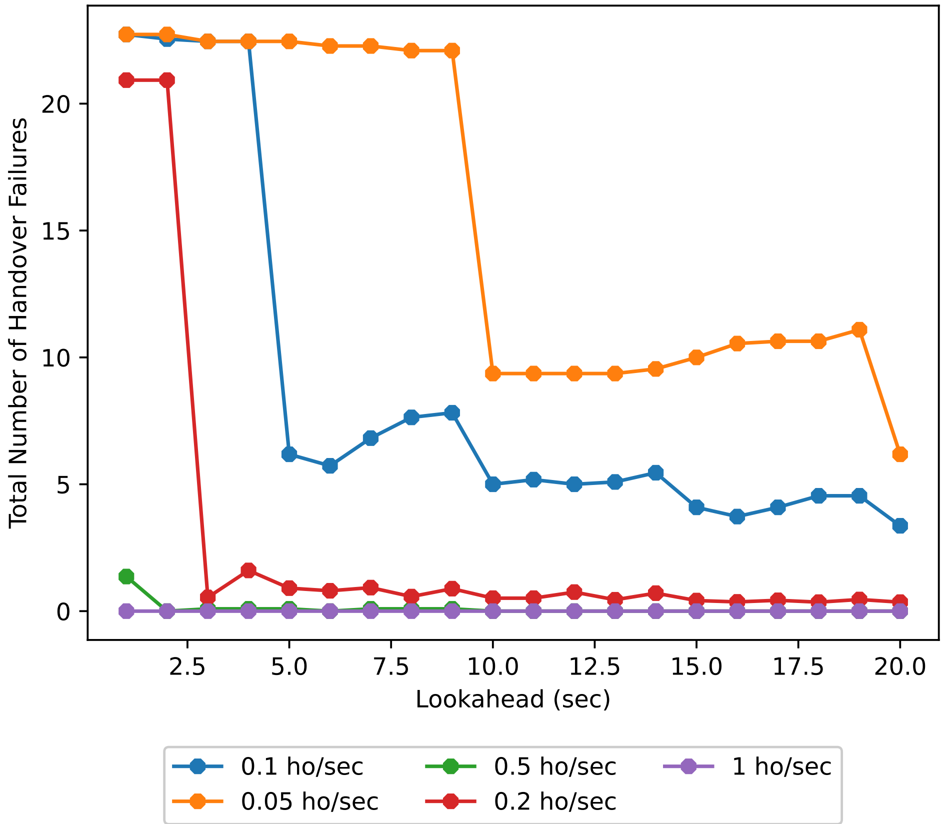


Figure 4.10: Average number of Handover Failures handovers for 100 simulations for decimal handover values

Figure 4.10 shows the number of HOF while using decimal numbers as a handover constraint in the optimization problem. As shown in the figure, the number of HOF is very high when the 2N < 1.

