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Executive Summary of the Thesis

Predictive Handover Optimization

Laurea Magistrale in Laurea Magistrale in Telecommunication Engineering - Ingegneria delle Telecomuni- cazion

Author: Vahid Rajabi

Advisor: Prof. Antonio Capone

Co-advisor: Dr. Jochen Fink, Dr. Renato l. g. Cavalcante, Dr. Martin Kasparick

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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 Failures (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 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 proposed scheme assigns UE to one cell at each time step by posing an IP optimization problem. The performance of solutions to the original IP problem with solutions to its LP (Linear Programming) 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.

Index Terms **Handover, Handover Failure, Too Late Handover, Too Early Handover, Wrong Cell Selection, Ping-pong Handover, Optimized Network, Convex Optimization**

1. Introduction

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 requires high network capacity, so it will be necessary to adopt small cell utilization[4] [8]. While the 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 [17]. During this period, the user cannot transmit data due to the signaling procedure.
Cells usually have overlaps in coverage. This over-

lap helps UE not fall into Radio Link Failure (RLF) while the handover is 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 a Handover Failure (HOF) due to RLF. If the RLF is due to the current cell's low signal quality, the HOF is called **too late handover**. If RLF is because of the target cell's low signal quality and the UE reconnects to its previous cell, 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 [10]. This process takes hundreds of milliseconds to a couple of seconds [3]. During this process, the UE does not 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 using small-cell technology. So, keeping the number of HOF and ping-pong handovers as little as possible is vital. In order to decrease the number of handovers and HOFs, networks use the concept called Self Organized networks (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)[12]. MRO tries to find the best handover parameters to minimize the number of handovers and HOF.
The remainder of this executive summary is organized as follows. Section II introduces the current handover method and related works. Section III presents the optimization problem with mathematical formulation and a proposed algorithm to solve it. Section IV provides simulation configuration, numerical analysis, and results.

2. Theoretical background and related work

One of the most critical steps of the handover decision is the **measurement report** from UE. In this report, the handover decision is made based on a series of actions called "Events." One of the most important types of event-based handover is the A3-event handover. A3-event Handover is triggered when the neighboring cell serves with a hysteresis better serving the cell for a specific amount of time. This amount of time is called Time To Trigger (TTT).

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

2.1. Related works

There are many types of research in order to decrease the number of handovers and HOFs. In this section, some of these methods are going to be explained.

2.1.1 Self Organized Networks

SONs are Radio Access Networks (RAN) that automatically configure, optimize and heal themselves to increase efficiency, stability, and quality of service in mobile networks [12].

2.1.2 Mobility Robustness Optimization

The 3GPP group has introduced the MRO as a part of the SON functions. The main aim of MRO is to optimize handover parameters such as hysteresis automatically [1]. In [16], the authors have proposed an algorithm for adjusting handover parameters, which is based on several influence factors such as distance, channel condition, cell load, and user velocity. Each function's weight is considered to estimate an accurate hysteresis and TTT. In [15], 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 [6], the authors propose an algorithm that updates hysteresis and TTT based on user speed and received signal reference power to adapt hysteresis and TTT to reduce the frequent handovers and HOF ratio. In [5], a handover mechanism is introduced that dynamically modifies handover parameters in response to the detection of HOF.

2.1.3 Fuzzy Logic Scheme

The fuzzy logic scheme is used to improve handover performance. In [9], 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 to decrease the number of ping-pong handovers and the HOF ratio while allowing UEs to benefit from dense small-cell deployment. In [14], The author has designed a Fuzzy Logic Controller (FLC) that inputs Call Drop Rate and HOF. The first step translates the input into a fuzzy set with linguistic terms such as high and low. In the second step, the fuzz sets are translated to the actions the FLC should execute. The output is Δhysteresis, which should be added to the hysteresis.

2.1.4 Conditional Handover

As a part of 3GPP Release, 16 [2], Conditional Handover (CHO) has been proposed. The idea has been discussed in [11] to improve the reliability of the handover. The idea is to divide the handover procedure into two steps. The preparation step, in which a set of target cells are prepared by allocating resources to the UE, and the execution step, where the handover is executed on one of the chosen cells.

2.1.5 Machine Learning Method

In recent years, Machine Learning (ML) methods have been used to improve handover optimization by decreasing the number of HOF and redundant handovers. In [7], the authors developed a handover management method that improves target cell selection. The algorithm learns from its previous experience using machine learning techniques how the handover decision to a specific cell influences HOF. A supervised learning approach based on a neural network predicts the most appropriate cell for handover. In [13], the author has presented a Data-driven Handover Optimization (DHO) strategy to mitigate HOFs and ping-ping 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 are tuned to minimize the HOFs.

3. Proposed Predictive Handover Optimization

The event-based handover schemes fall into many handovers and HOFs since they rely only on channel information from their current and past measurements. By predicting the channel values, the number of handovers and HOFs can be decreased. In order to decrease, the Model Predictive Control (MPC) scheme is used. Each time step has a time window in which the channel values are predicted. Then an optimizer computes the cell assignment based on the predicted data for time step t to the t + T where T is the window size. 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. The procedure is repeated over time. At each time step, there is an optimization problem being solved. Assume there are M cells, the time window consists of T time steps, and the handover constraint is N. The optimization problem can be written as follows:

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

The objective function of this optimization problem is the maximize the average predicted RSRQ achieved by the cell assignment according to X.

