SELF-TUNING OF SERVICE PRIORITY FACTOR FOR RESOURCE ALLOCATION OPTIMIZATION BASED ON QoE IN MOBILE NETWORKS

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การปรับตัวเองของปัจจัยลำดับความสำคัญของบริการสำหรับการเพิ่มประสิทธิภาพการจัดสรรทรัพยากรบนพื้นฐานคุณภาพของประสบการณ์ในเครือข่ายโทรศัพท์เคลื่อนที่

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

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ปัจจุบันเครือข่ายโทรศัพท์เคลื่อนที่กำลังถูกพัฒนาจากยุคที่ 4 ไปสู่ยุคที่ 5 ด้วยวิวัฒนาการของเทคโนโลยี Long-Term Evolution (LTE) และ New Radio (NR) ร่วมกันจัดหาวิธีการเข้าถึงวิทยุเพื่อเพิ่มความสามารถในการรองรับผู้ใช้งานและตอบสนองต่อการเข้าใช้บริการที่หลากหลาย ในอนาคตผู้ประกอบการโทรศัพท์เคลื่อนที่จำเป็นต้องให้ความสำคัญกับการยึดผู้ใช้เป็นศูนย์กลางบนพื้นฐานของตัวชี้วัดคุณภาพของประสบการณ์ (Quality of Experience: QoE) เทคโนโลยี NR ได้รับการออกแบบมาเพื่อให้สามารถรองรับแบนด์วิดท์ในการส่งข้อมูลที่กว้างมาก มีเวลาชักนำต่ำมาก มีอัตราการส่งข้อมูลที่สูงมาก ลดการแทรกสอดสัญญาณ และมีประสิทธิภาพในการใช้พลังงาน ในขณะที่เทคโนโลยี LTE ยังคงมีบทบาทสำคัญสำหรับเครือข่ายโทรศัพท์เคลื่อนยุคที่ 5 แต่ทรัพยากรแบนด์วิดท์จะไม่เพียงพอต่อความต้องการของผู้ใช้งานที่เพิ่มมากขึ้นในอนาคต จึงเป็นสาเหตุให้ผู้ใช้งานได้รับบริการที่ไม่ดีเนื่องจากมีทรัพยากรที่ไม่เพียงพอ หนึ่งในวิธีการแก้ปัญหาคือการเพิ่มสถานีฐานเพื่อให้มีทรัพยากรแบนด์วิดท์เพียงพอต่อความต้องการ แต่ผลเสียที่ตามมาคือค่าใช้จ่ายในการลงทุนและค่าใช้จ่ายในการดำเนินงานเพิ่มขึ้น ดังนั้นกลไกในการจัดสรรทรัพยากรวิทยุให้กับผู้ใช้งานจึงมีความสำคัญอย่างยิ่งเนื่องจากภายในเครือข่ายมีการเข้าใช้บริการที่หลากหลายพร้อมกันซึ่งในแต่ละบริการต้องการทรัพยากรและระยะเวลาหน่วงที่แตกต่างกัน เมื่อมีการจัดสรรทรัพยากรให้กับผู้ใช้อย่างเหมาะสมในแต่ละบริการจะช่วยให้สามารถรองรับผู้ใช้งานได้เพิ่มขึ้นและส่งผลถึง QoE ของผู้ใช้งาน โดยเฉลี่ยภายในพื้นที่ครอบคลุมเพิ่มขึ้น แม้ว่าจากการสำรวจปริทรรศน์วรรณกรรมที่ผ่านมายังไม่พบวิธีการในการจัดสรรทรัพยากรวิทยุที่สามารถกำหนดเงื่อนไขเพื่อรับประกัน QoE ให้กับแต่ละบริการ ดังนั้นงานวิจัยนี้จึงได้นำแนวคิดการปรับตัวเองของปัจจัยลำดับความสำคัญของบริการ (service priority factor) เพื่อเพิ่มประสิทธิภาพการจัดสรรทรัพยากรวิทยุ ซึ่งผลสำเร็จจากงานวิจัยนี้สามารถรับประกัน QoE เฉลี่ยของแต่ละบริการและเพิ่ม QoE รวมให้กับเครือข่าย รวมทั้งสามารถรองรับผู้ใช้งานเพิ่มขึ้นตลอดจนทั้งช่วยลดค่าใช้จ่ายในการลงทุนและค่าใช้จ่ายในการดำเนินงานของผู้ประกอบการโทรศัพท์เคลื่อนที่

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PATIKORN ANCHUEN : SELF-TUNING OF SERVICE PRIORITY FACTOR FOR RESOURCE ALLOCATION OPTIMIZATION BASED ON QoE IN MOBILE NETWORKS. THESIS ADVISOR : ASSOC. PROF. PEERAPONG UTHASAKUL, Ph.D. 146 PP.

LTE/NR/QoE/RB/ CAPEX/ OPEX/SELF-TUNING/SERVICE PRIORITY FACTOR

Currently, the mobile networks are being developed from 4G forward to 5G era based on the evolution of Long-Term Evolution (LTE) and New Radio (NR) technologies that jointly provides the radio access solution for supporting more users and responding various of use cases. In the future, mobile operators need to focus on user-centric perspective with a Quality of Experience (QoE) metric. NR technology is designed to deliver many properties such as supporting ultra-wide transmission bandwidths, very low latency, very high data rate and enhancing network energy performance. Meanwhile, LTE technology still plays an important role in 5G despite the limited spectrum bands for serving many users in the future. As a result, the users receive poor service due to insufficient Resource Blocks (RBs). One of the solutions is to add a cell site to have enough bandwidth resources, but it leads to more costs of Capital Expenditure (CAPEX) and Operating Expenses (OPEX). Thus, the mechanism for the allocation of RBs to provide the user is a very important solution due to the user requirements access to many different services at the same time, in which each service requires the different RBs and latency. When the RBs are appropriately allocated to users in each service, it can support more users and increase the average QoE of networks within the coverage area. Although the resource allocation optimization for maximizing the QoE with constraints has not found in the literature review. In this thesis, the self-tuning of service priority factor is used for optimizing the resource allocation to guarantee the average QoE of each service and maximize the average QoE of networks. The results of this thesis can support more users and reduce the CAPEX and OPEX of mobile operators.

School of Telecommunication Engineering Student's Signature ______

Academic Year 2019 Advisor's Signature ______

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SYMBOLS AND ABBREVIATIONS

LTE	=	Long-Term Evolution
NR	=	New Radio
eMBB	=	enhanced Mobile Broadband
mMTC	=	massive Machine-Type Communication
URLLC	=	Ultra-Reliable and Low-Latency Communication
3GPP	=	3rd Generation Partnership Project
NSA	=	Non-Standalone
RT	=	Realtime
NRT	=	Non-Realtime
IP	=	Internet Protocol
VoIP	=	Voice over IP
BE	=	Best Effort
MNO	=	Mobile Network Operator
QoS	=	Quality of Service
QoE	=	Quality of Experience
UE	=	User Equipment
eNB	=	eNodeB
RF	=	Radio Frequency
CAPEX	=	Capital Expenditure
OPEX	=	Operating Expenses

SYMBOLS AND ABBREVIATIONS (Continued)

RSRP	=	Reference Signal Received Power
SINR	=	Signal-to-Interference plus noise ratio
E-Tilt	=	Electrical Tilt
M-Tilt	=	Mechanical Tilt
PCI	=	Physical Cell ID
MAC	=	Medium Access Control
RRM	=	Radio Resource Management
RB	=	Resource Block
QCI	=	QoS Class Identifier
PF	=	Proportional Fair
MLWDF	=	Modified-Largest Weighted Delay
EXP/PF	=	Exponential/Proportional Fair
FLS	=	Frame Level Scheduler
EXP rule	=	Exponential rule
LOG rule	=	Logarithmic rule
GA	=	Genetic Algorithm
RNN	=	Random Neural Network
SON	=	Self-Organization Network
ML	=	Machine Learning
ANN	=	Artificial Neural Network
PSO	=	Particle Swarm Optimization
PGA	=	Particle Genetic Algorithm

SYMBOLS AND ABBREVIATIONS (Continued)

SMS	=	Short Message Service
AMPS	=	Advance Mobile Phone Service
FDMA	=	Frequency Division Multiple Access
GSM	=	Global System for Mobile communication
ETSI	=	European Telecommunication Standard Institute
TDMA	=	Time Division Multiple Access
GPRS	=	Generic Packet Radio Service
EDGE	=	Enhanced Data rate for GSM Evolution
Kbps	=	Kilobits per second
UMTS	=	Universal Mobile Telecommunication System
WCDMA	=	Wideband Code Division Multiple Access
HSDPA	=	High-Speed Downlink Packet Access
HSUPA	=	High-Speed Uplink Packet Access
HSPA	=	High-Speed Packet Access
HSPA+	=	High-Speed Packet Access Plus
HD	=	High Definition
MIMO	=	Multiple-Input Multiple-Output
OFDM	=	Orthogonal Frequency-Division Multiplexing
OFDMA	=	Orthogonal Frequency-Division Multiple Access
TD	=	Time Domain
FD	=	Frequency Domain
TC	=	Transport Channel

SYMBOLS AND ABBREVIATIONS (Continued)

QAM	=	Quadrature Amplitude Modulation
MHz	=	Megahertz
EPC	=	Evolved Packet Core
E-UTRAN	=	Evolved Universal Terrestrial Radio Access Network
MME	=	Mobility Management Entity
SGW	=	System Architecture Evolution Gateway
PGW	=	Packet Data Network Gateway
PRB	=	Physical Resource Block
TTI	=	Transmission Time Interval
PD	=	Packet Delay
PLR	=	Packet Loss Ratio
CRC	=	Cyclic Redundancy Check
RLC	=	Radio Link Control
HARQ	=	Hybrid Automatic Repeat Request
PHY	=	Physical
LC	=	Logical Channel
GBR	=	Guaranteed Bit Rate
Non-GBR	=	Nonguaranteed Bit Rate
MBR	=	the Maximum Bit Rate
SDU	=	Service Data Unit
TB	=	Transport Block
TM	=	Transportation Mode

SYMBOLS AND ABBREVIATIONS (Continued)

SAP	=	Service Access Point
SRS	=	Sounding Reference Signal
CQI	=	Channel Quality Indicator
PS	=	Packet Scheduling
LA	=	Link Adaptation
AMCS	=	Adaptive Modulation and Coding Scheme
PER	=	Packet Error Rate
PDCCH	=	Physical Downlink Control Channel
FDD	=	Frequency Division Duplexing
TDD	=	Time Division Duplexing
SC-FDMA	=	Single-Carrier Frequency Division Multiple Access
FTP	=	File Transfer Protocol
ULSCH	=	Uplink Shared Channel
DLSCH	=	Downlink Shared Channel
BLER	=	Block Error Rate
AMBR	=	Aggregate Maximum Bit Rate
ARP	=	Allocation and Retention Priority
PDB	=	Packet Delay Budget
HOL	=	Head-Of-Line
C-RNTI	=	Cell Radio Network Temporary Identifier
DCI	=	Downlink Control Information
QPSK	=	Quaternary Phase Shift Keying

SYMBOLS AND ABBREVIATIONS (Continued)

BSR	=	Buffer Status Report
SC	=	Sub Channel
VoLTE	=	Voice over LTE
ITU	=	International Telecommunication Union
ms	=	milliseconds
TP	=	Throughput
PLR	=	Packet Loss Rate
JT	=	Jitter
OS	=	Opinion Score
FDPS	=	Frequency Domain Packet Scheduler
MLP	=	Multi-Layer Perceptron
FFBP	=	Feed Forward Back Propagation
CPU	=	Central Processing Unit
GPU	=	Graphics Processing Unit
ASIC	=	Application-Specific Integrated Circuit
ROI	=	Return of Investment
MDP	=	Markov Decision Process
RL	=	Reinforcement Learning
KPI	=	Key Performance Indicator
DQN	=	Deep Q-Network
NFV	=	Network Function Virtualization
MEC	=	Mobile Edge Computing

CHAPTER I

INTRODUCTION

1.1 Background of problem

Currently, the mobile networks have been evolved from the Fourth Generation (4G) forward to the Fifth Generation (5G). The evolution of Long-Term Evolution (LTE) and New Radio (NR) technologies jointly provides the radio access solution to support more users and respond to various use cases (3GPP, TS 37.340, 2017). The context of 5G consists of three exclusive classes of use cases including enhanced Mobile Broadband (eMBB), massive Machine-Type Communication (mMTC) and Ultra-Reliable and Low-Latency Communication (URLLC) (ITU-R, M.2410-0, 2017). As NR technology is the new air interface developed to use in 5G mobile networks, it delivers many properties such as supporting ultra-wide transmission bandwidths, very low latency, very high data rate, reducing interference and enhancing network energy performance (3GPP, TS 38.802, 2017). While LTE was launched by the 3rd Generation Partnership Project (3GPP) Release 8 in 2008 as the basis for all the following LTE releases, and it still plays the Non-Standalone (NSA) mode of next mobile networks (Dahlman, Erik, Stefan Parkvall, and Johan Skold, 2018). Although the spectrum flexibility of the LTE basis has a range of bandwidths up to 20 MHz and supports carrier frequencies from 1 - 3 GHz generally, this spectrum band may cause insufficient bandwidth resources during the many users increased in the next mobile networks (Cisco, 2018–2023 White Paper).

In the next future, many users and more devices will greatly access internet data traffic through mobile networks to consume the multimedia services such as Voice over IP (VoIP), Video streaming, Best Effort (BE) and other emerging applications on Realtime (RT) and Non-Realtime (NRT) traffic. For this reason, it causes competition during Mobile Network Operators (MNOs) to occupy the market share (Ericsson, 2019). Hence, MNOs always need to develop our networks better than their competitors for business profits. For instance, they have various ways to attract mobile subscribers such as offering discounts, low-cost mobile with contracting and special services. However, one of the most solutions is a network improvement in technical technique from the metric as called Quality of Service (QoS), which can be directly measured by special tools to feedback to MNOs for the optimization (WANG, Zhengyou, et al, 2014).

In the past, MNOs have focused on network optimization from QoS as the measure of network performance to compare our competitors. Nevertheless, the QoS is just the network-centric perspective, which does not directly reflect the user satisfaction in any way. Although the measured signal quality is at a good level, sometimes the level of user satisfaction is poor. This reason is caused by a dense environment from many users accessing the network within a cell coverage area (P. Anchuen, P. Uthansakul and M. Uthansakul, 2016). To retain existing users and attract new users, the MNOs must access to user satisfaction in terms of Quality of Experience (QoE). Eventually, the operators need to offer the user-centric perspective as a dominant factor for improving the network performance based on the QoE metric (Agiwal, Mamta, Abhishek Roy, and Navrati Saxena, 2016). Network optimization needs to reach user satisfaction with a key variable of QoE while the operators are just only able to measure the QoS parameters from the special tool. Therefore, MNOs must create the relationship between the QoS and the Opinion Score (OS) to understand the user perspective from the existing QoS (LIOTOU, Eirini, et al, 2015). Any MNOs that can provide higher QoE levels than other competitors will be able to retain existing users and attract new subscribers significantly.

The communication in the LTE air interface between evolved Node B (eNB) and User Equipment (UE) is an important part of mobile communication by using Radio Frequency (RF) for serving high-speed data traffic. The operators must manage bandwidth to meet the user needs. It is well known that the resource of the radio spectrum may be licensed to operate at high-cost, and the increasing number of users makes insufficient resources for providing users (Sidak, J. G, 2016). For these reasons, MNOs need to improve their networks to provide enough resources and meet their needs without purchasing additional radio spectrum licenses. With the limited bandwidth, an increasing number of users and accessing emerging applications, the MNOs must manage the network to provide users with better user experience. Methods for solving this problem, there are two main approaches to improve the networks from the cause of the poor user experience due to the limited bandwidth on LTE networks (Héder, Balázs, Péter Szilágyi, and Csaba Vulkán, 2016). The first approach is to add the new cell sites to increase more air interface traffic, which leads be too high costs for both Capital Expenditure (CAPEX) and Operating Expenses (OPEX). Thus, this approach should be the last option. The second approach solves the problem by using QoS management. For the network management method between eNB and UEs, the MNOs always prioritize the optimization of their networks in the RF area before adding the new cell site. The main parameters of QoS consideration in LTE networks are the Reference

Signal Received Power (RSRP) and the Signal-to-Interference plus noise ratio (SINR), which have significant implications for network throughput. These parameters can be improved by adjusting Electrical Tilt (E-Tilt) (Buenestado, et al., 2017) and Mechanical Tilt (M-Tilt) on base station antennas (Ouyang, Ye, et al., 2017). Other concerns to improve the signal quality can pay attention to Physical Cell ID (PCI) planning (Premnath, K. N. et al., 2012) and the power allocation method (ul Islam et al., 2010). However, the signal quality was improved to a good level, sometimes if many users access different services from the limited bandwidth which causes the user experience as poor. The operators try their best to optimize their parameters for obtaining a good level of QoS, but sometimes the QoE metric is in the low level of user satisfaction (P. Anchuen and P. Uthansakul, 2019). Before the MNOs decide to add the new cell site, they should manage the network by optimizing the downlink packet scheduling in the Medium Access Control (MAC) layer that is the brains of LTE networks from the mechanism of Radio Resource Management (RRM) (Pedersen, K. I., et al., 2009). The Resource Block (RB) allocation in eNB with the limited bandwidth to provide many users, if each user has the right resources for the each service, this results in a better overall user experience by the average QoE of all services in the cell coverage area increased (Oliver-Balsalobre, Pablo, et al., 2016; Oliver-Balsalobre, Pablo, et al., 2018). Even though the QoS Class Identifier (QCI) has been defined for the resource management to guarantee the QoS to users in different services (3GPP, TS 23.203, 2018), but it cannot be used to efficiently allocate the radio resource with many users using the different services at the same cell site (Urgun, Y. and Kavak, A., 2016). For an effective method, Ph.D. candidate has recognized the importance of radio resource allocation by focusing on end-users to get better QoE with limited resources from network management by prioritizing the downlink packet scheduling. The literature review has found that several studies have investigated and developed the downlink scheduling algorithm in LTE networks to increase the efficiency of resource allocation. The survey of downlink packet scheduling in LTE networks for key design aspects focused on the resource allocation strategies such as channel-aware, QoS-aware and QoE-aware (Capozzi, F., Piro, et al., 2013; Sivasubramanian, A., et al., 2017). Currently, the downlink scheduling algorithm focuses on the QoE-aware with the development of channel-aware and QoS-aware to respond to the future networks. The channel-aware algorithms provide only the throughput among many users without consideration to the QoS from QCI such as the Maximum Throughput (MT) algorithm (J. Puttonen, et al., 2007) and Proportional Fair (PF) algorithm (Wengerter, Christian, et al., 2005). Therefore, these algorithms are unsuitable for RT multimedia traffics because some services need to guarantee time delay to prevent communication interruption. The QoS-aware algorithms consider the QoS requirements of the user from QCI such as delay and packet loss rate on RT and NRT services. These common algorithms of QoS-aware consist of Modified-Largest Weighted Delay (MLWDF) (P. Ameigeiras, et al., 2016), Exponential/Proportional Fair (EXP/PF) (R.Basukala, et al., 2009), Frame Level Scheduler (FLS) (Piro, G. et al., 2011), Exponential rule (EXP rule) (Ee Mae Ang et al., 2015), and Logarithmic rule (LOG rule) (Bilal Sadiq et al., 2009). These algorithms have different advantages and disadvantages, but they are not the appropriate algorithms in the future network because they are just a resource allocation from the network-centric perspective that does not consider the user satisfaction. Thus, the solution of downlink scheduler should be developed with the new resource allocation techniques based on the QoE-aware. From recently interesting research on multi-services about resource allocation and how to find the optimal parameters based on QoE-aware, the resource allocation with the optimal parameters of service priority index can balance the average QoE of each service in LTE networks with a heuristic method (Oliver-Balsalobre, et al., 2016). The resource allocation based on QoE using a heuristic method to find the appropriate service priority index can maximize the overall QoE of the network in the cell coverage area (Oliver-Balsalobre, et al., 2018). The Genetic Algorithm (GA) and Random Neural Network (RNN) are applied to find the suitable parameters of network configuration to improve QoE performance in Video service in the LTE networks (Ghalut, T., et al., 2016; Ghalut, T., Larijani, H., et al., 2017). However, the QoE-aware algorithms from previous research do not measure the number of users that can be significantly increased from resource allocation and these optimization methods cannot improve the network from the optimization with constraints from the condition of QoE threshold in each service. Although some researches allocate the radio resources based on QoE to balance the average QoE of each service and allocate resources to maximize the overall QoE of the nerworks, these methods cannot determine the QoE threshold in each service to guarantee the user experience. Hence, Ph.D. candidate has developed this thesis for resource allocation with limited bandwidth scenarios to support more users based on defining the service priority factor in the downlink scheduling algorithm for maintaining QoE with constrained of each service to guarantee QoE threshold.

The network optimization in the future must be automatically managed to reduce human error, CAPEX and OPEX due to many devices and heterozygous networks, which are difficult to handle with humans. Self-Organization Network (SON) is an important role in network enhancements such as self-configuration, self-optimization and self-healing (Aliu, O. G., et al., 2013). Besides, Machine Learning (ML) techniques can be used with SON to improve network and solve problems that are more complex than conventional mathematical methods. The process of solving problems from ML will be an important technique used in enhancing the performance of the network in the future (Valente Klaine, et al., 2017).

Recently, the optimization technique is developed into the modern method to be effective and able to solve problems extensively by using the ML method. In the field of optimization in the mobile networks, the GA algorithm is used to find the optimal parameters for setting the networks for maximizing the QoE under the existing resource limitations (Ghalut, T., et al., 2016; Ghalut, T., Larijani, H., et al., 2017), which this algorithm can reduce the time to search for an answer as compared to the exhaustive search method. Although the GA algorithm is widely used in the optimization of the engineering field (David E. Goldberg, 1889; K. F., Tang, et al., 2012), it has a limitation in the local search due to the mutation process causes only a small change from random. Meanwhile, the Particle Swarm Optimization (PSO) algorithm has the characteristic of exploitation (Kennedy J. and Eberthart R., 1995; Eberthart R. and Eberhart, R., 1995), which this characteristic can reduce the GA limitation in local search. Thus, the combination of GA and PSO, which is the hybrid method, is developed to use for finding the optimal answer in the models of Sphere, Rosebrock, Griewank and Rastrigin that have many local maximum (Løvbjerg, Morten, et al., 2001). With the apparent nature of surfaces in these models, it is not appropriate to find the answer using gradient descent, which is a popular method, due to the operation of this method may converge to the answer of a local maximum in these models. Thus, the exploration feature in the GA algorithm and the exploitation feature in the PSO algorithm can find the optimal answer quickly and efficiently with this hybrid method.

In this thesis, Ph.D. candidate has focused on the network optimization of radio resource allocation based on QoE-aware with constrained multivariable optimization from the heuristic search method to find the optimal parameters. The QoE model is created by using the Artificial Neural Network (ANN) algorithm to map the QoS and OS and use assess QoE score. Using GA and PSO jointly makes the possible to find the faster right value and have a higher probability of answer to converge the global maximum or best answer by the proposed algorithm as called Particle Genetic Algorithm (PGA). The proposed method can increase QoE to support the increasing number of users with the limited resources to reduce CAPEX, OPEX and guarantee the average QoE of each service.

1.2 Thesis objectives

The objectives of this thesis are as follows:

1.2.1 To study the relationship between the service priority factor and the average QoE of all services and the average QoE of each service within the cell coverage area.

1.2.2 To demonstrate the self-tuning in finding the optimal parameters of service priority factor for radio resource allocation optimization based on QoE-aware under the limited bandwidth scenario.

1.3 Scope and limitation of the study

1.3.1 According to the defined services, RT and NRT services consist of VoIP, Video, and BE in the simulation tool of LTE-Sim to demonstrate the situation of users who use the service at the same time.

1.3.2 Define the bandwidth that is equal to 5 MHz at the frequency center of 2.0 GHz in LTE-Sim to simulate the situation in the case that the RBs are not enough to provide many users.

1.3.3 Specify downlink scheduling algorithms that are compared to the performance of algorithms based on QoE-aware consisting of PF, MLWDF, EXP/PF, FLS, EXP rule, and LOG rule. EXP rule algorithm is chosen to increase resource allocation efficiency by using the appropriate service priority factor.

1.3.4 This thesis aims to optimize the RB allocation based on QoE-aware from defining the appropriate service priority factor from self-tuning to support more users and guarantee the average QoE of each service within the cell coverage area.

1.3.5 To realize the QoE from QoS parameters, the QoE model is created by using an effective method with the ANN.

1.3.6 The determination of the appropriate service priority factors is carried out by the proposed PGA algorithm for the optimization with constraints.

1.4 Contributions

1.4.1 Can guarantee the average QoE of each service and maximize the average QoE of all services within the cell coverage area.

1.4.2 Can support more users within the cell coverage area in the limited bandwidth scenario.

1.4.3 Can reduce CAPEX and OPEX to maintain the QoE.

1.5 Thesis organization

The remainder of this thesis is organized as follows. The background theory is discussed in Chapter II. This chapter presents a background theory for related resource allocation, which begins with the concept of mobile networks. Also, the main ideas and principles for this thesis are discussed in the self-optimizing concept consisting of QoE-aware and network optimization in mobile networks.

Chapter III mentions the system model and self-optimization. Moreover, the possibility of the implementation concept in this thesis is organized in this Chapter.

Chapter IV presents the details regarding the methodology for simulation steps. It consists of the LTE-Sim, downlink scheduling method, QoE model and the procedure of optimization technique to compute the optimal parameters of service priority factor.

Chapter V performs the simulation results and discussions. The simulation results are divided into three subsections. The first subsection shows the comparison of six common downlink scheduling algorithms in terms of QoE performance. The comparison of GA PSO and PGA algorithms is shown in the second subsection. The proposed algorithm for finding the optimal parameters with the condition of the QoE threshold is demonstrated in third subsection. In addition, the computational complexity of algorithms by Big O notation and the implementation concept are discussed in this Chapter.

Chapter VI presents the conclusions of the thesis and the suggestions of the future works.

CHAPTER II

BACKGROUND THEORY

2.1 Introduction

This chapter discusses a background theory for associated resource allocation, which begins with a brief concept of mobile communication. The evolution of mobile networks describes the gap of common technology to find the issue of improving this gap. Besides, the Long-Term Evolution (LTE) is mentioned in important parts including Quality of Service (QoS) and Media Access Control (MAC) protocol. In the resource allocation section, downlink scheduling procedure and common downlink scheduling algorithms in the MAC layer are discussed within the basic knowledge definition of LTE systems. Moreover, the main ideas and principles for this thesis are discussed in the self-optimizing concept consisting of Quality of Experience (QoE) awareness and network optimization in mobile networks. The techniques for resource allocations in the past to the present are compared to be a guideline for development in this thesis.

2.2 Evolution of mobile communication

The mobile communication system was the first mobile phone service for conversation. Afterward, the requirements for using other types of data communication such as voice communication, Short Message Service (SMS), computer data transmission, video streaming, Virtual Reality (VR) and so on, cause the development of technology to be more efficient and support the data transmission. The evolutions of mobile communication are discussed as follows:

First Generation: 1G

The 1st generation of mobile communication was in the form of analog communication with voice communication. For voice transmission with the technology used in this era, it is Advance Mobile Phone Service (AMPS). The audio signals are mixed with carrier wave and broadcasted using Frequency Division Multiple Access (FDMA) technique to use channels together and use circuit switching to set the conversation path. The systems have been designed to support conversation communication, but it has a limited number of channels that cannot support the expansion of user numbers.

Second Generation: 2G

The 2nd generation was intended to increase the ability to support more users. The standard of the 2G has many standards, but the important standard and occupy the market share of the mobile phone business around the world that is Global System for Mobile communication (GSM). This standard is introduced in 1989 by the European Telecommunication Standard Institute (ETSI). Data transmission via radio frequency between the User Equipment (UE) and the base station by using Time Division Multiple Access (TDMA) technique. Thereafter, 2G has been developed to 2.5G with the connection of circuit switch data for data transmission. And after that, packet switch data is used to be able to support more user datas as 2.75G developed as Generic Packet Radio Service (GPRS) technology. Subsequently, the radio transmitting device is developed for modulation to support faster data communication, resulting in the Enhanced Data rate for GSM Evolution (EDGE) that can support communication at the highest speed to 384 Kilobits per second (Kbps).

Third Generation: 3G

The 3rd generation was developed from 2.5G/2.75G by International Mobile Telecommunications-2000 (IMT-2000) to respond to the increased data transmission needs. 3G was developed as a digital packet focusing on supporting multimedia services for all users to access information with a target speed of 2 Mbps in buildings and 144 Kbps when moving. It can support all applications by providing multimedia communication services including data, voice, and animation from Universal Mobile Telecommunication System (UMTS) by using Wideband Code Division Multiple Access (WCDMA). Afterward, it is developed into High-Speed Downlink Packet Access (HSDPA) technology, High-Speed Uplink Packet Access (HSUPA) technology, High-Speed Packet Access (HSPA) technology, and High-Speed Packet Access Plus (HSPA+) to enable higher data transfer. For example, HSPA+ technology can transfer data from base stations to client devices up to 42 Mbps.

Fourth Generation: 4G

4G is designed to support the response of High Definition (HD) video and video communication including the ability of mobile devices that are more intelligent and the system has high-security support that can provide online financial services via mobile phones. In this era, the framework has been developed by using technology consisting of Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency-Division Multiple Access (OFDMA) technologies for data transmission. The key technology of 4G is LTE that is part of an international standard from the 3rd Generation Partnership Project (3GPP). It approved the use of the LTE standard from Release 8 in 2008. The main goal of LTE is to have a high data rate, supports more users and reduced latency. Moreover, OFDMA in LTE can effectively use limited bandwidth.

Fifth Generation: 5G

To meet the challenges of mobile communications, 5G has a mixture of new concepts including increasing spectrum efficiency, low latency, higher data rates and energy efficiency. The evolution of LTE and New Radio (NR) jointly provide the radio-access solution in Non-Standalone (NSA) mode as shown in Fig. 2.1 to increase the ability to support users and respond to various types of services in 5G mobile networks consisting of enhanced Mobile Broadband (eMBB), massive Machine-Type Communication (mMTC) and Ultra-Reliable and Low-Latency Communication (URLLC). In the radio access solution, the LTE spectrum is defined under carrier frequencies at 6 GHz, which is congested as the limited bandwidth to provide more users in the next future. While NR is created in the 3GPP standard release 15, which is designed to support a very wide range of data transmission frequencies and a greater number of device connections per area. As a result, all devices can connect all around. Various technologies move along with the world of communication such as medical, information technology, agriculture, industry and so on.

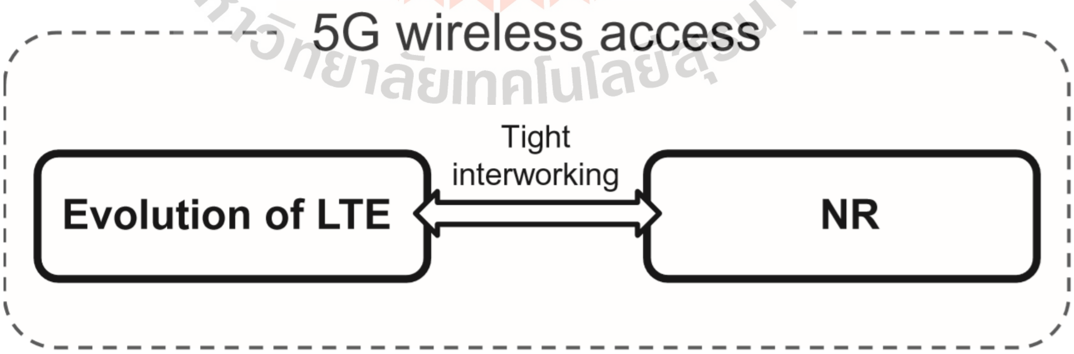


Figure 2.1 Evolution of LTE and NR technologies providing radio access solutions in 5G (Dahlman, Erik, Stefan Parkvall, and Johan Skold, 2018).

2.3 LTE systems

The LTE technology is launched by 3GPP Release 8, which is the key standard of 4G. This technology can guarantee data transmission with end-to-end Quality of Service (QoS) support. There are two important technologies in Radio Access Network (RAN) consisting of Orthogonal Frequency Division Multiplexing (OFDM) and MIMO. OFDM is applied for downlink in the air interface to reduce the effect of multipath delay spread in frequency selective fading, and MIMO is used to support the need for large multimedia to better performance. Also, the next generation still plays on LTE technology for NSA mode to jointly provide radio access solutions in conjunction with NR in 5G technology (Dahlman, Erik, Stefan Parkvall, and Johan Skold, 2018). The radio resource in LTE is distributed in Time Domain (TD) and Frequency Domain (FD) for flexibility in usage, which has been targeted at100 Mbps maximum data rate in downlink and 50 Mbps in uplink. In theory, the calculated maximum data rate at Transport Channel (TC) is equal to 75 Mbps in the uplink and 300 Mbps in the downlink by using OFDMA and MIMO technologies with bandwidth at 20 Megahertz (MHz) having the modulation with 64 Quadrature Amplitude Modulation (QAM).

The service architecture of LTE networks can be shown in Fig. 2.2. There are two main sections consisting of Evolved Universal Terrestrial Radio Access Network (E-UTRAN) and Evolved Packet Core (EPC). The EPC consists of Mobility Management Entity (MME), Serving Gateway (SGW) and Packet Data Network Gateway (PGW). The MME officiates for user mobility, handover, tracking and paging procedures among UE connections. The SGW routes and forwards user data packets and manages handover between LTE and non-3GPP technology. The PGW connects other IP networks to provide among UEs and external packet data. While E-UTRAN consists of eNodeB (eNB) and UE, both connections officiate signaling control between UE and EPC. The RAN is responsible for Radio Resource Management (RRM), header compression and security to be appropriate for data transmission between eNB and UEs that features point-to-point connection within eNB to allocate Resource Blocks (RBs) for providing all users in the cell. The resource allocation is based on scheduling algorithm by the number of RB including 6, 25, 50, 75 and 100 that depend on bandwidth range as 1.4, 5, 10, 15 and 20 MHz, respectively. The radio resource allocation proceeded in every 1 millisecond (ms) or 1 Transmission Time Interval (TTI).

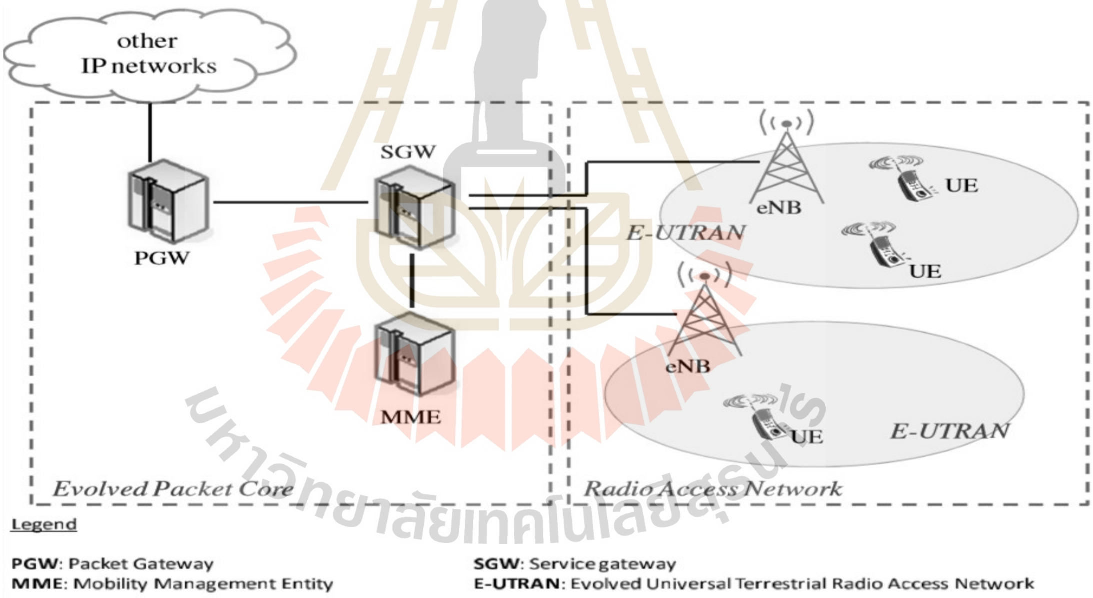


Figure 2.2 The service architecture of the LTE networks (Capozzi, F., Piro, et al, 2012).

The need for IP services such as Voice over Internet Protocol (VoIP), web browser, video streaming, social media and online game establishes the new challenge for network design. The minor faults in the bitstream may result in packet error in

Realtime (RT) service consisting of video conferencing and VoIP. This problem should be considered differently on LTE networks to meet QoS needs (Piro, G., Grieco, et al, 2011). The RT traffic requires packet delivery within the upper limits of latency that is sensitive to delay and loss, which must be low Packet Delay (PD) and low Packet Loss Ratio (PLR) more than Non-Realtime (NRT) services. When the packet error occurs at the MAC, the receiver can receive the bit error that occurs before decoding. The MAC inserts the Cyclic Redundancy Check (CRC) in the transmitter and detects on the receiver and sends the successful data unit to the Radio Link Control (RLC) layer. The purposed LTE is to high speed and more capacity for various multimedia applications by increasing the maximum data transfer rate with the help of Hybrid Automatic Repeat Request (HARQ) and suitable scheduling downlink.

HARQ is used for re-transmissions of faulty packets to regain error packets and to minimize the radio interface delay, which is controlled by the MAC layer and implemented at the Physical (PHY) layer. The resource needs of each sub-task vary according to the RT traffic. LTE system requires the processing time in MAC sub-tasks that should be less than 1 ms. Otherwise, MAC will not be able to forward data to the PHY. The processing time should be 800 microseconds to reduce the risk of over 1 ms. The MAC sub-tasks will be performed in every 1 ms or 1 TTI, which has 2 slots, while the Logical Channel (LC) is assigned in MAC from packet scheduling algorithms. However, more details for the importance of the QoS and the MAC layer is discussed in the following subsection.

2.3.1 Quality of Service

The IP combination point determines the convenience of sending the same data type in the same direction. The information flow in 1 direction still requires

1 EPS Bearer as shown in Fig. 2.3. The integration is performed at UE in the uplink direction and PGW in the downlink direction. The provision of the SAE Bearer service is responsible for the data transmission between SGW and eNB as per QoS profiles. The SAE Access Bearer interface that connects to the Radio Bearer is LC communication.

However, Bearer can be separated into 2 types which are Default Bearer and Dedicate Bearer. Default Bearer stores data throughput the traffic and it is Non-Guaranteed Bit Rate (Non-GBR) which can be affected by the loss of data group. Dedicate Bearer stores specific IP traffic in different forwarding sections, and it is a Guaranteed Bit Rate (GBR) service or the Maximum Bit Rate (MBR) service.