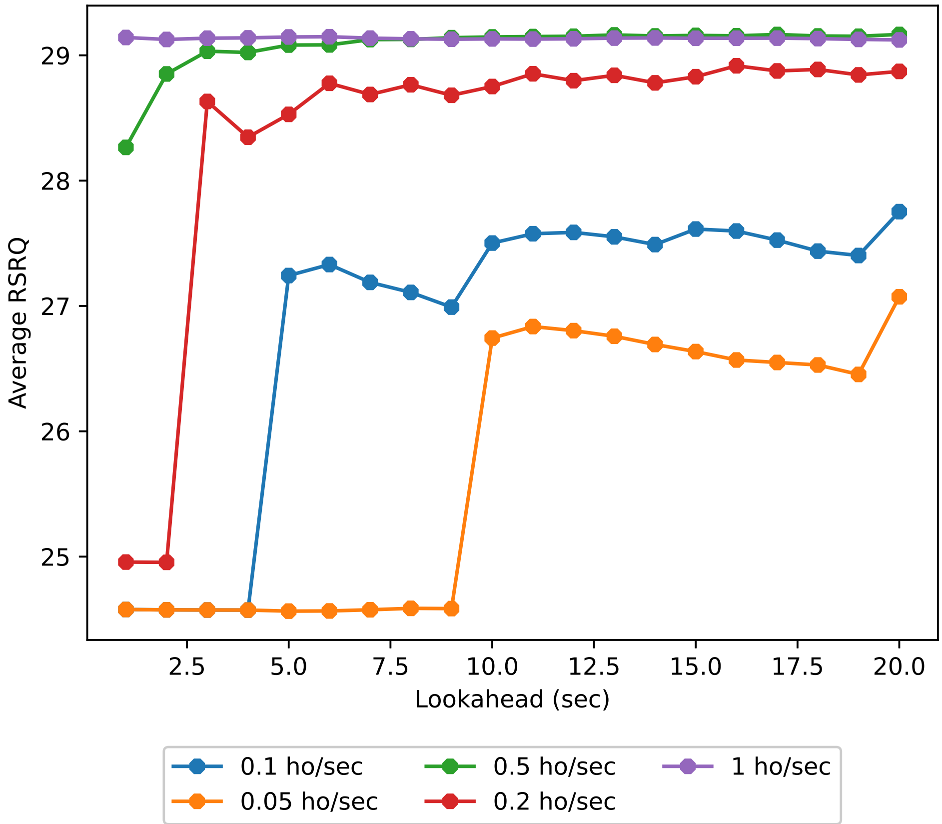


Figure 4.11: Average RSRQ for 100 simulations for decimal handover values

Figure 4.11 shows the average RSRQ of 100 simulations running for 400 seconds. As shown in the figure, the average RSRQ decreases between two consecutive handover constraints because the number of HOFs increases.

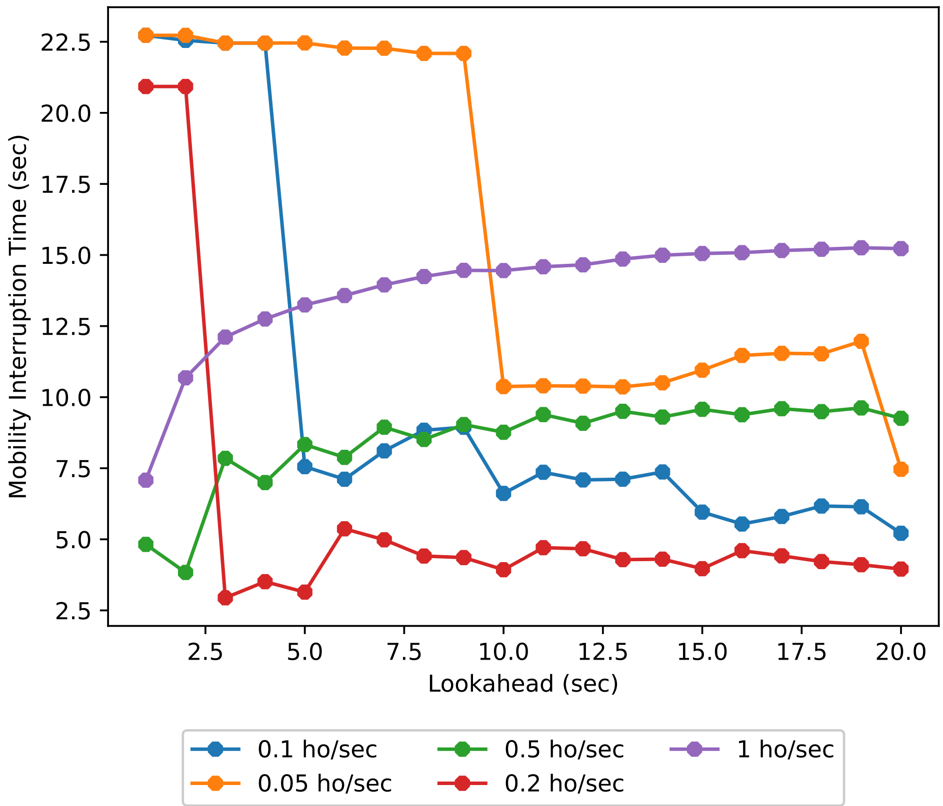
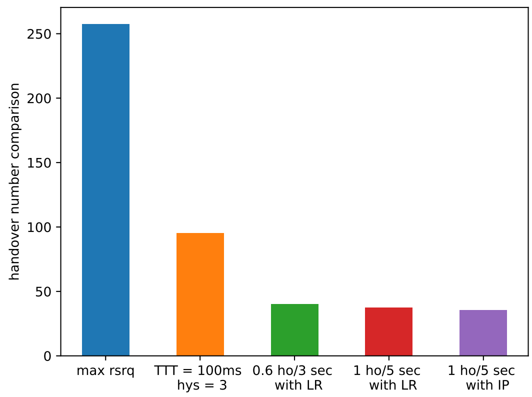