- **First constraint**: The decision variable $x_{i,j}$ is binary, which indicates whether the UE should connect to cell i at time step j.
- **Second constraint**: This constraint assures that the UE connects to one and only one cell at each time step.
- **Second constraint**: This constraint ensures that the number of handovers should be less or equal to N.

Note that the last constraint can be written as $\sum_{j=1}^{T-1}\sum_{i=1}^{M}|x_{ij+1}-x_{ij}| \leq 2N$
This is an Integer Programming(IP) optimization problem. Solving an IP problem could be computationally complex for large-scale problems. So relax the decision variable and let the x be any value between 0 and 1.
The original optimization problem will be relaxed to the following :

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

By relaxing the decision variable, we obtain a convex problem. 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 heuristic: 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 : $min\{i\in M | x_i = max\{x_1,\dots,x_M\}\}$
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 $\hat{\mathbf{X}}$ algorithm 1 shows how the proposed scheme works in detail.

4. Scenario Configuration and Result

In this section, the configuration of the simulation will be discussed, then the results will be explained. The map data has been gathered using OpenStreetMap. Then the data is exported to

Algorithm 1 Proposed Preditive Handover Optimization Algorithm

1: t = 0
2: Lookahead = T
3: Handover Budget = N
4: Connect to the strongest cell
5: **while** $t < \tau$ **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: $\mathbf{X}$ = optimize(data,N)
13: $\hat{\mathbf{X}} = \phi : \mathbb{R}^M \mapsto \{0,1\}^M$
14: next cell = argmax($\hat{\mathbf{X}}$[:,1])
15: go to step 6
16: **end while**

SUMO simulation, and the UE mobility is obtained. In our scenario, one three-sector Macrocell and 18 microcells with a transmission power of 40 dBm and 15 dBm with a distance of 300m have been used. The channel state information for optimization is Reference Signal Received Quality (RSRQ). In order to validate the results, 100 different simulations have been run with different users' trajectories, and the results are averaged.
Figure 1 compares the number of handovers using IP and LR while the prediction window is increasing and the number of handovers is limited. As can be seen, by increasing the prediction window, the number of handovers is decreasing. 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. The effect of this violation can also be seen in Figure 2 which the number of HOFs is being compared. As is shown, although by increasing the prediction window, the number of HOFs increases, the relaxed version falls into less number of HOFs. So, the relaxed problem finds a trade-off between the number of handovers and HOFs, and it has the capability to be run with a decimal value of handover constraint. In order to find this trade-off, the MIT is used for decimal values of the handover constraint.
Each point on the figure 3 is the MIT obtained by having the prediction window equal to the corresponding lookahead and the handover budget equal to the lookahead multiplied by the corresponding ho/sec. As it can be seen in the figure, based on $\sum_{j=1}^{T-1}\sum_{i=1}^{M}|x_{ij+1} - x_{ij}| \leq 2N$ while $2N < 1$, the

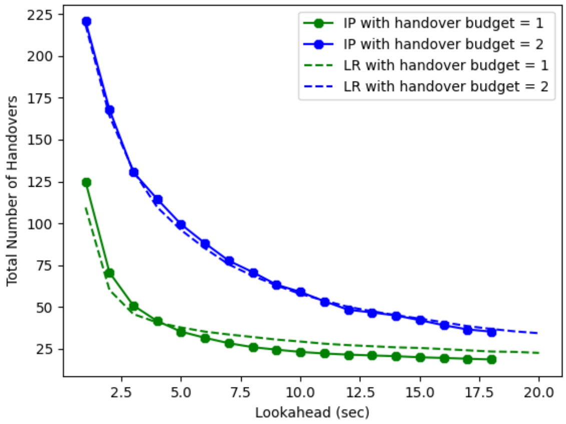

Figure 1: Average number of Handovers

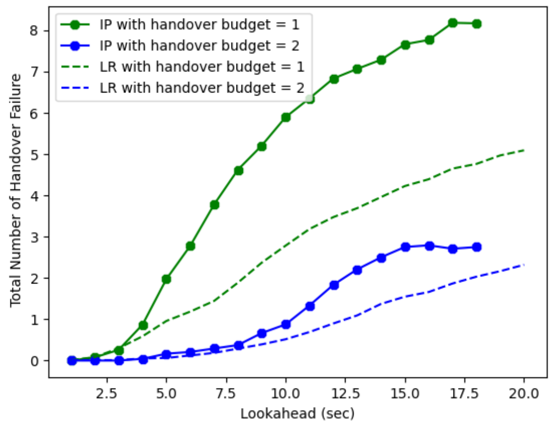

Figure 2: Average number of Handover Failures handovers

optimizer gives zero handovers as an output so the MIT is high. Furthermore, the 0.6 handover per 3 seconds has the minimum MIT.
Table 1 shows that using the conventional handover scheme, the UE experiences high MIT since the handover decision is based on current and previous measurements. So it falls into many numbers of HOFs, which leads to high MIT.
In order to compare the proposed method, two baselines are chosen. The first one is the A3-event handover with minimum MIT, and the second one is connecting the UE to the cell with maximum RSRQ. As it is shown in Table 2, the proposed method faces a lower number of handovers and ping-pong handovers compared to A3-event handovers and maximum RSRQ. Additionally, the proposed method falls into fewer HOFs compared to the conventional method. Even though in the proposed method, the UE experienced less number of handovers since it chose the proper cell to connect to, It receives higher RSRQ compared to the conventional method. In