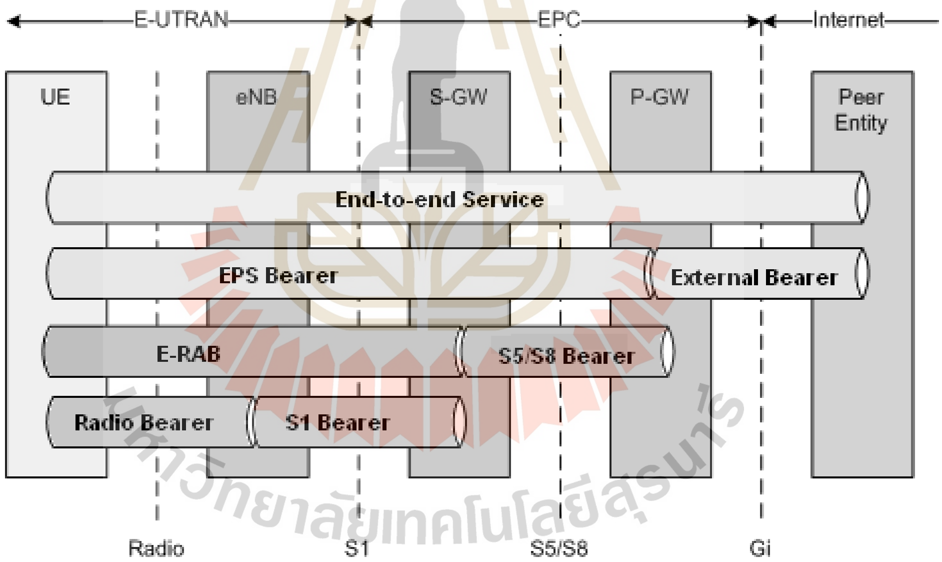


Figure 2.3 EPS Bearer service architecture (Bouallouche, Dalicia, 2012).

2.3.2 MAC protocol in LTE systems

The MAC protocol at UE and eNB is part of the user plane and control plane in the LTE air interface, which controls accessing the data transfers with the main function consisting of data mapping among RLC to PHY by multiplexing Service Data

Units (SDUs) to Transport Blocks (TBs) to send to PHY for the data transmission in the downlink direction, and Demultiplexing TBs from PHY to SDUs PHY in the uplink direction. Also, MAC protocol is responsibly consisted of reporting the scheduling information using metric calculations, error correction by using HARQ, priority management of UEs based on dynamic scheduling, Transportation Mode (TM) selection, reporting on the amount of traffic, service identification, padding and so on. Service Access Point (SAP) is located between PHY and MAC, which is TC, and SAP at between MAC and RLC is LC as shown in Fig. 2.4. When the process in the UE measures the channel quality of Signal to Interference and Noise Ratio (SINR) calculated from Sounding Reference Signal (SRS) at PHY for notification of current channel quality status to predict Channel Quality Indicator (CQI), and this information is sent back to the eNB. The eNB uses the received channel status of each UE to allocate the resource in TD and FD to provide every UEs in a cell from RRM functions, which consist of Link Adaptation (LA) and Packet Scheduling (PS). PS function assigns each UE in TD and FD from the calculated priority metric. LA function allocates the Physical Resource Blocks (PRBs) to UEs in every TTI and defines the Adaptive Modulation and Coding Scheme (AMCS) for expanding the data rate. To maintain the average Packet Error Rate (PER) for the performance of data transmission in radio air interface depends on the proportion of packets transmitted from the PER. The allocated PRBs and selected MCS are sent to the defined UEs with the Physical Downlink Control Channel (PDCCH). Although resource allocation is operated in MAC, it cannot be used to guarantee successful data without an effective scheduling algorithm. Thus, the format of scheduling at MAC is used to determine the data transmission time according to the limitations of PD and Throughput of each link to guarantee the quality and the spectral efficiency.

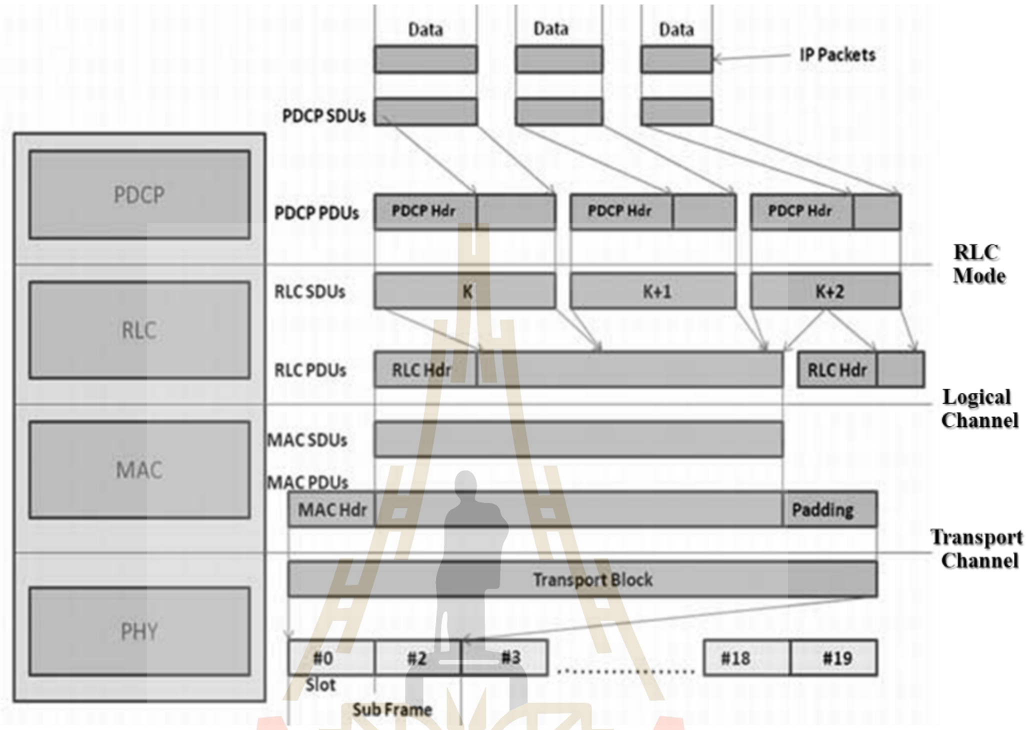


Figure 2.4 The LTE protocol data flow.

2.4 Radio resource allocation

LTE networks use OFDMA for the data transmission in downlink direction from eNB to UEs, which can choose the functions consisting of Frequency Division Duplexing (FDD) and Time Division Duplexing (TDD). The data transmission in the uplink direction from UE to eNB uses the Single-Carrier Frequency Division Multiple Access (SC-FDMA). The appropriate properties of OFDMA consist of high flexibility in resource allocation, simple equalization and robustness against frequency selective fading. The packet scheduler process is the importance of the RRM mechanism at eNB, which is actualized to provide resource allocation by multiplexing in packet level to guarantee the QoS need of each service type (Youngki Kim, et al, 2009). However, the appropriate downlink scheduling algorithm in the next mobile networks should be designed to equip various data transmission types by commanding the queue sizes, the priority of each service and the volume of total data transmission based on QoE consideration. RRM should have the mechanism to dynamically allocate the radio resources to UE with the scheduling algorithms implied to ensure that radio resource is effectively used from the self-tuning technique to provide the QoS need of the user. Normally, the RRM functions consisting of admission control, semi-persistent scheduling and QoS profiling at layer 3 as shown in Fig 2.5, are painted as semi-dynamic mechanisms because they have essentially executed the definition of new data flows.

QoS is utilized to define the trade-off performance in the LTE networks. To meet the QoS target, various scheduling algorithms have been developed to efficiently allocate the resource in TD and FD to provide the RT and NRT traffics. The scheduling is intended to guarantee QoS requirements and to obtain the high-performance with channel management within the resource allocation mechanism. RT traffic requires QoS of having low PD and low PLR whereas NRT traffic needs more throughput rate. To maximize the cell capacity with the minimum QoS, each algorithm under channel-aware and QoS-aware has different methods to determine the scheduling priority of users such as packet delay, bound buffer status, expected throughput, past average throughput, channel status and fairness to provide multiple services. Scheduling decisions are operated on per user, and the MAC protocol defines the data sending for each flow. The required RT traffic depends on the policy of scheduling algorithms whereas NRT traffic such as web browsing and File Transfer Protocol (FTP) with Best Effort (BE) do not have exacting requirements. The key metrics consisting of Throughput, PLR, and PD are the main indicator of QoS.

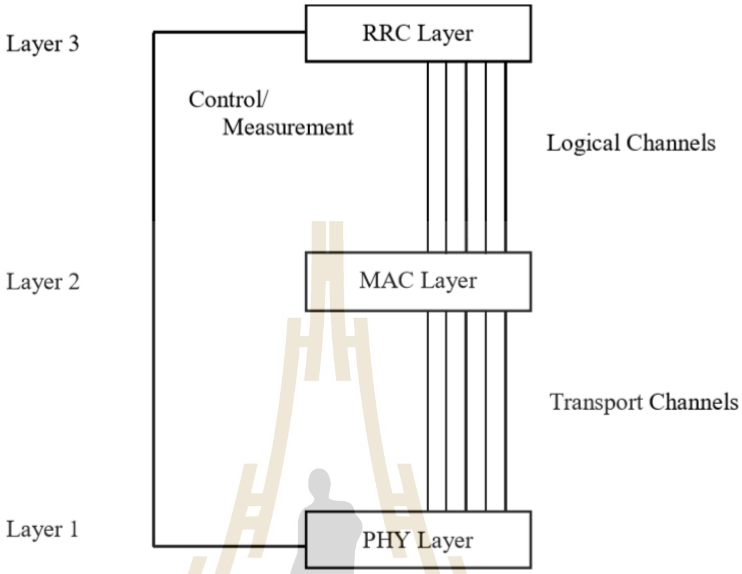


Figure 2.5 LTE protocol stack layers (Capozzi, F., Piro, G., Grieco, L. A., et al., 2013; Sivasubramanian, A., et al., 2017).

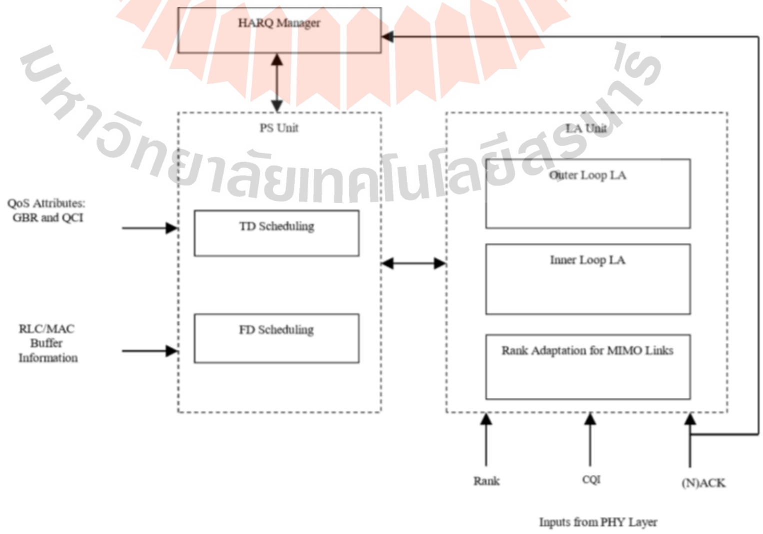


Figure 2.6 MAC layer functionalities (Pedersen, K. I., et al., 2009)

The Uplink Shared Channel (ULSCH) and the Downlink Shared Channel (DLSCH) in shared channel transmission are controlled at the MAC layer by allocating the resources in the uplink direction and downlink direction. To handle the traffic load in uplink and downlink, the switch periodicities of frames are used. Fig. 2.6 presents the interaction between the HARQ and the PS unit to be responsible for retransmissions and scheduling. The downlink scheduling must have the flexibility to manage the HARQ retransmissions in TD and FD. Scheduler to send a new transmission or retransmission must be scheduled within one TTI. LA unit gives the related information to PS unit regarding the supporting AMCS from the selected PRBs from the CQI feedback and the QoS requirement of users in the cell. Block Error Rate (BLER) in the first transmissions based on HARQ acknowledgments from the past transmissions is managed by the outer loop LA. TD scheduling chooses the users to allocate the resource in the next TTI whilst FD scheduling serves PRBs to the selected users at that time. Channel awareness is done by the FD scheduling, and QoS awareness is obtained by TD scheduling. To allocate the PRBs to the selected users, FD scheduling used the frequency selective fading with high channel quality to avoid the users that have deep fades. This operation can achieve 40% improved cell throughput when UE speeds up to 20 to 30 Kilometers per hour (Km/h) because the radio channel status is traceable via the periodic CQI reports from UE. While the user moves at high speed, the eNB cannot correctly detect tracking the channel status due to the CQI report process having delay, and the best performance of scheduling can be achieved by designing and incorporating the PS algorithm in the eNB. Thus, FD scheduling in PS and LA are the important units to optimize the resource allocation in the LTE networks.

Table 2.1 LTE service class (3GPP, TS 23.203, 2015)

QCI	Resource Type	Priority	Packet Delay Budget	Packet Error Loss Rate	Example Services
1	GBR	2	100ms	10^{-2}	Conversational Voice
2	GBR	4	150ms	10^{-3}	Conversational Video (Live Streaming)
3	GBR	3	50ms	10^{-3}	Real Time Gaming, V2X messages
4	GBR	5	300ms	10^{-6}	Non-Conversational Video (Buffered Streaming)
65	GBR	0.7	75ms	10^{-2}	Mission Critical user plane Push To Talk voice (e.g., MCPTT)
66	GBR	2	100ms	10^{-2}	Non-Mission-Critical user plane Push To Talk voice
75	GBR	2.5	50ms	10^{-2}	V2X messages
5	non-GBR	1	100ms	10^{-6}	IMS Signalling
6	non-GBR	6	300ms	10^{-6}	Video (Buffered Streaming) TCP-Based (for example, www, email, chat, ftp, p2p and the like)
7	non-GBR	7	100ms	10^{-3}	Voice, Video (Live Streaming), Interactive Gaming
8	non-GBR	8	300ms	10^{-6}	Video (Buffered Streaming) TCP-Based (for example, www, email, chat, ftp, p2p and the like)
9	non-GBR	9	300ms	10^{-6}	Video (Buffered Streaming) TCP-Based (for example, www, email, chat, ftp, p2p and the like). Typically used as default bearer
69	non-GBR	0.5	60ms	10^{-6}	Mission Critical delay sensitive signalling (e.g., MC-PTT signalling)
70	non-GBR	5.5	200ms	10^{-6}	Mission Critical Data (e.g. example services are the same as QCI 6/8/9)
79	non-GBR	6.5	50ms	10^{-2}	V2X messages

PS unit proceeds by considering the traffic load and the QoS profile consisting of GBR, MBR, Aggregate Maximum Bit Rate (AMBR), Allocation and Retention Priority (ARP), and QoS Class Identifier (QCI) of each data flow. The AMBR is specified for Non-GBR bearers. The ARP uses to primarily determine the prioritization for admission control. The QCI index is the details of QoS attributes, which consist of Packet Delay Budget (PDB) and PLR. The PDB is used to prioritize queues for fulfilling their Head-Of-Line (HOL) packet delay targets. The more details of QCI types are shown in Table 2.1.

Schedulers impose the radio resources regarding the immediate channel quality through the UE reports. Resource allocations work in the TD within one TTI and FD within every RBs. For the downlink management, the radio resources to UE are dynamically allocated from E-UTRAN in each TTI with Cell Radio Network Temporary Identifier (C-RNTI). The dynamic scheduling information in the uplink and downlink is carried by using PDCCH. Each UE scans to detect the PDCCH contents in Downlink Control Information (DCI) associated with C-RNTI to get the implicated information such as transmit power control, index to HARQ process, AMCS, the bitmap for allocation and resource allocation type. Table 2.2 is given the DCI formats. The used TB size is defined from the allocated resources which are combined with AMCS. The CQI report gets from the downlink channel status at the UE by estimating the measured channel quality, which it helps eNB for allocating the appropriate MCS and RB to provide the UE. The data transmission in downlink direction relies on fast LA with AMCS ranging from Quaternary Phase Shift Keying (QPSK) to 64QAM. The equal power in PRBs for a user from the assumption is frequently used for implementation as well as for analytic traceback for radio resource allocation in the downlink direction. Each user is assigned the buffer at eNB. The packet schedulers are considered by the Buffer Status Report (BSR) and priorities in their scheduling decisions as per service types, which must be allocated the resources before their PDB arrived.

From the past, the downlink scheduling algorithms are studied and indicated in terms of throughput, PLR, PD, fairness and spectral efficiency. For throughput, it is considered for RT and NRT services while PLR and PD for RT service and fairness for NRT services, which these re sults are just only the network perspective.

Table 2.2 Downlink Control Information (3GPP, TS 23.203, 2015)

DCI Formats	Purpose	
Uplink Scheduling	0	Scheduling and TPC for PUSCH
	1	Scheduling for PDSCH and TPC for PUSCH
Downlink Scheduling	1A	Compact Scheduling for PDSCH and TPC for PUSCH
	1B	MIMO Compact Scheduling for PDSCH and TPC for PUSCH
	1C	Very Compact Scheduling for PDSCH
	1D	Compact Scheduling for PDSCH with Power Offset and TPC for PUSCH
	2	Closed Loop MIMO Compact Scheduling for PDSCH and TPC for PUSCH
	2A	Open Loop MIMO Compact Scheduling for PDSCH and TPC for PUSCH
Uplink Power Control	3	TPC for PUSCH and PUCCH (2-bits Power Adjustment)
	3A	TPC for PUSCH and PUCCH (1-bit Power Adjustment)

2.4.1 Downlink scheduling procedure

Downlink scheduling is an important section to provide the resource to the UEs in the LTE networks effectively. There are many downlink scheduling algorithms for choosing by the service provider, which is no standard rule. It should be flexibly adjusted according to the changing trends of users and service provider strategic decisions. The resource is allocated to the UE with the defined Sub Channel (SC) beforehand in each TTI for the TD and PRB for the FD. The PRBs are managed with scheduling function at eNB on the MAC layer in every 1 TTI, which each PRB can be only allocated one flow for UE.

Downlink scheduling algorithm aims to increase the throughput, fulfill QoS for users, and provide fairness to users in NRT services. The resource allocation is considered as per the condition of important variables such as channel conditions, HOL packet delay, type of QCI service and so on. For the scheduling decision in each SC, priority metrics of each flow are computed from the defined variable as per scheduling algorithm. The flow with the maximum value in SC is allocated, and the process continues until each SC is fully allocated within one TTI.

HOL packet delay is the waiting time of packets for effective scheduling in the data flow buffer, which it should be less than defined PDB. Thus, the packets with a HOL delay value greater than PDB are discarded from the buffer. When the selected UE sends the data transmission, the number of data bits sent depends on the SINR of UE. Each UE has a different SINR in each SC in one TTI because of the frequency-selective of time-selective fading and multi-path propagation from user movement. When SINR is high value, UE decides high CQI according to the mapping scheme and sent to eNB to choose the high MCS level. As a result, data rates are achieved in a higher downlink direction. In general, UE near eNB tends to have a high CQI whereas the UE at edge cell is usually affected by the lower CQI. However, scheduling in flow with the highest CQI can help up the throughput of networks. The sequence of the downlink scheduling steps in the LTE network is as follows:

1. Creating a list of data flows to determine the time in the current TTI by eNB.

2. Recording CQI report and queue length of MAC in each flow.

3. Calculating the priority metric of each flow according to the downlink scheduling algorithm.

4. Calculating the size of TB for every allocated stream, the amount of data sent and the best AMCS selection (QPSK / 16QAM / 64QAM).

5. Submitting DCI in PDCCH for information about PRBs and AMCS users to UE.

6. Reading PDCCH payload by UE.

For the RT service such as VoIP and video streaming, the flow of these services has the QoS criteria requirements such as latency, average data rate and dateline expiry. On the other hand, the NRT flow does not have the obvious QoS to respond to the user needs. The scheduling algorithm should be considered to guarantee the bounded delay for the RT flow while maintaining data rates for important services in BE traffic.

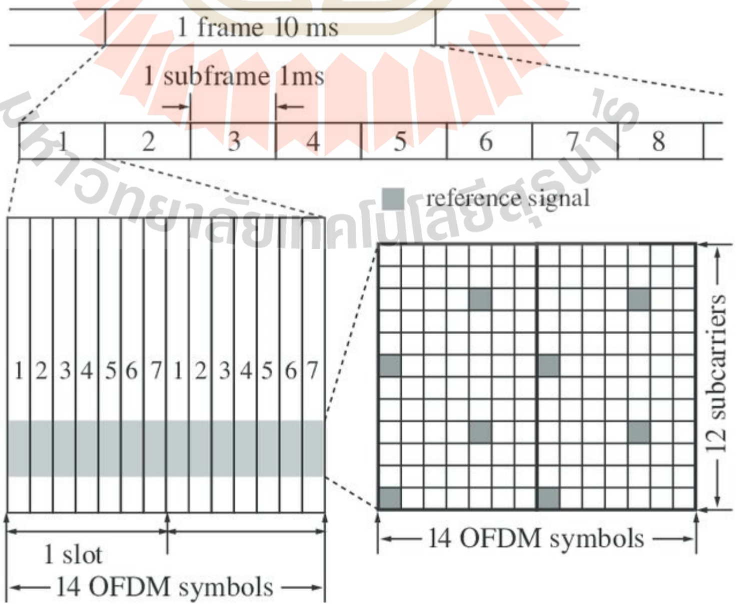


Figure 2.7 LTE frame structure (Wang, Q., et al., 2011).

Scheduling plays an important role in the RRM mechanism used in eNBs for allocating radio resources to UEs. The resource allocation is divided into TD and FD, in which TD is divided into radio frames, where 1 radio frame is equal to 10 subframes or 10 TTIs taking 10 ms, and each subframe has one TTI or 1 ms. One TTI consist of 2 slots and each slot consists of 7 OFDM symbols (normal) or 6 OFDM symbols (extended) as shown in Fig. 2.7. For the FD, it is divided into RB, which each bandwidth has 180 kHz, which is 1 SC, and each SC consists of 12 subcarriers, in which each subcarrier is equal to 15 kHz. To allocate radio resources to each flow, the allocated UE with the highest priority metric calculated in each SC from the downlink scheduling algorithm is shown in Fi g. 2.8.

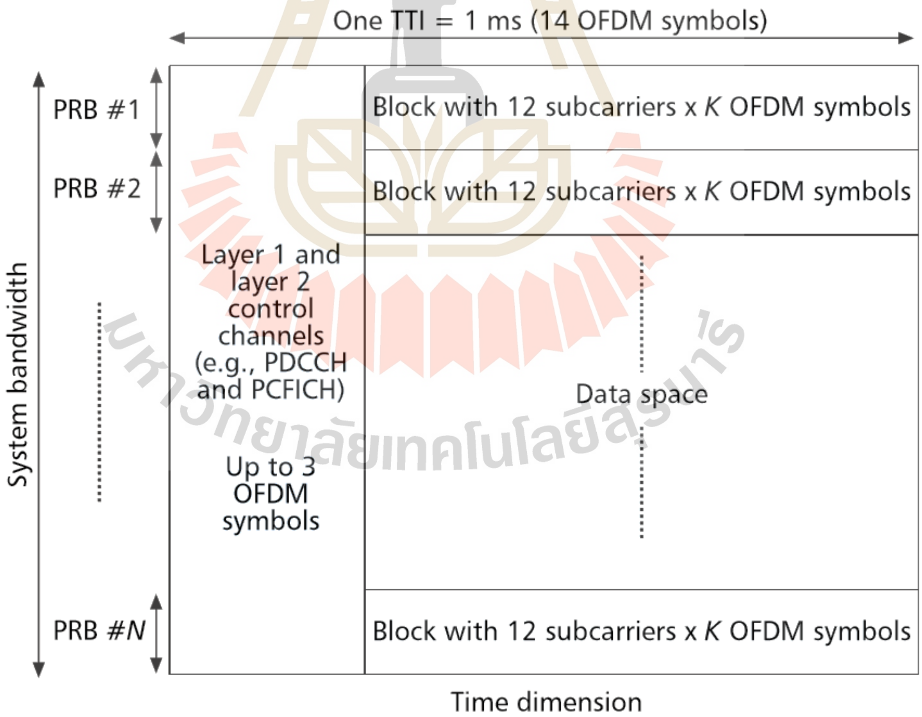


Figure 2.8 Downlink physical layer resource space for one TTI (Pedersen, K. I., et al., 2009).

2.5 Self-optimization concept

When the number of users and devices will be connected to a lot of mobile networks in the future, so it causes complex network management to respond to user needs. Whereas, multiple services have distinctly different needs including the need for high capacity, low latency, low loss, high mobility and good network reliability. For example, the Voice over LTE (VoLTE) service requires high latency-sensitive and high availability, but it does not require band width intense as shown in Fig. 2.9.

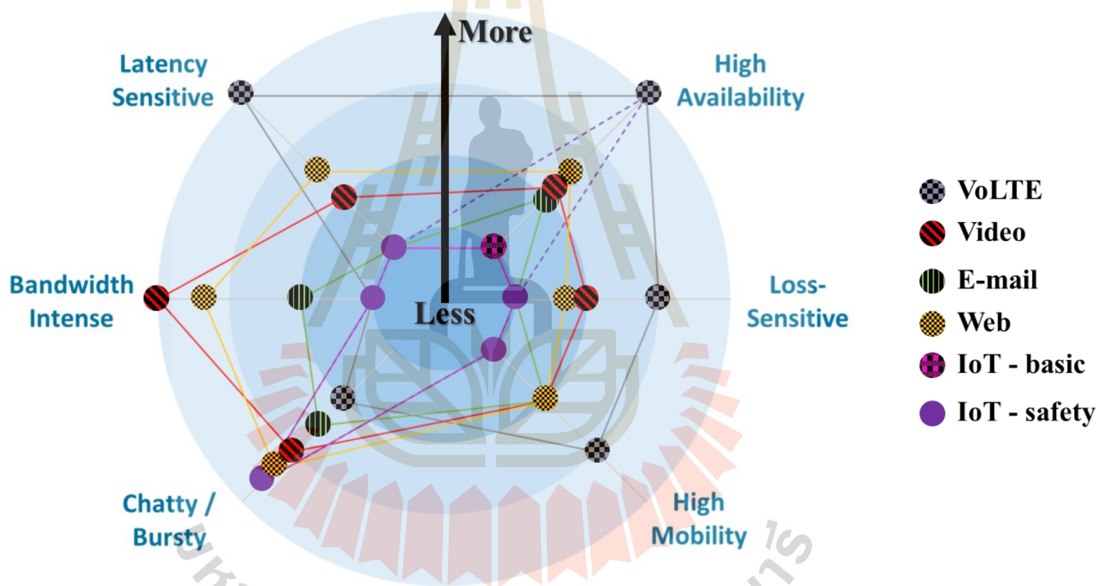


Figure 2.9 Characteristic requirement of multimedia services (Accedian, White Paper, 2016)

In the next mobile networks, network managements have a design concept that is automated and can increase efficiency by itself using three systems consisting of the nervous system, decision making and responsive control as shown in Fig. 2.10. When the nervous system is QoE awareness just like human senses, decision making is quickly data analysis, which is responsible for analytical thinking like the brain, and responsive control is the response to the network like human muscles.

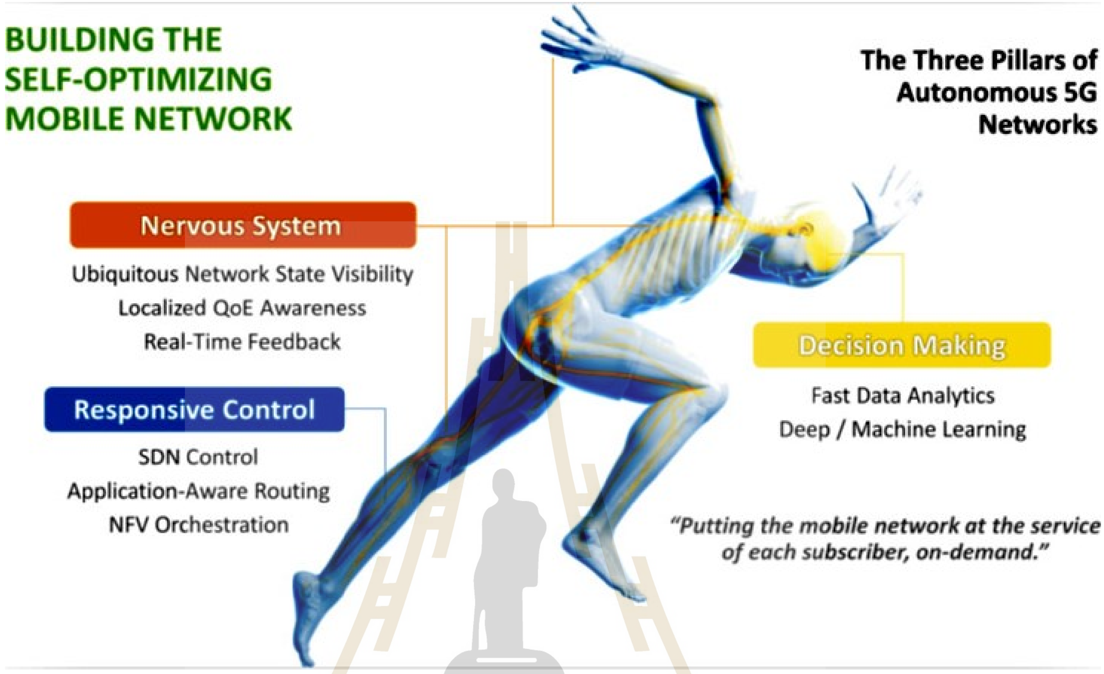


Figure 2.10 Concept of self-optimizing QoE (Accedian, White Paper, 2016)

MNOs need to reduce Capital Expenditure (CAPEX) and Operating Expenses (OPEX) while users need to access high-quality networks. Self-optimizing QoE is an important concept that can improve network performance in the future from the mechanism to automatically adjust parameters in the network with learning and adjusting using reliable methods. The method of Machine Learning (ML) is effective and is used in the context of self-optimizing. ML is a method that is flexible and can be used to solve problems effectively, in which it has been used to solve problems in a large amount of research (Valente Klaine, P., Imran, M. A., et al., 2017). However, Self-optimizing QoE must have two main components consisting of QoE-aware and network optimization.

2.5.1 QoE-aware

QoE awareness is leaning the relationship between the initial variable and the dependent variable in order to create an objective function for QoE perception by using parameters that can be measured from the system to predict the QoE score.

2.5.2 Network optimization

Network optimization with the self-optimization concept is an automatic operation to find the optimal parameters for increasing the QoE within the network.

2.6 Related work for radio resource allocation techniques

For the radio resource allocation in the LTE networks, there is research that offers various techniques used to allocate radio resources such as Channel-aware, QoS-aware and QoE-aware. For the Channel-aware technique, it is designed to provide only the throughput among many users without consideration of the QoS requirements. Thus, Channel-aware algorithms are unsuitable for RT traffic because some service needs to guarantee delay to protect the communication interruption. While the QoS-aware technique is suitable for RT and NRT traffics, but these algorithms are just a resource allocation from the network-centric perspective, which cannot access user satisfaction to indicate network success. When considering resource allocation techniques in different forms, Ph.D. candidate has found that QoE-aware resource allocation in terms of user-centric perspective, which is more important than any previous technique due to QoE is an indicator of entrepreneur success. Previous QoE-aware techniques mainly focus on MNOs to maximize the QoE of system overview.

However, User and MNO must receive mutual benefits by considering the allocation of radio resources to guarantee QoE in each service, which is beneficial to users, and at the same time also considering the radio resource allocation to maximize the QoE of systems under the condition of QoE threshold with limited bandwidth scenario, in which it is beneficial to MNOs. This thesis can be summarized in Table 2.3.

Table 2.3 Comparison of the proposed research for radio resource allocation

Research	**Service**		**Channel-aware**	**QoS-aware**	**QoE-aware**			**Method**
	RT	**NRT**			**Balancing QoE**	**Maximize QoE**	**Threshold QoE**	
Proportional Fair (PF)		✓	✓					
Modified-Largest Weighted Delay (MLWDF)	✓	✓		✓				
Exponential Proportional Fairness (EXP/PF)	✓	✓		✓				
Frame Level Scheduler (FLS)	✓			✓				
Exponential rule (EXP rule)	✓	✓		✓				
Logarithmic rule (LOG rule)	✓	✓		✓				
Self-tuning of scheduling parameters for balancing the quality of experience among services in LTE	✓	✓			✓			Heuristic method
Self-tuning of service priority parameters for optimizing Quality of Experience in LTE	✓	✓				✓		Heuristic method
Content-aware and QoE Optimization of Video Stream Scheduling over LTE Networks using Genetic Algorithm and Random Neural Networks	✓					✓		Heuristic method
Proposed research	✓	✓				✓	✓	Heuristic method

2.7 Summary

According to the above-mentioned content in this chapter, mobile communication systems have been continuously developed toward 5G mobile networks. NR is the new technology in 5G, which is designed to support more devices and respond to the various use cases consisting of eMBB, mMTC, and URLLC, but the existing technology is still important for the MNOs to provide users in the mobile device. The evolution of LTE and NR jointly provide the radio-access solution in NSA mode to be compatible with both technologies in 5G. Meanwhile, LTE technology still plays an important role in the current and future networks, but the increasing users in the next future may cause deficient radio resources to cannot respond to the needs of users due to the limited bandwidth. To maintain existing users and attract users from the user-centric perspective, QoE is an important measure of network performance of MNOs. The concept of resource allocation optimization based on the QoE metric can help network management to respond to users. Besides, Self-optimization concept can help MNOs to reduce CAPEX and OPEX.

From many types of research regarding radio resource allocation, they have been studied extensively to develop advanced methods of managing networks that respond to utilizer needs predicated on QoE. Consequently, this thesis has developed the method of radio resource allocation by self-tuning of service priority factors to multiply the priority metric within a downlink scheduling algorithm for optimizing resource allocation based on QoE metric in mobile networks from the self-optimization concept. Moreover, the QoE guarantee in each service is a challenge that adjusts the appropriate service priority factor by applying the ML in this research. The process of self-optimization in this thesis is described in the next chapter.

CHAPTER III

SYSTEM MODEL AND SELF-OPTIMIZATION

3.1 Introduction

This chapter discusses the system model and self-optimization. In the system model, the scope of the thesis including the different services considered in service models, four important QoS parameters to indicate the network quality, the objective function for OS estimation of each service, six common downlink scheduling algorithm for allocating the radio resource to users and priority service function to use resource allocation. While the self-optimization consists of Artificial Neural Network (ANN) to use the QoE model creation, the proposed Particle Genetic Algorithm (PGA) for optimizing the resource allocation in mobile networks to achieve the purpose of self-tuning techniques in this thesis. Besides, the possibility of the implementation concept is based on a lookup table. Finally, the last section concludes this chapter.

3.2 Service model

This section discusses the three main services with Realtime (RT) and Non-Realtime (NRT) specifically considered in this thesis, which consist of Voice over IP (VoIP), Video and the Best-Effort (BE). Each service is assigned with the different QoS Class Identifier (QCI) to prioritize data flow (Sivasubramanian A., et al., 2017). These services have demonstrated the difference in resource allocation to simultaneously serve the users, which are described as follows.

3.2.1 VoIP service

VoIP service or Internet Protocol (IP) telephony is a conversational RT that is defined by the International Telecommunication Union (ITU) G.729 (Ragot, Stephane, et al., 2007). The standard of G.729 is the narrow-band data compression to minimize the bandwidth requirements and still maintains the voice quality during a conversation to avoid interruption. In this thesis, the defined data source is generated with a packet size of 20 bytes in every 20 milliseconds (ms) accounted for 8 Kbps during the conversation.

3.2.2 Video service

In this thesis, Video service is considered as RT traffic by using the created trace tool from the video test sequence. The “foreman.yuv”, which is the trace file, is used for the packet flow, and it is compressed with the standard of H.264/ Advanced Video Coding (AVC) at the average coding rate of 242 Kbps (Ee Mae Ang, et al., 2015).

3.2.3 BE service

For BE service in this thesis, it is an NRT traffic that is considered as infinite buffer flows as though the user plays the web browser service for simulating access to these different services.

3.3 QoS parameters

QoS parameters are the quantitative information from the network-centric perspective to indicate the network quality. In this thesis, there are four main factors consisting of Throughput (TP), Packet Loss Rate (PLR), Packet Delay (PD) and the

Jitter (JT), which are measured on application level in the networks, these parameters are discussed as follows.

3.3.1 Throughput

The TP is the total throughput measured from the eNodeB (eNB) to User Equipment (UE) in the LTE networks, which is computed from the received successful bits at application level per duration time in Kbps unit. This parameter is based on the resource allocation mechanism within the Media Access Control (MAC) layer and Channel Quality Indicator (CQI) measured by each UE.

3.3.2 Packet Loss Rate

The PLR is the ratio of unsuccessful packet transmission to the total packet transmission in each UE, which is in percentage (%) unit. The good information transmission should be equal to 0 %.

3.3.3 Packet Delay

The PD is the duration time of a successful packet to travel from the eNB in each UE, which is computed in ms unit.

3.3.4 Jitter

The JT is the PD variance. It has a similar measurement unit with PD which is ms unit.

3.4 Objective function for OS estimation

It is a well-known Opinion Score (OS) measured from user satisfaction that is important for the operators to measure the success of network provider. To access user satisfaction, measured QoS parameters from the network are used to predict user satisfaction with the objective function created by mapping the relationship between

QoS and OS. Normally, the OS level is divided into five levels according to ITU-T P.800 consisting of Excellent (5), Good (4), Fair (3), Poor (2) and Bad (1) (ITU-T P.800, 1996). With the limitations on the measurement of the online networks, this thesis only focuses on the simulation of VoIP, Video and BE services to evaluate user satisfaction. Hence, it is necessary to introduce the objective function from the previous research to replace the real evaluator. The objective functions of each service are discussed as follows.

3.4.1 VoIP service

The VoIP service uses very few resources, it needs to send the packets at a continuous interval without the interruption during the conversation. For the objective function of VoIP service, this equation was derived from past research to evaluate mathematical functions using PLR in OS evaluation (Fiedler, M., et al., 2010).

$$OS_{VoIP}=3.010\cdot \exp(-4.473\cdot PLR)+1.065 \tag{3.1}$$

3.4.2 Video service

In the Video service, the author has defined the video trace file for simulation in the system and choose the objective function of the video trace file "foreman.yuv" as determined by the previous research (Nawaz, O., et al., 2017). The OS of video service evaluation from PLR.

$$OS_{Video}=-0.54\cdot \ln(PLR)+3.75 \tag{3.2}$$

3.4.3 BE service

To apply the flexible modeling methodology from my previous research to use in this service, Ph.D. candidate has implemented the datasets with the subjective evaluation method in the real environment from 92 undergraduate students for collecting more 400 datasets. From the result in the web browsing (P. Uthansakul and P. Anchuen, et al, 2020), the response time (rt) in second unit has a high relationship with the measured OS. Thus, the rt and OS are used to estimate the OS in the BE service in this thesis. However, there is the relevant research and defines an objective function to evaluate the satisfaction of accessing the web browser service from the throughput parameter in the simulation scenario under an average web page size of 130 Kbytes (Navarro-Ortiz, J., et al., 2010). When an average web page size in the simulation scenario, it is divided by the response time measured in the real users to compute as the throughput for estimating OS. Thus, the new objective function can be written as Equation 3.3, which is the subjective function to apply in terms of the simulation. Where 1040 is the average web page size in Kbps.

$$OS_{BE} = f_{Sub}\left(\frac{1040}{rt}\right) \qquad 3.3$$

From the literature (Fiedler, M., et al., 2010; Nawaz, O., et al., 2017; Navarro-Ortiz, J., et al., 2010), the objective functions consider only one factor to estimate the OS even if other factors may affect user satisfaction. This thesis uses objective functions 3.1 to 3.3 to predict the OS instead of the real user estimation. However, the objective function from works of literature does not have an exact QoE model for implementing in the network. The QoE model creation should be studied on how to create effective models with the designed methodology from this thesis by analyzing the affected parameter and using ANN to create the new objective function. The information between the QoS and OS obtained by simulation and objective evaluation is collected as the datasets. These datasets are used in the pre-processing process to select the factors for the QoE modelling and used in QoE model creation to create a more efficient objective function. The ANN is a powerful and flexible computational model and could implicitly detect the nonlinear relationships between the dependent and independent variables with a high degree of accuracy. Thus, it is suitable for using to create a new QoE model. Moreover, the QoE modeling of each service in the future needs to analyze the behavior of humans that change over time, so it is very important to use the ANN method for this independent modeling method.