Figure 4.12: Average MIT for 100 simulations for decimal handover values

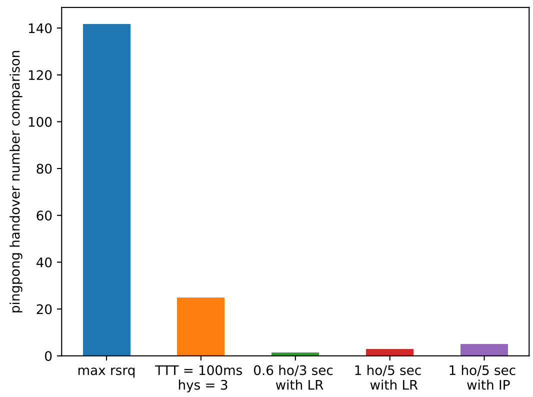
Figure 4.12 shows the MIT for different numbers of lookahead and handover budgets. MIT is the most important KPI. It brings a number of handovers and HOFs together. As shown, 0.2 ho/sec has the best performance and leads to having the minimum MIT, and 0.6 handover per 3 seconds has the minimum MIT.

4.5. Comparison of Linear Relaxation, Integer Programming, Decimal handover, and Conventional method

In order to evaluate the proposed handover optimization scheme, two baselines have been chosen. First, the UE gets connected to maximum RSRQ at each time step. The second one is the best configuration based on MIT in a conventional method which is TTT of 100 ms and hysteresis of 3dB. The option for decimal handover constraint is 0.6 handover per 3 seconds, and the best choice with integer value is one handover per 5 seconds. So one handover per 5 seconds using IP and LR has been included in the comparison.



(a) Comparison of Average Handover Numbers



(b) Comparison of Average Ping-Pong Handover Numbers

Figure 4.13a and figure 4.13b show that in the proposed handover optimization scheme with LR, the UE experiences a much lower number of handovers and ping-pong handover with respect to the best configuration in the conventional method and maximum RSRQ.

