SEAMLESS HANDOVER OPTIMIZATION FOR LTE-A COMMUNICATION USING KALMAN FILTERING AND DQN

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DEDICATION

In the name of Allah, the Most Gracious, the Most Merciful,

I humbly dedicate this thesis to Allah, the source of all knowledge, wisdom, and inspiration. With unwavering faith and profound gratitude, I acknowledge His guidance and blessings illuminating my path throughout this academic journey.

My great teacher and messenger, Mohammed (May Allah bless and grant him), who taught us the purpose of life;

My homeland, Iraq, the homeland of civilization, glories, and tournaments;

The great martyrs, the symbol of sacrifice;

to the memory of my beloved father, Talaat Shakir Altickriti, whose unwavering support and encouragement continue to inspire me, even in his absence. Although he is no longer with us, his values, wisdom, and love for learning have left an indelible mark on my journey.

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My beloved brothers

Mahmood and Abdulwahab, A sibling is the lens through which you see your childhood.

My friends who encourage and support me, especially;

Ahmed Salih, Mohammed Ahmed Jubair, and Ahmed Salih Khrebit;

All the people in my life who touch my heart,

I dedicate this research.

ABSTRACT

In LTE-A networks, achieving optimal Hard Handover (HHO) for uninterrupted connectivity and Quality of Service (QoS) adherence poses a persistent challenge, particularly in the context of Intelligent Transportation Systems (ITS) scenarios. Existing handover mechanisms often exhibit deficiencies in localization improvement, integration of process models and measurement data, and determining an optimal Time to Trigger (TTT) based on past learning experiences. These limitations are compounded by deterministic rules that fail to account for the dynamic nature of mobility and the multifaceted factors influencing handover decisions. To mitigate these challenges, this thesis proposes a novel hybrid model integrating a Map Sampling-based Kalman Filter (MA-KALMAN) and a Deep Q-learning Network (DQN) for HHO decision-making. The MA-KALMAN component improves the accuracy of mobility data by merging GPS measurements with process models, while the DQN framework optimizes decisions by learning from dynamic network conditions. Comparative evaluations against traditional models, including the Kalman filter for localization, Q-learning, and static approaches for handover decision-making, were conducted, focusing on key performance metrics such as RMSE, End-to-End delay (E2E delay), Packet Delivery Ratio (PDR), Number of Hard Handovers (No. of HHO), and Hard Handover Ping-Pong (HHO Ping-Pong) instances. Empirical findings substantiate the superior performance of the MA-KALMAN and DQN-based handover decision-making models, which minimize latency, enhance reliability, and determine an optimal TTT, ensuring seamless connectivity and QoS adherence in LTE-A networks. This research advances wireless communications by addressing critical issues in localization and TTT optimization.

PENGOPTIMUMAN SERAHAN TANPA GANGGUAN BAGI KOMUNIKASI LTE-A MANGGUNAKAN PENAPISAN KALMAN DAN DQN

ABSTRAK

Dalam rangkaian LTE-A, mencapai Penyerahan Keras (HHO) yang optimum untuk sambungan tanpa gangguan dan pematuhan Kualiti Perkhidmatan (QoS) merupakan cabaran yang berterusan, terutamanya dalam konteks senario Sistem Pengangkutan Pintar (ITS). Mekanisme penyerahan sedia ada sering menunjukkan kekurangan dalam penambahbaikan penentududukan, integrasi model proses dan data pengukuran, serta penentuan Masa untuk Mencetus (TTT) yang optimum berdasarkan pengalaman pembelajaran lepas. Kelemahan ini diperburuk oleh peraturan deterministik yang gagal mengambil kira sifat dinamik mobiliti dan pelbagai faktor yang mempengaruhi keputusan penyerahan. Untuk mengatasi cabaran ini, tesis ini mencadangkan model hibrid baru yang mengintegrasikan Penapis Kalman berasaskan Pengambilan Peta (MA-KALMAN) dan Rangkaian Pembelajaran Q-mendalam (DQN) untuk pembuatan keputusan HHO. Komponen MA-KALMAN meningkatkan ketepatan data mobiliti dengan menggabungkan ukuran GPS dengan model proses, manakala rangka kerja DQN mengoptimumkan keputusan dengan belajar daripada keadaan rangkaian dinamik. Penilaian perbandingan terhadap model tradisional, termasuk penapis Kalman untuk penentududukan, pembelajaran Q, dan pendekatan statik untuk pembuatan keputusan penyerahan, dijalankan dengan fokus pada metrik prestasi utama seperti RMSE, kelewatan End-to-End (E2E delay), Nisbah Penghantaran Pakej (PDR), Bilangan Penyerahan Keras (No. of HHO), dan kejadian Penyerahan Keras Ping-Pong (HHO Ping-Pong). Penemuan empirikal membuktikan prestasi unggul model pembuatan keputusan penyerahan berasaskan MA-KALMAN dan DQN, yang meminimumkan kependaman, meningkatkan kebolehpercayaan, dan menentukan TTT yang optimum, memastikan sambungan lancar dan pematuhan QoS dalam rangkaian LTE-A. Penyelidikan ini memajukan komunikasi tanpa wayar dengan menangani isu kritikal dalam penentududukan dan pengoptimuman TTT.