3.5 Downlink Scheduling Algorithms

Scheduling at eNB to allocate the resources of UEs has an important role in the Radio Resource Management (RRM) mechanism, and Ph.D. candidate consider the common downlink scheduling algorithms of the Frequency Domain Packet Scheduler (FDPS) in this thesis as shown in Table 3.1, and the details of each algorithm are discussed as follows.

3.5.1 Proportional Fair

The Proportional Fair (PF) algorithm aims to create a fair balance between the increasing bit rates and to users (Kushner, Harold J., et al., 2004). This algorithm effectively reduces the distinction of user bit rate.

3.5.2 Modified-Largest Weighted Delay First

The Modified-Largest Weighted Delay First (MLWDF) algorithm is developed to increase the efficiency of RT services by considering both the waiting time in queues and the capacity of the channel for each user as per the delay requirements (P. Ameigeiras et al., 2016). In the case of special MLWDF, it is optimized to reduce the delay and allowing users to have more channel capacity. For the NRT service, the priority metric can be calculated by using the same equation as PF.

3.5.3 Exponential/Proportional Fair

The Exponential/Proportional Fair (EXP/PF) algorithm is designed to support the multimedia application and increase the priority of RT services (R.Basukala, et al., 2009). It works by utilizing the characteristics of PF for the NRT services. The RT services require low PD, low PLR and high fairness, and this algorithm provides better performance than the MLWDF and PF.

3.5.4 Frame Level Scheduler

The Frame Level Scheduler (FLS) algorithm is a two-level resource allocation process, and it provides the resources in the form of RBs distribution among different types of traffics as per the load requirements (Piro, Giuseppe, et al., 2011).

3.5.5 Exponential rule

The Exponential (EXP) rule algorithm is a bounded delay scheme, and it is designed to guarantee the RT services (Ang, Ee Mae, et al., 2015). It is modified from the EXP/PF to have a low delay, less PLR and higher fairness.

3.5.6 Logarithm rule

The Logarithm (LOG) rule algorithm is also a bounded delay scheme, and it is designed to balance the QoS metrics (Sadiq, Bilal, Seung Jun Baek, et al., 2013). Also, it also allocates the resources of end users like the EXP rules to increase the data traffic.

Table 3.1 Common downlink scheduling algorithms for OFDM-Based in LTE networks and variable notation

Algorithm	Priority Metric
PF	$w_{ij}=\frac{r_{ij}}{\overline{R}_i}$
MLWDF	$w_{ij}=\alpha_i D_{HOL,i}\frac{r_{ij}}{\overline{R}_i}$; $\alpha_i=-\frac{log(\delta_i)}{\tau_i}$
EXP/PF	$w_{ij}=exp(\frac{\alpha_i D_{HOL,i}\text{-}X}{1+\sqrt{X}})\frac{r_{ij}}{\overline{R}_i}$; $X=\frac{1}{N_{rt}}\sum_{i=1}^{N_{rt}}\alpha_i D_{HOL,i}$
FLS	$w_{ij}=\frac{r_{ij}}{\overline{R}_i}$; $u_i(k)=h_i(k)*q_i(k)$
EXP rule	$w_{ij}=b_i exp(\frac{a_i D_{HOL,i}}{c+\sqrt{\frac{1}{N_{rt}}\sum_{i=1}^{N_{rt}}D_{HOL,i}}})\Gamma_j^i$ where $a_i\epsilon[\frac{5}{0.99\tau_i},\frac{10}{0.99\tau_i}]$, $b_i=1$ and $c=1$ (Capozzi, F., Piro, G., et al., 2013)
LOG rule	$w_{ij}=b_i\,log\,(c+a_i D_{HOL,i})\Gamma_j^i$ where $a_i=\frac{5}{0.99\tau_i}$, $b_i=1$ and $c=1.1$ (Capozzi, F., Piro, G., et al., 2013)

Description of Symbol

i, j, k: i^{th} user on j^{th} subchannel of the k^{th} service
r_{ij}: The throughput achieved for i^{th} user on j^{th} subchannel
$\overline{R}_i$: The average throughput achieved on i^{th} user
w_{ij}: The priority metric for i^{th} user on j^{th} subchannel
$D_{HOL,i}$: The Head of Line (HOL) delay for i^{th} user
α_i: The factor computed from QoS for i^{th} user
δ_i: The acceptable Packet Loss Rate for i^{th} user (from QCI)
τ_i: The Delay threshold for i^{th} user (from QCI)
N_{rt}: The number of active Realtime flows
$*$: The discrete time convolution operator
$h_i(k)$: The impulse response of Linear Time Invariant (LTI) filter
$q_i(k)$: The signal in queue level for filtering
Γ_j^i: The spectral efficiency for i^{th} user on j^{th} subchannel
a_i, b_i,c: The tunable parameters

3.6 Priority Service Function

This function is used to allocate the radio resource based on QoE-aware for maximizing the QoE having the limited bandwidth, and it can be calculated as:

$$pri_k = exp(pr_k) \qquad 3.4$$

when pr_k is a service priority factor of the k^{th} service. Thus, the new priority metric of the downlink scheduling algorithm is computed by the priority metric multiplying with the priority service function. This new priority metric can be calculated as:

$$F_{ijk} = w_{ij} \cdot pri_k \tag{3.5}$$

where F_{ijk} is a new priority metric for the i^{th} user on the j^{th} subchannel of k^{th} service.

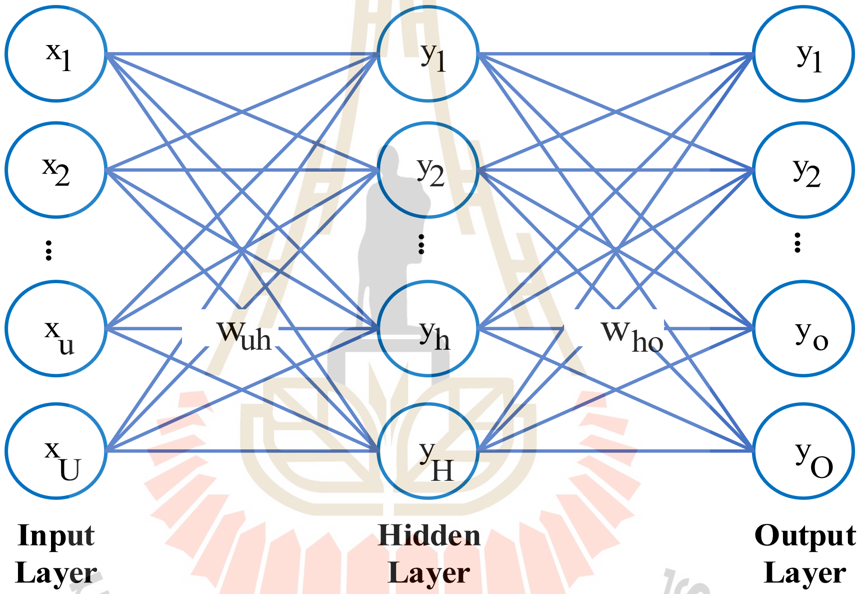


Figure 3.1 The structure of Artificial Neural Network (Uthansakul P., Anchuen P., et al, 2020)

3.7 ANN overview

The ANN is mathematical models for data processing with connectionism that has the parallelization of the sub-processing unit. It consists of many nodes which is like nerve cells in the human brain (Shanmuganathan, et al., 2016). The ANN structure has three main layers consisting of input layer, hidden layer, and output layer. Each layer consists of many nodes for processing to send information to other nodes as shown in Fig. 3.1. The input nodes receive data normalized to send to the hidden nodes, and the hidden nodes at between the input layer and output layer calculate the result in each node to send to the output nodes in the output layer. The output nodes evaluate the results of output in the ANN. These nodes are connected in a Multi-Layer Perceptron (MLP) for calculating the value of output node (F.S. Panchai, et al., 2014). This research uses the Feed Forward Back Propagation (FFBP) ANN to compute the gradient for the calculation of appropriate weight and threshold coefficients for ANN is a supervised learning algorithm. The ANN process is discussed as follows.

3.7.1 Pre-processing

This process is designed to analyze the relationship between QoS parameter and OS and to select the importance QoS parameter as per the condition of calculated coefficient between both variables. The selected QoS and OS are used to create the QoE model using the collected datasets. While the QoS parameters from the LTE simulation are shown in Table 3.2, the OS of each service is computed by entering the measured QoS parameter to the objective function of VoIP, Video and BE with the Equation 3.1, Equation 3.2 and Equation 3.3, respectively. The datasets consisting of QoS and OS are used to compute the correlation coefficients (r) that can be calculated as per Equation 3.6. However, the absolute correlation coefficients must be more than 0.20 for the selected QoS to use for creating the QoE model.

$$r=\frac{\sum_{n=1}^{N}(OS_n-\overline{OS})(QoS_n-\overline{QoS})}{\sqrt{\sum_{n=1}^{N}(OS_n-\overline{OS})^2}\sqrt{\sum_{n=1}^{N}(QoS_n-\overline{QoS})^2}} \quad 3.6$$

r is the Pearson correlation coefficients, n is the n^{th} dataset and N is the total amount of collected datasets. In addition, OS is the opinion score, $\overline{OS}$ is the average opinion score, $\overline{QoS}$ is the average QoS, and QoS_n is the QoS at n^{th} dataset. When value of r is computed as negative and positive values which are the relationship between the variables in the reverse and same direction respectively. Whereas, r comes out to be 0 which is no relationship of variable.

Table 3.2 The QoS parameters of services from the LTE simulation tool

VoIP	Video	BE
TP_{VoIP}	TP_{Video}	TP_{BE}
PLR_{VoIP}	PLR_{Video}	PLR_{BE}
DL_{VoIP}	DL_{Video}	DL_{BE}
JT_{VoIP}	JT_{Video}	JT_{BE}

After the QoS parameters are selected to create the QoE model, the QoS and OS are transformed into the appropriate data for the ANN process to use them in the learning process, and the input value (x_u) and target value can be written as:

$$c_u = \frac{\sum_{n=1}^{N} |OS_n \cdot QoS_{u,n}|}{\sum_{n=1}^{N} QoS_{u,n}^2} \quad 3.7$$

$$x_u = c_u \cdot QoS_u \quad 3.8$$

$$OS_{target} = \frac{4 \cdot (OS - OS_{min})}{OS_{max} - OS_{min}} + 1 \quad 3.9$$

Where u is the u^{th} selected QoS, c_u is a normalizing coefficient, QoS_u is the u^{th} QoS and x_u is the normalized input data of ANN. OS_{target} is the targeted opinion score in ANN process.

3.7.2 QoE model creation

The datasets consisting of QoS and OS are normalized and used to be input and target of ANN process for creating the objective function. The performance of created QoE model with the ANN process depends on the correlation coefficient between the QoS and OS, the hidden nodes depending on the variance data and the number of hidden layers. However, the number of hidden layers should be set as one layer to reduce the complexity of ANN and suitable for the prediction model. The input node is equal to the number of selected QoS parameters from the pre-processing process, and the hidden node is set as three nodes as per Try and Error method (F.S. Panchai and M. Panchal, 2014) whereas the output node is set as one node. Within the ANN equation, the link weights and thresholds are shown by using the variable symbols as w_{uh}, w_{ho}, θ_h and θ_o, and the values of these variables are used to define the objective function for evaluating the QoE score. In the operation of ANN, the result of each node is calculated by using the sigmoid function, which is the activation function, to output for adjusting the link weights and thresholds. The output of each node can compute as per sigmoid function:

$$S(Z) = \frac{1}{1+e^{-Z}} \qquad 3.10$$

where $S(Z)$ is the outpu t value of Z and e is mathematical constant as 2.71828.

The initial value of link weights and thresholds are set with random value from domain of the differential activation function from formulation of range value when the range of differential sigmoid function exists from 0 to 0.25. In this thesis, setting the learning rate in ANN process depends on during the range of differential sigmoid function. The steps of ANN learning are specified as follows.

Table 3.3 The variable ANN algorithm

Symbol	Description
p	The sequence of dataset
P	The total amount of datasets
U	The number of input nodes
H	The number of hidden nodes
O	The number of output nodes
u	The sequence of input nodes
h	The sequence of hidden nodes
o	The sequence of output nodes
$x_u(p)$	The value of input layer at the u^{th} input node
$y_h(p)$	The value of hidden layer at the h^{th} hidden node
$y_o(p)$	The value of output layer at the o^{th} output node
$w_{uh}(p)$	The link weight of input layer to hidden layer
$w_{ho}(p)$	The link weight of hidden layer to output layer
$\theta_h(p)$	The threshold of hidden layer at the h^{th} hidden node
$\theta_o(p)$	The threshold of output layer at the o^{th} output node
$e_o(p)$	The error value of output layer at the o^{th} output node
$t_o(p)$	The target value of output layer at the o^{th} output node
$\delta_h(p)$	The gradient error of hidden layer at the h^{th} hidden node
$\delta_o(p)$	The gradient error of output layer at the o^{th} output node
$\propto$	The learning rate
$w_{uh}(p+1)$	The new link weight of input layer to hidden layer
$w_{ho}(p+1)$	The new link weight of hidden layer to output layer
$\theta_h(p+1)$	The new threshold of hidden layer at the h^{th} hidden node
$\theta_o(p+1)$	The new threshold of output layer at the o^{th} output node
SSE	The sum of square error

First step, the initialization of learning rate, link weights and thresholds are random by using the differential activation function. While the output node has only one node, the OS is normalized in the range from 0 to 1 to be the target for learning process. The target value in the output node (t_o) can be written as:

$$t_o(p) = 0.2 \cdot OS_{target} \quad 3.11$$

Second step, this step is the activation process to predict the output of node by using the sigmoid function with the help of the following under equations when Table 3.3 notices the variable ANN algorithm in the equations 3.12 to 3.21.

$$y_h(p) = S(\sum_{u=1}^{U} x_u(p) \times w_{uh}(p) - \theta_h(p)) \quad 3.12$$

$$y_o(p) = S(\sum_{h=1}^{H} y_h(p) \times w_{ho}(p) - \theta_o(p)) \quad 3.13$$

Third step, the link weights and thresholds are adjusted as the new link weights and new thresholds in FFBP-ANN. The $x_u(p)$ is used to predict the $y_o(p)$ in (12) and (13). The error $e_o(p)$ can be evaluated by comparing the $t_o(p)$ and $y_o(p)$:

$$e_o(p) = t_o(p) - y_o(p) \quad 3.14$$

Therefore, $y_o(p)$ and $e_o(p)$ are used to compute the gradient error of output nodes:

$$\delta_o(p) = [1 - y_o(p)] \cdot y_o(p) \cdot e_o(p) \quad 3.15$$

The new link thresholds and weights can be computed as:

$$w_{ho}(p+1) = \alpha \cdot y_h(p) \cdot \delta_o(p) + w_{ho}(p) \quad 3.16$$

$$\theta_o(p+1) = -\alpha \cdot \delta_o(p) + \theta_o(p) \quad 3.17$$

We set the α to 0.25, and the gradient error of the hidden layer nodes can be calculated as:

$$\delta_h(p) = [1 - y_h(p)] \cdot y_h(p) \cdot \delta_o(p) \times w_{ho}(p) \qquad 3.18$$

Similarly, the new thresholds and link weights can be computed as:

$$w_{uh}(p+1) = \alpha \cdot x_u(p) \cdot \delta_h(p) + w_{uh}(p) \qquad 3.19$$

$$\theta_h(p+1) = -\alpha \cdot \delta_h(p) + \theta_h(p) \qquad 3.20$$

After that, the sequence of dataset is increased by one and the next dataset is entered into the equations 3.12 in the second step to operate to 3.20, and this process will continue until the value of p becomes equal to the total amount of information.

The *SSE* is computed by using the $e_o(p)$ with the help of Equation 3.21, and this process will continue until the *SSE* value becomes acceptable by getting equal to 0.00001.

$$SSE = \sum_{p=1}^{P} \sum_{o=1}^{1} e_k(p)^2 \qquad 3.21$$

The values of w_{uh}, w_{ho}, θ_h and θ_o will be updated when the *SSE* gets acceptable in the process of QoE creation.

In the next step, it is testing the ANN model to measure the efficiency of the model. The QoS parameters are entered in Equation 3.12 to Equation 3.13. To estimate the QoE score, the output node is multiplied by 5 for estimating the QoE score that exists from 1 to 5 as per ITU-T P.800 as Equation 3.22.

$$QoE = 5 \cdot y_o \tag{3.22}$$

The performance of QoE model is calculated by the Correlation Model (CM) from the OS and QoE of datasets:

$$CM = \frac{\sum_{p=1}^{P}(QoE_p - \overline{QoE})(OS_p - \overline{OS})}{\sqrt{\sum_{p=1}^{P}(QoE_p - \overline{QoE})^2}\sqrt{\sum_{p=1}^{P}(OS_p - \overline{OS})^2}} \tag{3.23}$$

Where QoE is the estimated QoE score, the CM is the correlation coefficient between the QoE_p and OS_p. Furthermore, $\overline{OS}$ is the average opinion score, OS_p is the p^{th} opinion score, $\overline{QoE}$ is the average of p^{th} QoE score, and QoE_p is the p^{th} QoE score.

Table 3.4 Determining the model reliability levels with respect to the correlation model

Model Reliability	Correlation Model
Very weak	0.01 - 0.20
Weak	0.21 - 0.40
Moderate	0.41 - 0.60
Strong	0.61 - 0.80
Very strong	0.81 - 1.00

The CM value is interpreted with respect to five different reliability levels as per the Evant (J.D. Evans, 1996) as can be seen in Table 3.4. The function of QoE score estimation can be written as:

$$QoE = f(QoS) \tag{3.24}$$

Where QoS is the selected Quality of Service to estimate the QoE, it is multiplied by the normalizing coefficient to operate with Equation (3.12) and Equation (3.13) from the link weights and thresholds of QoE model that are received from the ANN method. Whereupon, the result is fed into Equation (3.22) to predict the QoE score.

3.8 Proposed PGA algorithm

The proposed PGA algorithm is the hybrid approach combining the advantages of Particle Swarm Optimization (PSO) (Kennedy J. and Eberthart R., 1995) and Genetic Algorithm (GA) (David E. Goldberg, 1989) which are applied to be suitable for use in finding the answer in this research. Likewise, a hybrid approach was presented in 2001 (Løvbjerg, Morten, et al., 2001), where this approach is used to effectively solve the problems. Besides, this concept of the hybrid approach is also utilized to predict the parameters for a full power quality disturbance parameterized model (Rodriguez-Guerrero, Marco Antonio, et al., 2018). The feature of PSO can reduce the GA limitation in local search to increase the accuracy and speed. However, the exploitation of PSO to find the answer does not guarantee the optimal answer since there are some events that the initial all particles are randomized near the position of the local optimum. As a result, the answer obtained by using PSO may not be the global optimum. Besides, the PSO cannot always be used to guarantee a global optimum, but it can be applied to increase the possibility of global optimum (Pandi, V. R., Panigrahi, B. K., et al., 2011; Feng, P., Xiao-Ting, et al., 2013).Thus, the advantage of GA with exploration, which can increase the chances of finding the optimal answer in search space, is jointly applied among PSO and GA to effectively find the optimal answer on PGA algorithm. The PGA process consist of population selection, crossover, and mutation like the GA algorithm, and the position and velocity are changed like the PSO algorithm. The list of the selected population into the new generation does not only be crossover and mutation in the GA process but also moves the position and velocity in local search like the PSO process. When the local search in this thesis, it is defined that the search space is bounded in the particle swarm, which is exploitation more than exploration. After the mutation process in GA is completed, the chromosome in GA is converted to the particle for PSO process by transformation operation, which particles are converted from chromosome, to operate in the PSO process. After that, the most suitable populations are selected for the next generation. Fig. 3.2 represents the proposed PGA processes, and each process of PGA is summarized as follows:

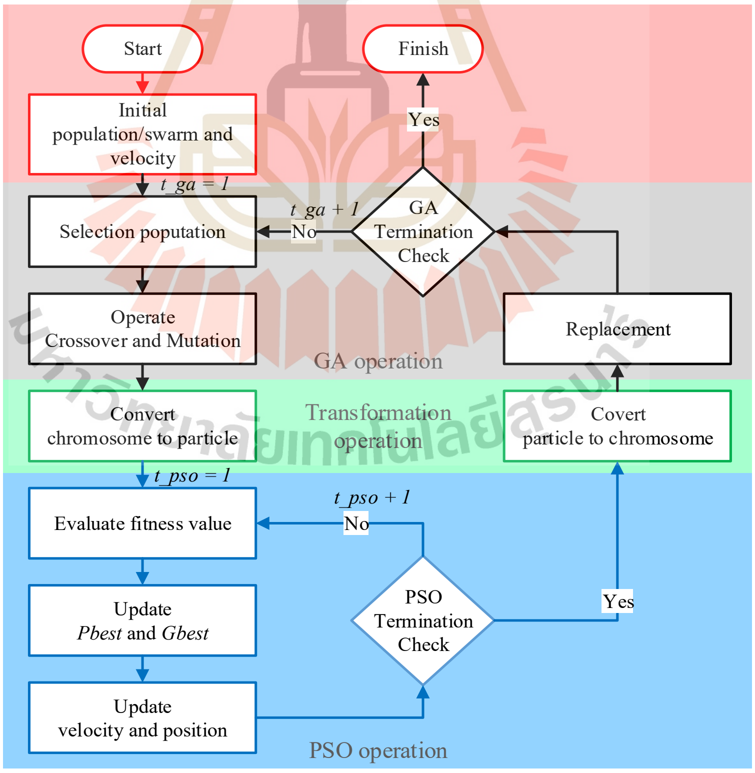


Figure 3.2 The proposed PGA processes (Uthansakul P., Anchuen P., et al, 2020)

3.8.1 Initial population and velocity

In the first process of PGA, the initial population in the GA algorithm and the swarm in the PSO algorithm are the same process for the initial member group to find the answer. The population is randomized from the search space to be the initial population by using Equation 3.25. Within the population consists of many chromosomes, each chromosome consists of many genes, and each gene is the service priority factor of each service. When the service priority factor is the parameter used to optimize the radio resource allocation in LTE networks for this thesis. Likewise, the population is the swarm, and the particle in the PSO algorithm is similar to the chromosome in the GA algorithm. The swarm consists of many particles and each particle is the service priority factor as the same as the gene in the GA algorithm. Besides, the additional process must random the velocity of the particle that is seen as a chromosome by using Equation 3.26.

$$P_{old} = R_p(N) \tag{3.25}$$

$$V = R_v(N) \tag{3.26}$$

where P_{old} is the old population, $R_p(N)$ is the random population function with N chromosomes. Each chromosome is contained with the gene information ($Chromosome = \{gene_1, gene_2, \ldots, gene_D\}$), and D is the dimension number. N is the chromosome number in each generation (t_ga). V is the particle velocity, and $R_v(N)$ is the random velocity function with N particles. The randomization process of P_{old} and V are shown in Fig. 3.3.

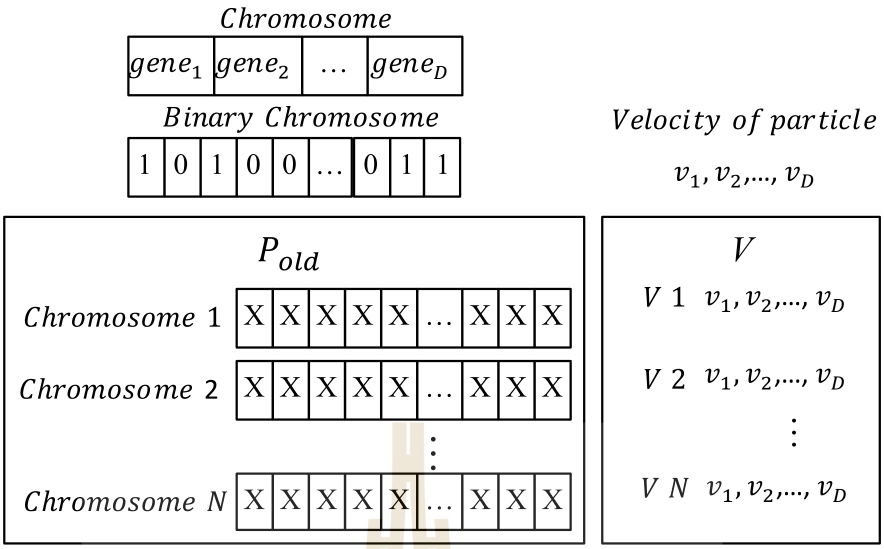


Figure 3.3 Initial population and velocity (Uthansakul P., Anchuen P., et al, 2020)

3.8.2 Selection population

In the selection population process in the GA operation, the old population from the previous processes is proceeded to choose the appropriate population to be the new population in the next generation by using the combined rank method, which is the combination of fitness rank and diversity rank to deeply search in a narrow range for the optimal results. The selection function chooses the new population with the help of combined rank method until the number of chromosomes becomes equal to N as per Equation 3.27.

$$P_{new} = f_s(P_{old}) \tag{3.27}$$

where P_{new} is the new population, and $f_s(P_{old})$ is the selection function from P_{old}. This process is shown in Fig. 3.4.

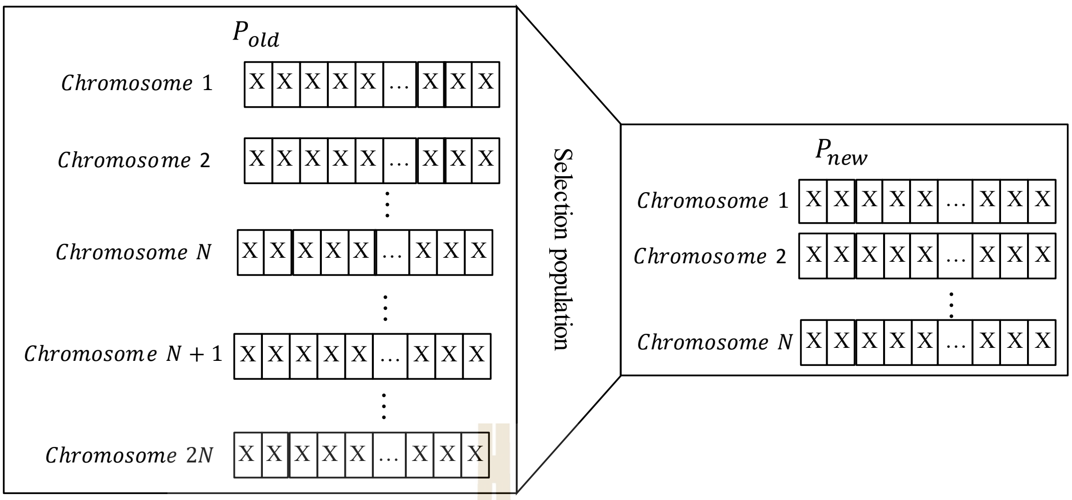


Figure 3.4 Selection population (Uthansakul P., Anchuen P., et al, 2020)

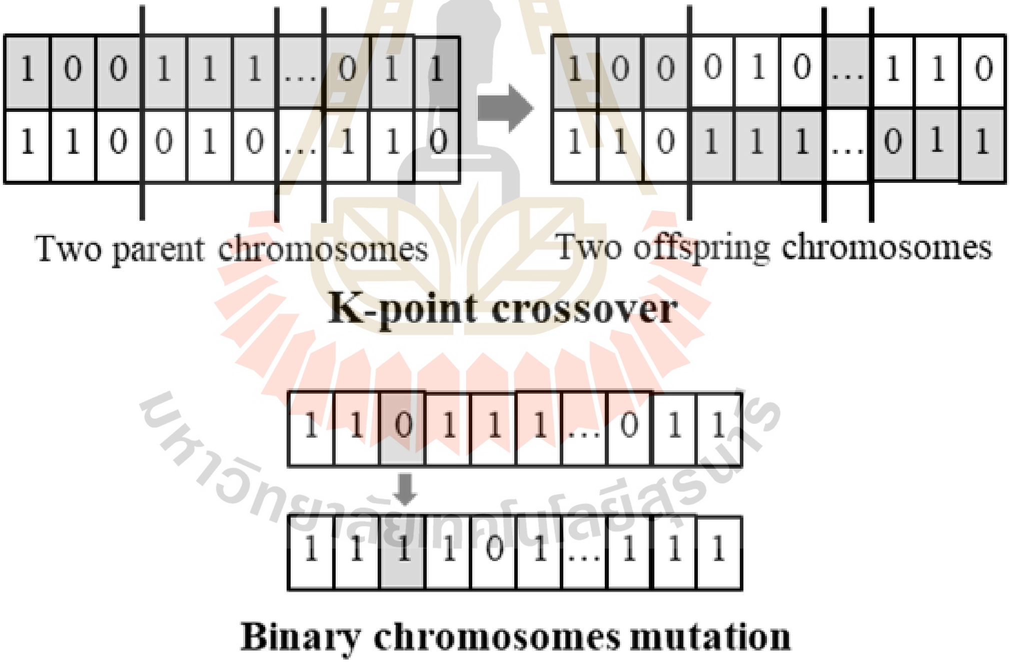


Figure 3.5 Crossover and Mutation (Uthansakul P., Anchuen P., et al, 2020)

3.8.3 Operate crossover and mutation

The processes of crossover and mutation in the GA operation are shown in Fig. 3.5. The crossover process is the transfer of internal genes among the chromosomes to create a new genetic feature that is different from the original. The crossover process has many methods such as single-point crossover, two-point crossover and multiple-point crossover (Z. Michalewicz, 1992). The new population from the previous process and crossover probability (p_c) executes the crossover function (f_c) and updates the P_{new} using Equation 3.28.

$$P_{new}=f_c(P_{new},p_c) \qquad 3.28$$

Whereupon, the P_{new} is led to the next process. The mutation process is changing in genes within the chromosome to generate the new genetic features that are slightly different from the original with the mutation probability (p_m) by using Equation 3.29.

$$P_{new}=f_m(P_{new},p_c) \qquad 3.29$$

3.8.4 Convert chromosome to particle

To perform the GA operation toward the PSO operation, the chromosome is changed into the particle in transformation operation. When each particle including the position and velocity of dimension, each gene in the chromosome is the position in each dimension. The position and velocity in each dimension are included as particle. The transformation of the chromosomes into the particle can be written Equation 3.30.

$$[X,V]=f_{cp}(Chromosome,\ V) \qquad 3.3$$

where X is the particle position, which is the service priority factor, and f_{cp} is the function to convert the chromosome to the particle as shown in Fig. 3.6.

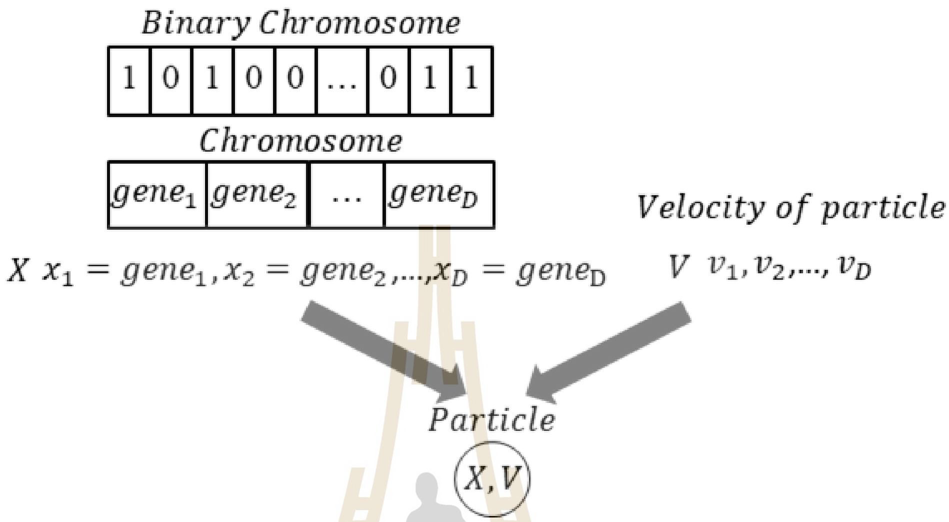


Figure 3.6 Conversion from chromosome to particle (Uthansakul P., Anchuen P., et al, 2020)

3.8.5 Evaluate fitness value

To evaluate the fitness value of particle in this process, the objective function is used to compute the fitness value that can be calculated as:

$$F(X) = f_o(X) \tag{3.31}$$

where $F(X)$ is the fitness value of X and f_o is the objective function.

3.8.6 Update Pbest and Gbest

The particle position with the highest fitness value from the swarm in the current cycle and all cycles are updated as $Pbest$ and $Gbest$, respectively.These operations are calculated by using the following equations:

$$If\ F(X_{kD}) > F(Pbest)\ THEN$$

$$Pbest_D = X_{kD}\ ENDIF \tag{3.32}$$

$$If\ F(X_{kd}) > F(Gbest)\ THEN$$

$$Gbest_D = X_{kD}\ ENDIF \tag{3.33}$$

where $Pbest$ is the position where the particle has the highest objective value in the current cycle i.e. $Pbest_D = \{Pbest_1, Pbest_2, \ldots, Pbest_D\}$, and $Gbest$ is the position where the particle has the highest objective value in all the cycles i.e. $Gbest_D = \{Gbest_1, Gbest_2, \ldots, Gbest_D\}$. The $X_{kD}(t) = \{x_{k1}(t), x_{k2}(t), \ldots, x_{kd}(t), x_{kD}(t)\}$ where D is the dimension number, d is the sequence of dimensions, k is the sequence of particles and t is the sequence of cycles (*t_pso*).

3.8.7 Update velocity and position

The velocity and position of each particle in the next cycle are updated and can be calculated by using the following equations:

$$\begin{aligned} v_{kd}(t+1) = {} & w(t)v_{kd}(t) \\ & + c_p u_p\left(Pbest_d - x_{kd}(t)\right) \\ & + c_g u_g(Gbest_d - x_{kd}(t)) \end{aligned}$$

$$v_{kd}(t+1) = \begin{cases} v_{min}\ if\, v_{kd}(t+1) \le v_{min} \\ v_{max}\ if\, v_{kd}(t+1) \ge v_{max} \end{cases} \tag{3.34}$$

$$x_{kd}(t+1) = x_{kd}(t) + \alpha v_{kd}(t+1)$$

$$x_{kd}(t+1) = \begin{cases} x_{min}\ if\, x_{kd}(t+1) \le x_{min} \\ x_{max}\ if\, x_{kd}(t+1) \ge x_{max} \end{cases} \tag{3.35}$$

where v_{kd} and x_{kd} are the velocity and position of a k^{th} particle in the d^{th} dimension. $Pbest_d$ and $Gbest_d$ are the positions where the particle has the highest objective value in the current cycle and all cycles at the d^{th} dimension, respectively. w and α are the weight values to determine the distance for changing the velocity and the position. The c_p and c_g are the acceleration constant of personal best position and the global best position, respectively. The u_p and u_g are the constants for the searching of personal best position and global best position, respectively.

3.8.8 PSO termination check

To terminate the PSO operation, there are three conditions for the PSO termination check. The first condition considers when the $F(X_{kD})$ has a higher than the desired answer, it will terminate in the PSO operation and proceed to the next process. The second condition considers when the number of search cycles exceeds the set value, it will terminate working. The last condition considers when all particles in a swarm have the same X value, it will terminate working. The PSO termination check can choose only one condition to terminate in the PSO operation, in which each condition have different performance. However, this thesis chooses the second condition to aim the quick and effective working in PSO operation.

3.8.9 Convert particle to chromosome

When the PSO operation is terminated with some condition, the particle is converted to the chromosome by separating the position of particle to gene and the velocity of particle to use in the next generation in the PGA algorithm. The change from particle to chromosome is preceded by using Equation 3.36.

$$[Chromosome, V] = f_{pc}(X, V) \qquad 3.36$$

where f_{pc} is the function in order to convert the particle to chromosome.

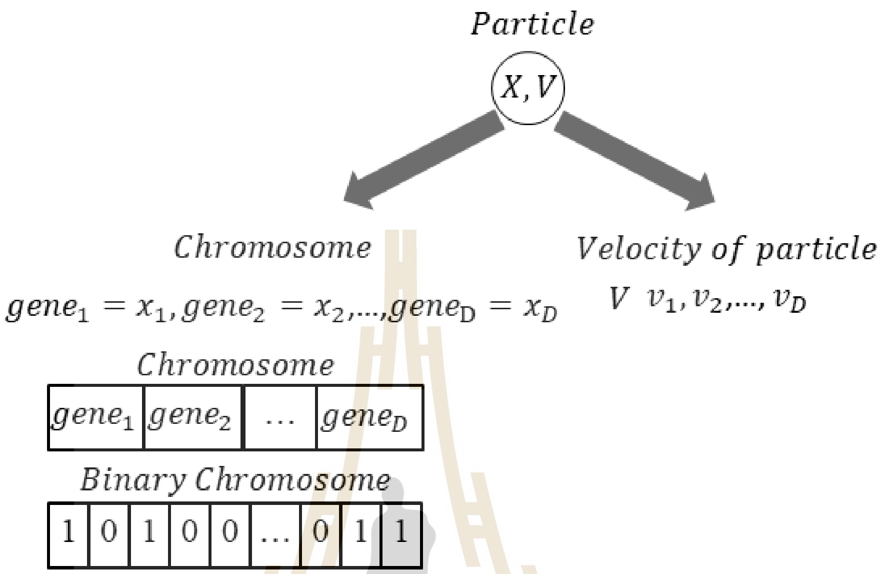


Figure 3.7 Conversion from particle to chromosome (Uthansakul P., Anchuen P., et al, 2020)

3.8.10 Replacement

In this process, the new population is replaced with the appropriate value for the next generation by using the following equation:

$$P_{old} = f_r\ (P_{old}, P_{new}) \qquad 3.37$$

where f_r is the function of population replacement.

3.8.11 GA termination check

To terminate the GA operation in PGA algorithm, the GA termination check has two conditions. The first condition considers when the results better or equal to the desired answer, it will stop finding the answer. The second condition considers when the number of search generation exceeds the set value, it will stop finding the answer.

The operation to find the answer of optimal parameter by using PGA algorithm can be written as Equation 3.38.

$$[X, N_{used}] = f_p(pr_k, \varphi) \tag{3.38}$$

where X is the answers of optimal parameter, and N_{used} is the number of used members in the search space to find the answer with the φ, which is PGA algorithm in this part. The ANN model is used to calculate the QoE in the process function (f_p), which it is explained in chapter IV. The integration of the ANN and PGA in the proposed system can be seen in Fig. 3.8.