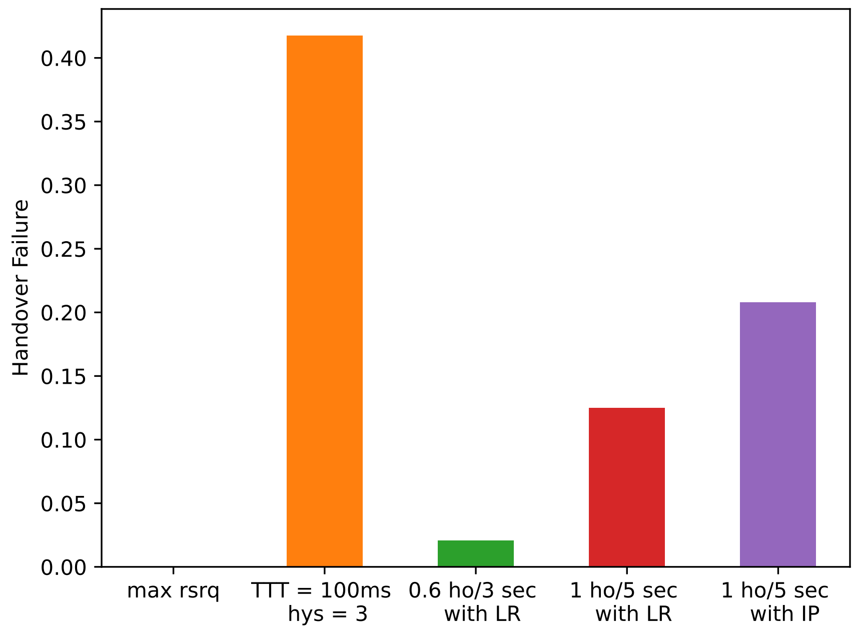
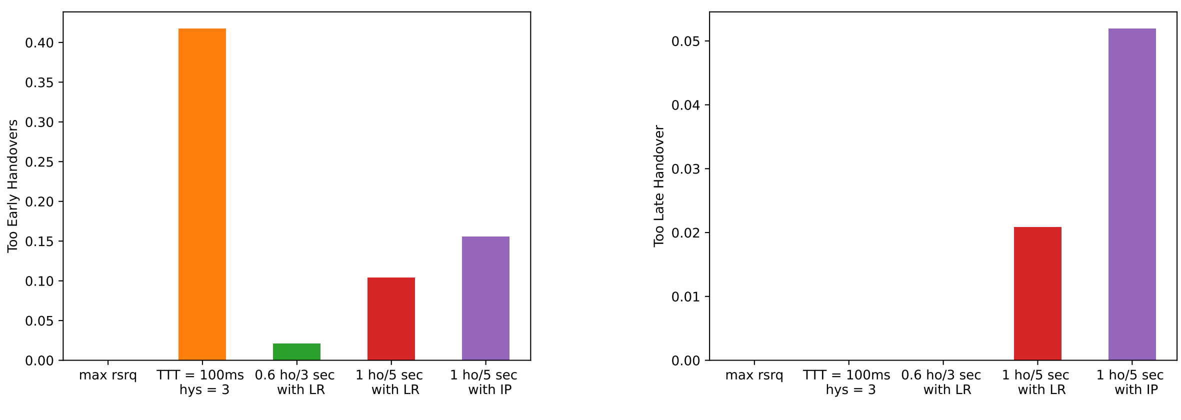


Figure 4.13: Comparision of average number of Handover Failures



(a) Comparision of average number of too early handovers

(b) Comparision of average number of too late handovers

Figure 4.13 shows that by using a predictive handover optimization scheme with LR, the number of HOF is much lower than the best configuration in the conventional method. Figure 4.14a and figure 4.14b show that the number of too late handover and too early handovers are both less that the conventional method.

By connecting the UE to maximum RSRQ at each time step, the UE falls into no HOF but at the same time experiencing many numbers of handovers leads to having massive

signaling for the network.
Note that 0.4 number of HOFs means that there are 40 HOFs in 100 simulations.

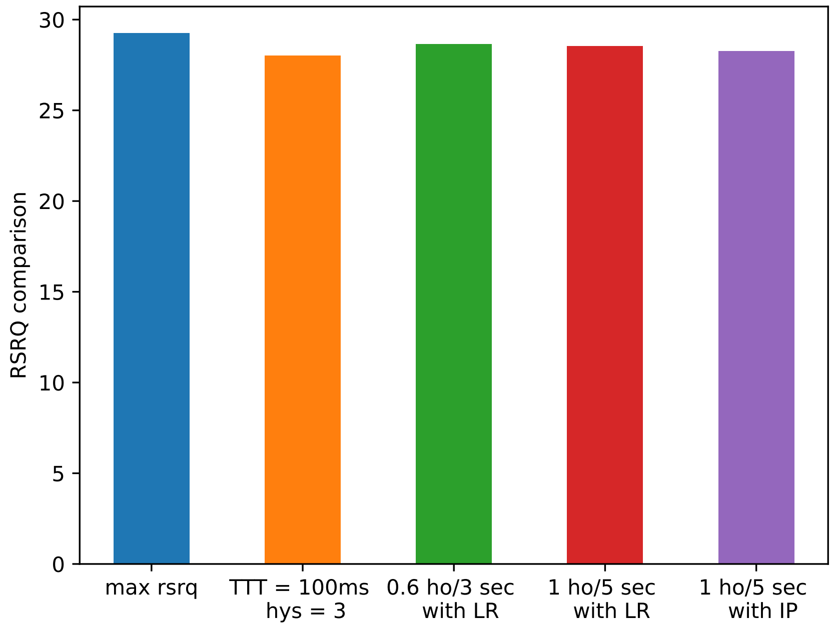


Figure 4.14: Comparision of average received RSRQ

Figure 4.14 shows that even though in the proposed method the UE falls into less number of handovers with respect to the conventional method,by choosing the right cell, the average RSRQ is more than the conventional method.

