



# **OPTIMIZATION OF USER BEHAVIOR BASED HANDOVER USING FUZZY Q-LEARNING FOR LTE NETWORKS**

By

**Rana DiaaElDin Mohamed Hegazy**

A Thesis Submitted to the  
Faculty of Engineering at Cairo University  
in Partial Fulfilment of the  
Requirements for the Degree of  
**MASTER OF SCIENCE**  
in  
Electronics and Communications Engineering

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Optimization of User Behavior Based Handover Using Fuzzy Q-Learning for  
LTE Networks

**Key Words:**

Handover; Categorization; Fuzzy Q-Learning; LTE

**Summary:**

In LTE networks, choosing the handover parameters is critical due to the two contradictory handover problems: radio link failures and ping-pongs. In this thesis, the users in the network are categorized according to their speed and data traffic, where each category of users is assigned different handover parameters to enhance its experience. An optimization algorithm is developed and then fuzzy Q-learning optimization technique is used to optimally choose the handover parameters for the different users. Consequently, the optimum handover parameters can be reached automatically. Simulations show that the proposed techniques can optimize the handover parameters for each category of users by minimizing the effect of the handover problems in this category. Also, simulations show that fuzzy Q-learning has the minimum handover problems compared to other techniques in the literature. Moreover, it has the optimum results even when the number of users in the network changes and it is not affected by the dynamic variations of the users' speeds.

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# List of Abbreviations

<b>Abbreviations</b>	<b>Description</b>
<b>3GPP</b>	Third Generation Partnership project.
<b>BLER</b>	Block Error Rate.
<b>CBR</b>	Call Block Ratio.
<b>CDR</b>	Call Drop Ratio.
<b>CIO</b>	Cell Individual offset.
<b>DC</b>	Dropped Calls.
<b>E-UTRAN</b>	Evolved Universal Terrestrial Radio Access Network.
<b>EH</b>	Extremely High.
<b>EL</b>	Extremely Low.
<b>eNB</b>	E-UTRAN Node B.
<b>EPS</b>	Evolved Packet System.
<b>FLC</b>	Fuzzy Logic Controller.
<b>H</b>	High.
<b>HN</b>	High speed non-real time.
<b>HO</b>	Handover.
<b>HOF</b>	Handover failure.
<b>HOM</b>	Handover Margin.
<b>HOPP</b>	Handover ping-pong.
<b>HPI</b>	Handover performance indicator.
<b>HR</b>	High speed real time.
<b>Hys</b>	Hysteresis.

<b>ID</b>	Identity.
<b>L</b>	Low.
<b>LB</b>	Load Balancing.
<b>LTE</b>	Long Term Evolution.
<b>MLB</b>	Margin Load Balancing.
<b>MRO</b>	Mobility Robustness Optimization .
<b>N</b>	Neutral.
<b>OAM</b>	Operation And Management.
<b>OF</b>	Optimization with Fuzzy logic controller.
<b>Off</b>	Offset.
<b>OFQ</b>	Optimization with Fuzzy Q-learning.
<b>OFQL</b>	Optimization with Fuzzy Q-learning as literature.
<b>OL</b>	Optimization as Literature.
<b>OR</b>	Oscillation Rate.
<b>PLB</b>	Pilot Load Balancing.
<b>QMLB</b>	Q-learning with Margin Load Balancing.
<b>QOS</b>	Quality Of Service.
<b>QPLB</b>	Q-learning with pilot load balancing.
<b>RACH</b>	Random Access Channel.
<b>RLC</b>	Radio Link Control.
<b>RLF</b>	Radio Link Failure.
<b>RSRP</b>	Reference Signal Received Power.
<b>RSRQ</b>	Reference Signal Received Quality .
<b>SINR</b>	Signal to interference and noise ratio.
<b>SN</b>	Slow speed non-real time.
<b>SNR</b>	Signal-to-Noise Ratio.
<b>SON</b>	Self Organizing Networks.
<b>SR</b>	Slow speed real time.