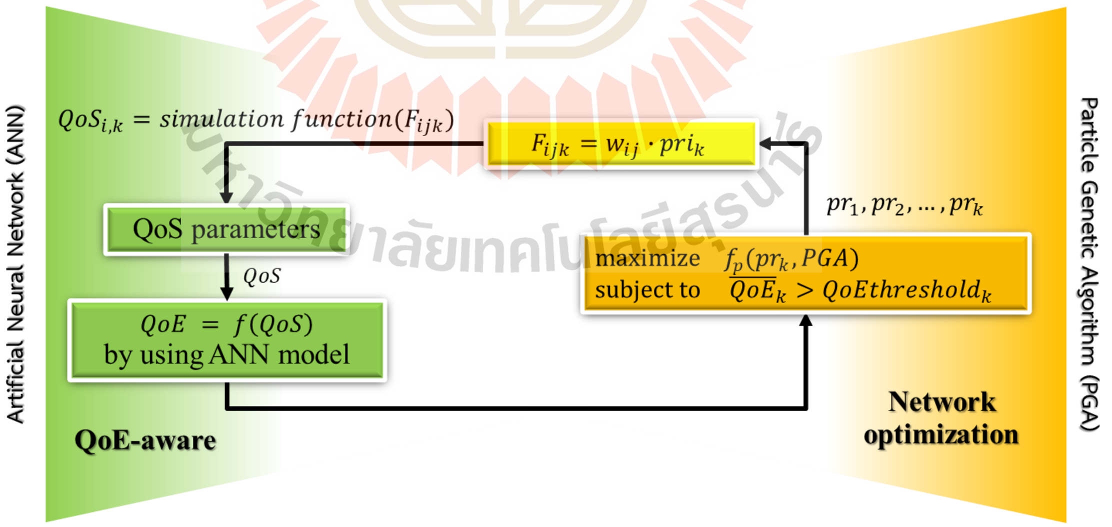


Figure 3.8 The integration of ANN and PGA in the proposed system (Uthansakul P., Anchuen P., et al, 2020)

3.9 Possibility of implementation concept

When the Orthogonal Frequency-Division Multiple Access (OFDMA) technology is used for downlink to data transmission from eNB to UEs, the radio resources are divided into Frequency Domain (FD) and Time Domain (TD). The FD is divided into Resource Block (RB), which is Sub Channel (SC), the number of RB depends on the used bandwidth i.e., bandwidth 5 MHz has 25 RBs or SCs. The TD is divided into radio frame, where 1 radio frame is equal to 10 subframes which takes 10 ms or 10 Transmission Time Interval (TTI). RBs are allocated to each flow in every 1 subframe at the eNB on the MAC layer. However, the processing time should be less than 1 ms to reduce the risk, so the process to deliver all RBs should be completed within 800 microseconds from the specification 80 percent of 1 ms. Therefore, the scheduling algorithm design should also be considered the computational complexity for the possibility of implementation under the ability of processing.

When the technology for creating the Central Processing Unit (CPU) is continuously developed, the processing unit can quickly respond to the complex calculations. Also, the use of the Graphics Processing Unit (GPU) applies for computing many sub-tasks, and Application-Specific Integrated Circuit (ASIC) uses for the specific working, they make the possibility in modern computer science to quickly apply complex calculations. When designing new methods to increase efficiency, it is very necessary for considering the computational complexity of the algorithm with Big O notation for the possibility of implementation. With orders of common functions, the least complex is constant that is computed as *O(1)*, where the highest complex is factorial with *O(n!)*. When the proposed algorithm may be effective more than other algorithms, it does not guarantee that it will actually be implemented because it is too complex to design a system. Thus, the algorithm for optimizing the network that can implement in the real environment must have low complexity for the computation of processing. The processing time of method in this thesis for radio resource allocation should be operated within 800 microseconds. For this reason, it is impossible if the system will require more complicated calculations. Hence, one of the methods to effectively allocate the radio resource to UEs is a lookup table creation by using the proposed algorithm to find the optimal parameters. The result obtains the appropriate service priority factor of each service that is the constant to multiply the existing algorithm in the system, the computational complexity of method is equal to *O(1)*. The details of the lookup table will be discussed as below.

3.9.1 Lookup table

In the computer science, a lookup table is created to reduce the processing time, in which it replaces runtime computation with the produced array index. The processing time reduced from reading the values from memory, in which these index values may be precalculated and stored in static program. Lookup table creation were one of the prior methods used in the spreadsheets in computer with the initial version in 1979 (Bill Jelen, 2012). It makes sense to reduce the processing process with use a lookup table by manual caching form created with static lookup tables or dynamic prefetched arrays and it can proceed with the system automatically and improve performance for data.

In this thesis focuses on the optimization of radio resource allocation with use the appropriate service priority factor, this parameter is used to define the new priority metric for providing the appropriate resource to UEs based on the optimal QoE with constraint. The PGA algorithm is used to find the optimal parameters of service priority factor, but the process of finding the answer, which can implement in the system may take too much work. Thus, the results are obtained from finding the optimal parameters in the PGA algorithm, which are used to create lookup table. However, the purpose of setting the static values of appropriate parameters is to guarantee the QoE of system with constraint and to support more users in the cell coverage with the limited bandwidth scenario. Thus, the possibility of implementation in this work should be operated with the simple static lookup table to optimize the networks as per the purpose.

Table 3.5 is the Lookup table obtained from recent research (Uthansakul P., Anchuen P., et al, 2020), which is service priority factor of each service to use optimizing the radio resource allocation, where the cell has just only bandwidth as 5 MHz, it can support users from 25 to 31with the average QoE of all services with 3. Besides, the configuration of optimal parameters from this lookup table can guarantee the average QoE of each service with 2, which is the condition of QoE threshold to provide good services to users based on the mutual benefits of service providers and users.

Table 3.5 Lookup table of service priority factor for optimizing the radio resource allocation in downlink of LTE networks

State			**Action**		
Bandwidth	**UE**	**Target of provider**	pr_{VoIP}	pr_{Video}	pr_{BE}
5 MHz	25	Average QoE of all service > 3	8	13	2
5 MHz	25	Average QoE of all service > 3 and Average QoE of each service > 2	2	4	5
5 MHz	31	Average QoE of all service = 3	12	1	16

3.10 Summary

In this chapter, the system model and self-optimization are explained in detail for this thesis based on simulation results. The service model has defined as the tool of LTE-Sim to illustrate the different types of services that require QoS differently, in which services consist of VoIP, Video and BE. The QoS parameters have four main factors including TP, PLR, PD and the JT. These measured factors depend on the resource allocation of each data flow with the help of LTE-Sim for simulation. The objective functions of each service are used to estimate the OS from considering only one parameter even though other parameters may affect the OS. However, these functions have not defined requirements and formats for estimating the OS, so they are just only used to evaluate instead of real users. The datasets consisting of collected QoS and estimated OS are used in the pre-processing process to analyze and choose the QoS for the QoE modeling. The QoE model creation with the proposed ANN method can be not only predictive behavior similar to the original function, but also create a model that meets the needs of users with fluctuations as per the summary in recent research (Uthansakul P., Anchuen P., et al, 2020).

To the QoE awareness perspective, the common downlink scheduling algorithms are studied to compare the performance of an appropriate algorithm to be used for further development. To optimize the radio resource allocation, the service priority factor is entered the priority service function to multiply the priority metric computed by the downlink scheduling algorithm to define the radio resource allocation based on the QoE perspective. However, the challenge of finding the optimal parameter to achieve the highest QoE with constraints, which cannot know from the calculations of conventional mathematical equations. Thus, self-optimization with finding the optimal parameter of service priority factor from the proposed PGA algorithm is carried out in this thesis. Besides, the possibility of implementation concept is considered with the lookup table creation for assigning constants to multiply by downlink scheduling algorithm to reduce the complexity and the time that resources are allocated. It is a challenge to put into practice, while the algorithm must be based on the use of methods that are minimal computational complexity. A detailed explanation of the methodology in this thesis will be discussed in the next chapter.

CHAPTER IV

METHODOLOGY

4.1 Introduction

In this chapter, Ph.D. candidate has explained the details regarding the methodology including simulation steps. The detail of methodology consists of LTE-Sim, downlink scheduling procedure, QoE model and Optimization technique procedure. The overall content of this chapter is concluded in the summary.

4.2 LTE-Sim

Almost tools to simulate the LTE protocol stack for scheduling the radio resource in the MAC layer. They have the limitation of access to the program with the unpopular tools, which is not appropriate to use as a research development tool. However, the appropriate tool must be an open-source framework to easily access from the researcher. One of the LTE simulation tools is LTE-Sim that is developed by G. Piro (Giuseppe Piro, et al., 2011) to simulate the working scenario instead of the operation in the real environment to reduce the risk and damage to the service provider. Thus, LTE-Sim is used to simulate in the resource allocation process with the condition and scenario designed in this thesis, in which LTE-Sim topology can be seen in Fig. 4.1.

This simulation tool can simulate several scenarios such as single/multi-cell scenario, single/multi-service scenario, indoor/outdoor scenario and so on. In this thesis, the scenario is configured as an outdoor simulation with single-cell and multiple services under the condition of the limited bandwidth scenario to allocate the radio resource for providing the multiple users in the cell coverage area. LTE-Sim is modified in the process of resource allocation for the downlink scheduling algorithm with the priority service function as seen in Equation 3.5.

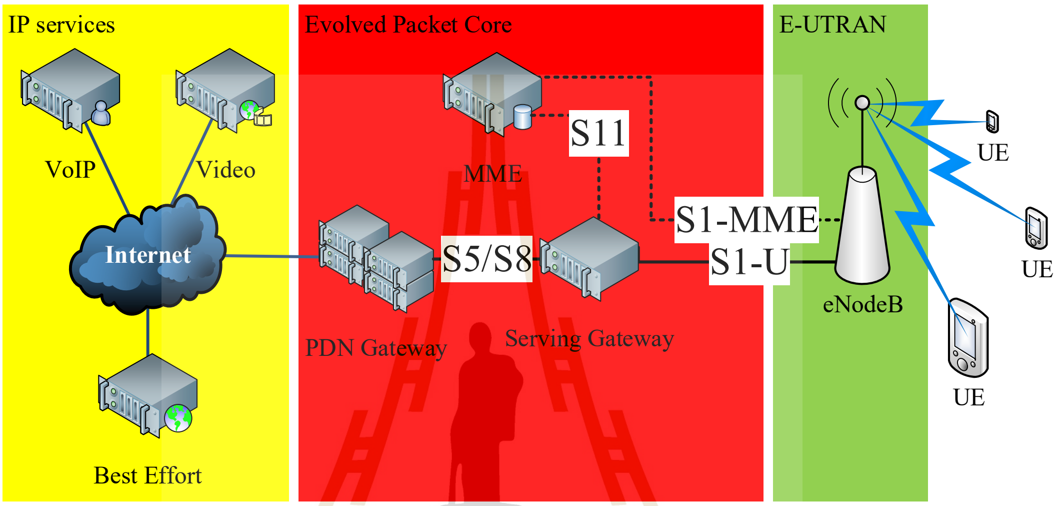


Figure 4.1 LTE-Sim topology

The results of the simulation with the LTE-Sim tool have provided the QoS parameters, which are measured from the created track file to sniff the packet data allocated to users in each service. The QoS parameters have four main factors explained in Chapter 3.3, which consist of TP, PLR, PD, and JT of each data flow as per user and service as shown in Equation 4.1.

$$QoS_{i,k} = simulation\ function(F_{ijk}) \quad 4.1$$

where $QoS_{i,k}$ is the QoS of i^{th} user for the k^{th} service and QoS = *{TP, PLR, PD, JT}* and k = *{VoIP, Video, BE}*.

The obtained QoS from the simulation is entered into the QoE model to evaluate the QoE score for each service in each user, where the service priority factor affects the received resource of each service differently. This effect causes average QoE of all services and average QoE of each service changes as per the definition of service priority factor. Hence, the optimal parameters of service priority factor can optimize the downlink scheduling based on QoE awareness. In this thesis, the used algorithm for finding the optimal parameters to maximize average QoE of all services and to guarantee the QoE threshold of each service is very important. The proposed algorithm and common algorithms are compared in terms of accuracy, search speed for answers and complexity.

4.3 Downlink Scheduling Procedure

The downlink scheduling mechanism is used to manage the radio resource allocation. The allocated resource in the units of Physical Resource Blocks (PRBs) is provided to the UEs. In general, the traditional procedure often chose the scheduling algorithm that can provide flexible resources based on traffic needed with channel awareness and QoS awareness, which consider the variables such as channel conditions, Head-of-line (HOL) packet delay targets, buffer status and service types from QoS Class Identifier (QCI) for using the computation of priority metric. However, the procedure in QoE perspective should consider internal mechanism to increase efficiency based on QoE awareness. In this thesis, the service priority factor is added to the procedure in the downlink scheduling procedure to compute the new priority metric that can allocate the radio resource to the UEs effectively based on QoE-aware by using Equation 3.5, where the data flow of user with the highest new priority metric in the Sub Channel (SC) will be allocated. The downlink scheduling procedure is operated by the chosen scheduling algorithm in conjunction with the service priority factor in the MAC layer of eNB. Fig. 4.2 shows the downlink scheduling process of LTE technology. The operation between UE and eNB in this process can be explained below:

1. The UE decodes the reference signal to define the CQI from the measured SINR, and then UE sent the CQI value of each SC to eNB by containing in Physical Uplink Control Channel (PUCCH) or Physical Uplink Shared Channel (PUSCH).

2. The eNB uses the information of CQI from the active UEs in the cell coverage and the additional information from the higher layer to decide the PRBs in the packet scheduler at the MAC layer, in which the service priority factor is added to consider for allocating the resource.

3. Adaptive Modulation and Coding (AMC) is used to tune the proper coding as per Block Error Rate (BLER) target by selecting the best Modulation and Coding Scheme (MCS) to provide the data to the selected UE from the highest new priority metric in each SC.

4. The information of allocated UE in each PRB and MCS is contained in the Physical Downlink Control Channel (PDCCH) to send the UEs.

5. Each UE reads the PDCCH, if it finds that the selected UE is assigned to receive information. It will access the Physical Downlink Shared Channel (PDSCH) payload. These processes will repeat every 1 Transmission Time Intervals (TTI) or 1 millisecond.

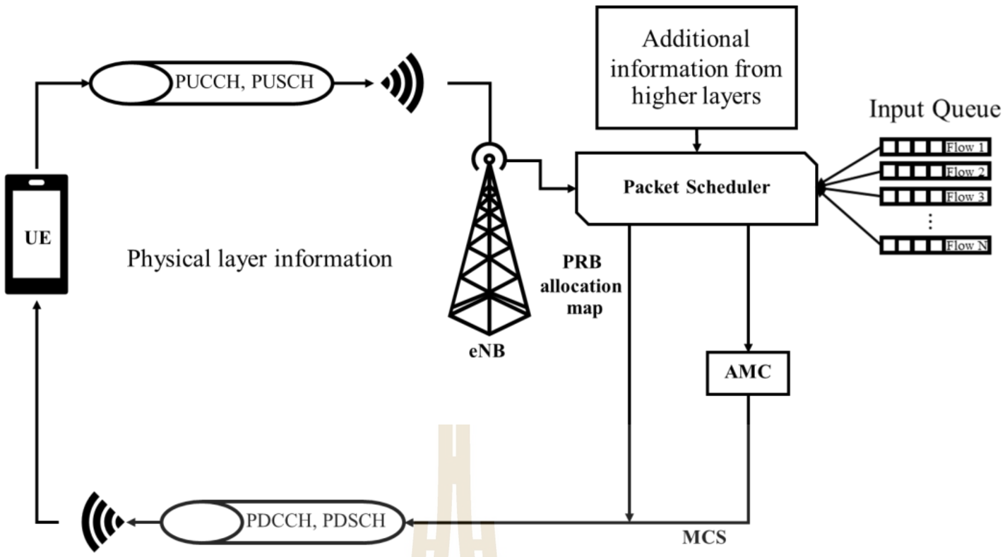


Figure 4.2 The downlink scheduling process of LTE technology

4.4 QoE model

The received simulation results from LTE-Sim provide the database consisting of QoS parameters of each user for VoIP, Video and BE services. These collected QoS parameters of each service are used to estimate the OS from the objective function in Equation 3.1, Equation 3.2 and Equation 3.3 for VoIP, Video and BE services, respectively. The OS and QoS parameters of each service from every user are combined into the datasets to create the new objective function by using the ANN algorithm. The datasets of each service are analyzed the correlation between each QoS factor and OS to select the predictive variable. From the results in the pre-processing process, the TP, PLR, PD and JT are chosen to use the QoE estimation of VoIP service due to the absolute correlation coefficients of four factors are more than 0.20. Whereas, the video services use the TP and PLR to estimate the QoE because the absolute correlation coefficients PD and JT are not more than 0.20 and BE service use only TP to estimate the QoE. Table 4.1 shows the information of the QoE model created with the ANN method. The Correlation Models (CM) of every model are the reliability model with a very strong level making the highly effective model, where hidden nodes are set as 3 and input nodes depend on the number of selected QoS. The QoE modelling results with the ANN algorithm are the link weights and thresholds as shown in Fig. 4.3.

Table 4.1 The information of QoE model crated by using the ANN algorithm

Information	**VoIP service**	**Video service**	**BE service**
r_{TP}	0.34	0.88	0.74
r_{PLR}	-0.99	-0.82	-
r_{PD}	-0.69	-	-
r_{JT}	-0.29	-	-
Input nodes	4	2	1
Hidden nodes	3	3	3
Output nodes	1	1	1
SSE	0.00001	0.00001	0.00800
CM	0.99	0.98	0.87
Reliability model	Very strong	Very strong	Very strong

When the link weights and thresholds as per Fig. 4.3, are entered in Equation 3.24 to estimate the QoE score from the measured QoS parameters in the simulation of LTE-Sim. The QoE models of each service are defined as easily understanding function to estimate the QoE score for VoIP, Video and BE services as per Equation 4.2, Equation 4.3 and Equation 4.4, respectively. These functions are the new objective function for mapping the network-centric perspective into the user-centric perspective.

$$QoE_{VoIP} = f(TP, PLR, DL, JT)_{VoIP} \tag{4.2}$$

$$QoE_{Video} = f(TP, PLR)_{Video} \tag{4.3}$$

$$QoE_{BE} = f(TP)_{BE} \tag{4.4}$$

VoIP

$$w_{ij} = \begin{bmatrix} 0.872 & 0.010 & -0.053 \\ -2.244 & -0.557 & 3.010 \\ -0.537 & -0.028 & 0.425 \\ 0.215 & -0.091 & 0.478 \end{bmatrix} w_{ij} = \begin{bmatrix} 1.106 \\ -3.531 \\ 5.264 \end{bmatrix}$$

$$\theta_j = [-0.774 \quad 1.402 \quad -0.926] \; \theta_k = [-1.456]$$

$$x_i = [0.544TP \quad -0.264PLR \quad -0.060PD \quad -0.006JT]$$

Video

$$w_{ij} = \begin{bmatrix} 0.342 & -1.211 & 0.002 \\ 2.785 & -4.033 & 1.090 \end{bmatrix} w_{ij} = \begin{bmatrix} 2.189 \\ -3.322 \\ 2.048 \end{bmatrix}$$

$$\theta_j = [2.738 \quad -5.125 \quad -0.924] \; \theta_k = [-1.198]$$

$$x_i = [0.015TP \quad -0.014PLR]$$

BE

$$w_{ij} = [0.376 \quad 2.068 \quad -3.383] \; w_{ij} = \begin{bmatrix} 6.123 \\ -0.313 \\ -2.137 \end{bmatrix}$$

$$\theta_j = [2.540 \quad -1.580 \quad -3.824] \; \theta_k = [-0.280]$$

$$x_i = [0.013TP]$$

Figure 4.3 The link weights and thresholds of QoE model for VoIP, Video and BE services

In the computation of the average QoE of each service within the cell coverage area from the active user, the average QoE of VoIP service, the average QoE of Video service and the average QoE of BE service can compute from Equation 4.5, Equation 4.6 and Equation 4.7, respectively, where N is the number of active UEs and n is the sequence of active UE.

$$\overline{QoE_{VoIP}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{VoIP,n} \qquad 4.5$$

$$\overline{QoE_{Video}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{VIDEO,n} \qquad 4.6$$

$$\overline{QoE_{BE}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{BE,n} \qquad 4.7$$

For the QoE overview of system, the average QoE of all services or the network can be computed by using Equation 4.8, where K is the number of services and k is the sequence of service.

$$QoE = \frac{1}{K}\sum_{k=1}^{K} \overline{QoE_k} \qquad 4.8$$

4.5 Optimization technique procedure

The appropriate service priority factors of each service are adjusted by using the optimization technique procedure in order to allocate the radio resource to maximize the average QoE of all services along with maintaining the average QoE of each service with the QoE threshold. The configuration process of service priority factors of each service pr_k to optimize the resource allocation based on QoE-aware is as follows: start by setting the pr_k and compute pri_k by using Equation 3.4, multiply pri_k with w_{ij} to calculate the new priority metric F_{ijk} by using Equation 3.5. The F_{ijk} is used to define the service priority during the RBs allocation. And then the obtained QoS parameters of each service from the network simulation are used to estimate the average QoE of each service by using Equation 4.5, Equation 4.6, and Equation 4.7, and the average QoE of all services in the cell coverage can be computed by using Equation 4.8. These processes are operated to find the QoE from entering the pr_k into the objective function of system. Therefore, the process function proceeds for finding the pr_k. Fig.4.4 shows the procedure of optimization as per Equation 4.9.

$$\text{maximize} \quad f_p(pr_k, \varphi)$$

$$\text{subject to} \quad \overline{QoE_k} > QoEthreshold_k \tag{4.9}$$

where f_p is a process function, pr_k is a service priority factor of the k^{th} service. Besides, φ= {*GA, PSO, PGA*} and they are the considered algorithm to find the optimal parameter of pr_k. $\overline{QoE_k}$ is the average QoE of the k^{th} service and $QoEthreshold_k$ is the QoE threshold of the k^{th} service.

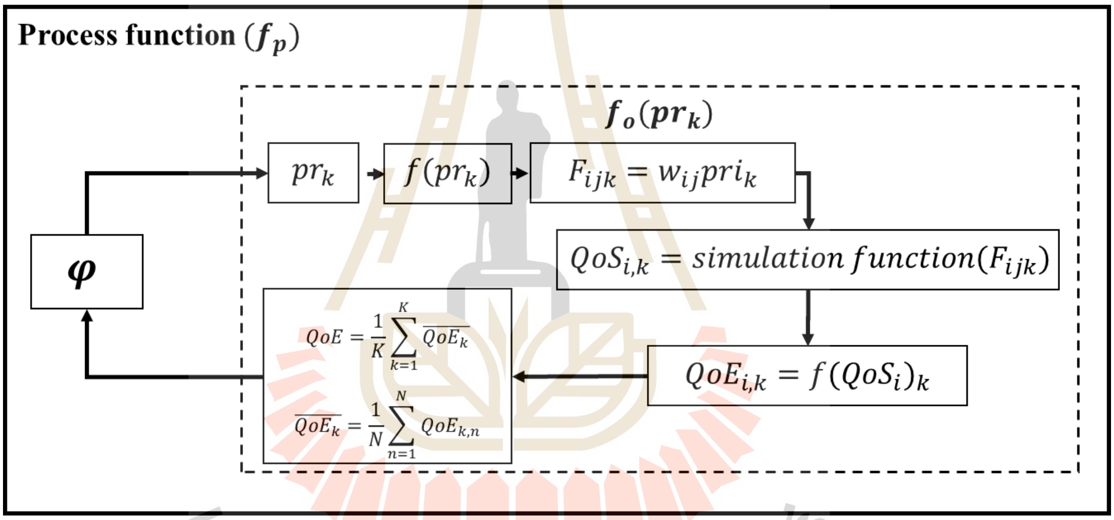


Figure 4.4 The procedure of the process function

4.6 Summary

In this chapter, the methodology has been discussed in detail regarding this thesis operation from the thesis design to simulate the results under the scope of the hypothesis and objectives of the thesis. The results of this thesis will be shown in the next chapter.

CHAPTER V

SIMULATION RESULTS AND DISCUSSION

5.1 Introduction

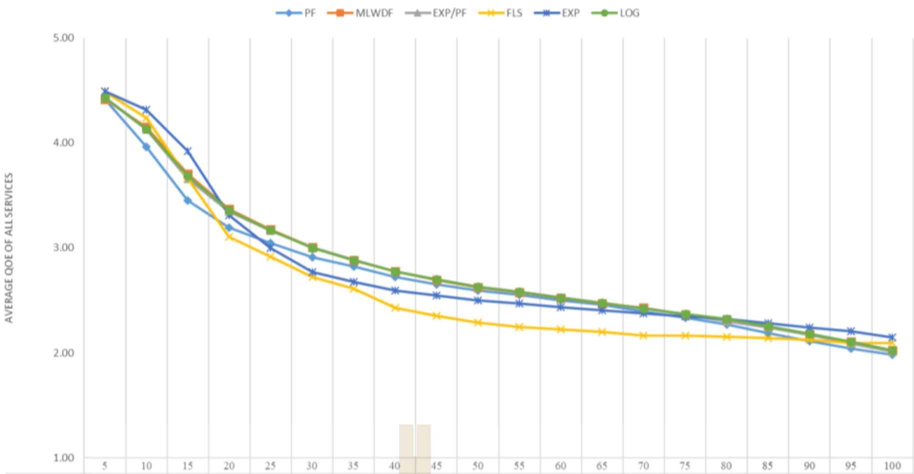
This chapter presents the simulation results divided into three subsections. In the first subsection, the QoE-aware packet scheduling is compared to the performance of the six common scheduling algorithms in terms of QoE performance. As a result, the appropriate downlink scheduling algorithm is chosen to use in the self-tuning in this thesis for finding the optimal parameters of service priority factor by using Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Particle swarm optimization and Genetic Algorithm (PGA) algorithms based on QoE-aware by maximizing the average QoE of the network. The performance of these algorithms is compared by accuracy and speed for finding the optimal parameters in the second subsection. And the last subsection, the proposed algorithm is chosen to the use of finding the optimal parameters with the condition of the QoE threshold. Also, the computational complexity of optimization algorithms is computed by Big O notation, and the possibilities of implementation are introduced by using the created lookup table.

5.2 The resource allocation from the scheduling algorithms based on QoE-aware

The simulation results focused on the six downlink scheduling algorithms based on the QoE-aware from LTE-Sim with the single cell with interference scenario for multi-users and multi-services. Table 5.1 unveils the simulation parameters based on the limited bandwidth scenario. In the limited bandwidth scenario, the bandwidth is set as 5 MHz, which can support 200 User Equipments (UEs) as per the Third Generation Partnership Project (3GPP) in Release 9 (3GPP TS 25.913, 2009). When many active UEs connect to the network simultaneously and each service requires the different resources, 5MHz bandwidth may not be enough to allocate all active UEs. Therefore, this thesis sets the number of UEs within the limited scope from 5 to 100 UEs for the simulation to compare the performance of scheduling algorithms.

Table 5.1 Simulation parameters in LTE-Sim

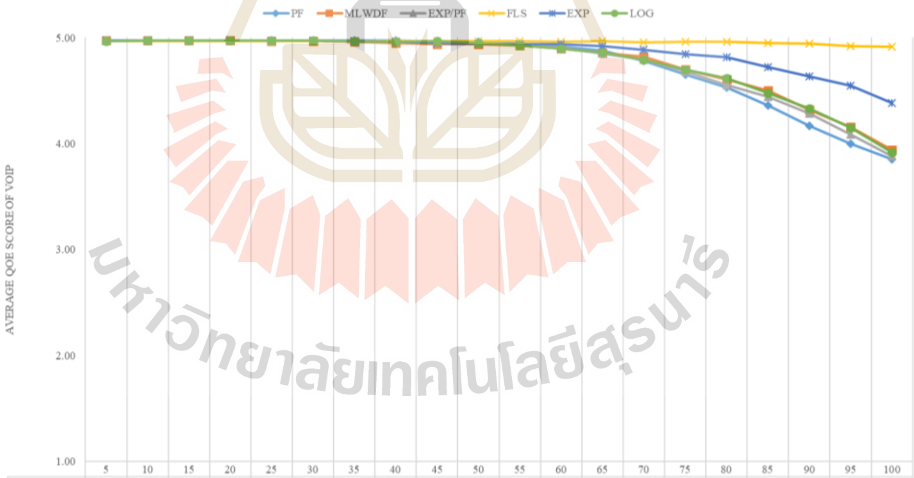
Parameters	Value
Simulation duration	120 seconds
Frame structure	FDD
Symbol for TTI	14
Carrier frequency	2 GHz
Bandwidth	5 MHz
Number of RBs	25
Channel model	Typical Urban (TU)
Cell radius	1 km
Scheduling time	Every 1 TTI
Mobility model	Random
Mobile speed	3 km/h
Simulation scenario	Single Cell with Interference
Max delay	0.1 s
Traffic model	VoIP – G.729 (8.2 kbps) Video – Trace based H.264 (242 kbps) Best Effort – Infinite buffer
UE application flow	One VoIP, one Video and one BE
Number of Users	5:5:100
Scheduling Algorithm	PF, MLWDF, EXP/PF, FLS, EXP rule and LOG rule



	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
PF	4.41	3.97	3.45	3.19	3.05	2.91	2.82	2.72	2.65	2.59	2.55	2.50	2.46	2.40	2.33	2.27	2.19	2.11	2.04	1.98
MLWDF	4.41	4.15	3.70	3.37	3.17	3.01	2.88	2.77	2.69	2.62	2.58	2.52	2.47	2.43	2.36	2.31	2.25	2.18	2.11	2.03
EXP/PF	4.43	4.13	3.66	3.34	3.16	3.00	2.89	2.78	2.70	2.63	2.58	2.53	2.48	2.42	2.37	2.30	2.24	2.17	2.09	2.01
FLS	4.48	4.24	3.66	3.10	2.92	2.72	2.61	2.43	2.35	2.29	2.25	2.22	2.20	2.17	2.16	2.15	2.14	2.13	2.10	2.09
EXP	4.49	4.31	3.92	3.31	3.00	2.77	2.68	2.60	2.54	2.50	2.47	2.43	2.41	2.37	2.35	2.33	2.28	2.24	2.20	2.14
LOG	4.43	4.13	3.68	3.36	3.17	3.00	2.88	2.77	2.70	2.63	2.58	2.53	2.48	2.42	2.37	2.32	2.25	2.18	2.11	2.02

NUMBER OF USERS

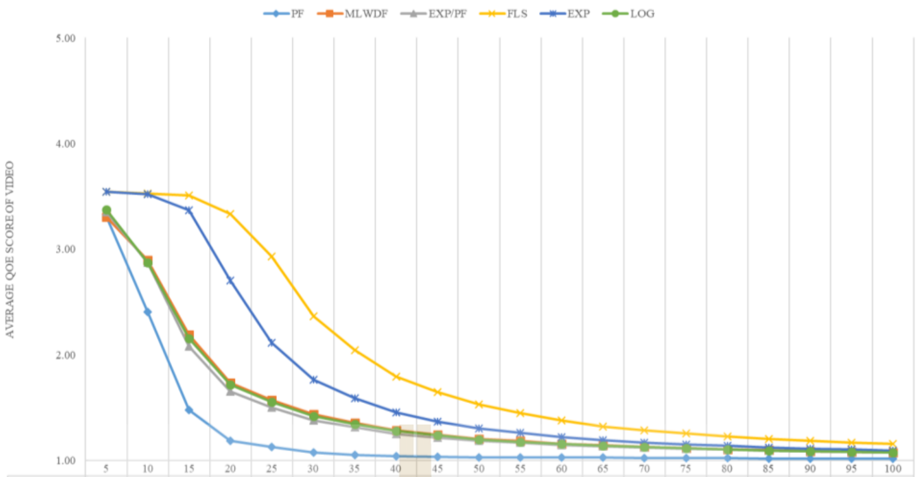
Figure 5.1 The average QOE of all services per cell by using the six common scheduling algorithms at the bandwidth of 5 MHz



	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
PF	4.97	4.97	4.98	4.97	4.98	4.97	4.97	4.97	4.96	4.96	4.95	4.91	4.88	4.78	4.65	4.53	4.36	4.17	4.00	3.85
MLWDF	4.97	4.97	4.97	4.97	4.97	4.97	4.96	4.95	4.94	4.94	4.93	4.89	4.86	4.82	4.70	4.60	4.50	4.32	4.16	3.94
EXP/PF	4.97	4.97	4.98	4.97	4.97	4.97	4.97	4.96	4.97	4.96	4.93	4.90	4.85	4.79	4.68	4.55	4.44	4.29	4.09	3.88
FLS	4.97	4.97	4.97	4.97	4.97	4.97	4.97	4.97	4.97	4.97	4.97	4.96	4.96	4.96	4.96	4.96	4.95	4.94	4.92	4.92
EXP	4.98	4.98	4.97	4.97	4.97	4.97	4.97	4.96	4.95	4.94	4.94	4.94	4.92	4.88	4.85	4.82	4.72	4.64	4.55	4.38
LOG	4.97	4.97	4.98	4.97	4.97	4.97	4.97	4.96	4.96	4.95	4.93	4.90	4.86	4.79	4.70	4.62	4.48	4.33	4.15	3.91

NUMBER OF USERS

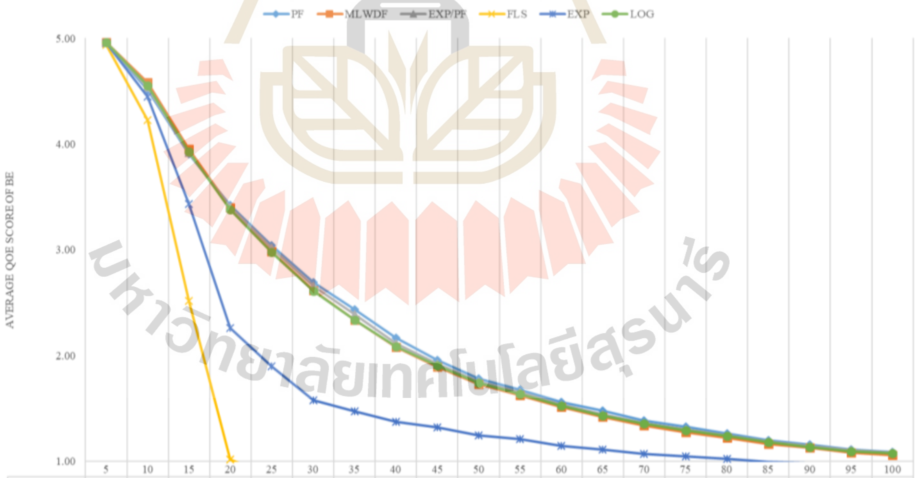
Figure 5.2 The average QOE of VoIP service per cell by using the six common scheduling algorithms at the bandwidth of 5 MHz



	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
PF	3.31	2.41	1.48	1.18	1.13	1.07	1.05	1.04	1.03	1.03	1.03	1.03	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
MLWDF	3.31	2.90	2.19	1.73	1.57	1.43	1.35	1.29	1.24	1.21	1.18	1.16	1.14	1.13	1.12	1.11	1.09	1.09	1.08	1.08
EXP/PF	3.35	2.87	2.08	1.65	1.50	1.38	1.31	1.25	1.22	1.18	1.17	1.15	1.13	1.12	1.11	1.10	1.09	1.09	1.08	1.07
FLS	3.54	3.52	3.51	3.33	2.93	2.37	2.04	1.79	1.65	1.53	1.45	1.38	1.32	1.28	1.25	1.23	1.20	1.18	1.17	1.16
EXP	3.55	3.52	3.37	2.70	2.12	1.76	1.59	1.45	1.37	1.30	1.26	1.22	1.19	1.17	1.15	1.14	1.12	1.11	1.10	1.09
LOG	3.37	2.87	2.15	1.71	1.55	1.42	1.34	1.28	1.23	1.20	1.18	1.15	1.14	1.12	1.11	1.10	1.09	1.09	1.08	1.07

NUMBER OF USERS

Figure 5.3 The average QOE of Video service per cell by using the six common scheduling algorithms at the bandwidth of 5 MHz



	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
PF	4.96	4.51	3.90	3.42	3.04	2.69	2.43	2.17	1.96	1.78	1.67	1.56	1.47	1.39	1.33	1.26	1.20	1.15	1.11	1.08
MLWDF	4.96	4.58	3.95	3.40	2.98	2.61	2.33	2.08	1.89	1.73	1.62	1.51	1.42	1.34	1.27	1.22	1.16	1.12	1.08	1.06
EXP/PF	4.96	4.53	3.92	3.41	3.02	2.66	2.39	2.12	1.92	1.75	1.65	1.53	1.44	1.36	1.30	1.25	1.19	1.15	1.10	1.08
FLS	4.94	4.23	2.51	1.01	0.86	0.83	0.83	0.52	0.44	0.37	0.32	0.33	0.32	0.26	0.28	0.27	0.27	0.25	0.20	0.21
EXP	4.96	4.45	3.43	2.26	1.90	1.58	1.47	1.37	1.32	1.24	1.21	1.14	1.11	1.07	1.05	1.02	1.00	0.98	0.96	0.96
LOG	4.96	4.55	3.93	3.38	2.98	2.61	2.34	2.08	1.90	1.74	1.64	1.52	1.43	1.35	1.29	1.24	1.18	1.14	1.09	1.07

NUMBER OF USERS

Figure 5.4 The average QOE of BE service per cell by using the six common scheduling algorithms at the bandwidth of 5 MHz

The simulation results in this subsection for comparing the performance of downlink scheduling algorithms with the QoE perspective are shown in Fig. 5.1, Fig. 5.2, Fig. 5.3 and Fig. 5.4 for the average QoE of all services, the average QoE of VoIP service, the average QoE of Video service and the average QoE of BE service, respectively.

Fig. 5.1 shows the average QoE of all services calculated by Equation 4.8, which is the overall QoE from the average of each service consisting of VoIP, Video and BE services, to use as metric for comparing the performance of each downlink scheduling algorithm. As the number of UEs continuously increases in the network with 5 MHz bandwidth, the result presents that the average QoE of all services in each algorithm decreases significantly due to the available bandwidth is distributed to provide many active users with the limited resource scenario. When comparing the effectiveness of six scheduling algorithms to allocate the radio resource from Fig. 5.1, the Exponential rule (EXP rule) algorithm provides the highest average QoE of all services when UEs are equal to100 in 5 MHz bandwidth, which is the limited bandwidth scenario. Thus, this algorithm is more suitable than other algorithms for using resource allocation in terms of the QoE perspective from overall networks. In addition, Fig. 5.2, Fig. 5.3 and Fig. 5.4 show the average QoE of VoIP service, the average QoE of Video service and the average QoE of BE service, which are computed by Equation 4.5, Equation 4.6, Equation 4.7, respectively. These results have found that the Frame Level Scheduler (FLS) algorithm, which is designed to allocate on Realtime (RT) services having the highest average QoE for RT service including VoIP and Video as shown in Fig. 5.2 and Fig. 5.3, and the lowest average QoE for the Non-Realtime (NRT) that is BE service as shown in Fig. 5.4, when this algorithm used in the limited bandwidth scenario, which is UEs as equal to100. Whereas, the QoE of BE service becomes 0 for the UEs that are not allocated. The results from previous research show that each algorithm designed for specific use in terms of the QoS perspective (Sivasubramanian A., et al., 2017) while the appropriate algorithm to use the resource allocation in the QoE perspective should be considered from this subsection result, which found that the EXP rule algorithm is suitable to develop with the solution of this thesis.

In the next subsection, the resource allocation optimization with the optimal parameters of service priority factor will be presented in terms of the QoE metric. The optimal parameters can help to maximize the average QoE of all services within the serving cell while the service priority factor of each service is searched by using the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and the proposed algorithm in this thesis. The performance of these algorithms is compared to choose the best algorithm to operate the optimization with constraints to guarantee the average QoE of each service for UEs and maximize the average QoE of all services in the last subsection.

Table 5.2 Search space size deepened on the range of service priority factor with the consideration of 3 services

Range of pr_k	**The number of pr_k**	**Search space size**
1 to 8	8	512
1 to 16	16	4,096
1 to 32	32	32,768
1 to 64	64	262,144
1 to 128	128	2,097,152

5.3 Finding the optimal parameters using GA PSO and PGA algorithms

To demonstrate the QoE-aware in the designed optimization method in this thesis by using the service priority factor of each service to allocate the radio resource, the EXP rule is used to allocate the radio resources in this subsection. The simulation parameters as shown in Table 5.1 are readjusted with assigning the number of UEs equal to 25, scheduling algorithm by choosing EXP rule algorithm, and implementing the service priority factor of each service to determine the new priority metric in the resource allocation mechanisms to UEs that can compute from Equation 3.5 for the purpose of increasing QoE. However, the average QoE of all services is set as 3.00 to be the threshold of networks to guarantee the overall services of active UEs as per ITU-T P.800 (ITU-T Rec. P.800, 1996), when 3.00 is the fair level that is defined in the qualitative feel. Moreover, the defined QoE threshold should be considered for the trade-off between the used radio resources and the received QoE. When the QoE threshold is set too high, the system uses a lot of radio resources to respond to the needs of the user from the defined QoE, resulting in the investment expenses increased for improving the networks. The result from first subsection, the average QoE of all services is equal to 3.00, which can just only support the number of 25 UEs as shown in Fig. 5.1.