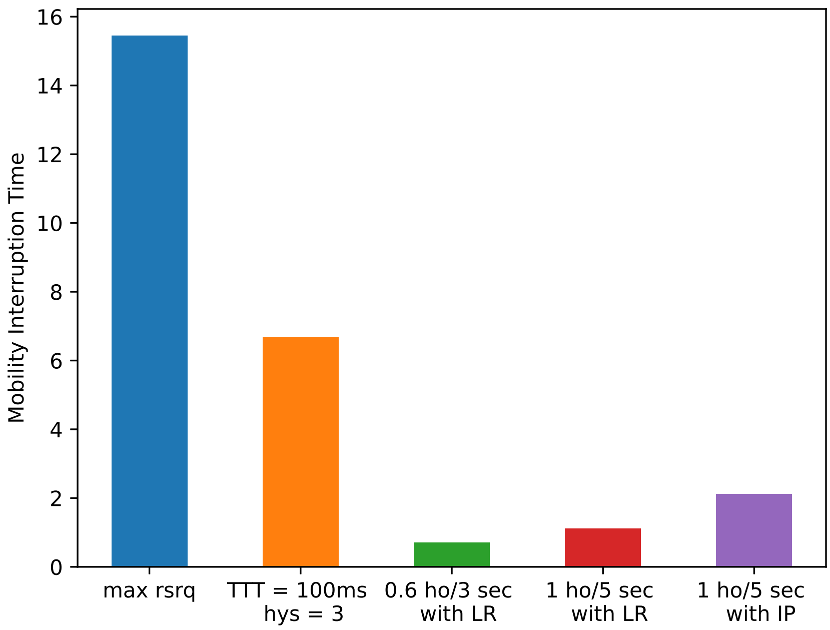


Figure 4.15: Comparision of average MIT

Fig 4.15 is the most important KPI. As shown, in the proposed method, the UE experiences MIT much less than the conventional method and maximum RSRQ.

The described comparison can be summarized as follows :

	Maximum RSRQ	Conventional Method	0.6 ho / 3 seconds	1 ho / 5 seconds of LR	1 ho / 5 seconds of IP
Handover	257.5	95.3	40	37	35
Ping-Pong	141	28	1.3	2.9	5
HOF	0	0.4	0.02	0.12	0.2
Too Late	0	0	0	0.02	0.05
Too Early	0	0.4	0.02	0.1	0.15
RSRQ	29.25	28	28.83	28.52	28.25
MIT	15.45 (sec)	6.68 (sec)	0.71 (sec)	1.11 (sec)	2.11 (sec)

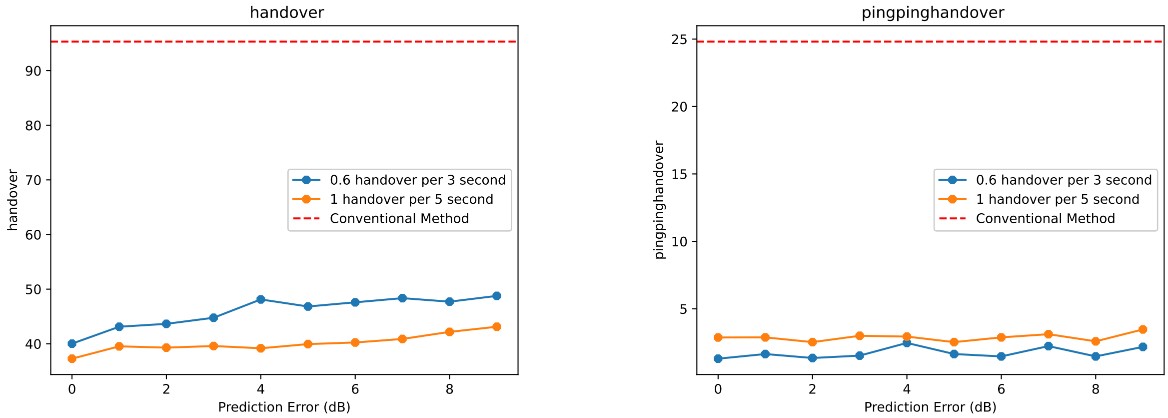
Table 4.2: Comparison of LR, IP, Decimal number of handovers, and Conventional method