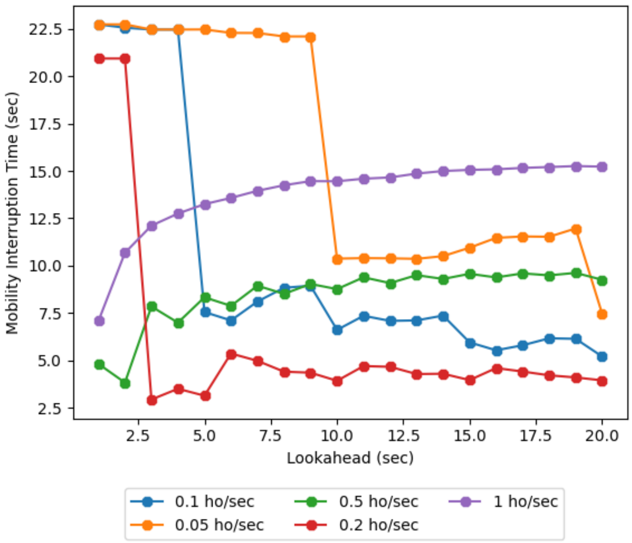

Figure 3: Average MIT for decimal handover values

TTT \ Hysteresis	1 dB	2 dB	3 dB	4 dB
100 ms	8.03	6.84	7.07	6.68
200 ms	8.28	8.21	7.79	7.65
400 ms	10.53	16.04	11.66	13.39
800 ms	30.22	31.30	30.67	31.45
1200 ms	28.98	26.57	28.30	27.58
1600 ms	23.87	23.81	23.09	23.88
2000 ms	23.39	24.44	23.42	24.42

Table 1: MIT of A3-event scheme

the proposed method, the UE experiences much less MIT compared to the conventional method and maximum RSRQ.

Table 3 shows the effect of adding constant prediction error to the RSRQ. As can be seen, by increasing the error, the number of handovers, ping-pong handovers, and HOF increases while the UE receives a higher RSRQ for the prediction errors of less than the standard deviation of 9 dB. Furthermore, the UE experiences less MIT compared to the best configuration in the conventional method.

As it is shown in Table 4, as the time-variant prediction error increases, the number of handovers, ping-pong handovers, and HOFs are increasing; however, they are still lower than for the conventional method. Furthermore, the average RSRQ decreases as the number of HOFs increases, but since the number of HOFs is still less than for the conventional method, the UE receives a higher RSRQ. As a result, MIT remains below the conventional method.

5. Conclusion

In this executive summary, 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 HOF. 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 show that the proposed method is able to decrease the number of ping-pong handovers and HOF simultaneously. 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 that by prediction error, the number of HOFs and averaged MIT increases while the average RSRQ decreases. However, the number of HOFs and average MIT remains lower than the conventional method, and the average RSRQ is higher. So the proposed method is robust to prediction errors.

	Max RSRQ	Conv.	0.6 ho / 3 sec
Handover	257.5	95.3	40
PingPong	141	28	1.3
HOF	0	0.4	0.02
Too Late	0	0	0
Too Early	0	0.4	0.02
RSRQ	29.25	28	28.83
MIT(sec)	15.45	6.68	0.71

Table 2: Comparison of LR, and Conventional

	Handovers	ping-pong	HOF	RSRQ dB	MIT (sec)
Conv	95.3	28	0.4	28	6.68
0 dB	40	1.3	0.02	28.63	0.82
1 dB	43.1	1.6	0.64	28.49	0.70
3 dB	44.7	1.5	0.52	28.39	0.47
5 dB	46.8	1.6	1.35	28.22	1.53
7 dB	48.3	2.2	1.64	27.96	1.82
9 dB	48.7	2.1	3	27.74	3.18

Table 3: Effect of adding prediction error with constant standard deviation

	Handovers	ping-pong	HOF	RSRQ dB	MIT (sec)
Conv	95.3	24.8	0,97	28	6.68
0 dB/s	40	1.3	0.02	28.63	0.82
1.5 dB/s	44.7	2.29	0.4	28.5	3
3 dB/s	46.7	3	0.51	28.4	3.3
4.5 dB/s	47.7	3.5	0.29	28.5	3.1
6 dB/s	51.6	5.2	0.7	28.2	3.7

Table 4: Efect of adding Time Variant Prediction Error

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