In the configuration of the service priority factor, Table 5.2 shows the size of the search space that depends on the range of service priority factor. When the range of service priority factor is enlarged, it will increase the search space exponentially, resulting in the search for answers lasted for a long time. Meanwhile, determining the range of service priority factor needs to consider the size of the search space that is appropriate and still be effective in finding answers by thinking about the implementation. Therefore, the service priority factor has been defined as $pr_k \in I^+ = \{1,2,\ldots,16\}$, which is a positive integer from 1 to 16 for the pr of each service consisting of VoIP, Video and BE. The possible answer in search space is equal to the number of pr members power the number of services, which are equal to $16^3 = 4096$ members. However, the range of positive integer is defined by using the Try and Error method to find the appropriate data range with the high QoE change between two adjacent points without exceeding significant QoE values (less than 5 percent).

The original method to find the optimal parameters of service priority factor is necessary to use the exhaustive search method by finding all possible answers in the search space, which consists of 4096 members to find the service priority factors that result in the highest average QoE of all services. From the simulation results by using the exhaustive search method in EXP rule algorithm at 25 UEs, bandwidth equal to 5 MHz, found that the optimal parameters of service priority factor in each service as pr_{VoIP} =11, pr_{Video} =1 and $pr_{BE} = 16$, which the average QoE of all services is equal to 3.33 as shown in Fig. 5.5.

When the set of $\{11,1,16\}$ is one of 4096 members , it is the optimal parameters that makes the highest average QoE of all services then $\overline{QoE_{VoIP}} = 4.96$, $\overline{QoE_{Video}}$ =1.06 and $\overline{QoE_{BE}} = 3.97$ as shown in Fig. 5.6, Fig. 5.7 and Fig. 5.8, respectively. From the results, the results can observe that the way to define the service priority factor will make the average QoE of all services increase by 11 percent in this case with EXP rule algorithm at 5 MHz bandwidth.

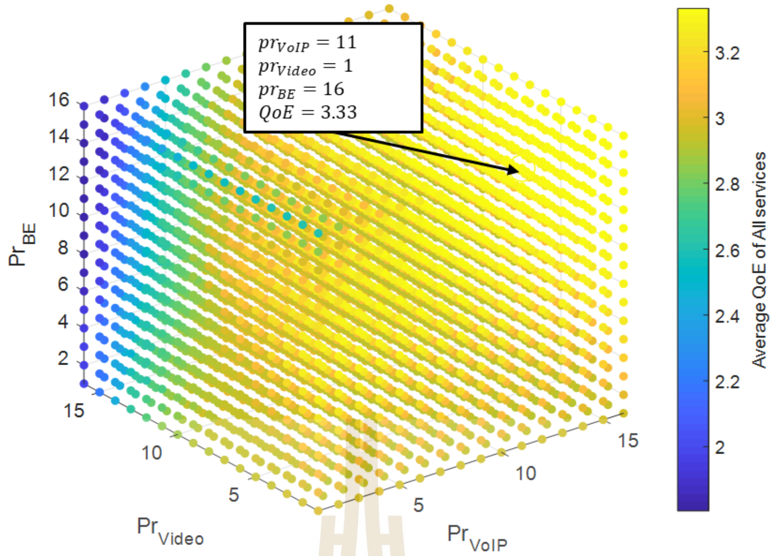


Figure 5.5 The average QoE of all services by defining the service priority factor with the EXP rule algorithm at 25 UEs (4096 members)

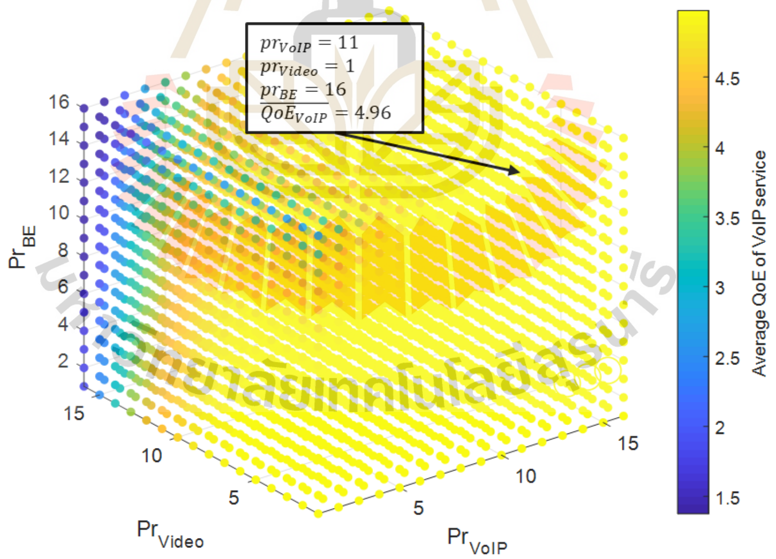


Figure 5.6 The average QoE of VoIP service by defining the service priority factor with the EXP rule algorithm at 25 UEs (4096 members)

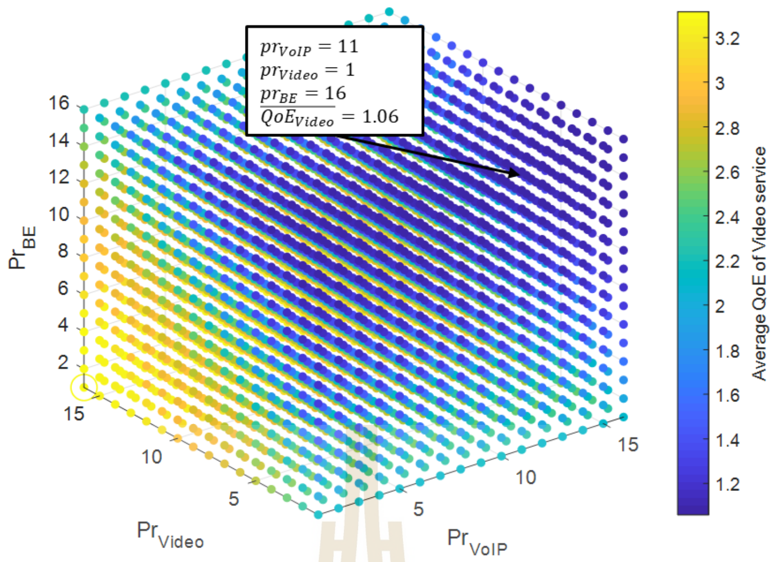


Figure 5.7 The average QoE of Video service by defining the service priority factor with the EXP rule algorithm at 25 UEs (4096 members)

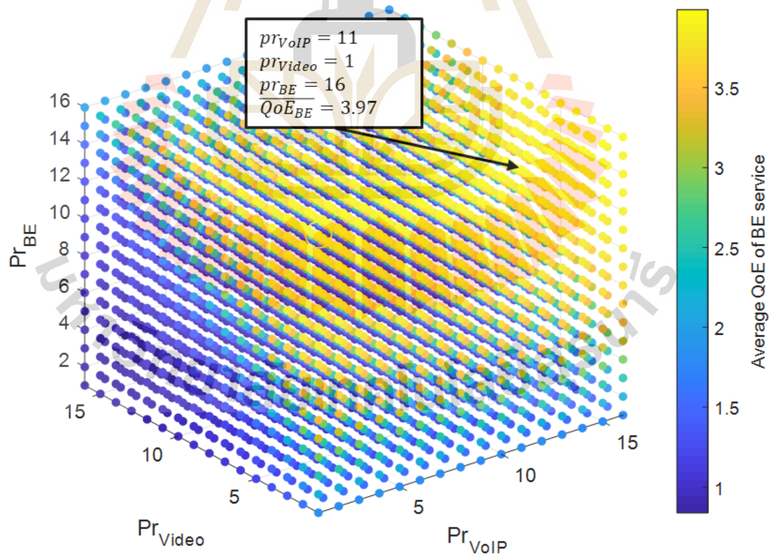
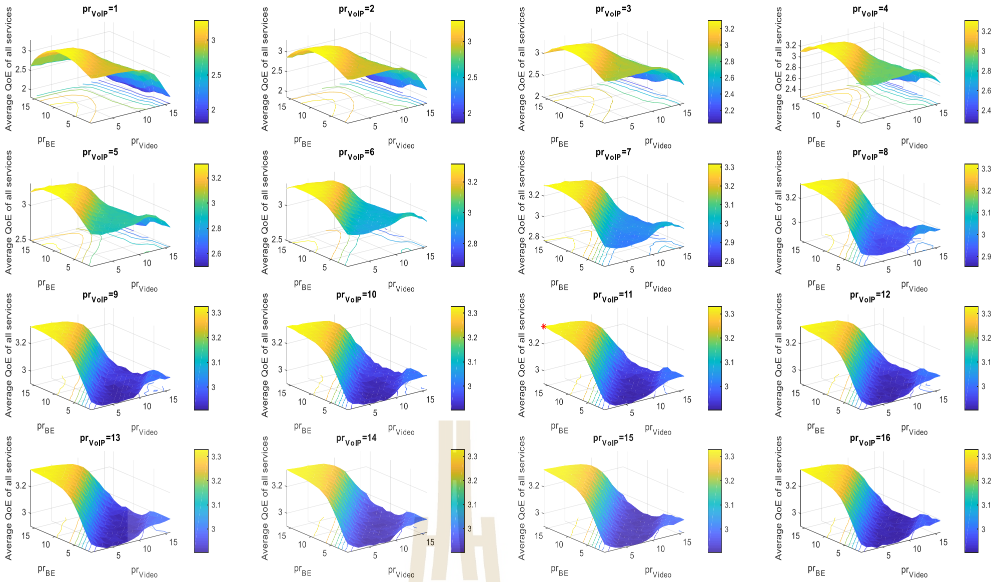
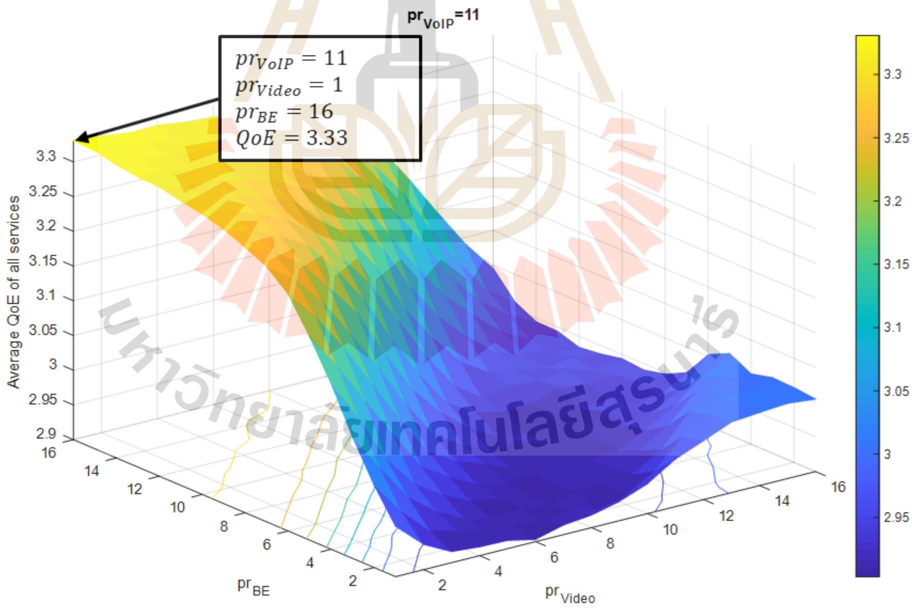


Figure 5.8 The average QoE of BE service by defining the service priority factor with the EXP rule algorithm at 25 UEs (4096 members)



a. The projection graph of average QoE of all services on the pr_{VoIP} from 1 to 16



b. The projection graph of average QoE of all services on the $pr_{VoIP} = 11$

Figure 5.9 The projection graph of average QoE of all service by defining the service priority factor with the EXP rule algorithm at 25 UEs

To demonstrate the experimental results of the optimal parameters in the search space using the exhaustive search method, the graph of Fig. 5.5 which is the average QoE of all services, is screened to clearly explain the problem of search space with the projection of the pr_{VoIP} axis from 1 to 16 as shown in Fig. 5.9 a. When the answer in each sub-graph of pr_{VoIP} has the highest average QoE of all services at pr_{Video} =1 and pr_{BE} = 16, the global maximum of the average QoE of all services is at pr_{VoIP} =11, pr_{Video} =1 and pr_{BE} = 16 as shown in Fig. 5.9 b. With the apparent nature of concave surfaces, it caused many local optimums. Although the gradient descent method is used to effectively find the global optimum in other works, the nature of the answer in this thesis is not appropriate for this method due to the operation of gradient descent may converge to a local optimum. Thus, the problem should be considered with the heuristic method with the exploration and exploitation features that are suitable for finding the answer in the search space of this thesis.

According to finding the optimal parameters in this method, it is the exhaustive search method that is finding all answers in search space for the best answer. In general, the search space is large, so it takes a long time to find all the answers. Therefore, the exhaustive search method is replaced by using the modern method with the constrained multivariable optimization for this thesis in the inequality constrained of the QoE threshold. This optimization technique is the direct method by a heuristic search. It can search for answers from a large search space much faster than the exhaustive search method, but the disadvantage is that the answer is not sure is the best answer. Although some problems have a very large search space and it is impossible to do the search with the exhaustive search method, so the process of heuristic is necessary. In this thesis, Ph.D. candidate has used the optimization technique with GA, PSO, and PGA algorithms to find the optimal parameters of service priority factor that cause the highest average QoE of all services. These algorithms are compared to the results obtained in finding the answer in the search space for the probability of obtaining the best answer.

In this thesis, the appropriate parameters within GA, PSO, and PGA by determining the number of populations in each generation is equal to 4, for use in the operations of each cycle in GA and PGA, the number of particles in each generation equal to 16 for PSO. The number of populations and particles is the member in search space which is equal to 4096. To stop working for finding the optimal parameters in these algorithms, Ph.D. has assigned two important conditions. First condition, the number of members in the search space used to find answers (N_{used}) must not exceed 10 percent (410 members). Second condition in GA and PGA, if found that the answer for the average QoE of all service does not increase more than 50 generations, and the condition of PSO is stopped when it is found that the position of all particle in generation is the same. The experimental results to find the optimal parameters of service priority factor with GA, PSO, and PGA algorithms in 1000 times, the best algorithm must have a high probability for the best answer and find the answer quickly. The algorithm must find the best answer under the conditions that have been set for the algorithm downtime which is calculated as the percentage of accuracy (P_{global}). Meanwhile, it must have an average of the number of members in the space used to find answers at a low value which is calculated as the percentage of average N_{used}. Results from the experiment by defining the service priority factor with EXP rule algorithm at 25 UEs, the comparison of these above-mentioned algorithms are unveiled in Table 5.3. It can be seen that the PGA performs better than the other two algorithms with the percentage accuracy (P) of 97.3 percent and the average number of used members (Avg. N_{used}) is 58 members by running the different simulation 1000 times. This average number of used members are accounted as 1.42 percent of the 4096 members.

Table 5.3 Performance comparison of GA, PSO and PGA algorithms for finding the optimal parameters with maximizing QoE

Algorithm	$\boldsymbol{P}$ **(%)**	**Avg.** $\boldsymbol{N_{used}}$	**Max.** $\boldsymbol{N_{used}}$	**Min.** $\boldsymbol{N_{used}}$	**Avg.** $\boldsymbol{N_{used}}$ **(%)**
GA	94.2%	64	178	8	1.56%
PSO	87.3%	186	408	48	4.55%
PGA	97.3%	58	196	20	1.42%

When the PGA is an algorithm that is more effective than the remaining algorithms, it is implemented to determine the optimal parameters of service priority factors to increase UEs. The average QoE of all services is equal to 3.00 from EXP rule at 25 UEs without optimization in this thesis. If the operators need to maintain the quality of network from requiring the average QoE of all services to be no less than 3 which is in the fair level according to ITU-T P.800 standard, when the EXP rule algorithm has been used without adjusting the service priority factor at bandwidth equal to 5 MHz, it can support only 25 UEs as simulation results in Fig. 5.10. Thus, the designed methodology has been adopted the from this thesis to increase the efficiency of resource allocation, so it can support users from the specified QoE threshold. From the simulation results, it was found that when increasing the efficiency of the network with the technique of resource allocation in this thesis, the proposed solution can increase the number of users up to 46 UEs with adjusting the service priority factor when $pr_{VoIP} = 11$, $pr_{Video} = 1$ and $pr_{BE} = 16$, $\overline{QoE_{VoIP}} = 4.94$, $\overline{QoE_{Video}} = 1.04$ and $\overline{QoE_{BE}} = 3.02$, while the network still maintains the average QoE of all service at least 3 as shown in Fig. 5.11. With this technique, it can support the UE up to 46 − 25 =21 UEs, which increases 84 percent at 5 MHz bandwidth by maintaining the average QoE of all services.

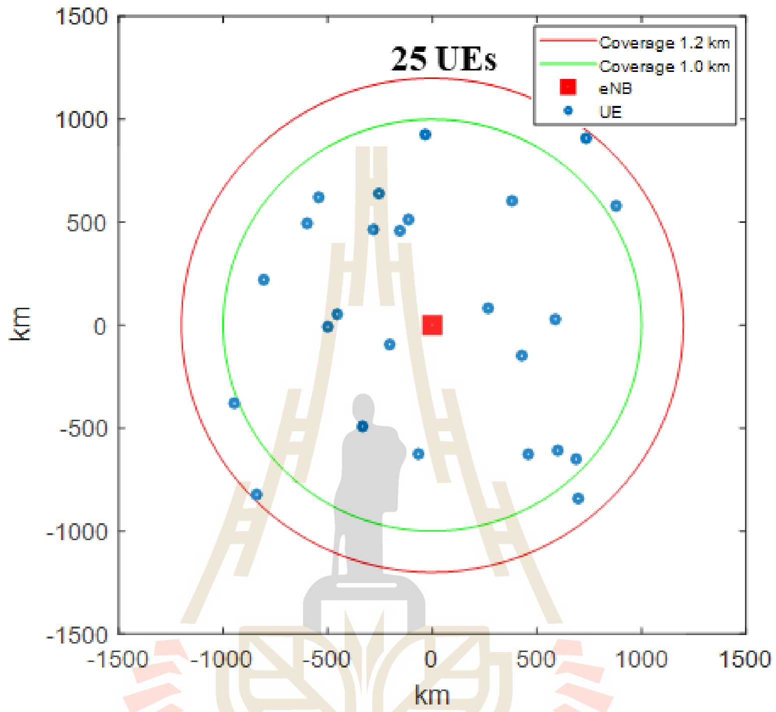


Figure 5.10 Simulation scenario from EXP rule algorithm without adjusting the service priority factor at bandwidth 5 MHz at the average QoE of all services is equal to 3.00 and 25 UEs

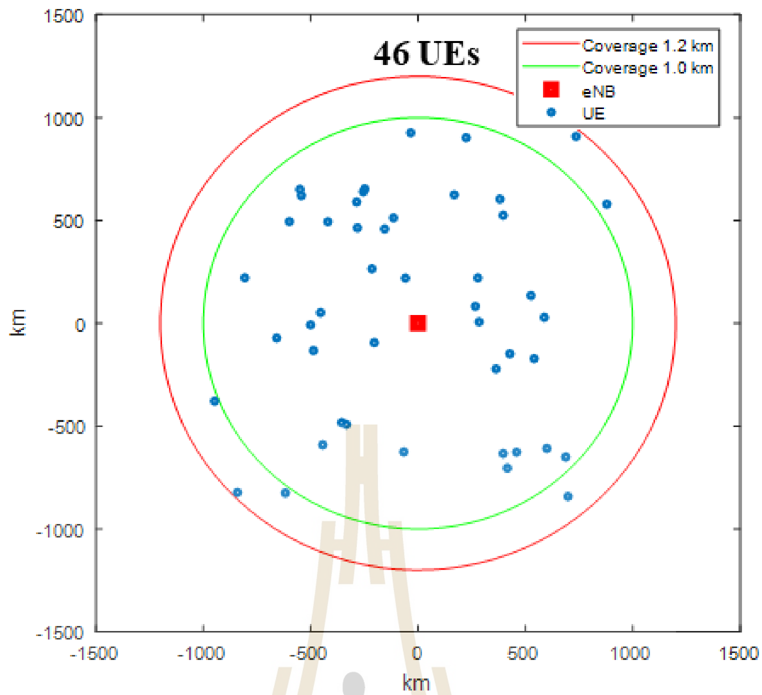


Figure 5.11 Simulation scenario from EXP rule algorithm with adjusting the service priority factor at bandwidth 5 MHz at the average QoE of all services is equal to 3.00 and 46 UEs

5.4 Finding the optimal parameter with the condition of QoE threshold using PGA algorithm

From the results of the previous subsection, Ph.D. candidate has noticed that this optimization method increases the average QoE of all services and can support more users. But, it is found that some services have a low average QoE. In the Mobile Network Operators (MNOs) perspective, it is important to solve the problem of this point to improve the services making the coverage of all user needs. Thus, the importance of this problem should be seen and improved from the proposed solution in this thesis by using the modern method to solve problems effectively. With the advantages of the methodology designed, it is possible to find the best answer with conditions, which are assigned to the condition of the QoE threshold in each service that is equal to 2. This proposed subsection is to enable users to gain better experience and operators can also allocate resources effectively to ensure a higher average QoE of all services with the QoE threshold of each service.

In this subsection, the simulation parameters have been still re-adjusted as shown in Table 5.3 with 25 UEs, EXP rule algorithm, and bandwidth is equal to 5 MHz. The QoE threshold in each service is defined in the PGA, the QoE condition can be shown as Equation 4.9. In the PGA operation mechanism for finding the optimal parameters of service priority factor, it random the population in search space. After that, it sends to the next step to crossover and mutation and the PSO process in the PGA algorithm. The PSO process is important for the exploitation with the multiple-goal objective that considers the optimal points of the average QoE of all services and the average QoE of each service. When the operation in the PSO process completed, it will be forwarded to the next generation and proceeded until the best answer with the QoE conditions. The PSO operations equations with the multiple-goal objective techniques are written in Appendix A.

From the simulation results by using EXP rule algorithm, it found that the average QoE of all services is equal to 3.04 when $pr_{VoIP} = 4$, $pr_{Video} = 7$, $pr_{BE} = 8$, $\overline{QoE_{VoIP}} = 4.95$, $\overline{QoE_{Video}} = 2.01$ and $\overline{QoE_{BE}} = 2.17$. The members in search space with the average QoE of each service more than 2 as shown in Fig. 5.12, Fig. 5.13 and Fig. 5.14 for VoIP, Video and BE services, respectively. The same members in search space in each service are possible answers that are just equal to 74 members as shown in Fig. 5.15. The best answer in these members have been found with the PGA, which can be displayed as shown in Table 5.4.

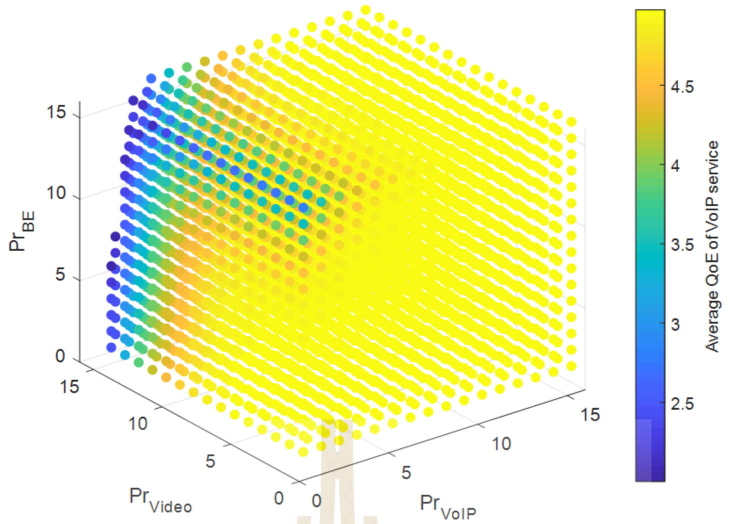


Figure 5.12 The average QoE of VoIP service by defining the service priority factor with the EXP rule algorithm at 25 UEs to be more than 2 at the bandwidth of 5MHz (4054 Members)

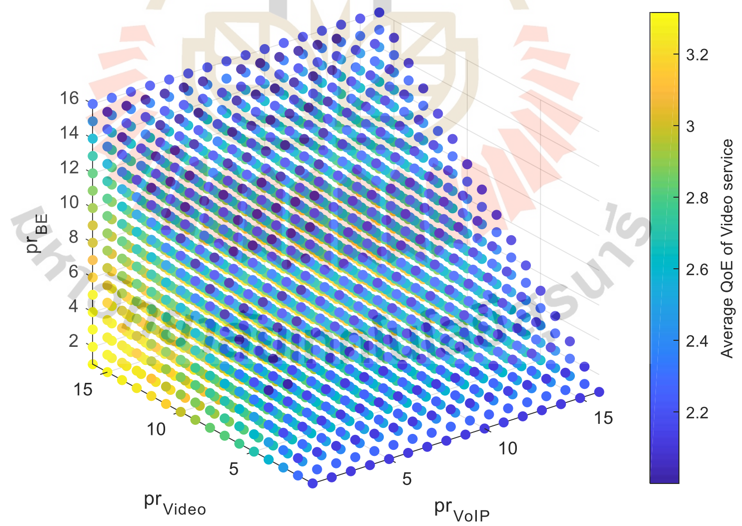


Figure 5.13 The average QoE of Video service by defining the service priority factor with the EXP rule algorithm at 25 UEs to be more than 2 at the bandwidth of 5MHz (2253 Members)

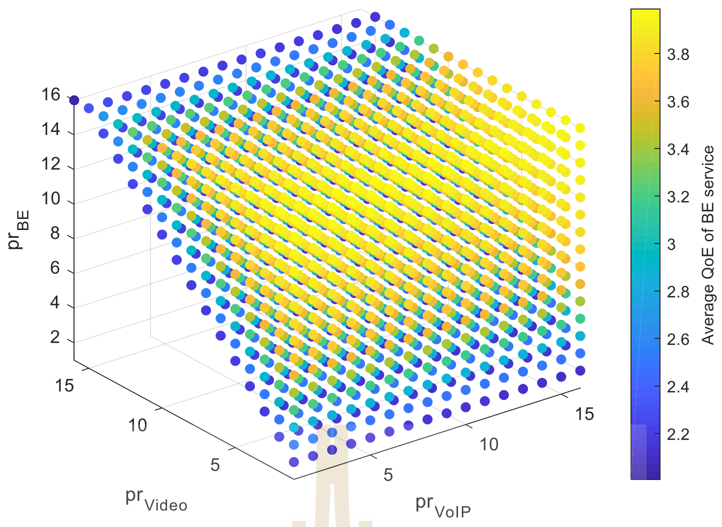


Figure 5.14 The average QoE of BE service by defining the service priority factor with the EXP rule algorithm at 25 UEs to be more than 2 at the bandwidth of 5MHz (1921 Members)

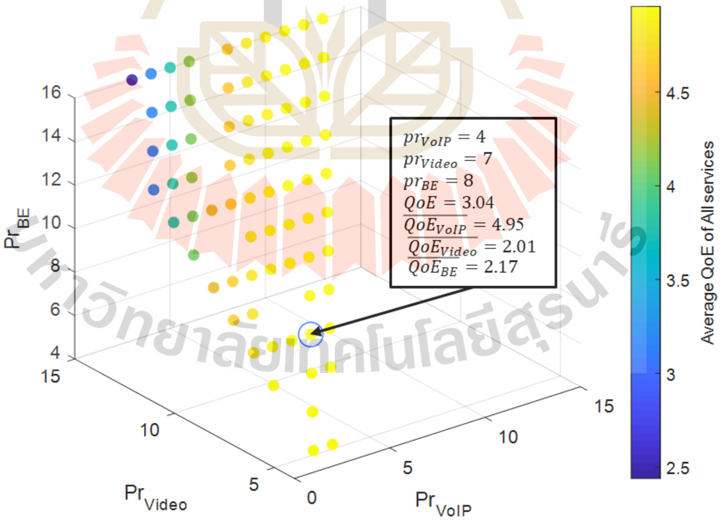


Figure 5.15 The average QoE of all services by defining the service priority factor with the EXP rule algorithm at 25 UEs with the average QoE of VoIP, Video and BE services to be more than 2 at the bandwidth of 5MHz (74 Members)

Table 5.4 Result from finding the optimal parameters with the condition of QoE threshold by using PGA algorithm

Algorithm	P (%)	Avg. N_{used}	Max. N_{used}	Min. N_{used}	Avg. N_{used} (%)
PGA	54.5%	116	406	20	2.83%

In addition, the optimization with constrains from this technique is used to find the optimal parameters that affect to the overall QoE more than QoE threshold. When the result of optimal parameters as $pr_{VoIP} = 4$, $pr_{Video} = 7$ and $pr_{BE} = 8$, it causes the average QoE of all service is equal to 3.00, $\overline{QoE_{VoIP}} = 4.94$, $\overline{QoE_{Video}} = 2.01$ and $\overline{QoE_{BE}} = 2.05$. It can support the UE up to 26 UEs, which the overall QoE increases 4 percent with exiting 5 MHz bandwidth.

Table 5.5 Computational complexity comparison between GA, PSO and PGA algorithms (n=population size)

Process	Computational complexity of algorithms		
	GA	**PSO**	**PGA**
Initial population/swarm and velocity	$O(1)$	$O(1)$	$O(1)$
Selection population	$O(n^2)$		$O(n^2)$
Operate crossover and mutation	$O(n)+ O(n)$		$O(n)+ O(n)$
Convert chromosome to particle			$O(n)$
Evaluate fitness value		$O(n)$	$O(n^2)$
Update Pbest and Gbest		$O(n)+ O(n)$	$O(n^2)+ O(n^2)$
Update velocity and position		$O(n)+ O(n)$	$O(n^2)+ O(n^2)$
PSO termination check		$O(n)$	$O(n^2)$
Convert particle to chromosome			$O(n)$
Replacement	$O(n.log(n))$		$O(n.log(n))$
GA termination check	$O(n)$		$O(n)$
Total	$O(n^2+n.log(n)+3n+1)$ $=\boldsymbol{O(n^2)}$	$O(6n+1)$ $=\boldsymbol{O(n)}$	$O(7n^2+n.log(n)+5n+1)$ $=\boldsymbol{O(n^2)}$

5.5 Computational complexity of optimization algorithms

The computational complexity of the proposed algorithm has been compared and discussed in terms of Big O notation. Table 5.5 unveils the complexity comparison between the proposed and reference algorithms including GA and PSO. As seen in Table 5.5, the computational complexity of the PSO is less than the other algorithms, but the percentage accuracy of PSO is very low. The complexity of the GA and PGA is similar, but the percentage accuracy of the PGA is more than GA. Furthermore, the number of used members in the search space of the PGA is less than GA. Therefore, the PGA algorithm performs between the GA and PSO without a substantial increment in the computational complexity.

5.6 Implementation concept

From the results in this thesis, the network configuration is adjusted with the action as per the policy of the network state for the self-tuning system. In the implementation concept, the policy of a created lookup table is very useful to use the implementation of the networks to provide the UEs according to the condition of service. Table 5.6 shows the policy table to quickly improve the network from the conditions of the state consisting of bandwidth, the number of UEs and the target of provider to find the action of service priority factor for operating the network optimization. This table shows an example of a network configuration in the resource scheduler process to meet the objectives of the target, which include the function of the service guarantee. There are four states under the limited bandwidth scenario based on resource allocation optimization having different benefits. The first state enhances the overall QoE of the system from the configuration with the optimal parameters of the service priority factor. The second state is the network optimization to support more the UEs, which can help reduce the investment costs for setting up a base station. The third state can maximize the average QoE of all services and guarantee the average QoE of each service, which this state contributes to the mutual benefit between MNOs and UEs. In the last state, it helps to support more UEs and guarantee the average QoE of all services and maximize the average QoE of each service. However, the decision of state selection depends on the MNO needs to the Return of Investment (ROI). When ROI is computed as $\frac{UEs_{new}-UEs_{old}}{UEs_{old}} \times 100$, UEs_{new} is the number of supported UEs in the network after optimization and UEs_{old} is the number of UEs before optimizing. Thus, the contributions of this thesis do not only maximize the average QoE of all services and guarantee the average QoE of each service but also can reduce the Capital Expenditure (CAPEX) and Operating Expenses (OPEX) of MNOs.

Table 5.6 The policy table of state and action for optimizing the radio resource allocation in downlink of LTE networks with the service priority factors at 5 MHz bandwidth

State			Action		
Bandwidth	**UE**	**Target of provider**	pr_{VoIP}	pr_{Video}	pr_{BE}
5 MHz	25	Average QoE of all services > 3 (ROI=0%)	11	1	16
5 MHz	46	Average QoE of all services = 3 (ROI=84%)	11	1	16
5 MHz	25	Average QoE of all services > 3 and Average QoE of each service > 2 (ROI=0%)	4	7	8
5 MHz	26	Average QoE of all services = 3 and Average QoE of each service > 2 (ROI=4%)	4	7	8

5.7 Summary

This thesis has focused on resource allocation optimization with the limited bandwidth scenario based on QoE-aware by using the service priority factor in scheduling algorithm to maintain the user experience and support more UEs. The ANN algorithm is used to create an effective QoE model based on the CM value which is very strong. The QoE model is used to evaluate the QoE score from the QoS parameters measured by the simulation. The QoS parameters depend on the determined service priority factor of each service. The proposed PGA algorithm is applied from the advantages of GA and PSO to find the optimal parameters of service priority factor. Based on the simulation results, Ph.D. candidate has found that the PGA was able to find answers quickly with the number of members used in the search space less than GA and PSO methods. Also, the proposed algorithm in this thesis has a high opportunity to find the best answer for a global answer in the search space. With the advantages of the PGA, it can be used to find answers to the service priority factor that make the average QoE of all services with the QoE threshold of each service from the multiple-goal objective technique of PSO process in the proposed PGA algorithm.

CHAPTER VI

CONCLUSIONS

6.1 Conclusions

This thesis has focused on the network optimization of radio resource allocation based on QoE-aware under the limited bandwidth scenario in the LTE technology. To access the user-centric perspective, the QoE model has been created from the help of the Artificial Neural Network (ANN) algorithm that is an effective and accurate method for estimating the QoE score from QoS. Under the limited bandwidth situation, the performance of six common downlink scheduling algorithms from the QoE perspective found that some algorithms can efficiently allocate the resource for the Realtime (RT) service while some works efficiently for the Non-Realtime (NRT) service. However, the method for creating new algorithms is not appropriate due to the resource requirements of each service are different, but the algorithm with the highest overall QoE under this scenario was chosen to allocate the resource with the designed concept from this thesis.

The service priority factor has been used to determine the resource allocation of each service data flow in the downlink scheduling algorithm for maximizing the QoE with constraints. From the simulation results, the different service priority factors of each service affect to the average QoE of each service along with the average QoE of all service. The optimal parameters of service priority factor are used to determine the resource allocation of each service data flow in the downlink scheduling algorithm for maximizing the QoE with constraints. The establishment of the service priority factor operated efficiently, where the QoS Class Identifier (QCI) cannot be effectively used under the limited resources scenario. The proposed Particle Genetic Algorithm (PGA) applied the benefits of the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for finding the optimal parameters, and the simulation results have showed the effectiveness of the proposed algorithm.

The existing works focus on increasing the average QoE of all services, whereas this thesis does not only maximize the average QoE of all services but also maintain the average QoE for each service above the QoE threshold with the optimization with constraints. Besides, the resource allocation by using the optimal parameters found from the proposed algorithm can support more users in the cell coverage with the QoE condition with the limited resource scenario to reduce the Capital Expenditure (CAPEX) and Operating Expenses (OPEX).

The optimal parameters and the state of the network can be recorded in the lookup table. When the state of the limited resource scenario, it triggered the self-tuning to improve the networks automatically from the action of the state in the created lookup table. However, the possibility of an implementation concept was proceeded by creating the lookup table solution in the case of limited resources only.

The solution designed to optimize the network can be so much beneficial for the operators to allocate the effective resources based on QoE-aware to support more users. This self-tuning concept can be taken as the guiding paradigm for supporting the concept of self-optimization (Accedian, White Paper, Q1: 2016).

6.2 Future works

As everyone knows, 5G communications are designed to support three use cases consisting of enhanced Mobile Broadband (eMBB), Ultra-Reliable and Low-Latency Communication (URLLC) and massive Machine-Type Communication (mMTC). Each use case needs the different Key Performance Indicators (KPIs) such as eMBB requires a higher data rate, URLLC must impose very low latency and high reliability, mMTC needs more connectivity density and so on. When three use cases in the next future network lead to the complex network management, Mobile Network Operators (MNOs) must manage networks with the concept of Self-Organizing Network (SON).

In future work, the self-optimizing concept should be comprehensively considered to implement for optimizing and managing the networks in the real environment. The appropriate solution for automatic optimization is essential to be developed to instantly improve the network and to update the system at any time. The self-optimizing concept created by using Machine Learning (ML) technique should be considered from many related factors to optimize the network based on a user-centric perspective.

The network optimization on the next generation, the possibility of implementation concept is based on the ability to improve the network to respond to user needs instantaneously. Therefore, self-optimization is necessary to have the equipment or module within the network that can manage the system from the commands programmed by the embedded system software. When the most important part is the created virtual brain, it is used by using the ML method for getting the state of network to analyze and decide the action that sends the command to the equipment of networks quickly. With the features of Reinforcement Learning (RL) in the Deep Q-

Network (DQN), it can be used to create a virtual brain in the embedded system software, which is the special function to optimize the networks depended on the decided action from the state of networks.

6.3 Thesis suggestions

From the concept of self-optimizing QoE in this thesis, the optimization of radio resource allocation based on the appropriate service priority factors in each service is necessary to have three components for the purpose of implementation. These components consist of nervous system, decision making and responsive control. In the nervous system, the end-device or cell must report the estimated QoE to the network for processing all the time. Meanwhile, the decision making requires the properties of network slicing to simulate the network in the real environment for collecting the datasets to create the virtual brain. Besides, the responsive control needs the equipment and working function with the module of Network Function Virtualization (NFV), Mobile Edge Computing (MEC) and so on to configure the parameters in the network to meet the needs of service. However, this thesis has focused on the network optimization of radio resource allocation based on QoE from adjusting the appropriate service priority factors. Thus, the importance of self-optimizing QoE depends on the predictive function of networks at the cell in the MAC layer to calculate the priority metric from the downlink scheduling algorithm.

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APPENDIX

APPENDIX A

MULTIPLE-GOAL OBJECTIVE

A.1 The multiple-goal objective in Particle Swarm optimization

In this thesis, the proposed algorithm is used in terms of the optimization with constraints. When $Pbest$ and $Gbest$ in Equation 3.34 are the key of determination of particle velocity direction. In the multiple-goal objective technique, the objective values and the condition of threshold values are considered to find the optimal point that refects to overall results of answer from the appropate $Pbest$ and $Gbest$, which can increase efficiency the proposed algorithm as follows:

$$Pbest = \underset{Pbest}{argmax} \prod_{Obj=1}^{N} [e^{m_{Obj} \cdot (f_{Obj}(Pbest) - QoEthreshold_{Obj})}] \quad \text{A.1}$$

$$Gbest = \underset{Gbest}{argmax} \prod_{Obj=1}^{N} [e^{m_{Obj} \cdot (f_{Obj}(Gbest) - QoEthreshold_{Obj})}] \quad \text{A.2}$$

$$m_{Obj}(X) = \begin{cases} 1 \; if \; f_{Obj}(X) - QoEthreshold_{Obj} \geq 0 \\ 10 \; if \; f_{Obj}(X) - QoEthreshold_{Obj} < 0 \end{cases} \quad \text{A.3}$$

where $Pbest$ is the position where the particle has the highest multiple-goal objective in the current cycle, and $Gbest$ is the position where the particle has the highest multiple-goal objective in all the cycles. f_{Obj} is the obj^{th} objective function, $QoEthreshold_{Obj}$ is the obj^{th} condition of defined QoE threshold, and N is the number of objective funtion considered.