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LIST OF ABBREVIATIONS

3G	3rd Generation
1G	First Generation
2G	Second-Generation
3GPP	3rd Generation Partnership Project
4G	4th Generation
5G	Fifth Generation
ACB	Access Class Barring
AHP	Analytical Hierarchical Process
AMPS	Advanced Mobile Phone System
ANDSF	Access Network Discovery and Selection Function
ANR	Automatic Neighbor Relation
CDMA	Code Division Multiple Access
CIR	Carrier Interference Ratio
CAN	Candidate Network
CN	Core Network
CSG	Closed Subscriber Group
CSI	Channel State Information
DDPG	Deep Deterministic Policy Gradients
DNN	Deep Neural Networks
DQN	deep Q-learning
DSDP	Discrete Stochastic Dynamic Programming

DSSS	Direct Sequence Spread Spectrum
EKF	Extended Kalman Filter
eNB	evolved NodeB
EPC	Evolved Packet Core
E-UTRAN	Evolved Universal Terrestrial Radio Access
FDD	Frequency Division Duplex
FDMA	Frequency Division Multiple Access
GPRS	General Packet Radio Service
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HCPs	Handover control parameters
HeNB	Home-eNB
HeTNet	heterogeneous network
HO	Handover
HHO	Hard Handover
HM	hysteresis margin
HOF	handover failure
IMT	International Mobile Telecommunications
INS	Inertial Navigation System
ITU	International Telecommunication Union
ITUR	International Telecommunication Union Radio communication
LTE	Long-Term Evolution
LTE-A	LTE-Advanced

MA-KALMAN	MAP-based Kalman filter
MDP	Markov Decision Process
MIMO	Multiple-Input Multiple-Output
MRO	Mobility robustness optimization
NLOS	Non-Line-of-Sight
OFDMA	Orthogonal Frequency-Division Multiple Access
PPO	Proximal Policy Optimization
QoS	Quality of Service
RAN	Radio Access Network
RAT	Radio Access Technology
RL	Reinforcement Learning
RLF	Radio Link Failure
RRM	Radio Resource Management
RSQ	Received Signal Quality
RSRQ	Reference Signal Received Quality
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SAE	System Architecture Evolution
SC- FDMA	Single-Carrier Frequency Division Multiple Access
SN	Serving Network
SNR	Signal-to-Noise Ratio
SON	self-optimization network
TACS	Total Access Communication System

TDD	Time Division Duplex
TDMA	Time Division Multiple Access
TD-SCMA	Time Division Synchronous Code Division Multiple Access
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TTT	time-to-trigger
UE	User Equipment
UKF	Unscented Kalman Filter
UL	UpLink
UMTS	Universal Mobile Telecommunications Service
VANET	Vehicular Ad hoc NETwork
VoIP	Voice over Internet protocol
WAN	Wireless Wide Area Network
WCDMA	Wide Code Division Multiplexing Access
WiMAX	Worldwide Interoperability for Microwave Access

LIST OF PUBLICATIONS

The following is the list of publications related to the work of this thesis:

1- Shakir, A., Alsaqour, R., Abdelhaq, M., Alhussan, A., Othman, M., and Mahdi, A. (2019). Novel method of improving quality of service for voice over internet protocol traffic in mobile ad hoc networks. *International Journal of Communication Networks and Information Security*, *11*(3), 331-341.

2- Al-Obaidi, A. S., Jubair, M. A., Aziz, I. A., Ahmad, M. R., Mostafa, S. A., Mahdin, H., ... and Hassan, M. H. (2022). Cauchy density-based algorithm for VANETs clustering in 3D road environments. *IEEE Access*, *10*, 76376-76385.