<b>TTT</b>	Time To Trigger.
<b>TXP</b>	Transmit Power Pilot.
<b>UE</b>	User Equipment.
<b>VH</b>	Very High.
<b>VL</b>	Very Low.
<b>VOIP</b>	Voice over Internet Protocol.
<b>WCDMA</b>	Wideband Code Division Multiple Access.
<b>WLAN</b>	Wireless Local Area Network.
<b>WO</b>	Without Optimization.

# Abstract

In Long Term Evolution networks, the aim of self-optimization is to collect the measurements from the users and network nodes to enhance the network performance. Mobility robustness optimization (handover) is one of the main goals of self-optimization networks where the handover parameters are chosen automatically to cope with the changes in the network. Usually, there are two contradictory handover problems: radio link failures and unnecessary handovers (*ping-pongs*). Decreasing some handover parameters (e.g. handover margin) leads to less radio link failure, but higher *ping-pongs*. This is not good for the network operators, as high *ping-pongs* rate causes large signalling overhead to the network. However, having a high radio link failure decreases the users' satisfaction, especially the users using real time data (VOIP and video). For the users using non-real time data (e.g. web browsing and *FTP* download), the radio link failure problem will not severely affect their satisfaction.

In the first part of the thesis, a new algorithm is introduced to choose the most suitable values of the handover parameters, based on the user's behavior. This is done by categorizing the users in the network into four categories. The categorization is done according to the users' speeds and the data traffic used (real time traffic versus non-real time traffic). The handover parameters in each category are optimized independent from the other categories. The proposed algorithm shows a better performance for each category of users in terms of the most preferred metric for this category compared to dealing with all users as a single category. The drawback of this algorithm is that the values by which the handover margin changes should be determined by human experience or by trial and error.

Therefore in the second part of the thesis, fuzzy logic controller is used to automatically minimize the handover problems. The best actions of the fuzzy logic controller system are chosen using *Q*-learning technique, which is a popular reinforcement learning technique. Since the users are categorized into four categories according to their speed and the data traffic they use, the fuzzy *Q*-learning technique is applied to each category of users solely. Fuzzy *Q*-learning proved its effectiveness than the first proposed solution and the previous work on the category scale. Also, it has the minimum total handover problems. Moreover, the system depended less on the human experience, as the parameters of the fuzzy logic controller are determined using the *Q*-learning technique. The proposed fuzzy *Q*-learning technique showed robustness to changes in the number of users in the system, as it is still the best solution when the number of users is halved or even doubled.

# Chapter 1

## Introduction

In this chapter, we explain the concept of self-organizing networks in LTE, which is divided into self-configuration, self-optimization and self-healing. Within the self-optimization, we explain the mobility robustness optimization (handover) problem which is required to be solved within the network automatically. Also, we explain the fuzzy logic controller,  $Q$ -learning technique and how they are used together.

### 1.1 Self-Organizing Networks (SON)

In Long Term Evolution (*LTE*), the network size increased dramatically. The number of network nodes (*eNBs*) as well as the number of users (*UEs*) has increased, so the term self-organizing networks (*SONs*) has arisen. The aim of *SON* networks is to automatically configure the network parameters and decrease human intervention to just monitoring the *SON* processes. In other words, performance measurements are collected from the network and then the parameters are set according to the configuration management [1]. Moreover, the network should be tolerable to any fault in the elements. *SON* is divided into three cases: Self-configuration, self-optimization and self-healing. In the first, the new nodes are automatically configured during installation process [2]. The second is considered the process in which the measurements of the users and the network nodes are used to enhance the network performance. The last aims at reducing the impact that arises from the failure of a network node. This healing is done by re-adjusting the parameters in the neighbor cells so they can serve the users of the failed node. Self-configuration is handled before the operation of the network nodes, while self-optimization is applied during the operation of the network nodes [2].

#### 1.1.1 Self-Configuration

Self-configuration is a pre-operational stage to minimize the long periods of getting the optimum configuration at the deployment stage of new cells. It is divided into auto-connectivity, auto-commissioning and dynamic radio configuration. Auto connectivity is to set up the connection between the *eNB* and the network's Operation And Management (*OAM*) [1]. Auto-commissioning is to test the software and configuration of data,