APPENDIX B

PUBLICATIONS

List of Publications

International Journal Paper

P. Uthansakul, P. Anchuen, M. Uthansakul and A. A. Khan, "**QoE-Aware Self-Tuning of Service Priority Factor for Resource Allocation Optimization in LTE Networks**," in IEEE Transactions on Vehicular Technology, vol. 69, no. 1, pp. 887-900, Jan. 2020.

P. Uthansakul, P. Anchuen, M. Uthansakul and A. Ahmad Khan, "**Estimating and Synthesizing QoE Based on QoS Measurement for Improving Multimedia Services on Cellular Networks Using ANN Method**," in IEEE Transactions on Network and Service Management, vol. 17, no. 1, pp. 389-402, March 2020.

International Conference Paper

Patikorn Anchuen and Peerapong Uthansakul (2019). **Investigation into User-Centric QoE and Network-Centric Parameters for YouTube Service on Mobile Networks.** In: Proceedings of the 7th International Conference on Communications and Broadband Networking. ACM, 2019. p. 28-32.

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QoE-Aware Self-Tuning of Service Priority Factor for Resource Allocation Optimization in LTE Networks

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***Abstract*—Long Term Evolution (LTE) brings to the theory of advanced leading-edge technologies which guarantees ubiquitous broadband access. As a result, the continuous increment in the number of user terminals (UT) and their expectation leads to the importance of managing and updating the networks as per the expectation of users. In this paper, the concept of self-tuning is used for adjusting the service priority factor in the scheduling algorithms to allocate the resource blocks (RBs) in order to give the appropriate Quality of Service (QoS) based on Quality of Experience (QoE). To access QoE-aware, a QoE model is created by using the Artificial Neural Network (ANN) algorithm to estimate the QoE score by using the QoS parameters. We propose the Particle Genetic Algorithm (PGA) to find the optimal parameter of service priority factors, and the proposed algorithm works efficiently by increasing the average QoE of the network along with maintaining the QoE threshold for each of the multi-service. The detailed comparison is presented between the proposed and reference algorithms to highlight the significance of the proposed algorithm and the simulation and analytical results show that the proposed algorithm outperforms the existing ones in terms of improving the allocation of resources under the environment of limited resources.**

***Index Terms*—LTE, NR, QoE, Self-Organizing Networks, services priority factor, QoS, ANN, Particle Genetic Algorithm.**

I. Introduction

INTERNET data traffic has been increasing exponentially, and the future generation networks are expected to deal with the large number of users, offering the higher data rate, low latency, reduction in the transmitted and radiated power, and the enhancement in the network energy performance [1]. These expectations lead to the evolution of cellular networks from the Fourth Generation (4G) to Fifth Generation (5G) [2]. The Long Term Evolution (LTE) and New Radio (NR) technology are jointly proved to be an auspicious candidate for providing the radio access solution [3] on the 5G cellular networks. The LTE, launched by the 3rd Generation Partnership Project (3GPP) Release 8 in 2008, is the initial version of 4G and it has been incessantly evolving in parallel with NR for the 5G radio access [4]. Therefore, the technology of LTE still plays a significant role in both the current 4G and future 5G networks.

The technology of LTE offers a comprehensive number of applications and services [5], but the continuous increment in the number of user terminals and their demands to access various types of multimedia services such as VoIP, video streaming and other emerging applications lead to the importance of updating the network management as per the expectation of users [6]. The management of mobile networks has become so competitive in this modern era of technology due to the huge number of subscribers and their need to have the continuous connection and ubiquitous broadband access of various applications. Meanwhile, the market of mobile operators has become so profitable, and the mobile operators need to develop their network better than their competitors in terms of network performance [7]. In the past, the mobile operators were keen to improve and maintain the quality of their network by using the traditional Quality of Service (QoS) metrics [8], but the traditional QoS metrics do not directly reflect the user's satisfaction in any way [9]. This drawback shifted the focus of the researchers towards the user-centric approach in order to survive under the competitive environment of the market. Therefore, the traditional QoS metrics need to be replaced by the Quality of Experience (QoE) metrics [10]. The mobile operators must establish a relationship between the QoS and Opinion Score (OS) to understand the user perspective [11], and the user-centric approach, also called as QoE, should be a dominant factor for improving the network performance.

The communication on the LTE air interface happens between the evolved Node B (eNB) and User Equipment (UE) and it is very vital to manage the resources due to the continuous allocation of resources on the LTE network [12]. There are two main approaches to improve the LTE networks in terms of limited bandwidth [13]. The first approach is to add the new cell sites in order to have more available resources, but it leads to higher costs of Capital Expenditure (CAPEX) and Operating Expenses (OPEX), and the second approach is to manage the resource blocks (RBs) allocation of the network. In the current mobile networks, the RBs are managed with the help of downlink packet scheduling [14], [15], and it is responsible for the distribution of resources to the end users in order to meet the required QoS as per the mechanism of Radio Resource Management (RRM) [16]. In the past, the packet schedulers were designed to cope with the multiple users of the same services, and the QoS Class

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Identifiers (QCI) were defined in order to deal with the users using the different services through which the schedulers can set the priority among the services [17]. However, the schedulers based on the QCI, do not provide the optimal performance and cannot be used effectively to allocate the limited resource among the multiple users using the different services in the network.

In [18], the authors use the Channel-aware algorithm to allocate the resources for the users on the basis of Maximum Throughput (MT), and the users having the more channel quality will get more throughput, but its algorithm does not work for the users who are located far from the eNB. This work is further extended in [19], where the authors improve the allocation of resources by using the Proportional Fair (PF). In these above-mentioned researches [18], [19], the authors use the algorithm without considering the QCI, which in turn let them to be unsuitable for the Realtime (RT) services. The most common basic algorithms of QoS-aware consist of Modified-Largest Weighted Delay First (MLWDF) [20], Exponential/Proportional Fair (EXP/PF) [21], Frame Level Scheduler (FLS) [22], Exponential rule (EXP rule) [23] and Logarithmic rule (LOG rule) [24]. These above-mentioned algorithms, based on network centric approach, were developed to achieve the higher throughput and fairness among the user terminals with less delay and losses in order to fulfill the QoS requirements of RT and Non-Realtime (NRT) services, but these algorithms are not suitable in terms of the future generation networks. Therefore, the future resource allocation algorithms need to be based on the QoE-aware in order to have the user centric approach. In [25], the authors propose the QoE-aware scheduling algorithm to allocate the resources for the multi-services by computing the optimal parameter along with balancing the QoE of each service with the help of heuristic method. This research is further extended in [26], where the authors propose the scheduling algorithm to maximize the overall QoE in the cell coverage area by the efficient allocation of resources. The overall QoE of network maximizes, but some services possess the bad QoE.

In terms of next generation networks, the future networks are required to be Self-Organizing Networks (SON) in order to improve the performance of the network by making it self-configuration, self-optimization and the self-healing [27]. The concept of Machine Learning (ML) can be used for the SON to automatically manage the network by reducing the human error, CAPEX and OPEX [28]. By utilizing the benefits of ML, the authors in [29], [30] use the Genetic Algorithm (GA) and Random Neural Network (RNN) to allocate the resources and adjust the optimal parameter of the network in order to improve the QoE for the video services. In the corpus of the existing researches, the QoE-aware algorithms do not deal with the number of users that can be significantly increased during the resource allocation. Furthermore, the scheduling algorithms in the existing researches work by maximizing the overall QoE of the network without determining the QoE threshold of each service in order to guarantee the better user experience.

In this paper, we modify the allocation of resources on the basis of QoE-aware by utilizing the self-tuning concept to support more users under the scenario of limited bandwidth for the multi-services. The services of Voice over Internet Protocol (VoIP), Video and Best-Effort (BE) are considered in this paper, and the QoE model is created by using the Artificial Neural Network (ANN) algorithm to map the QoS and OS to assess the QoE score. Furthermore, the performance of different downlink scheduling algorithms is evaluated and compared in terms of QoE-aware. The new priority metric, calculated from the service priority factor, is introduced, and the new priority metric is bringing the downlink scheduling algorithms to allocate the resources for UEs having the highest priority metric. In addition, we propose the Particle Genetic Algorithm (PGA) to find the optimal parameter values of service priority factor, and the proposed algorithm converges the optimal parameter to a global maximum. The proposed PGA jointly utilizes the benefits of GA and Particle Swarm Optimization (PSO) and allocates the resources to support more users along with maintaining the QoE threshold of each service. The simulation results show the effectiveness of the proposed algorithm, where it can be seen that the proposed algorithm effectively allocates the resources and results into the higher average QoE of the network, allowing more users to be accommodated and maintaining the condition of QoE threshold for each service. The contributions and novelties of this article are summarized as follows:

1. The QoE model is created by using the ANN in order to access the QoE score of multi services.
2. The new priority metric is introduced for the allocation of RBs to UEs on the basis of highest priority metric.

The new optimization algorithm is proposed to compute the optimal parameter of service priority factors.

3. The proposed algorithm not only increases the average QoE of the network, but also maintains the condition of QoE threshold for each service.

The remainder of this article is organized as follows: Section II presents the system models where we discuss the service models, objective function for the OS estimation, scheduling algorithms and priority service function. In Section III, we describe the working of ANN algorithm, and the PGA for the proposed scheme is explained in Section IV. In Section V, we discuss the methodology and the simulation steps. The Section VI belongs to the simulation results, and we conclude in Section VII.

II. System Models

In this section, the system models are discussed for the multi-service LTE system and it consists of service models, QoS parameters, objective function for the OS estimation, scheduling algorithms and the priority service function.

A. Service Models

In this paper, we consider the three main services which consist of VoIP, Video and the BE, and each service is assigned a different QCI [31]. Both the RT and NRT services are considered in this paper to simultaneously serve the users. These services are described as follows.

1) VoIP Service: The VoIP is a conversational RT service defined as per the G.729 that is the narrow-band data compression algorithm to maintain the voice quality during the minimum bandwidth requirements. In this paper, the data source generates the packet of 20 bytes size every 20 milliseconds (ms) or 8 kilobits per second (kbps) during the conversation.

2) Video Service: The Video is an RT service, and we use the trace tool during the video test sequence. In this paper, we use the trace file called "foreman.yuv" during the packet flow, and the video sequence is compressed by using H.264/AVC with the average coding rate of 242 kbps [23].

3) BE Service: The BE is an NRT service, and we use the web browser services for considering the infinite buffer in this paper.

B. QoS Parameters

QoS parameters are the quantitative information, and it is an important metric for accessing the quality of networks. These QoS parameters are based on the following four main factors, i.e., Throughput (TP), Packet Loss Rate (PLR), Packet Delay (PD) or latency and the Jitter (JT) or delay variation.

1) Throughput: It is the number of information bits received per duration time from the eNB to UE on the LTE network for each type of service. The information bits are counted only for the successful packets in kilobits per second (kbps) unit.

2) Packet Loss Rate: The PLR is the ratio of unsuccessful packet transmission to the total packet transmission for each UE, and it is calculated in percentage (%). The PLR should be equal to 0% for the good information transmission.

3) Packet Delay: The PD is the duration time, which the packets take to travel from the eNB to UE for the successful packet transmission, and it is calculated in millisecond (ms).

4) Jitter: The JT is the variance of PD, and it is measured in millisecond as well.

C. Objective Function for the Estimation of OS

The OS represents the user satisfaction, and it is typically divided into five levels consisting of Excellent = 5, Good = 4, Fair = 3, Poor = 2 and Bad = 1 [32] as per the ITU-T P. 800. In this subsection, we define the objective function for the evaluation of OS for each of the above-mentioned services.

1) VoIP Service: The VoIP service needs to send the packets at a continuous interval without the interruption during the conversation. The objective function for the VoIP service in order to evaluate the OS can be written as [33]:

$$OS_{VoIP} = 3.010 \cdot \exp\left(-4.473 \cdot PLR\right) + 1.065 \quad (1)$$

2) Video Service: For the Video service, we use the video trace file "foreman.yuv" and the opinion score of this trace file can be written as [34]:

$$OS_{Video} = -0.54 \cdot \ln\left(PLR\right) + 3.75 \quad (2)$$

3) BE Service: The traffic flow speed of the services can affect the user's satisfaction. In this paper, we consider the web browser services to evaluate the user's satisfaction, and the OS of web browser services in terms of TP (kbps) can be written as [35]:

$$OS_{Web} = 5 - \frac{578}{1 + \left(\frac{\mathrm{TP}+541.1}{45.98}\right)^2} \quad (3)$$

In the existing researches [33]–[35], the authors consider only one QoS parameter to predict the OS even though other parameters may affect user satisfaction. In this paper, we use the objective functions (1) to (3) to evaluate the OS instead of evaluating from the real users. There is no exact model in the existing literature so that's why these objective functions are used in this paper. The estimated OS and the collected QoS parameters are used in the pre-processing process to analyze the relationship and select the QoS parameters for the QoE modelling. An ANN is a powerful data-driven and the flexible computational tool, and has the ability to implicitly detect the nonlinear relationships between the dependent and independent variables with a high degree of accuracy. Therefore, the ANN is used to create the objective function for the estimation of the QoE score with the help of QoS parameters.

D. Downlink Scheduling Algorithms: Scheduling plays an important role in the RRM mechanism of eNB to allocate the resources of UEs. Many downlink scheduling algorithms have been developed for the efficient allocation of resources for the multiple services [36], [37]. These algorithms, based on QoS metric, have many advantages and disadvantages when deployed for the different services, but these algorithms don't work effectively under the scenario of limited resources. In this paper, the performance of the most common downlink scheduling algorithms is evaluated in terms of QoE metric for the allocation of RBs with the proposed mechanism to increase the QoE under the scenario of limited resources. Table I shows the six general downlink scheduling algorithms in LTE networks for the allocation of RBs. These algorithms are just considered in order to select the appropriate algorithm for the demonstration of self-tuning concept in this paper.

E. Priority Service Function

The priority service function is designed for the RBs allocation based on QoE-aware to increase the QoE with the limited bandwidth, and it can be calculated as:

$$pri_k = \exp\left(pr_k\right) \quad (4)$$

when pr_k is a service priority factor of the k^{th} service. Therefore, the new priority metric of the downlink scheduling algorithm is bringing the priority metric of downlink scheduling algorithms to multiply with the priority service function in order to allocate the resources for the UEs on the basis of highest priority metric. This new priority metric can be calculated as:

$$F_{ijk} = w_{ij} \cdot pri_k \quad (5)$$

where F_{ijk} is a new priority metric for the i^{th} user on the j^{th} subchannel of k^{th} service.

III. Overview of the ANN

A. ANN

The ANN, also called a connectionist system, consists of sub-processing units and nodes for the processing of data like the human brain [38]. The structure of ANN consists of three layers that are interconnected, and each layer consists of an input

TABLE I
GENERAL DOWNLINK SCHEDULING ALGORITHMS IN LTE NETWORKS AND VARIABLE NOTATION

Algorithm	Priority Metric
PF [19]	$w_{ij}=\frac{r_{ij}}{\overline{R}_i}$
MLWDF [20]	$w_{ij}=\alpha_i D_{HOL,i}\frac{r_{ij}}{\overline{R}_i}$ $\alpha_i=-\frac{\log(\delta_i)}{\tau_i}$
EXP/PF [21]	$w_{ij}=exp(\frac{\alpha_i D_{HOL,i}-X}{1+\sqrt{X}})\frac{r_{ij}}{\overline{R}_i}$ $X=\frac{1}{N_{rt}}\sum_{i=1}^{N_{rt}}\alpha_i D_{HOL,i}$
FLS [22]	$w_{ij}=\frac{r_{ij}}{\overline{R}_i}$ $u_i(k)=h_i(k)*q_i(k)$
EXP rule [23]	$w_{ij}=b_i exp(\frac{a_i D_{HOL,i}}{c+\sqrt{\frac{1}{N_{rt}}\sum_{i=1}^{N_{rt}}D_{HOL,i}}})\Gamma_j^i$ where [37]: $a_i\epsilon[\frac{5}{0.99\tau_i},\frac{10}{0.99\tau_i}]$, $b_i=1$ and $c=1$
LOG rule [24]	$w_{ij}=b_i\log(c+a_i D_{HOL,i})\Gamma_j^i$ where [37]: $a_i=\frac{5}{0.99\tau_i}$, $b_i=1$ and $c=1.1$

Description of Symbol

i, j, k: i^{th} user on j^{th} subchannel of the k^{th} service
r_{ij}: The throughput achieved for i^{th} user on j^{th} subchannel
$\overline{R}_i$: The average throughput achieved on i^{th} user
w_{ij}: The priority metric for i^{th} user on j^{th} subchannel
$D_{HOL,i}$: The Head of Line (HOL) delay for i^{th} user
α_i: The factor computed from QoS for i^{th} user
δ_i: The acceptable Packet Loss Rate for i^{th} user (from QCI)
τ_i: The Delay threshold for i^{th} user (from QCI)
N_{rt}: The number of active Realtime flows
$*$: The discrete time convolution operator
$h_i(k)$: The impulse response of Linear Time Invariant (LTI) filter
$q_i(k)$: The signal in queue level for filtering
Γ_j^i: The spectral efficiency for i^{th} user on j^{th} subchannel
a_i, b_i, c: The tunable parameters

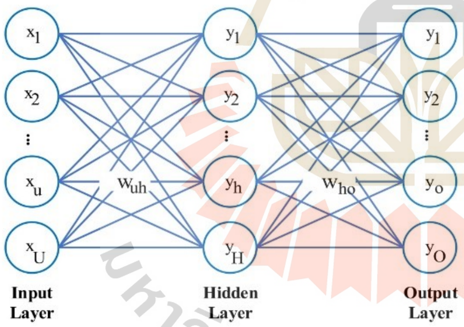


Fig. 1. The structure of artificial neural network.

layer, hidden layer and the output layers respectively as can be seen in Fig. 1. These layers are connected in a Multi-Layer Perceptron (MLP) to process the data from the input layer to output layer [39]. In this paper, the appropriate weight and threshold coefficients are computed by using the Feed Forward Back Propagation (FFBP) neural network, which is the supervised

TABLE II
INFORMATION OBTAINED FROM MEASURING THE QOS PARAMETERS ON THE LTE NETWORK

VoIP	Video	BE
TP_{VoIP}, PLR_{VoIP}, DL_{VoIP} and JT_{VoIP}	TP_{Video}, PLR_{Video}, DL_{Video} and JT_{Video}	TP_{BE}, PLR_{BE}, DL_{BE} and JT_{BE}

learning in order to estimate the desired QoE. The working of ANN is described in the following subsections:

1) Pre-Processing: The pre-processing is used to analyze the relationship and select the QoS parameters for the QoE modeling by using the collected datasets with the help of LTE simulation. The QoS parameters of each service are shown in Table II. We use the objective function to estimate the OS of each service and the OSs are calculated by using the (1), (2) and (3). The datasets of each service are used to analyze the correlation coefficients. The absolute correlation coefficients of these variables must be greater than 0.20 for the selection of QoS parameters to create the QoE model. The correlation coefficient (r) can be calculated as:

$$r=\frac{\sum_{n=1}^{N}(OS_n-\overline{OS})(QoS_n-\overline{QoS})}{\sqrt{\sum_{n=1}^{N}(OS_n-\overline{OS})^2}\sqrt{\sum_{n=1}^{N}(QoS_n-\overline{QoS})^2}} \quad (6)$$

where r represents the Pearson correlation coefficients between the QoS and OS, n represents the n^{th} dataset, and N represents the total amount of datasets or information. Furthermore, OS represents the opinion score, $\overline{OS}$ represents the average opinion score or Mean Opinion Score (MOS) as defined by ITU-T [32], $\overline{QoS}$ represents the average QoS parameter, and QoS_n represents the QoS parameter at n^{th} information. The r is representing the relationship between the variables, and the negative and positive values of r represent the relationship between the variables in the reverse and same direction respectively. Whereas, the variables will have no relationship if the r comes out to be 0.

The QoS parameters and OSs are transformed into the appropriate data for the ANN process in order to use them in the learning process, and the input values (x_u) and target values for the ANN processes can be written as:

$$c_u=\frac{\sum_{n=1}^{N}|OS_n\cdot QoS_{u,n}|}{\sum_{n=1}^{N}QoS_{u,n}^2} \quad (7)$$

$$x_u=c_u\cdot QoS_u \quad (8)$$

$$OS_{target}=\frac{4\cdot(OS-OS_{\min})}{OS_{\max}-OS_{\min}}+1 \quad (9)$$

where $\boldsymbol{u}$ is the $\boldsymbol{u^{th}}$ selected metric, $\boldsymbol{c_u}$ is a normalizing coefficient, $\boldsymbol{QoS_u}$ is the $\boldsymbol{u^{th}}$ QoS parameter and $\boldsymbol{x_u}$ is the normalized input data of ANN. $\boldsymbol{OS_{target}}$ is the targeted opinion score for the learning in ANN.

2) QoE Model Creation: The input data (x_u) and the target of teaching $(\mathrm{OS_{target}})$ are used to get the relationship between the OS and QoS. The effective learning of ANN depends on the hidden nodes and correlation coefficient between the QoS and OS. We set the number of hidden layers to one layer to reduce the complexity of ANN process. The number of input nodes is equal to the number of selected QoS parameters. The number of hidden nodes is set to three nodes by using the Try and Error method [39]. Whereas, the output node is set to one node. The thresholds and the link weights are represented by using the following variables w_{uh}, w_{ho}, θ_h and θ_o, and the values of these variables are constant within the ANN equation to evaluate the QoE score. In the ANN process, the output of each node is computed by using the activation function that is the sigmoid function to find the error for adjusting the thresholds and link weights. The sigmoid function can be written as:

$$S(Z) = \frac{1}{1+e^{-Z}} \tag{10}$$

where Z is the output value of the node and $e = 2.718$.

The initial thresholds and link weights are set with the random values from the domain of the differential sigmoid function. The range and domain of the differential sigmoid function exist from 0 to 0.25. In this paper, we determine the learning rate $(\propto)$ in ANN within the range of differential sigmoid function. The main steps of ANN learning are given as follows.

The first step in ANN process is the initialization of learning rate, weight and threshold. When the output node consists of one node, then the OS is normalized in the range that exists from 0 to 1 in the ANN learning process. This target value of the output node (t_o) can be written as:

$$t_o(p) = 0.2 \cdot OS_{\text{target}} \tag{11}$$

The second step is the activation process to predict the output value of a node by using the sigmoid function with the help of the following equations:

$$y_h(p) = S\left(\sum_{u=1}^{U} x_u(p) \times w_{uh}(p) - \theta_h(p)\right) \tag{12}$$

$$y_o(p) = S\left(\sum_{h=1}^{H} y_h(p) \times w_{ho}(p) - \theta_o(p)\right) \tag{13}$$

Table III shows all the used variables in the equations (12) to (21). The third step is the weight and threshold learning to adjust the weight and threshold in FFBP-ANN. The $x_u(p)$ is used to predict the $y_o(p)$ in (12) and (13). The error $e_o(p)$ can be evaluated by comparing the $t_o(p)$ and $y_o(p)$:

$$e_o(p) = t_o(p) - y_o(p) \tag{14}$$

Thus, the $y_o(p)$ and $e_o(p)$ are used to compute the gradient error of output nodes:

$$\delta_o(p) = [1 - y_o(p)] \cdot y_o(p) \cdot e_o(p) \tag{15}$$

The new link thresholds and weights can be computed as:

$$w_{ho}(p+1) = \alpha \cdot y_h(p) \cdot \delta_o(p) + w_{ho}(p) \tag{16}$$

$$\theta_o(p+1) = -\alpha \cdot \delta_o(p) + \theta_o(p) \tag{17}$$

We set the α to 0.25, and the gradient error of the hidden layer nodes can be calculated as:

$$\delta_h(p) = [1 - y_h(p)] \cdot y_h(p) \cdot \delta_o(p) \times w_{ho}(p) \tag{18}$$

TABLE III
VARIABLE NOTATIONS OF THE ANN ALGORITHM

Symbol	Description
p	The sequence of dataset
P	The total amount of information.
U	The number of input nodes
H	The number of hidden nodes
O	The number of output nodes
u	The sequence of input nodes
h	The sequence of hidden nodes
o	The sequence of output nodes
$x_u(p)$	The value of input layer at the u^{th} input node
$y_h(p)$	The value of hidden layer at the h^{th} hidden node
$y_o(p)$	The value of output layer at the o^{th} output node
$w_{uh}(p)$	The link weight of input layer to hidden layer
$w_{ho}(p)$	The link weight of hidden layer to output layer
$\theta_h(p)$	The threshold of hidden layer at the h^{th} hidden node
$\theta_o(p)$	The threshold of output layer at the o^{th} output node
$e_o(p)$	The error value of output layer at the o^{th} output node
$t_o(p)$	The target value of output layer at the o^{th} output node
$\delta_h(p)$	The gradient error of hidden layer at the h^{th} hidden node
$\delta_o(p)$	The gradient error of output layer at the o^{th} output node
$\propto$	The learning rate
$w_{uh}(p+1)$	The new link weight of input layer to hidden layer
$w_{ho}(p+1)$	The new link weight of hidden layer to output layer
$\theta_h(p+1)$	The new threshold of hidden layer at the h^{th} hidden node
$\theta_o(p+1)$	The new threshold of output layer at the o^{th} output node
SSE	The sum of square error

Similarly, the new thresholds and link weights can be computed as:

$$w_{uh}(p+1) = \alpha \cdot x_u(p) \cdot \delta_h(p) + w_{uh}(p) \tag{19}$$

$$\theta_h(p+1) = -\alpha \cdot \delta_h(p) + \theta_h(p) \tag{20}$$

The process increases the sequence of dataset by one and then the next data set is entered into the equations (12) to (20) in the second step, and this process will continue until the value of p becomes equal to the total amount of information.

The *SSE* is computed by using the $e_o(p)$ for every value of p with the help of (21), and this process will continue until the SSE value becomes acceptable by getting equal to 0.00001.

$$SSE = \sum_{p=1}^{P}\sum_{o=1}^{1} e_k(p)^2 \tag{21}$$

The values of w_{uh}, w_{ho}, θ_h and θ_o will be updated when the SSE gets acceptable in the process of QoE creation.

The next step is to test the QoE model by using the data set from the learning process to measure the efficiency of the model. The QoS parameters are entered in the (12) to calculate the output by using (13). In order to estimate QoE score, the output node is multiplied by a coefficient value to estimate the QoE score that exists from 1 to 5 as per ITU-T P.800 because the maximum

TABLE IV
DETERMINING THE MODEL RELIABILITY LEVELS WITH RESPECT TO THE CORRELATION MODEL (CM)

Model Reliability	Very weak	Weak	Moderate	Strong	Very strong
Correlation Model	0.01-0.20	0.21-0.40	0.41-0.60	0.61-0.80	0.81-1.00

value of output node can be 1:

$$QoE = 5 \cdot y_o \tag{22}$$

The OS of dataset and QoE score are compared to evaluate correlation metric for the Correlation Model (CM):

$$CM = \frac{\sum_{p=1}^{P}\left(QoE_p - \overline{QoE}\right)\left(OS_p - \overline{OS}\right)}{\sqrt{\sum_{p=1}^{P}\left(QoE_p - \overline{QoE}\right)^2}\sqrt{\sum_{p=1}^{P}\left(OS_p - \overline{OS}\right)^2}} \tag{23}$$

where QoE represents the estimated QoE score, and the CM represents the correlation coefficient between the QoE_p and OS_p. Furthermore, $\overline{OS}$ represents the average opinion score, OS_prepresents the p^{th} opinion score, $\overline{QoE}$ represents the average of p^{th} QoE score, and QoE_p represents the p^{th} QoE score.

The CM value can be interpreted with respect to five different reliability levels as per the Evant (1996) [40] as can be seen in Table IV.

The function of QoE score estimation can be written as:

$$QoE = f\left(QoS\right) \tag{24}$$

IV. THE PROPOSED PGA SCHEME

A. PGA

In this paper, we propose the hybrid approach called PGA that combines the advantages of PSO [41] and GA [42]. A hybrid approach based on the standard PSO and GA was presented in [43], where the authors conclude that the hybrid model comes out to be effective in solving problems that are superior to using only PSO or GA. The concept of hybrid approach based on the standard PSO and GA is also utilized in [44], where the authors estimate the parameters for a full power quality disturbance parameterized model. The PSO helps to reduce the limitation of GA in terms of local search by increasing the speed and accuracy. Therefore, the PSO is used to find the answers in the neighbor search space in the PGA. The PGA consists of population selection, crossover, and mutation like the GA approach and changes the position and velocity like the PSO approach. The entry of selected population into the new cycle will not only be crossover and mutation, but also moves the position in local search like the PSO process. After the completion of the mutation process in GA process, the chromosome is converted to the particle by the PSO method, where the population is the swarm, and each chromosome is a particle. After the PSO process, the particle is converted to chromosome. The most suitable populations are selected for the next cycle. Fig. 2 shows the process of proposed PGA method, and the process of the PGA is summarized as follows:

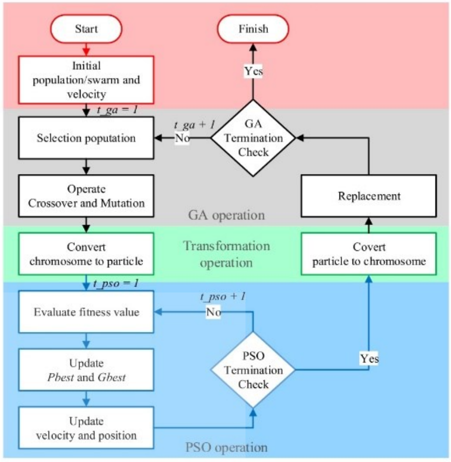


Fig. 2. The process of the particle genetic algorithm.

1) Initial Population/Swarm and Velocity: In this process of the PGA, the random population is computed in a similar way as in the GA algorithm by using the (25). The chromosome consists of many genes and each gene is the parameter of service priority factors. The swarm consists of many particles and each particle is a parameter. Hence, the chromosome is similar to the particle. The additional part of this process is the random velocity V of particles, and it can be written by using the (26):

$$P_{old} = R_p\left(N\right) \tag{25}$$

$$V = R_v\left(N\right) \tag{26}$$

where P_{old} is the old population, V is the velocity of the particle, $R_p(N)$ is the function of random population with N chromosomes, and $R_v(N)$ is the function of random velocity with N particles. Each chromosome is packed with the information of many genes $(Chromosome = \{gene_1, gene_2, \ldots, gene_D\})$, and D is the number of dimensions. N is the number of populations in each generation (t_ga). The randomization process of P_{old} and V are shown in Fig. 3.

2) Selection Population: The selection function chooses the population for the next genetic operation from the old population (P_{old}) with the combined rank method that is the combination of fitness rank and diversity rank. The combined rank method uses the fitness function for the chromosome selection and the local search method can search in depth to reach the optimal results in a narrow range. The selection function chooses the population for the next genetic operation from the old and new population with the help of combined rank method until the number of populations becomes equal to N, and it can be written as:

$$P_{new} = f_s\left(P_{old}\right) \tag{27}$$

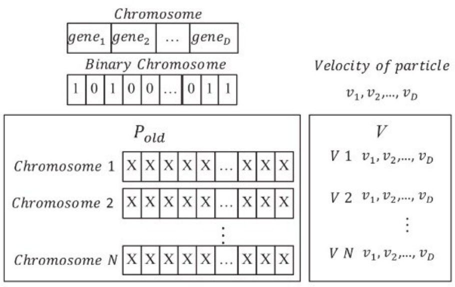


Fig. 3. Initial population and velocity process.

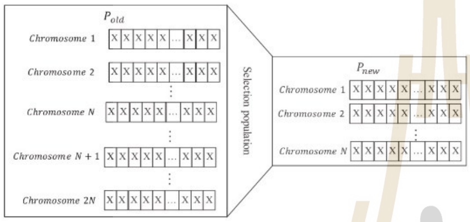


Fig. 4. Selection population process.

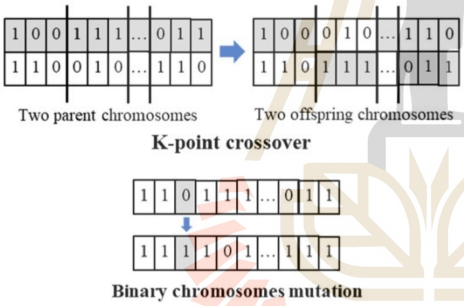


Fig. 5. Crossover and mutation process.

where P_{new} is the new population and $f_s(P_{old})$ is the selected population from P_{old}. The process of population selection is shown in Fig. 4.

3) Operate Crossover and Mutation: The genetic operation consists of crossover and mutation as shown in Fig. 5. The crossover is the transfer of internal genes in the chromosomes. There are many crossovers methods [45] such as single-point crossover and multiple-point crossover and p_c is the crossover probability. The P_{new} and p_c performs the crossover function and updates the P_{new} by using the following equation:

$$P_{new} = f_c(P_{new}, p_c) \tag{28}$$

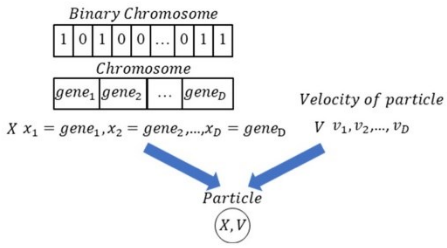


Fig. 6. Conversion from chromosome to particle process.

Following the crossover process, the P_{new} is entered into the mutation process. A mutation process is a randomization of new parameter to a gene with the mutation probability of p_m. The chromosome gets slightly altered to a random position by the change of genes with the following mutation function:

$$P_{new} = f_m(P_{new}, p_c) \tag{29}$$

where f_c is the crossover function and f_m is the mutation function.

4) Convert Chromosome to Particle: In this process, the chromosome is transformed into the particle. The particle consists of position and the velocity of each dimension. The conversion of chromosomes into the particle is shown in Fig. 6 and can be written as:

$$[X, V] = f_{cp}\,(Chromosome, V) \tag{30}$$

where X is a position of the particle, and it is also called the service priority factor. f_{cp} is the function in order to convert the chromosome to particle.

5) Evaluate Fitness Value: The PSO process uses the objective function to compute the fitness value. The fitness value can be calculated as:

$$F\,(X) = f_o\,(X) \tag{31}$$

where $F(X)$ is the fitness value of X and f_o is the objective function.

6) Update Pbest and Gbest: The position of particles that causes the highest fitness value in the current cycle and the position of particles that causes the highest fitness value in all cycles are updated to $Pbest$ and $Gbest$, respectively, and these operations can be calculated by using the following equations:

$$\text{If } F\,(X_{kD}) > F\,(Pbest)\ THEN$$
$$Pbest_D = X_{kD}\ ENDIF \tag{32}$$
$$\text{If } F\,(X_{kd}) > F\,(Gbest)\ THEN$$
$$Gbest_D = X_{kD}\ ENDIF \tag{33}$$

where $Gbest$ is the position where the particle has the highest objective value in all the cycles i.e., $Gbest_D = \{Gbest_1, Gbest_2, \ldots, Gbest_D\}$, and $Pbest$ is the position where the particle has the highest objective value in the current cycle i.e., $Pbest_D = \{Pbest_1, Pbest_2, \ldots, Pbest_D\}$. The $X_{kD}(t) = \{x_{k1}(t), x_{k2}(t), \ldots, x_{kd}(t), x_{kD}(t)\}$ where D is the number of dimensions, d is the sequence of dimensions, k is the sequence of particles and t is the sequence of cycles (t_pso).

7) Update Velocity and Position: The velocity and position of each particle in the next cycle can be calculated by using the following equations:

$$\left.\begin{array}{l} v_{\min} \text{ if } v_{kd}(t+1) \leq v_{\min} \\ v_{kd}(t+1) = w(t)\, v_{kd}(t) \\ +c_p u_p \left(Pbest_d - x_{kd}(t)\right) \\ +c_g u_g \left(Gbest_d - x_{kd}(t)\right) \\ v_{kd}(t+1) = \begin{cases} v_{\min} & \text{if } v_{kd}(t+1) \leq v_{\min} \\ v_{\max} & \text{if } v_{kd}(t+1) \geq v_{\max} \end{cases} \end{array}\right\} \tag{34}$$

$$\left.\begin{array}{l} v_{kd}(t+1) = x_{kd}(t) + \alpha v_{kd}(t+1) \\ x_{kd}(t+1) \begin{cases} x_E & \text{if } x_{kd}(t+1) \leq x_{\min} \\ x_{\max} & \text{if } x_{kd}(t+1) \geq x_{\max} \end{cases} \end{array}\right\} \tag{35}$$

where v_{kd} and x_{kd} are the velocity and position of a k^{th} particle in the d^{th} dimension. $Pbest_d$ and $Gbest_d$ are the positions where the particle has the high objective value in the current and history cycles at the d^{th} dimension, respectively. w and α are the weight values to determine the distance for changing the position, c_p and c_g are the acceleration constant of personal best position and the global best position, u_p and u_g are the constants for the searching of personal best position and global best position, respectively.

8) PSO Termination Check: The PSO termination check has three conditions as mentioned in the termination check. In the first condition, when the $F(X_{kD})$ has a higher value than the desired answer, it will stop working. In the second condition, when the searching takes a long time and the number of search cycles exceed the set value, it will stop working. And in the last condition, when all the values of X are equal in the particle swarm, it will stop working. We can choose only one condition for stopping the process in PSO algorithm. Each condition will have different performance, and we set the second condition in this paper aiming to have the quick and effective working.

9) Convert Particle to Chromosome: When the PSO process gets completed, then the particle converts to chromosome, and it is entered again in GA algorithm as shown in Fig. 7 by using the following equation:

$$[Chromosome, V] = f_{pc}(X, V) \tag{36}$$

where f_{pc} is the function in order to convert the particle to chromosome.

10) Replacement: In this process, the population is replaced with the appropriate value for the next generation by using the following equation:

$$P_{old} = f_r\ (P_{old}, P_{new}) \tag{37}$$

where f_r is the function of population replacement.

11) GA Termination Check: There are two conditions for the GA termination. In the first one, if the results are better or equal to the desired one then it will stop working. In the second condition, if the number of search cycles takes a long time, then it will stop finding the answer.

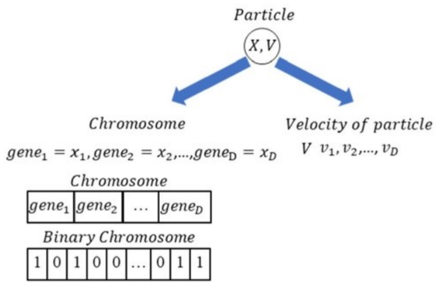


Fig. 7. Conversion from particle to chromosome process.

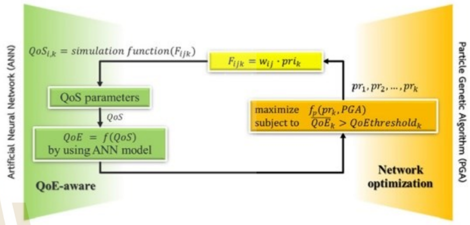


Fig. 8. The integration of ANN and PGA in the proposed system.