4.5.1. Effect of Prediction Error

In this subsection, the effect of inaccurate predicted channel state information has been examined.

Constant Prediction error :

In order to see how robust is our optimization method to prediction error, a normal Gaussian noise prediction error was added to the RSRQ with zero mean and standard deviation starting from 1 to 9 dB. The reason that the constant normal noise over time is chosen is that we have assumed to have a map of RSRQ, and we know in advance where the UE is going. Since the error of your map is constant in space, the RSRQ prediction error will be consistent over time. The result is compared with the best configuration using the conventional method.



(a) Average number of handovers by adding constant prediction error

(b) Average number of ping-pong handovers by adding constant prediction error

As it is shown in fig 4.16a and fig 4.16b, adding the prediction error leads to increasing the number of handovers and ping-pong handovers, but they are still much lower than the number handovers and handover failure in the conventional method.

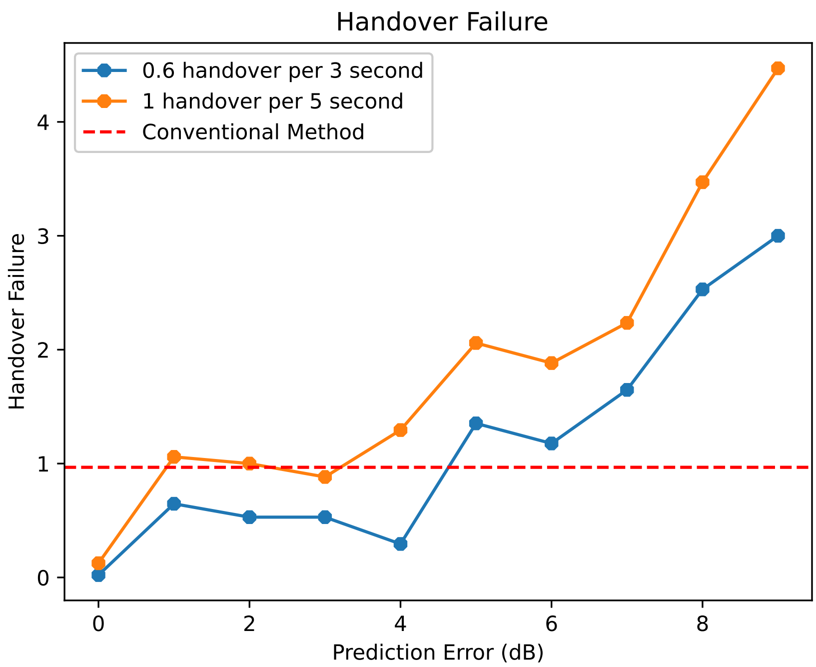


Figure 4.16: Average number of Handover Failures by adding constant prediction error

Fig 4.16 shows that by increasing the prediction error, the UE falls into more number of HOF.this is due to the fact that the UE chooses the wrong cell to do a handover and falls into RLF.however, the number of HOF remains less than the conventional method for a prediction error of less than 5 dB.