CHAPTER 1

INTRODUCTION

1.1 Introduction

As the growing multimedia, the demand for high data rate and capacity in wireless communication is increasing nowadays. Furthermore, the 3rd Generation (3G) and Universal Mobile Telecommunication System (UMTS), can no longer support the recent, rapidly growing demand for high-speed multimedia applications like voice over Internet Protocol (VoIP), video streaming, online gaming, and Internet surfing due to their limited capacity and data rates. Recognizing this limitation, drove the 3rd Generation Partnership Project (3GPP) to create the Long-Term Evolution (LTE) cellular system. to achieve higher data rates and capacity.(Krasniqi, Maraj, and Blaka, 2018).

LTE-Advanced (LTE-A), as an evolution of LTE, aims to surpass the performance specifications set by the International Mobile Telecommunications (IMT)-Advanced standards, earning it the moniker "True 4th Generation (4G)". LTE-A introduces innovations such as small cells, or Femtocells, within heterogeneous networks (HetNets) of a mix of cell types. These advancements enable high-velocity data communication and enhance network efficiency (Ibrahim et al., 2020).

A key feature of LTE-A is its support for User Equipment (UE) mobility at high velocities, ensuring seamless connectivity even in fast-moving environments (Hosny et al., 2019; Vegni). Additionally, LTE-A employs a two-tier cell deployment strategy comprising macro cells and femtocells. Macro cells cover larger geographical areas and are typically mounted on masts or rooftops (Ahmad et al., 2020). providing broad outdoor coverage. In contrast, femtocells, or Home-eNBs (HeNBs), cover smaller areas and offer cost-effective solutions for extending network coverage and capacity, As shown in Figure 1.1.

Handover procedures, crucial for maintaining uninterrupted connections as users move between cells, are a significant aspect of mobile wireless networks (Abdelmohsen, Abdelwahab, Adel, Darweesh, and Mostafa, 2018). LTE-A introduces challenges in achieving seamless handovers, particularly when transitioning between different types of cells, such as eNodeBs (eNBs) and Home eNodeBs (HeNBs). HHO procedures in LTE-A pose specific challenges, including interruptions in handover timing and potential data loss, necessitating solutions to ensure optimal performance. (Ahmad, Sundararajan, Othman, and Ismail, 2018 and J. Li et al., 2019).), as depicted in Figure 1.1.

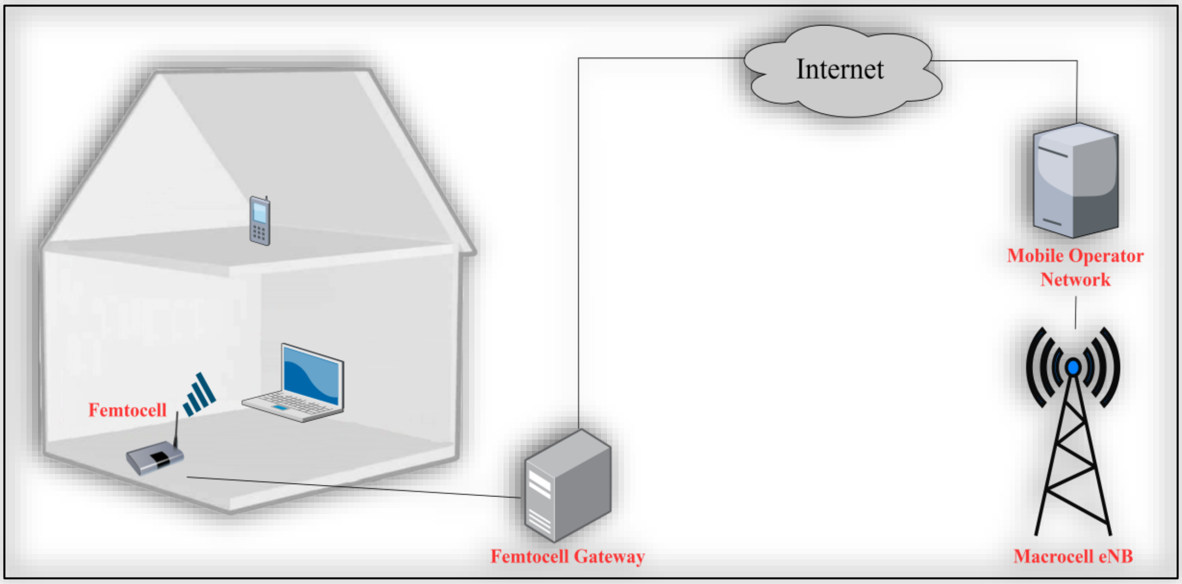

Figure 1.1: Handover scenario in femtocell networks (Ahmad, Sundararajan, and Khalifeh, 2020).