The function of PGA for the computation of optimal parameter can be written as:

$$[\mathrm{X}, N_{used}] = f_p(pr_k, PGA) \tag{38}$$

where X is the answers of optimal parameter in PGA algorithm, and N_{used} is the number of used populations to find the answer. The ANN model is used to calculate the QoE in the process function (f_p), and it is explained in details in Section V. The integration of the ANN with PGA in the proposed system can be seen in Fig. 8.

V. Methodology and Simulation

In this section, we explain the methodology and simulation steps. It consists of LTE-Sim, downlink scheduling method, QoE model, and the procedure of optimization technique to compute the optimal parameter of service priority factors.

A. LTE-Sim

The LTE-Sim is an open source framework developed by G. Piro [46] to simulate the protocol stack of LTE network in the resource allocation process, and the network topology of LTE-Sim can be seen in Fig. 9. Several simulation scenarios can be created by using the LTE-Sim. In this paper, we use the single-cell/multi-service scenario under the condition of limited bandwidth for the multi-user simulation, and modify the process

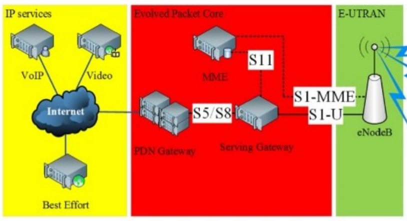


Fig. 9. The network topology of the LTE-Sim [46].

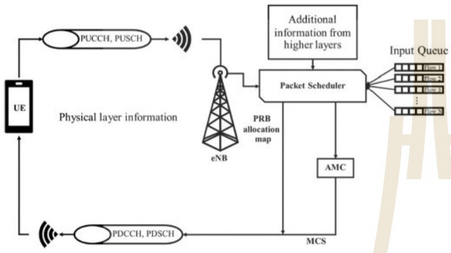


Fig. 10. The model of the scheduling process.

of downlink packet scheduling algorithms by using the priority service function as can be seen in the (5). The simulation results provide the QoS parameters consisting of TP, PLR, PD, and JT of every type of service for all the UEs as shown in the (39).

$$QoS_{i,k} = simulation\ function(F_{ijk}) \tag{39}$$

where $QoS_{i,k}$ is a QoS of i^{th} user for the k^{th} service and $QoS = \{TP,\ PLR,\ DL,\ JT\}$ and $k = \{VoIP,\ Video,\ BE\}$.

B. Downlink Scheduling Method

The downlink scheduling is a mechanism for the allocation of resources to the UEs. The resources are allocated in the units of PRBs, and the operators prefer to provide flexible resources [47] because LTE uses the OFDMA in the downlink. In this paper, we use the service priority factor for the computation of priority metric to have the efficient resource allocation on the bases of QoE-aware by using the (5). The data flow of users with the highest new priority metric in subchannel will be allocated. This process is operated by the scheduling algorithms in the MAC layer of eNB until all the packets get allocated. Fig. 10 unveils the model of packet scheduling.

C. QoE Model

The simulation results provide the database, which includes the QoS parameters of each user for every type of service by using the LTE-Sim. The OS and QoS parameters of each user for every type of service are combined into the dataset, and the collected datasets are used to create the QoE model. To evaluate the QoE for the VoIP services, the TP, PLR, PD and JT are used

TABLE V
INFORMATION OF QOE MODEL BY USING THE ANN ALGORITHM

Information	VoIP service	Video service	BE service
r_{TP}	0.34	0.88	0.78
r_{PLR}	-0.99	-0.82	-0.38
r_{DL}	-0.69	-0.19	0
r_{JT}	-0.29	-0.18	0
Input nodes	4	2	2
Hidden nodes	3	3	3
Output nodes	1	1	1
SSE	0.00001	0.00001	0.00001
CM	0.99	0.98	0.97
Reliability model	Very strong	Very strong	Very strong

because the absolute correlation coefficients of each parameter come out to be greater than 0.20 in the pre-processing. Whereas, we use the TP and PLR to access the QoE for the video and BE services because the correlation coefficients of PD and JT do not come out to be more than the set threshold in the pre-processing process. Table V shows the information of QoE model generated by using the ANN algorithm.

The QoE estimation function that is the objective function in (24) is converted to (40), (41) and (42) to evaluate the QoE score for VoIP, Video and the BE services, respectively.

$$QoE_{VoIP} = f(TP,\ PLR,\ DL,\ JT)_{VoIP} \tag{40}$$

$$QoE_{Video} = f(TP, PLR)_{Video} \tag{41}$$

$$QoE_{BE} = f(TP,\ PLR)_{BE} \tag{42}$$

The average QoE for the services of VoIP, Video and BE services can be computed by using the following equations:

$$\overline{QoE_{VoIP}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{VoIP,n} \tag{43}$$

$$\overline{QoE_{Video}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{VIDEO,n} \tag{44}$$

$$\overline{QoE_{BE}} = \frac{1}{N}\sum_{n=1}^{N} QoE_{BE,n} \tag{45}$$

where N is the number of UEs within the cell and n is the sequence of UEs.

The average QoE of the network can be calculated by using the following equation:

$$QoE = \frac{1}{K}\sum_{k=1}^{K} \overline{QoE_k} \tag{46}$$

where K is the number of services within the cell and k is the sequence of service.

D. Optimization Technique Procedure

The optimization technique is used to find the optimal parameter of a service priority factors in order to have the highest average QoE of the network along with maintaining the QoE threshold of each service. The process of pr_k configuration to

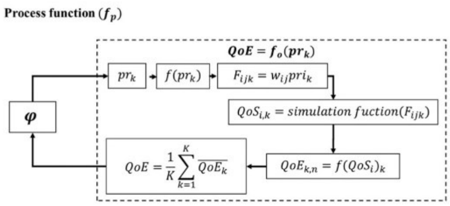


Fig. 11. The procedure of the process function.

obtain the average QoE of the network is as follows: start by setting the pr_k and calculate pri_k by using the (4), multiply pri_k with w_{ij} to compute the new priority metric F_{ijk} by using the (5). The new priority metric F_{ijk} is used to set the parameters during the RBs allocation. The QoS parameters are used to estimate the average QoE score for each type of service by using the (43), (44), and (45) respectively, and the average QoE of network in the cell can be computed by using the (46). Fig. 11 shows the process of optimization technique and the optimization problem is defined as:

$$\begin{aligned} &\text{maximize} \quad f_p(pr_k, \varphi) \\ &\text{subject to} \quad \overline{QoE}_k > Qo\ Ethreshold_k \end{aligned} \tag{47}$$

where f_p is process function, pr_k is a service priority factor of the k^{th} service. In addition, $\varphi = \{GA,\ PSO,\ PGA\}$ and it represents the considered algorithm to compute the optimal parameter of pr_k. $\overline{QoE}_k$ is the average QoE of the k^{th} service and $QoEthreshold_k$ is the QoE threshold of the k^{th} service.

VI. Simulation Results

In this section, we perform the simulations and discuss the simulation results. The simulation results are divided into three subsections. In the first subsection, we compare the performance of above mentioned six scheduling algorithms in terms of QoE performance. In the second subsection, we define the service priority factor for the efficient allocation of resources. The optimal parameter of service priority factors is computed by using GA, PSO, and the PGA algorithm, based on QoE-aware, by maximizing the average QoE of the network. In the third subsection, the optimal parameter is computed by using the PGA algorithm with the condition of QoE threshold.

A. QoE-Aware Packet Scheduling

In this subsection, we compare the performance of six scheduling algorithms based on QoE-aware by using the LTE-Sim under the scenario of multi-users and multi-services. Table VI unveils the simulation parameters and we create the limited bandwidth scenario by setting the bandwidth of 5 MHz in the simulation parameters. The bandwidth of 5 MHz can support 200 UEs in 3GPP [48]. In this paper, we set the number of UEs from 5 to 100 and when many active UEs will be connected to the network, then each service may require different resources.

TABLE VI
Simulation Parameters

Parameters	Value
Simulation duration	120 seconds
Frame structure	FDD
Symbol for TTI	14
Carrier frequency	2 GHz
Bandwidth	5 MHz
Number of RBs	25
Channel model	Typical Urban (TU)
Cell radius	1 km
Scheduling time	Every 1 TTI
Mobility model	Random
Mobile speed	3 km/h
Simulation scenario	Single Cell with Interference
Max delay	0.1 s
Traffic model	VoIP – G.729 (8.2 kbps) Video – Trace based H.264 (242 kbps) Best Effort – Infinite buffer
UE application flow	One VoIP, one Video and one BE
Number of UEs	5:5:100
Scheduling Algorithm	PF, MLWDF, EXP/PF, FLS, EXP rule and LOG rule algorithms

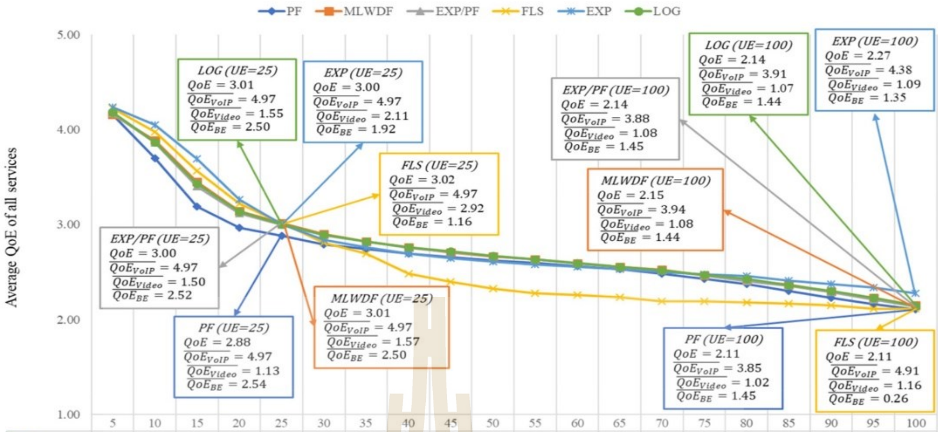
Fig. 12 shows the average QoE of the network for each of the scheduling algorithm, where it can be seen that when the number of UE increases, then the average QoE of the network decreases significantly due to the limited allocation of resources. Furthermore, when the number of UEs is 25 and 100, then the FLS has the highest average QoE for the VoIP service and lowest average QoE for the NRT BE service.

Whereas, the QoE of BE becomes 0 for the users that are not allocated. As can be seen in Fig. 12, the EXP rule provides the higher average QoE of all services compared to other algorithms when the users increase, and when the users are 100 then the EXP rule has the highest average QoE for all services.

B. Finding the Optimal Parameter Using GA PSO and PGA Algorithms

Due to the better performance of EXP rule in terms of QoE [31], we choose the EXP rule for the allocation of resources in this paper. We set the number of UEs to 25 and implement the service priority factor to determine the new priority metric for the mechanism of resource allocation in order to have a better QoE. The average QoE of all the services is set to 3.00 prior to optimization as can be seen in Fig. 12.

We define the service priority factor to be a positive integer from 1 to 16 for each of the service consisting of VoIP, Video and BE ($pr_k \in I^+ = \{1, 2, \ldots, 16\}$). Therefore, the total number of sample space can be written as $16^3 = 4096$, and it is necessary to use the exhaustive search method to find the optimal parameter of service priority factor that ensure the highest average QoE of all the services. Fig. 13 shows the average QoE of all the services by using the exhaustive search method in EXP rule, and the optimal parameter of service priority factor comes out to be $pr_{VoIP} = 8, pr_{Video} = 13$ and $pr_{BE} = 2$ with the average QoE of 3.13 for all the services.



	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
PF	4.16	3.70	3.19	2.96	2.88	2.79	2.74	2.69	2.66	2.62	2.60	2.56	2.53	2.48	2.43	2.37	2.30	2.23	2.16	2.11
MLWDF	4.16	3.89	3.45	3.14	3.01	2.90	2.82	2.76	2.71	2.67	2.63	2.59	2.55	2.52	2.47	2.42	2.37	2.30	2.23	2.15
EXP/PF	4.17	3.86	3.40	3.12	3.00	2.89	2.82	2.76	2.71	2.67	2.63	2.59	2.55	2.52	2.46	2.40	2.35	2.29	2.21	2.14
FLS	4.22	3.98	3.56	3.22	3.02	2.81	2.69	2.48	2.40	2.33	2.28	2.26	2.23	2.19	2.19	2.18	2.17	2.15	2.11	2.11
EXP	4.24	4.05	3.69	3.26	3.00	2.84	2.76	2.69	2.65	2.61	2.58	2.55	2.53	2.50	2.48	2.46	2.41	2.37	2.34	2.27
LOG	4.18	3.87	3.43	3.13	3.01	2.89	2.82	2.76	2.72	2.67	2.63	2.59	2.56	2.52	2.47	2.43	2.36	2.30	2.23	2.14

UE

Fig. 12. The average QoE of all services per cell by using the six scheduling algorithms at the bandwidth of 5 MHz.

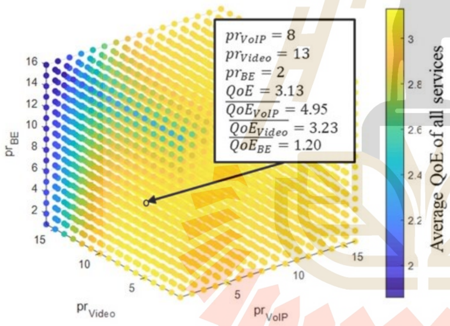


Fig. 13. The average QoE of all services by defining the service priority factor with the EXP rule algorithm at 25 UEs (4096 members).

TABLE VII
COMPARISON BETWEEN THE GA, PSO AND PGA ALGORITHMS IN TERMS OF THE OPTIMAL PARAMETER

Algorithm	P (%)	Avg. N_{used}	Max. N_{used}	Min. N_{used}	Avg. N_{used} (%)
GA	71.8%	118	369	8	2.88%
PSO	52.1%	161	238	98	3.93%
PGA	85.1%	102	347	12	2.49%

The exhaustive search method takes so long to find the optimal parameter due to the large sample space. Therefore, the exhaustive search needs to be replaced with the quick modern method. In this paper, we use the heuristic search method and use the GA, PSO, and PGA algorithms to find the optimal parameter of service priority factor that causes the highest average QoE of all the services. The number of populations in each generation is set to 4 for the GA and PGA, and the number of particles in each generation is set to 16 for PSO. Two conditions are set to stop the above-mentioned optimization algorithms. In the first condition, the number of used members or populations in the search space to find the answers (N_{used}) must not exceed more than 10 percent (410 members). In the second condition, the value of average QoE of all services should not increase more than the 50 generations for the GA and PGA, and the algorithm of PSO stops working when the position of all the generations is same.

Table VII unveils the comparison between these above-mentioned algorithms, where it can be seen that the PGA performs better than the other two algorithms with the percentage accuracy (P) of 85.1 percent and the average number of used members (Avg. N_{used}) is 102 members by running the different simulation 1000 times. This average number of used members are accounted as 2.49 percent of the 4096 members in this search space.

Table VIII unveils the complexity comparison between the proposed and reference algorithms in terms of Big O notation. As it can be seen in Table VIII, the computational complexity of the PSO is less than the other algorithms, but the percentage

TABLE VIII
COMPUTATIONAL COMPLEXITY COMPARISON BETWEEN THE GA, PSO AND PGA ALGORITHMS

Algorithm	Computational Complexity
GA	$O(n^2)$
PSO	$O(n)$
PGA	$O(n^2)$

accuracy of PSO is very low. The complexity of the GA and PGA is similar, but the percentage accuracy of the PGA is more than GA. Furthermore, the number of used members in the search space of the PGA is less than GA. Therefore, the PGA algorithm performs between than the GA and PSO without the substantial increment in the computational complexity.

Furthermore, the service priority factor can be effectively used to increase the number of UEs by determining the optimal parameter of service priority factors. In Fig. 12, we use the EXP rule algorithm without adjusting the service priority factor with the bandwidth of 5 MHz and it can be seen that it can support only 25 UEs by maintaining the average QoE of all services not to be less than 3.00. Whereas, when the resources are efficiently allocated by adjusting the service priority factor of $pr_{VoIP} = 12$, $pr_{Video} = 1$ and $pr_{BE} = 16$ with the average QoE of $\overline{QoE_{VoIP}} = 4.97$, $\overline{QoE_{Video}} = 1.06$ and $\overline{QoE_{BE}} = 2.97$, then the number of users that can be accommodated in the network comes out to be 31 while the network still maintains the average QoE of all services to be at least 3.

C. Finding the Optimal Parameter With the Condition of QoE Threshold Using PGA Algorithm

The average QoE of a network increases along with supporting more number of users, but some of the services experience a low average QoE. Therefore, it is necessary to maintain the QoE of all services to be more than the QoE threshold. In this subsection, we set the threshold of QoE for each service to be 2, and use the PGA algorithm to ensure the higher overall QoE of network along with maintaining the condition of QoE threshold for each of the considered services.

The QoE threshold is set in the PGA algorithm, and the QoE condition can be seen in the (47). During the PGA mechanism, it works by randomizing the population until it finds the required members in the sample space that meet the desired conditions, and then it moves to the next step of crossover, mutation and the PSO process in PGA algorithm. The PSO process is important for the local search of average QoE of the network along with checking the QoE threshold condition for each of the considered services. When it meets the desired conditions, it will be forwarded to the next generation until it finds the best optimal parameter with the desired QoE conditions. From this result, it can be seen that the average QoE of all the services comes out to be 3.01 when $pr_{VoIP} = 2$, $pr_{Video} = 4$, $pr_{BE} = 5$, $\overline{QoE_{VoIP}} = 4.96$, $\overline{QoE_{Video}} = 2.01$, $\overline{QoE_{BE}} = 2.08$ along with maintaining the average QoE of each service to be more than 2 as shown in Fig. 14. Table IX shows the best optimal parameter found by using the PGA algorithm.

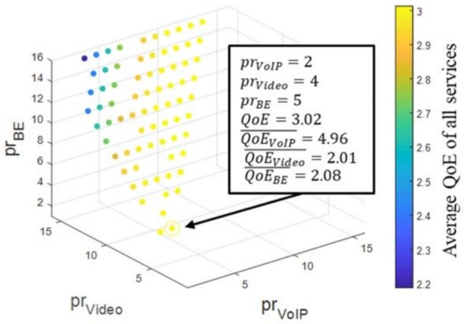


Fig. 14. The average QoE of all services by defining the service priority factor with the EXP rule algorithm at 25 UEs with the average QoE of VoIP, Video and BE services to be more than two at the bandwidth of 5 MHz (74 Members).

TABLE IX
OPTIMAL PARAMETER WITH THE CONDITION OF QOE THRESHOLD BY USING THE PGA ALGORITHM

Algorithm	P (%)	Avg. N_{used}	Max. N_{used}	Min. N_{used}	Avg. N_{used} (%)
PGA	52.8%	355	690	147	8.67%

VII. CONCLUSION

In this paper, we focused on the optimization of the network during the packet scheduling process under the scenario of limited bandwidth based on QoE aware with the service priority factor. The simulation results evaluated the performance of six scheduling algorithms to allocate the resources for the multi users and multi services, where we noticed that some algorithms can efficiently allocate the resources for the RT services while some works efficiently for the NRT services. The introduction of service priority factor worked efficiently under the scenario of limited resources where the QCI cannot be effectively used. The service priority factors were configured by using the proposed PGA algorithm. The proposed PGA utilized the benefits of GA and PSO for finding the optimal parameter of service priority factor and the simulation results showed the effectiveness of the proposed algorithm. The existing algorithms focus on increasing the average QoE of the network, whereas the proposed algorithm not only increased the average QoE of the network, but also maintained the average QoE for each of the services above than the QoE threshold. Due to the efficient allocation of resources by using the proposed algorithm, more number of users can be accommodated by the network as can be seen in the simulation results. This study and the experimental results can be so much beneficial for the operators in order to allocate the effective resources based on QoE-aware to support more users. In addition, the benefits of this self-tuning concept can be implemented in the next generation networks and can be taken as the guiding paradigm to support the concept of self-optimization in order to reduce the CAPEX and OPEX of mobile network operators [49].

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Estimating and Synthesizing QoE Based on QoS Measurement for Improving Multimedia Services on Cellular Networks Using ANN Method

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Abstract*—A quarter of the world population uses the smartphones to access the Internet and various types of multimedia services on the cellular networks, leading to the importance of focusing on user-centric approach, based on the Quality of Experience (QoE) metric, to measure the business success for the Mobile Network Operator (MNO). Although, the quality of the network can be improved with the help of Quality of Service (QoS), but it does not indicate the user satisfaction. Therefore, it is of vital importance to use the QoE along with the QoS parameters to evaluate and improve the quality of the network. In this paper, we propose the QoE modelling, based on the QoS parameters, by using the Artificial Neural Network (ANN) method to evaluate and synthesize the QoE in the actual environment, with the help of Drive Tests. The relationship between the QoS parameters and Opinion Score (OS) has been analyzed and investigated, prior to the selection of QoS parameters for the creation of QoE model and the process of parameter synthesis. The datasets of QoS parameters and OS have been collected with the help of end devices and the subjective evaluation method from the group of defined users, for each of the following multimedia services, i.e., YouTube, Facebook, Line, and the Web browser, in the real environment. The human behavior can be efficiently learned by using the properties of ANN from the collected datasets, to generate the QoE model along with the estimation of QoE score, instead of using the real humans. The results obtained from the process of parameter synthesis have been used as the main guiding paradigm for improving the performance of the networks in terms of user-centric approach based on the QoS parameters.

***Index Terms*—Cellular networks, MNO, user-centric, QoE, QoS, ANN, drive tests, opinion score, parameter synthesis.**

I. INTRODUCTION

INTERNET data traffic has been increased exponentially with every passing day and with the ever-increasing speed of advances in the technologies, more and more users connect to the Internet to access the services such as video, audio, and other multimedia applications on the cellular networks [1]–[2]. According to the International Telecommunication Union, there are currently almost 4.3 Billion mobile subscribers [3], and the number of users who access the multimedia services will occupy about 33 percent of the total global Internet Protocol (IP) by 2021 [4], which in turn attracts the business community due to enormous business returns [5]. The survival of the Mobile Network Operators (MNOs) has become more competitive in this modern era of technology and they need to maintain the quality of their networks as per the requirements of the users. Therefore, the MNOs need to constantly respond as per the need of the users. The user-centric approach, also known as the user's perspective, can be deemed as a business key for the service providers [6]. Therefore, the appropriate indicator is required in order to reflect the user's satisfaction, because it will be easy for the network operators to attract the new customers along with retaining the current number of users if they have the deep knowledge of user's perspective in terms of Quality of Experience (QoE) metric. The QoE, also known as the quality of user experience, is the degree of measurement about the mood of a user, with respect to the accomplishment of its expectations, regarding any particular service or application [7]. Most MNOs rely on the Quality of Service (QoS) measurements to reflect in terms of network-centric perspective, and these QoS parameters (delay, throughput, packet loss, signal strength, etc.) are used as an information for the engineers to improve the network. Unfortunately, the QoS parameters cannot reflect the user satisfaction.

The perception of user's satisfaction regarding any network can be evaluated with the help of two methods, including the subjective evaluation method and objective evaluation method. In the subjective evaluation method, the user's satisfaction is evaluated by using the average of Opinion Score (OS), from the defined demographic group, in order to have the reflection of user's satisfaction with respect to the service provider, and it is called a Mean Opinion Score (MOS) as defined by ITU-T [8]. This method has been applied to the most widely in the existing researches. The authors assess the user's satisfaction by considering the effects of transmission delay on the perceived quality in [9]. Furthermore, the authors discuss the subjective evaluation method for the assessment of the quality of television pictures in [10], and for the assessment of the video quality of multimedia applications in [11]. Although, the most reliable way to measure the user satisfaction is the subjective evaluation method. On the other hand, the drawback

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of this method is the repetition of the collection of datasets in a test area, resulting into the costly and time-consuming way to get the MOS [12]–[13]. This drawback shifted the focus of the researchers towards the objective evaluation method for the acquisition of objective function to estimate the user satisfaction in term of QoE score.

In the objective evaluation method, the relationship between the QoS and OS has been created for the acquisition of the objective function. The objective evaluation method is a way of predicting the QoE by using the effective mathematical techniques, and it is useful for real-time implementation. For example, the objective functions obtained from ITU-T standards such as Perceptual of Speech Quality (PESQ) in P.862 [14], and G.107 E-Model [15]. Furthermore, the objective method is applied to create the function for measuring and improving the network based on the user-centric approach. In [16], Brooks and Hestnes model the QoE by using the QoS measurements from the actual users along with the subjective surveys. Many authors use different techniques and approaches to map the relationship between the QoE and QoS for different types of services in order to monitor the quality of the network. In [15], the authors use the objective assessment in order to have the resource allocation for the entrepreneurs. In [17], the authors describe and discuss different methods to collect the datasets for the generation of QoE model, and determine the most reliable one in terms of the correlation of QoE/QoS. One of the interesting research investigates and uses the objective method to indicate the performance of the network [18]. Thus, the appropriate techniques are essential for the generation of effective QoE models and the generated QoE models should be implementable in terms of current and next generation of networks.

Different approaches and techniques have been proposed to map the relationship between the QoE and QoS for different type of services in the literature. In [19], the authors propose the generic function, also called as IQX hypothesis to estimate the QoE for the Voice over IP (VoIP) and Web browser services. The IQX hypothesis are created through an exponential relationship between the QoE and QoS, and it performs better than the logarithm function. Moreover, the authors employ the IQX hypothesis for the efficient QoE modeling of the Internet Protocol Television (IPTV) services in [20], and for the Cloud Multimedia services on the 5G networks in [21]. In [22], the authors employ the nonlinear equation to predict the user satisfaction in terms of QoE for the video streaming services with the Image Damage Accumulation (IDA) factor in the User Datagram Protocol (UDP) protocol. In [23], the relationship between the QoE and QoS has been created by using the Video Quality Metric (VQM) method along with the evaluation of QoE, based on these three parameters (e.g., dropped packet, jitter, and delay) for the video streaming services. In [24], the authors model the QoE with the help of quality management of services based on the statistical analysis on the video streaming services. This model is used to predict the levels of user satisfaction and allocate the resources in the network. In [25], the authors focus on the QoE instead of QoS and summarizes the types of Influence Factors (IFs) in order to predict the QoE score from the statistical analysis. However, these mathematical techniques have the limitations for creating the effective QoE model based on real environment from many datasets, and they are not flexible to be implemented for the next generation of cellular networks.

Recently, Artificial Neural Networks (ANN), a Machine Learning (ML) approach, for the acquisition of QoE model have been a source of attraction for the researchers due to their ability to create the flexible and effective models of QoE in terms of the next generation cellular networks. For instance, the authors map the relationship between the QoE and QoS for the video services on wireless networks by using ANN with Back Propagation (BP) algorithm in [26]. In [27], the ANN method has been introduced to efficiently create the QoE model for the video services on the Long-Term Evolution (LTE) networks. In the above-mentioned researches [26]–[27], the authors employ the ANN to efficiently create the recognized QoE with the complex methods, but the MNO also needs to utilize the QoS parameters, measured by using the end devices, to reflect and improve the network quality. Therefore, the QoS parameters, measured with end devices, is an important parameter to measure the performance of the network. In [28], the authors conclude that the Reference Signal Received Power (RSRP) is a fundamental indicator of network performance on the LTE networks, and the Drive Test results are used to evaluate and compare the QoE score between the MNOs. For the multimedia services on the cellular networks, the authors estimate the QoE by measuring the QoS of users in the network with the help of specific devices or smartphones. The special applications are installed on the end devices to collect the datasets for the multimedia services such as YouTube, Facebook, Web browsing through Chrome, Google Maps, and WhatsApp information on the cellular networks [29]. In [30], the authors access the QoE for the services of YouTube and Facebook with the help of Drive Tests. In the above-mentioned researches [29]–[30], the authors evaluate the QoE for several multimedia services, but they have not introduced any sort of guiding paradigm to maintain and improve the network quality in terms of future generation networks.

In the corpus of the existing researches, it can be seen that the QoE models have been created by using several approaches. There is not as such any fixed rule to set the standard in the existing researches, rather, it depends upon the authors and MNOs. Furthermore, the proposed model of QoE by using the ANN is not flexible to use in terms of practical scenario due to not having any sort of guiding paradigm to maintain and improve the LTE network quality based on QoE in the existing researches. Hence, the QoE modelling for the next generation of cellular networks should focus on the effective and flexible methods, which can select the parameter from the interesting section of networks. Therefore, the OS and selected QoS parameters are mapped for the generation of QoE model and the selected parameters are synthesized to maintain and improve the network quality.

In this paper, we propose the empirical QoE modelling along with a special ANN approach, which utilizes the QoS instead of evaluating the actual user's satisfaction, to estimate and synthesize the QoE based on QoS measurements.

TABLE I
INFORMATION OBTAINED FROM MEASURING THE QOS PARAMETERS ON THE LTE NETWORKS WITH THE HANDSET DEVICE [31]

QoS parameters	Meaning
End Parameters of YouTube service	
Throughput Download App (kbps.)	Average throughput of this session.
YouTube Duration To First Play (s.)	Duration when start loading video until start playing video
YouTube Buffering Count (n.)	Sum of buffering number of times in this session
YouTube Buffering Duration (s.)	Sum of buffering duration in this session
End Parameters of Facebook service	
Post photo duration time (s.)	Duration for posting photo calculated from event post photo start to post photo success
Download photo duration time (s.)	Duration for downloading photo calculated from event download photo start to Download photo success
Throughput post photo (kbps.)	It is calculated from Facebook Post Photo, Photo size (kilobit) per Post photo duration time (s)
Throughput download photo (kbps.)	It is calculated from Facebook Download Photo, Photo size (kilobit) per Download photo duration time (s)
End Parameters of Line service	
LINE Send Time (ms.)	Time when program start sending content
LINE Send Duration (s.)	Duration for sending data by timer from press send until able to read the results from the database that was successfully delivered
LINE Load Photo Result Time(ms.)	Time when the image was successfully loaded
LINE Load Photo Duration (ms.)	Duration for downloading photo by timer from press download until the image is finished loading
End Parameters of Web browser service	
Web Duration Time (s.)	Duration when start until the end of session. (Respond Time)
Web Throughput Download App (kbps.)	Average download throughput from application layer of session
Radio Parameters	
RSRP (dBm)	Reference Signal Received Power
RSRQ (dB)	Reference Signal Received Quality
RSSI (dBm)	Received Signal Strength Indicator
SINR (dB)	Signal to Interference and Noise Ratio
Data Parameters	
CQI	Channel Quality Index
PDSCH Stream0 Block Size	Stream Block Size of Physical Downlink Shared Channel at 0
PDSCH Traffic To Pilot Ratio	Traffic To Pilot Ratio of Physical Downlink Shared Channel
PDSCH Stream1 Block Size	Stream Block Size of Physical Downlink Shared Channel at 1
LTE BLER	Block Error Ratio in LTE networks
LTE Tx Power	Transmission power in LTE networks
LTE MCS Index	Modulation Coding Scheme index in LTE networks
LTE L1 PDSCH Throughput All Carriers	Throughput of Physical Downlink Shared Channel from all carriers in Layers 1 in LTE networks
LTE PUCCH Tx Power	Transmission power of Physical Uplink Control Channel in LTE networks
LTE PUSCH Tx Power	Transmission power of Physical Uplink Shared Channel in LTE networks

In the QoE model creation, there are three special processes consisting of pre-processing for QoS parameter selections, QoE model creation to effectively create the objective function and a parameter synthesis for finding the relationship between the QoS and QoE as a guideline to improve the network. These processes use the collected datasets in the real environment with the help of subjective evaluation method from the groups of users of four different services such as YouTube, Facebook, Line, and the Web browser respectively. In this paper, we have used the Google Chrome for the Web browsing. When the estimated QoE comes out to be lower than the specified threshold, then the QoE synthesizing proves to be handy for the MNOs in order to improve the quality of network by increasing the QoE score. The contributions and novelties of this article are summarized as follows:

1. We propose the QoE modelling, based on the QoS parameters, by using the ANN method to evaluate and synthesize the QoE in the actual environment, with the help of Drive Tests.
2. The proposed model of QoE helps to reduce the expensive and time-consuming way to access the user's satisfaction and has the high accuracy with very low error percentages.
3. The synthesis of the parameters can benefit the MNOs as they can serve as relevant data for the service provider to improve the quality of the network by maximizing the QoE score.

The remainder of this article is organized as follows: The materials and subjective testing are explained in Section II. Section III presents the design and methodology of the conducted research for the modeling of QoE. The results of the conducted experiments are discussed in Section IV, and Section V belongs to the conclusion where we summarize and conclude all the discussions.

II. MATERIALS AND SUBJECTIVE TESTING

In this section, we explain the QoS parameters and the methods of acquiring the datasets for the QoE modelling.

A. *QoS and Handset*

In this paper, we focus on the measurement of QoS parameters by using the end-devices through which we can have the direct reflection of end-users regarding the quality of the network. In the end-devices, the special application is installed on the smartphones to collect the QoS parameters for each of the four services (YouTube, Facebook, Line and Web browser) on the LTE or LTE-Advanced networks. The QoS parameters consist of End Parameters, Radio Parameters and the Data Parameters. End Parameters can also be deemed as the indicator regarding the feelings of users for each of the above-mentioned multimedia applications, Radio Parameters are the indicators regarding the strength and quality of signals. Data Parameters are the indicators of data during the transmission of information. These QoS parameters consist of 28 metrics measured by using the end-devices in this paper. We have taken these parameters as the only quantitative data to evaluate and synthesize the QoE, these metrics are described in Table I [31].

B. *Subjective Testing and Data Collection*

In this paper, we use the subjective method to evaluate the user satisfaction by using the end device as shown in Fig. 1. Whereas, the smartphone stores the QoS parameters,

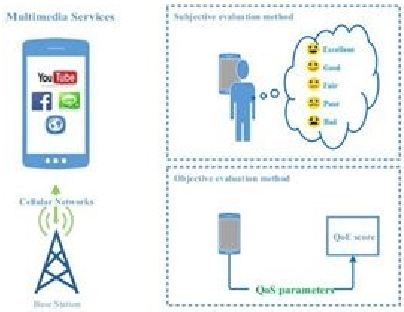


Fig. 1. The evaluation method of the Quality of Experience.

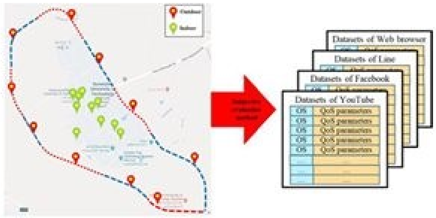


Fig. 2. Locations for collecting the datasets at Suranaree University of Technology, Nakhon Ratchasima, Thailand.

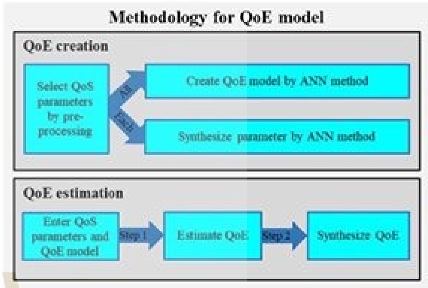


Fig. 3. The QoE architecture of research with the ANN method.

geographic coordinates and other parameters. The QoS and OS are collected to have the dataset during each time. The collected datasets will be used for the modelling of QoE along with the synthesizes of parameters. We define the group of 92 undergraduate students, where the age of each student is in between 18-25 years old and all the students are enrolled in the field of Telecommunication Engineering at Suranaree University of Technology (SUT), Nakhon Ratchasima (NMA), Thailand. Contrary to the existing research in [32], the sample size taken from the 92 undergraduate students is much larger.

All the users were fully trained prior to the collection of information about the network by using the special devices. In every session of the subjective assessment, each user is asked to view the smartphone screen, where the script is running on the special application, and the smartphone displays each service to allow the user to see and estimate the satisfaction score, while the QoS parameters are also collected at the same time. All the services do not take more than 8 minutes.The collected information consists of QoS and OS obtained from the trained users, and this collected information is used as the datasets for the generation of QoE model. The OSs in the datasets must have the levels of satisfaction with a range of five levels (e.g., Excellent (5) Good (4) Fair (3) Poor (2) and Bad (1)). It is necessary to conduct the satisfaction test at several points in the designated areas, which consist of indoor, outdoor, and the high-density area of users in the SUT area to have the OS in all levels of satisfaction. Each user will have to repeatedly test its satisfaction in different environments of the SUT area as shown in the Fig. 2. This process of subjective testing took approximately three weeks to obtain the datasets, whereas, the total number of collected datasets for each service consists of more than 550 sets.

III. Methodology for QoE Model

In this section, we discuss the methodology for the creation of QoE model and the estimation of QoE score. The OS evaluated with the help of subjective method can be used to measure the MOS in the group and the area, but we focus on the objective evaluation methods to determine the levels of user satisfaction in terms of QoE with the help of QoS parameters. The collected datasets are used to generate the QoE model along with the parameter synthesizes by using the ANN method. The methodology used for the generation and estimation of QoE has been shown in the Fig. 3. The methodology can be divided into two parts. The first part is the generation of QoE and the second part is the QoE evaluation. The process of each part is discussed as follows:

A. QoE Creation

In the QoE creation, we use the datasets collected from the group of users in the real environment with the help of the subjective evaluation method. The collected datasets consist of QoS and OS, and it is used for the generation of the QoE model with the following three processes, i.e., pre-processing, QoE model creation, and parameter synthesis as shown in the Fig. 3. In the pre-processing process, the analyzation of QoS parameters, which affects the user's satisfaction in term of OS, is based on the relationship between the Pearson's correlation coefficients and the significance of variables. The selected QoS parameters are normalized to the suitable QoS parameters, which is input to the learning process in the ANN method. In the generation of QoE model, the selected QoS parameters and OS from the datasets are used to create the objective function by using the ANN method. The generated objective function is used to estimate the QoE score from the selected QoS parameters. In the parameter synthesis process, each of the selected QoS and OS from the datasets are used to learn the relationship by using the ANN method for finding the response between the QoS parameter and QoE score as a guideline to improve the network. The results from this process outline the trend of QoS parameters and must be taken into account to improve the MNO network along with achieving the best QoE score. The processes of QoE creation are discussed in detail as follows.

1) Pre-Processing for QoS Parameter Selections: The pre-processing process is used to select the appropriate parameters for the QoE modeling, by using the datasets of each QoS parameter and OS, to analyze the correlation coefficients and the significance of each variable. In this paper, we have filtered the appropriate data of each service to only 550 datasets. In addition, we have defined the absolute correlation coefficient of each variable to be greater than 0.08, and it is the threshold of correlation coefficient for the selection of QoS parameter to generate the QoE model. Please note, 0.08 is the lowest selected value in this paper, because the QoS parameters measured from the actual environment, and the opinion in a group of defined users may have some discrepancies. The correlation coefficients are calculated by using the Equation (1).

$$r = \frac{\sum_{p=1}^{N}\left(OS_p - \overline{OS}\right)\left(QoS_p - \overline{QoS}\right)}{\sqrt{\sum_{p=1}^{N}\left(OS_p - \overline{OS}\right)^2}\sqrt{\sum_{p=1}^{N}\left(QoS_p - \overline{QoS}\right)^2}} \quad (1)$$

where r is the Pearson correlation coefficients between the *OS* and *QoS*, N is the total amount of information or datasets and p is p^{th} information or datasets. In addition, *OS* is an opinion score, $\overline{OS}$ is an average opinion score or *MOS*, *QoS* is the QoS parameter and it consists of End Parameters, Radio Parameters, and the Data Parameters respectively as shown in Table I, and $\overline{\text{QoS}}$ is the average QoS parameter. If r comes out to be negative ($-$), then it indicates the relationship between the variables in the reverse direction and if r comes out to be positive ($+$), then it indicates the relationship between the variables in the same direction. When r is equal to 0, then the variables have no relationship with each other.