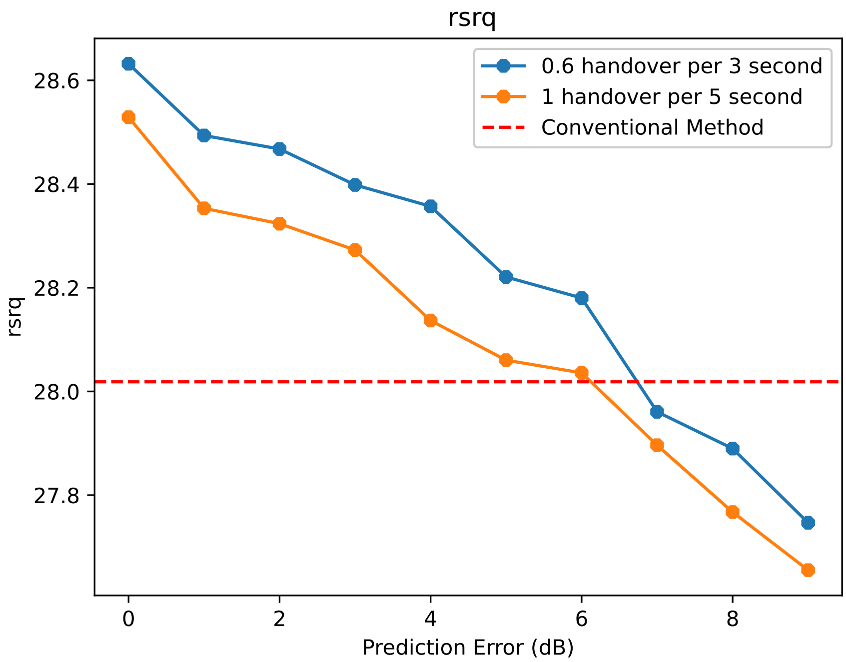


Figure 4.17: Average obtained RSRQ by adding constant prediction error

Figure 4.16 shows that by increasing the prediction error, the UE receives less RSRQ. This is because the UE chooses the wrong cell to do a handover and falls into RLF so it receives less RSRQ. However, the UE still receives a higher RSRQ than the conventional method for a prediction error of less than 7 dB.

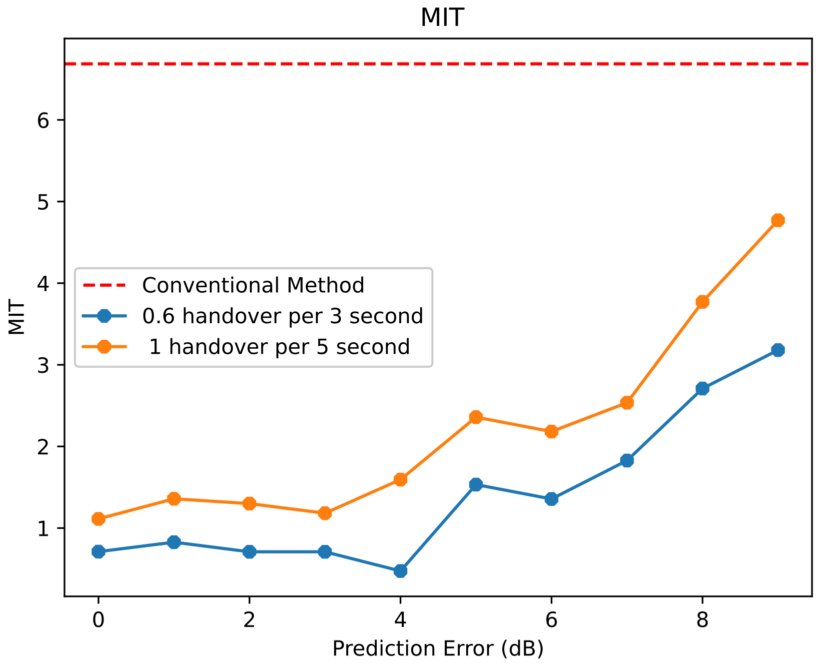


Figure 4.18: Average MIT by adding constant prediction error

Figure 4.16 shows that by increasing the prediction error, the UE experiences more MIT, however; it still experiences less MIT compared to the conventional method.