HHO disadvantages include carrier interference, high data loss, and difficulty in keeping up with QoS necessities due to delays in handover during network cell migration (Otsetova-Dudin, 2019). Despite this setback, the HHO is useful for UEs because it minimizes the complexity of wireless networks and is reliable for high-velocity users. However, the HHO procedure also results in apacket drop. This, in turn, may reduce the outcome of lost data during an active session. Thus, new techniques must be applied to avoid data loss.

To address these challenges and enhance Quality of Service (QoS) requirements, researchers propose algorithms that optimize the time-to-trigger (TTT) of handover processes using deep Q-learning (DQN). This approach dynamically adjusts handover parameters based on real-time network conditions, improving efficiency and minimizing disruptions.

Furthermore, machine learning techniques, including convolutional neural networks and reinforcement learning algorithms, are increasingly leveraged to optimize network performance and enhance user experience, as underscored by Wei et al. (2017) and Ray (2019). Recent advancements in deep learning, facilitated by developments in graphical processing units (GPUs) and the availability of vast amounts of data, have enabled significant breakthroughs in telecommunications technologies.

These advancements have led to exploring novel machine learning algorithms, such as Reinforcement Learning (RL) and Q-learning-based approaches, to optimize network performance and enhance user experience G. Cao, Lu, Wen, Lei, and Hu (2017).

Experimental analyses often utilize the Kalman filter (KF) as a prediction algorithm, leveraging artificial neural networks to improve accuracy. Despite its reliance on linear motion assumptions, KF remains a widely used tool for tracking moving objects and estimating their velocity and acceleration based on location measurements Chen, Wang, and Xuan (2018).

1.2 Motivation

The study investigates the role of handover processes in maintaining seamless connectivity within LTE and LTE-A wireless communication networks. Handovers facilitate uninterrupted calls and data sessions as users transition between cell towers. In urban environments, for instance, handovers are crucial for maintaining connectivity amidst changing cell coverage.

LTE-A technology, capable of supporting devices moving at speeds of up to 500 km/h, underscores the importance of fast and seamless transitions between LTE and LTE-A network cells. This is particularly pertinent for users engaging in bandwidth-intensive activities such as streaming media or real-time video communication while on the move (Ahmad, Sundararajan, Othman, and Ismail, 2017).

Furthermore, the diverse typology of LTE and LTE-A network cells, ranging from macrocells providing expansive outdoor coverage to femtocells catering to indoor environments, necessitates efficient handover mechanisms capable of seamlessly transitioning between different cell types without service disruption. (Ahmad et al., 2017).

Researchers are actively exploring advanced techniques such as Q-learning and subtractive clustering to optimize LTE and LTE-A handover processes. These efforts aim to mitigate the challenges associated with handover management in dynamic network environments, ensuring robust connectivity and quality of service for users across various mobility scenarios.

1.3 Problem Statement

Various researchers have developed some approaches to select a suitable target eNB or HeNB like, prediction and filtering approach. (Ahmad et al., 2018), other models are based on (Spatial information, Mobility prediction, RSS-based, and UE velocity-based).

Reading the literature work that was developed for solving these problems, can conclude the following:

1. The prediction approaches that have been used lack wise fusion between measurement and process models. As an example, in the work of (Ahmad et al., 2018), the polynomial model was fitted based on the historical positions of the UE with no consideration of the dynamics of the trajectory. In other words, the model of UE mobility includes a dynamical nature that can be estimated based on velocity and acceleration, which was unfortunately ignored. (Houssaini, Zaimi, Drissi, Oumsis, and Ouatik, 2018) Leveraging such variables in a concrete process model and fusing it with the measurement model represented by the vehicle's Global Positioning System (GPS) plays a crucial role in accurately predicting the UE future trajectory points, which is an essential factor in achieving target eNB/HeNB selection.
2. The approaches that have been selected for choosing the target node are based on deterministic filtering rules; for example (Ahmad et al., 2018) used two filters, one based on distance and the other based on angle, then a weighting mechanism was used for selecting the closest candidate target. This approach will fail in choosing a suitable target in the long term because of ignorance of other valuable information, like handover decisions for other UEs that passed in a similar trajectory of the subject UE. However, using this information requires incorporating a learning agent that has the capability of updating its knowledge in an online way to accommodate dynamic change. Reinforcement learning is a