Time Variant Prediction Error :

In a real scenario, the prediction error increases as the value is predicted for a longer time instant. So we assumed the following model for the channel state information : $\mathrm{RSRQ}_{i,j} = \mathrm{RSRQ}_{i,j} + \mathcal{N}(\mu, \sigma^2)$
where $\sigma = j * 0.2$
The reason is that each time step in RSRQ represent 0.2 second.The simulation was run for lookahead of 3 seconds and handover budget of 0.6 seconds.

	Conventional	1.5 dB/s	3 dB/s	4.5 dB/s	6 dB/s
Handover	95.3	44.7	46.7	47.7	51.6
PingPong	24.8	2.29	3	3.5	5.2
HOF	0,97	0.4	0.51	0.29	0.7
RSRQ	28	28.5	28.4	28.5	28.2
MIT	6.6(sec)	3(sec)	3.3(sec)	3.1(sec)	3.7(sec)

As it is shown in the table 4.5.1, as the time proportional prediction error increases, the number of handovers, ping-pong handovers, and HOFs are increasing; however, they are still lower than the conventional method. Furthermore, the average RSRQ decreases as the number of HOFs increases, but since the number of HOFs are still less than the conventional method, the UE receives higher RSRQ. As a result, the MIT remains below the conventional method.

5 | Conclusions and future developments

In this thesis, an overview of the existing handover techniques was provided. Since existing techniques result in many ping-pong handovers and HOFs, the predictive handover optimization scheme was introduced to perform cell assignment based on the predicted RSRQ to minimize the number of handovers and HOFs. In this method, at each time step t, the cell assignment is computed for the next T time steps to maximize the average RSRQ while constraining the number of handovers. Then the UE gets connected to the cell based on the cell assignment at t+1.
The results in section 4.4 show that the proposed method is able to decrease the number of ping-pong handovers and HOF simultaneously and the UE falls into much lower number of handovers and HOFs compared to conventional schemes. Using this method, the UE receives higher RSRQ on average compared to the best configuration in the conventional method. Higher RSRQ means that more sophisticated MCS can be used to transmit and receive data, leading to an increase in the maximum achievable data rate. Furthermore, using the proposed method, the UE experiences lower MIT compared to the A3-event handover.

The effect of inaccurate channel state information has also been examined in this thesis. The results show, by the prediction error, the number of HOFs and averaged MIT increases while the average RSRQ decreases. However, the number of HOFs and average MIT remain lower than for the conventional method, and the average RSRQ is higher. So the proposed method is robust to prediction errors.
As a future extension of the thesis, the proposed handover scheme could be evaluated using multi-users. A realistic prediction error should be added to the predicted RSRQ. Since the algorithm to solve optimization problems is general purpose, it can be replaced with a dedicated algorithm with lower complexity.

6 | List of Abbreviations

3GPP 3rd Generation Partnership Project

5G five-generation

5G five-generation

6G six-generation

ACK acknowledgment

ACK acknowledgment

AI Artificial Intelligence

ANRF Neighboring Relation Function

ATO Auto Tuning Optimization

ATO Auto Tuning Optimization

CHO Conditional Handover

DBRs Dedicated Radio Bearers

DHO Data-driven Handover Optimization

DL Downlink

eNB eNodeB

EPC Evolved Packet Core

FLC Fuzzy Logic Controller

HCP Handover Control Parameter

HIT Handover Interruption Time

HOF Handover Failure

IP Integer Programming

LP Linear Programming

LR Linear Relaxation

LTE Long Term Evolution

MCS Modulation and Coding Schemes

MIP Mixed Integer Programming

MIT Mobility Interruption Time

ML Machine Learning

MPC Model Predictive Control

MRO Mobility Robustness Optimization

NLOS Non Line of Sight

QoE Quality of Experience

RAB Radio Access Beare

RAN Radio Access Network

RE Resource Element

RLF Radio Link Failure

RRC Radio Resource Control

RSRP Reference Signal Received Power

RSRQ Reference Signal Received Quality

RSRQ Reference Signal Received Quality

RSSI Received Signal Strength Indicator

SINR Signal to Interference and Noise Ratio

SN Sequence Number

SON Self Organized Network

SRBs Signalling Radio Bearers

TTT Time To Trigger

UE User Equipment

UL Uplink

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