To comply with preliminary statistical principles, the selected QoS parameters for the modelling of QoE must be statistically significant. In this paper, we have defined the significance level of 0.05 or greater than 95 percent confidence, and it is commonly used in many researches. Thus, the t-value is considered, which can be calculated by using Equation (2).

$$t = \frac{|r|\sqrt{N-1}}{\sqrt{1-r^2}} \quad (2)$$

The value of t must be greater than the critical t-value, and it is obtained from the t-distribution table [33]. The critical t-value is equal to 1.96, when N is greater than 550 at the significance level of 0.05. When we substitute $N = 550$ and $t = 1.96$ in Equation (2), then the result of r comes out to be approximately equal to 0.08. Thus, the QoS parameter with r greater than 0.08 will be selected to use for the generation of QoE model.

Following the selection of QoS parameters, the corresponding normalizing coefficients and the input values (x_i) for the

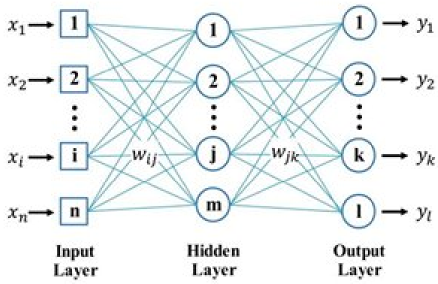


Fig. 4. The structure of an ANN.

ANN processes can be written as:

$$c_i = \frac{\sum_{p=1}^{N}\left|QoS_{i,p} \cdot OS_p\right|}{\sum_{n=1}^{N} QoS_{i,p}^2} \quad (3)$$

$$x_i = c_i \cdot QoS_i \quad (4)$$

where i is the i^{th} selected metric, QoS_i is the i^{th} selected QoS parameter and $QoS_{i,p}$ is the i^{th} selected QoS parameter at p^{th} information, and c_i is the normalizing coefficient in order to set the selected QoS parameters within the data range before proceeding to the next process in QoE modelling.

2) QoE Model Creation by Using the ANN Method: The ANN is mathematical or computational models for the processing of data with connections along with the parallelization of sub-processing unit. The structure of ANN has three main layers consisting of an input layer, hidden layer, and output layer as shown in the Fig. 4. Each layer consists of many nodes to receive data, compute the results and send the computed results as input to the other layer nodes. The input nodes receive the normalized data from the selected QoS parameter and sends the data to the hidden nodes, and the hidden nodes compute and send the computed results to the output nodes.

The input data of ANN and the target of teaching in ANN are entered to ANN in order to learn the relationship between the QoS parameters and OS. The learning ability of ANN depends on the number of input layer nodes, the number of hidden layers, the number of hidden layer nodes, the correlation coefficients between the selected QoS and OS in the pre-processing process, and the configuration of initial parameters within the learning process in the ANN. While, on the hidden layer, located between the input and output layer, each node computes the output value by using the activation functions and becomes the input of other nodes in another layer. In this paper, we define the hidden layer as the one layer in order to get faster results along with the less complexity of ANN. When the number of hidden layer nodes are too high, then, there will be an overfitting problem, and when the number of hidden layer nodes is too less, then there will be an under fitting problem. These problems can reduce the efficiency of QoE model. It has been seen that the effective method to determine the number of hidden layer nodes is the Try and Error method, when the input data consists of more

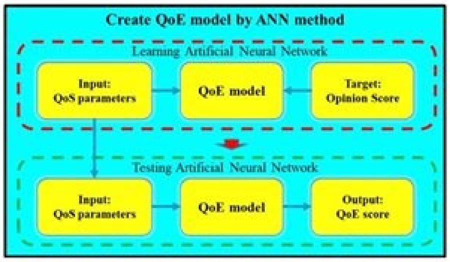


Fig. 5. The QoE model creation by using the ANN method.

than two variables [34]. In the learning process of ANN, we use the Try and Error method in both the forward as well as the backward approaches to find the appropriate number of hidden layer nodes for the effective QoE modeling. To make it easier to use, we develop the Equation (5) to calculate the total number of nodes from the experimental results, and it is explained in Section IV. The number of hidden layer nodes in this paper is computed by using the following equation:

$$m = \frac{N(n+l)}{200} \tag{5}$$

where m is the number of hidden layer nodes ($m \in I^+$), n is the number of input layer nodes, and l is the number of output layer nodes. Where N is the number of datasets and must be more than 100. Similarly, when the input data consists of only one variable, then the effective method to determine the number of hidden layer nodes is the Rule of Thumb method, where m equal to two nodes during the process of parameter synthesis.

During the training of ANN, the input data are computed by using the activation function, and it is forwarded to the next layer in order to find the error between the output and target. The error value is used to adjust the reverse weight coefficients and bias coefficients from the output layer to hidden layer and vice-versa.The above-mentioned activation function is the sigmoid function in order to get the decision at the output. The sigmoid function and the differential sigmoid function can be written with the help of the following equations:

$$sigmoid(X) = \frac{1}{1+e^{-X}} \tag{6}$$

$$sigmoid'(X) = \frac{e^{-X}}{(1+e^{-X})^2} \tag{7}$$

where X is the input value, e is a mathematical constant and it is approximately equal to 2.718. This activation function is the sigmoid function to calculate the decision at the output. The domain of sigmoid function exists from negative to positive infinity $(-\infty, \infty)$, and the range exists from 0 to 1, and the domain of the differential sigmoid function exists from negative to positive infinity $(-\infty, \infty)$, and the range exists from 0 to 0.25.

The Fig. 5 unveils the methodology of QoE model creation by using the ANN method, and it consists of learning and testing of an ANN to create the objective function for the estimation of QoE score. The learning and testing of an ANN are based on 5-fold cross-validation test. Therefore, 80 percent of the collected 550 datasets is a good proportion for modelling nonlinear functions [35], which comes out to be 440 datasets. These datasets are used in the learning process. During the learning process, the appropriate weight coefficients along with the bias coefficients are obtained for the QoE modelling. Whereas, during the testing process, the generated QoE model is tested with the QoS parameters to measure the effectiveness of QoE model. The weight coefficients are the link weights, which connect the nodes among each layer in ANN, and the bias coefficients are the bias coefficients of each node. The link weight and the bias are represented with the following variables w_{ij},w_{jk}, θ_j and θ_k.

TABLE II
TARGET CONFIGURATION IN EACH NODE OF THE OUTPUT LAYER

User satisfaction	OS	Target value of output layer nodes				
		t_5	t_4	t_3	t_2	t_1
Bad	1	0	0	0	0	1
Poor	2	0	0	0	1	0
Fair	3	0	0	1	0	0
Good	4	0	1	0	0	0
Excellent	5	1	0	0	0	0

The steps of ANN leaning, used in this paper, are explained as follows:

The first step is the initialization of parameters in ANN, and the parameters consist of Sum of Square Error (*SSE*), learning rate ($\propto$), link weight and the bias (w_{ij}, w_{jk}, θ_j and θ_k). These parameters are defined with the help of differential sigmoid function. In this paper, the appropriate value of $\propto$ is set to 0.08 when the Equation (7) becomes equal to $\propto$, and the domain of the differential sigmoid function is -2.4 to 2.4 in Equation (7). Therefore, the initial values of $\mathrm{w_{ij}}$, $\mathrm{w_{jk}}$, θ_j and θ_k are the randomized values from $\frac{-2.4}{n}$ to $\frac{2.4}{n}$, where n is the previous number of nodes. The *SSE* is set appropriately to stop learning during the learning process of ANN. If the *SSE* is set to a very low value, then the learning process in the ANN becomes time-consuming and causes the answer of the result to converge to the global maximum. On the other hand, if the *SSE* is set to a very high value, then the learning process in the ANN takes less time, but it may cause the answer of the result to converge to the local maximum, which in turn affects the performance of the QoE model. The number of output layer nodes is set to be five nodes, and they are dependent on the levels of user satisfaction, whereas, the output of each node, lies from 0 to1, are calculated by using the sigmoid function. The output values are compared with the target values ($\boldsymbol{t_k}$) to find the error value ($\boldsymbol{e_k}$), and the Table II unveils the target values of each node in the output layer.

The second step is the activation process in order to predict the output by using the Equation (8) and Equation (9) respectively. Table III unveils the description of all the variables used in the ANN method.

$$y_j(p) = sigmoid\left[\sum_{i=1}^{n} x_i(p) \times w_{ij}(p) - \theta_j(p)\right] \tag{8}$$

TABLE III
VARIABLES NOTATIONS

Symbol	Description
p	The sequence of information
P	The total amount of information
n	The number of input layer nodes
m	The number of hidden layer nodes
l	The number of output layer nodes
i	The sequence of input layer nodes
j	The sequence of hidden layer nodes
k	The sequence of output layer nodes
$x_i(p)$	The value of input layer nodes
$y_j(p)$	The value of hidden layer nodes
$y_k(p)$	The value of output layer nodes
$w_{ij}(p)$	The link weight of input layer to hidden layer
$w_{jk}(p)$	The link weight of hidden layer to output layer
$\theta_j(p)$	The bias of hidden layer nodes
$\theta_k(p)$	The bias of output layer nodes
$e_k(p)$	The error value of output layer nodes
$t_k(p)$	The target value of output layer nodes
$\delta_j(p)$	The gradient error of hidden layer nodes
$\delta_k(p)$	The gradient error of output layer nodes
$\propto$	The learning rate
$w_{ij}(p+1)$	The new link weight of input layer to hidden layer
$w_{jk}(p+1)$	The new link weight of hidden layer to output layer
$\theta_j(p+1)$	The new bias of hidden layer nodes
$\theta_k(p+1)$	The new bias of output layer nodes
SSE	The sum of square error

$$y_k(p) = sigmoid\left[\sum_{j=1}^{m} y_j(p) \times w_{jk}(p) - \theta_k(p)\right] \quad (9)$$

The third step is the weight learning process where we adjust the backward weights during the process of ANN. The default is used to find the error from $x_i(p)$ in order to predict the $y_k(p)$ in the Equation (8) and Equation (9) .The $y_k(p)$ and $t_k(p)$ are compared in Table II to find the error value $e_k(p)$ of output layer node, and it can be expressed in the Equation (10).

$$e_k(p) = t_k(p) - y_k(p) \quad (10)$$

Therefore, $y_k(p)$ and $e_k(p)$ are used to calculate the gradient error of output layer nodes:

$$\delta_k(p) = y_k(p) \cdot [1 - y_k(p)] \cdot e_k(p) \quad (11)$$

The new link weights and bias to adjust the value of output layer nodes to hidden layer nodes can be computed by using the Equation (12) and Equation (13) respectively.

$$w_{jk}(p+1) = w_{jk}(p) + \alpha \cdot y_j(p) \cdot \delta_k(p) \quad (12)$$
$$\theta_k(p+1) = \theta_k(p) - \alpha \cdot \delta_k(p) \quad (13)$$

We set the α, which is the learning rate in ANN, equal to 0.08 and the gradient error of the hidden layer nodes can be calculated by using the following Equation:

$$\delta_j(p) = y_j(p) \cdot [1 - y_j(p)] \cdot \delta_k(p) \times w_{jk}(p) \quad (14)$$

Similarly, the new link weights and bias in order to adjust the values of hidden layer nodes to input layer nodes can be computed by using the Equation (15) and Equation (16) respectively.

$$w_{ij}(p+1) = w_{ij}(p) + \alpha \cdot x_i(p) \cdot \delta_j(p) \quad (15)$$
$$_j(p+1) = _j(p) - \cdot _j(p) \quad (16)$$

The process will increment the sequence of dataset by 1, and then the next dataset is entered into Equation (8) in order to calculate the output layer nodes by using the Equation (9), and the process will continue until the value of p in the learning process becomes equal to the total amount of information (P) used in the learning process, and it is counted as 1 epoch.

The $e_k(p)$ is used to calculate the *SSE* for every value of p by using the Equation (17). The process will return to the second step and continue until the *SSE* value becomes acceptable:

$$SSE = \sum_{p=1}^{P}\sum_{k=1}^{5} e_k(p)^2 \quad (17)$$

When the learning process gets the acceptable *SSE*, the ANN will stop and updates the important variable values (e.g., w_{ij}, w_{jk}, θ_j and θ_k) to predict the QoE score.

In addition, we define the numbers of epoch to stop the learning process of ANN, because in some cases, the *SSE* is not able to have the specific value leading to the too long learning. Therefore, we set the epoch threshold equal to 20,000, and the *SSE* threshold equal to 0.0001 to stop the learning of ANN.

Following the learning process of ANN, the next process is to test the QoE model, which measures the performance of the model by using the defined datasets with cross-validation test. The QoS parameters are entered into the Equation (8) in order to predict the output by using the Equation (9). The output layer nodes are multiplied with k, where k is the constant at each output layer node and it depends upon the level of user satisfaction to estimate the QoE score by using the Equation (18).

$$QoE = \frac{\sum_{k=1}^{5} k y_k}{\sum_{k=1}^{5} y_k} \quad (18)$$

To measure the efficiency of the generated QoE model, the QoE score and OS are used to compute the Correlation Model (CM) for comparing the relationship between the user satisfaction estimated by using the subjective evaluation method and objective evaluation method. The OS is a numerical measure of the human-judged overall quality of any service, whereas, the QoE score is a numerical measurement regarding the fulfillment of users' expectation and it is measured by entering QoS to the generated QoE model. The efficiency of QoE model is computed as follow:

$$CM = \frac{\sum_{p=1}^{P}(OS_p - \overline{OS})(QoE_p - \overline{QoE})}{\sqrt{\sum_{p=1}^{P}(OS_p - \overline{OS})^2}\sqrt{\sum_{p=1}^{P}(QoE_p - \overline{QoE})^2}} \quad (19)$$

The *CM* is the correlation coefficient between the OS_p and QoE_p (p is the sequence of datasets), and *P* is the total amount of information. In addition, OS_p is the p^{th} opinion score, $\overline{OS}$

TABLE IV
DETERMINING THE MODEL RELIABILITY LEVELS WITH RESPECT TO THE CORRELATION MODEL

Reliability	Correlation Model
Very Weak	0.00-0.19
Weak	0.20-0.39
Moderate	0.40-0.59
Strong	0.60-0.79
Very Strong	0.80-1.00

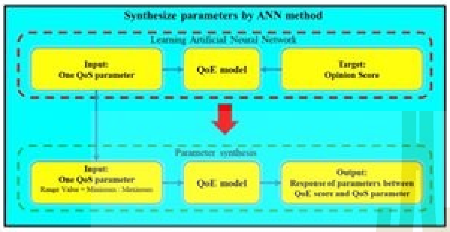


Fig. 6. Parameter synthesis by using the ANN method.

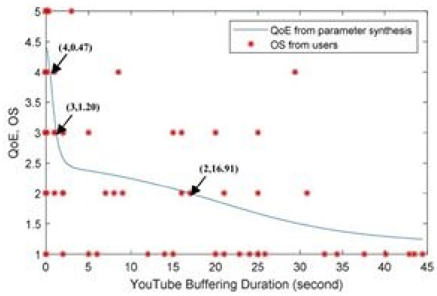


Fig. 7. The response of QoE score and the YouTube Buffering Duration with the parameter synthesis.

is an average opinion score, QoE_p is the p^{th} QoE score, and $\overline{QoE}$ is the average of QoE score.

The CM value is interpreted with the five different reliability levels, according to the Evans (1996) [36], as shown in Table IV. The best performing model should approach to 1.

3) Parameter Synthesis by Using ANN Method: In this sub-section, we discuss the methodology to synthesize the parameters by using the ANN technique in order to get the response of parameters affecting the QoE score as shown in the Fig. 6. Parameter synthesis is an integration of the relationship between the input and target variable to obtain the response between two variables as a guideline to improve the network. To synthesize parameters, the process is divided into two steps and it consists of ANN learning and the parameter synthesis. During the learning of ANN, the QoE is modeled with the QoS parameters and OS's with the same parameter setting as explained in the previous subsections, but there is a difference in some parameters in terms of the number of inputs and hidden layer nodes. During this process, the ANN has only one node in the input layer, two nodes in the hidden layer as per the Rule of Thumb method [34], and five nodes in the output layer. For this reason, the learning process may take longer because one node in the input layer takes more time to adjust the weights and bias coefficients in ANN as compared to multiple nodes. For example, in the input layer on Web browser service, Web Duration Time is selected to be a QoS parameter for one node. When the number of input nodes, hidden nodes, output nodes are 1, 17 and 5 respectively, the *SSE* cannot be reduced to 0.1 and it can be only 0.278 at *epoch* = 20,000. The duration time in the process comes out to be 115.741 seconds. For multiple nodes, the selected QoS parameters consist of Web Duration Time, RSSI, PDSCH Traffic To Pilot Ratio, LTE BLER and LTE MCS Index which they are used in the learning process. When the number of input nodes, hidden nodes, output nodes are 5, 28 and 5 respectively, we found that the *SSE* reduces to 0.1 at *epoch* = 1,752 and the duration time in the process comes out equal to 30.109 seconds. As a result, we can conclude that the multiple nodes take less time than the one node and can adjust the weight and bias coefficients faster than the one node along with causing the results to rapidly converge to the desired number.

However, the parameter synthesis process, by using the ANN method, can continuously provide the response of QoS and QoE in the range of real numbers. Instead, OS values are discrete levels from 1 to 5. The use of OS for synthesis process cannot be helpful to provide discrete outputs of such continuous QoS parameters. Hence, ANN model is necessary to contribute on synthesis process. During the parameter synthesis, all values of the QoS parameter, ranges from minimum to maximum, are entered into the ANN equation to determine the response of each parameter in terms of the QoE score. This process of parameter synthesis continues until we have the response for all the QoS parameters, and the responses of these parameters are taken into account as guidelines to improve the network of MNO. The threshold of the QoE is set against the QoS parameter in order to improve the network. In this paper, we have set the QoE threshold against the QoS parameter to be 3, and it is the fair level as per the ITU-T P.800 standard, and this threshold is used to specify the direction of QoS parameters for the guideline in improving the network to have a more QoE threshold.

Fig. 7 unveils the process of parameter synthesis between the QoE score and YouTube Buffering Duration for the services of YouTube, where the Asterisk (*) is showing the QoS data and OS measured by the users, and these datasets are used to create the relationship between the QoS and OS by using the ANN equation where we enters all the values of QoS parameters, ranges from minimum to maximum, to get the response of each parameter in terms of QoE as can be seen in the Fig. 7. As it can be seen in the Fig. 7, when we need to have the QoE score of more than 3, then the MNO should make the YouTube Buffering Duration to be less than 1.2 seconds in order to improve the network quality. The significance of the parameter synthesis process can be seen in the Fig. 7.

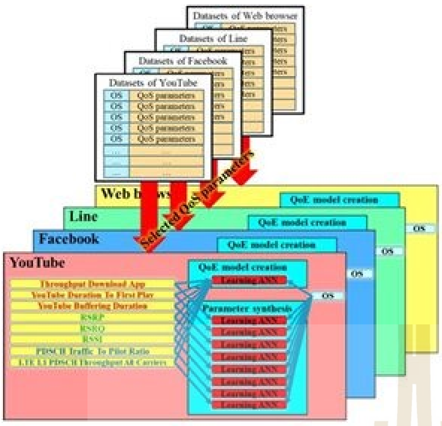


Fig. 8. Selected QoS parameters to create the QoE models and synthesize the parameters of undergraduate student group at SUT area, Thailand.

B. QoE Estimation

Following the generation of QoE model, the QoE model is used to estimate the QoE score along with the parameter synthesis to improve the network. In the QoE estimation, the datasets are collected with the Drive Test method on the desired route or defined area for estimating and synthesizing the QoE. The collected datasets in this part consist of QoS parameters and the device location in the real environment with the help of end devices. The processes of QoE estimation are discussed as follows.

1) Input Data: The input data consists of QoS parameters (e.g., End Parameters, Radio Parameters, and Data Parameters) and the device location is entered into the QoE model to estimate and synthesize the QoE. We have used the Drive Test or Walk Test method for the collection of these above-mentioned input data.

2) QoE Score Estimation: The QoE score is estimated with the help of objective function created by using ANN method. The QoS parameters of each service are entered into the QoE model to estimate the QoE score by using only the QoS parameters.

3) QoE Synthesis: The results obtained from the QoE score are compared with the threshold of QoE score, and if the QoE score is lower than the threshold value, then the QoE synthesis is used to analyze the cause of each QoS parameter. Furthermore, the data of the parameter synthesis, by using the ANN method, is used to identify the direction of each QoS parameter in order to improve the network. The value of the QoE score should be higher than the pre-defined threshold, and it will benefit the MNOs to improve the network efficiency in terms of the user's satisfaction. The results obtained from the parameter synthesis are explained in more details in Section IV.

TABLE V
SELECTED QoS PARAMETERS TO CREATE THE QoE MODELS AND SYNTHESIZE THE PARAMETERS OF UNDERGRADUATE STUDENT GROUP AT SUT AREA, THAILAND

	QoS parameters	Correlation coefficient	Direction
YouTube	Throughput Download App (kbps)	0.36	(+)
	YouTube Duration To First Play (s)	-0.38	(-)
	YouTube Buffering Duration (s)	-0.63	(-)
	RSRP (dBm)	0.13	(+)
	RSRQ (dB)	0.20	(+)
	RSSI (dBm)	0.13	(+)
	PDSCH Traffic To Pilot Ratio	0.12	(+)
	LTE L1 PDSCH Throughput All Carriers	0.38	(+)
Facebook	Post photo duration time (s)	-0.31	(-)
	Download photo duration time (s)	-0.17	(-)
	Throughput post photo (kbps)	0.17	(+)
	Throughput download photo (kbps)	0.13	(+)
	RSRP (dBm)	0.16	(+)
	RSRQ (dB)	0.14	(+)
	RSSI (dBm)	0.16	(+)
	CQI	0.11	(+)
	PDSCH Stream(0) Block Size	0.15	(+)
	PDSCH Traffic To Pilot Ratio	0.10	(+)
	PDSCH Stream(1) Block Size	0.15	(+)
	LTE PUSCH Tx Power	-0.11	(-)
Line	RSRP (dBm)	0.09	(+)
	RSSI (dBm)	0.09	(+)
	PDSCH Traffic To Pilot Ratio	0.10	(+)
	LTE MCS Index	0.09	(+)
Web	Web Duration Time (s)	-0.54	(-)
	RSSI (dBm)	0.10	(+)
	PDSCH Traffic To Pilot Ratio	0.18	(+)
	LTE BLER	-0.14	(-)
	LTE MCS Index	0.09	(+)

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, we have discussed the experimental results. We have selected appropriate groups and areas in order to conduct the experiment as discussed in the previous sections. The experimental results of QoE model are discussed as follows.

A. Experimental Results of QoE Model

The data are collected from the 92 undergraduate students in the SUT area, where the age of each student is in between 18-25 years old, and the collected dataset consists of more than 550 sets for each of the services including YouTube, Facebook, Line and the Web browser respectively. The collected datasets are used to create and synthesize the QoE in this paper. The experimental results of this part are described in the following subsections:

1) The Results of QoS Parameter Selections in the Pre-Processing Process: The QoS parameters including End Parameters, Radio Parameters, and the Data Parameters along with the OS are used to calculate the correlation coefficients by using Equation (1) and it must be more than 0.08 in order to select the QoS parameters from the given datasets. The selected QoS parameters are shown in the Fig. 8 and Table V, respectively.

The multimedia services, targeted in this paper, consist of YouTube, Facebook, Line and the Web Browser services on the LTE networks. The absolute correlation coefficients of each

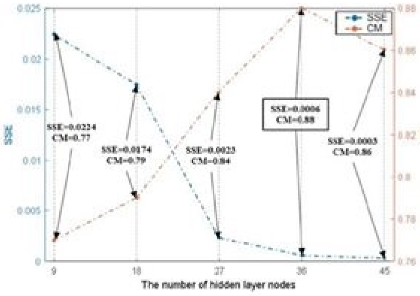


Fig. 9. The graph of SSE and CM depend on the number of hidden layer nodes during the QoE model creation for the YouTube service by using the ANN method.

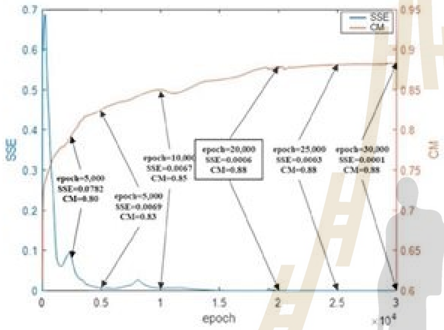


Fig. 10. The graph of SSE and CM depend on epoch in the QoE model creation of YouTube service by using ANN method.

variable are interpreted with respect to the five different reliability levels by using the CM as can be seen in Table IV. The best variable should approach to 1. The correlation coefficients indicate the relationship between the selected QoS parameter and the OS along with *r*. When the correlation coefficients indicate the negative relationship, it means that one parameter increases, another one decreases and vice versa. The plus or minus sign of the correlation coefficients is used to identify the trend of each parameter as guidelines to improve the network.

The selected QoS parameters are used to create QoE model and synthesize the respond of parameters by using the ANN method. The processes of QoE model creation and parameter synthesis are discussed in the following subsections.

2) The Results of QoE Model Creation: In the learning process of ANN, it is necessary to determine the appropriate parameters in order to generate the effective QoE model. The number of input layer nodes is the number of selected QoS parameters in the pre-processing process and the number of output layer nodes is set to five nodes as per the levels of user satisfaction, and the number of hidden layer nodes is

TABLE VI
THE INFORMATION OF THE QOE MODELS BY USING THE ANN METHOD

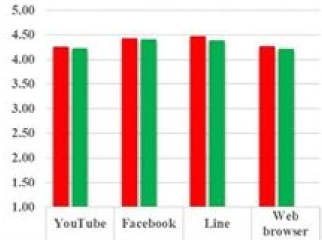
Indicator of ANN	YouTube	Facebook	Line	Web browser
Input nodes	8	12	4	5
Hidden nodes	36	47	25	28
Output nodes	5	5	5	5
Datasets	550	550	550	550
SSE	0.0006	0.0002	0.1691	0.0146
Epoch	20,000	20,000	20,000	20,000
CM	0.88	0.95	0.48	0.77
Reliability of QoE model	Very Strong	Very Strong	Moderate	Strong

determined by using the Equation (5) to generate an effective QoE model.

We conducts the experiments for the YouTube service and $n = 8$, $l = 5$ and $N = 550$ are entered into the Equation (5) to compute the number of hidden layer nodes and it comes out to be a positive integer, equal to 36. In the experiment, the number of hidden layer nodes is set to be 9, 18, 27, 36 and 45, and the comparison is performed by using these different nodes for the calculation of CM with the help of Equation (19), and the model performance indicator comes out to be $epoch = 20000$ and SSE = 0.0001 for stopping the learning process of ANN as can be seen in the Fig. 9. As it can be seen in the Fig. 9, when the number of hidden layer nodes is equal to 36, then the QoE model has the highest CM (0.88). Meanwhile, when the number of hidden layer nodes is greater than the 36, then the CM and SSE of the QoE model gets decreased and leads to an overfitting problem. Similarly, when the number of hidden layer nodes is less than the 36, then the CM of the QoE gets decreased and leads to an underfitting problem. Therefore, we can conclude that the different number of hidden layer nodes affects the performance of the model and the appropriate number of hidden layer nodes can be calculated with the help of Equation (5) for all the services.

Fig. 10 unveils the appropriate values of the *SSE* and epoch, where m = 36 and epoch has values from 1 to 30000 for the YouTube service. As it can be seen in the Fig. 10, the *CM* of the QoE model increases and the *SSE* decreases rapidly during the first phase of the graph when epoch equals from 1 to 5000. When the epoch becomes equal to 30000 then the *CM* and *SSE* come out to be 0.88 and 0.0001 respectively. Therefore, we can conclude that when the epoch is too high and the *SSE* is too low, then it leads to the global maximum for the *CM* of QoE model and becomes time-consuming, and vice versa. The *CM* stays equal to 0.88 when the *epoch* has values 20000, 25000 and 30000. Therefore, we have defined the values of *epoch* and *SSE* to be 20000 and 0.0001 respectively to reduce the learning time of ANN.

In the QoE model creation, the selected QoS parameters and OS from the collected datasets are used in the learning and testing of an ANN. In the learning process of ANN, the QoE model is created to estimate the QoE score by using the QoS parameters. In the testing process of an ANN, the model is tested based on 5-fold cross-validation test with the CM value, which can be calculated by using the Equation (19). The results of QoE model are shown in Table IV.



	YouTube	Facebook	Line	Web browser
MOS	4.26	4.43	4.48	4.27
Average QoE	4.23	4.41	4.39	4.22
Percent of Error (%)	0.70	0.45	2.01	1.17

Fig. 11. Comparing between the MOS and Average QoE by using the datasets of undergraduate student group at SUT area, Thailand.

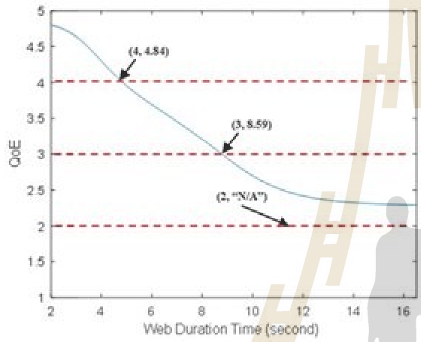


Fig. 12. The response of the QoE score and Web Duration Time for Web browser service by using the datasets of the undergraduate group at SUT area, Thailand.

Table VI unveils the different parameters of QoE model creation for the services of YouTube, Facebook, Line and the Web Browser. The *SSE* is the error measurement between the target value and the output value of ANN in the learning process, and *CM* is a performance indicator of the model. As it can be seen in Table VI, where the value of the *CM* is interpreted according to Table IV, the reliability of the QoE model is Very Strong for the services of YouTube and Facebook because these services have more input nodes compared to other services and the absolute correlation coefficients of some selected QoS parameters is higher. Furthermore, a large number of hidden nodes result into the lower *SSE* due to the adjusting weight and bias coefficients in ANN. For the Web browser service, it has only five factors consisting of one Moderate factor and three Very Weak factors. The reliability of QoE model is Strong for the Web browser service. For the Line service, the number of parameters which affect the OS has only four factors as can be seen in Table V, and each factor has a low correlation coefficient or Very Weak. The reliability of QoE model, created for the Line service, has the Moderate level.

TABLE VII
QoS PARAMETERS FOR IMPROVING THE NETWORK BY USING THE PARAMETER SYNTHESIS

	QoS parameters	QoE>3	QoE>4	CM
YouTube	Throughput Download App (kbps)	>1440	>1793	0.69
	YouTube Duration To First Play (s)	<4.00	<3.30	0.64
	YouTube Buffering Duration (s)	<1.20	<0.47	0.70
	RSRP (dBm)	>-121	>-114	0.25
	RSRQ (dB)	N/A	>-10	0.22
	RSSI (dBm)	>-91	>-86	0.28
	PDSCH Traffic To Pilot Ratio	N/A	>1.00	0.31
	LTE L1 PDSCH Throughput All Carriers	>1.88	>2.17	0.63
Facebook	Post photo duration time (s)	N/A	<4.31	0.37
	Download photo duration time (s)	<12.89	<5.74	0.19
	Throughput post photo (kbps)	N/A	N/A	0.43
	Throughput download photo (kbps)	>107	>179	0.25
	RSRP (dBm)	N/A	>-118	0.25
	RSRQ (dB)	N/A	N/A	0.15
	RSSI (dBm)	N/A	>-88	0.26
	CQI	N/A	>7.32	0.22
	PDSCH Stream(0) Block Size	N/A	>485.97	0.25
	PDSCH Traffic To Pilot Ratio	N/A	N/A	0.15
	PDSCH Stream(1) Block Size	N/A	N/A	0.17
	LTE PUSCH Tx Power	N/A	N/A	0.14
Line	RSRP (dBm)	N/A	N/A	0.09
	RSSI (dBm)	N/A	N/A	0.09
	PDSCH Traffic To Pilot Ratio	N/A	N/A	0.15
	LTE MCS Index	N/A	N/A	0.09
Web	Web Duration Time (s)	<8.59	<4.84	0.63
	RSSI (dBm)	N/A	N/A	0.12
	PDSCH Traffic To Pilot Ratio	N/A	N/A	0.19
	LTE BLER	N/A	<13.95	0.17
	LTE MCS Index	N/A	>6.81	0.13

In order to compare the subjective and objective evaluation methods from the datasets of the undergraduate student group in the SUT area, QoS parameters are entered to estimate the QoE score with the objective method. The scores of QoE, obtained from each dataset, are used to compute the average QoE. For the subjective method, the OSs from each dataset are used to compute the average OS or MOS as can be seen in the Fig. 11.

The average QoE (obtained from the QoE model) and the MOS (obtained from the assessment of the undergraduate student group in the SUT area) is approximately the same, and the percent of error is computed between the average QoE and MOS for different type of applications as can be seen in the Fig. 11. The error percentage of QoE model for the services of YouTube, Facebook, Line, Web browser comes out to be 0.70%, 0.45%, 2.01% and 1.17%, respectively.

3) The Results of Parameter Synthesis: We have set the threshold of QoE score to be 3 to identify the threshold value of each parameter in the parameter synthesis process aiming to improve the network. The best QoE score should be close to 5, indicating the excellent service. In the parameter synthesis process, it is very necessary to take the advantage of ANN that can learn the human behavior from the collected datasets. Therefore, the parameter synthesis by using ANN method can continuously provide the response of QoS and QoE in the range of real numbers. Instead, OS values are discrete levels from 1 to 5. The use of OS for synthesis process cannot be helpful to provide discrete outputs of such

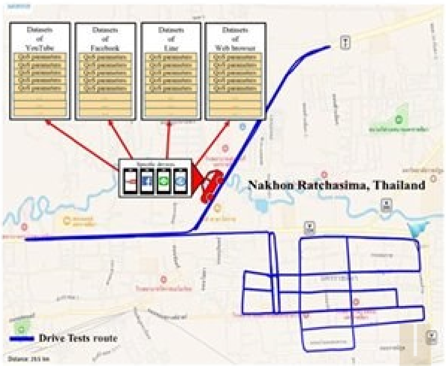


Fig. 13. Drive Tests route to collect the QoS parameters with the specific devices at NMA downtown area, Thailand.

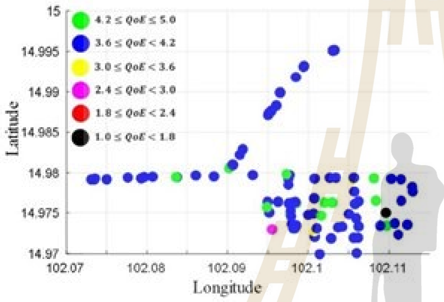


Fig. 14. QoE score map for the YouTube service on the LTE networks at NMA downtown area, Thailand.

continuous QoS parameters. Hence, ANN model is necessary to contribute on synthesis process. We obtain the QoE score to be 3 with the specifying direction of QoS parameter for guidelines to improve the network as shown in the Fig. 12. The Fig. 12 unveils the response between the QoE score and Web Duration Time for the Web browser service on the LTE networks. The QoE score comes out to be 3 when the Web Duration Time is 8.59 seconds as shown in the Fig. 12. If the MNO needs to have the QoE score to be greater than 3, the MNO must improve the Web Duration Time to be less than 8.59 seconds. However, the results of parameter synthesis by using the ANN method provides better performance compared to using the linear regression between the CM in Table VII and absolute correlation coefficient in Table V.

The Table VII unveils the specifying direction of other QoS parameters as guidelines to improve the network. In order to achieve the QoE score of more than 3, we need to adjust each parameter according to the mark of trends such as the (>) sign means that the parameters are supposed to be increased, and vice versa. When the mark of trends is Not Applicable (N/A), the parameter cannot determine the direction of network improvement because the response between QoE score and Web Duration Time does not lie in the defined QoE line as shown in the Fig. 12, and the QoE threshold is set to 2.

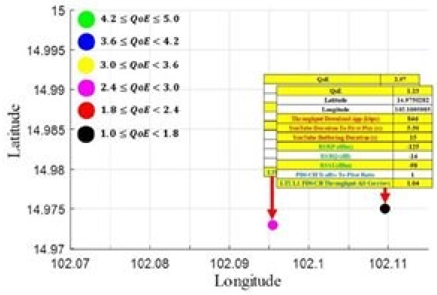


Fig. 15. QoE score map for the YouTube service on the LTE networks, when the QoE score is lower than 3 at NMA downtown area, Thailand.

4) The Results of Implementing QoE Model to Estimate and Synthesize the QoE From Drive Tests Method: After the creation of QoE model, the QoE model and the data from the Drive Test method are used to estimate and synthesize the QoE in the defined area. We have collected the data in the Nakhon Ratchasima (NMA) downtown area, Thailand and the collected datasets consists of QoS parameters (e.g., End Parameters, Radio Parameters, and Data Parameters), technical information about the geographic location and other information about the services of YouTube, Facebook, Line and Web browser by using the specific devices with the distance of 25 kilometers as shown in the Fig. 13.

The QoE estimation and parameter synthesis of YouTube service, on the LTE network in the NMA downtown area, can be seen in the Fig. 14 and Fig. 15 respectively. The collected data, with the Drive Test method, provides the total amount of information at 102 points or datasets in the above-mentioned route. The collected data is entered into the QoE model in order to estimate the QoE score as shown in the Fig. 14, where each point on the map is representing the QoE score and the average QoE score comes out to be 4.02, and it lies in the range of Good level.

The Fig. 15 unveils the positions where the QoE is less than the threshold and there are 2 points out of 102 points, where the QoE score is less than the set threshold level of 3, and these 2 points accounted approximately 1.67 percent of the total area. We have synthesized the QoS parameters in these above mentioned 2 points in order to improve the network. The guidelines, for improving the network from the Table VII, are compared with the measured QoS to find the reason when the QoE is less than the QoE threshold as shown in the Fig. 15. The QoE is equal to 1.23 on the black point, and following the synthesizes of QoE, we get to know that the Throughput Download App, YouTube Duration To First Play, YouTube Buffering Duration, RSRP, RSSI and

TABLE VIII
THE INFORMATION OF QOE ESTIMATION AND SYNTHESIS PARAMETER WITH THE DRIVE TEST METHOD AT NMA DOWNTOWN AREA, THAILAND

Service	You Tube	Face book	Line	Web
The number of datasets	102	355	94	607
Average QoE	4.02	4.39	4.05	4.71
QoE threshold	3	3	3	3
The number of datasets (When QoE <QoE threshold)	2	1	0	14
Percent of unsuccessful Area (when QoE<QoE threshold)	1.97%	0.28%	0%	2.31%
Percent of successful Area (when QoE>QoE threshold)	98.03%	99.72	100%	97.69%
Average QoE of All services	4.29			

LTE L1 PDSCH Throughput All Carriers were not according to the conditions specified in Table VII. Whereas, the pink points in the Fig. 15 have the QoE score less than the threshold because the following three parameters, i.e., Throughput Download App, YouTube Buffering Duration and LTE L1 PDSCH Throughput All Carriers don't follow the conditions specified in Table VII. The Table VIII unveils the information for the rest of the services.

B. Discussions

As per the experimental results of the pre-processing process, the selected QoS parameters must have more correlation coefficient than the threshold of the correlation coefficient, and the End Parameters often have more absolute correlation coefficients as compared to the Radio Parameters and Data Parameters because the End Parameters are the parameters that the users can recognize such as response time, speed, jerk of video clips, etc. In the QoE model creation, the number of hidden layer nodes, *SSE* and the *epoch* are appropriately defined in the learning ANN, and it causes the *CM* of QoE model to converge into a global maximum. Moreover, the number of selected QoS parameters and the correlation coefficients of each parameter directly affect the *CM*. During the testing of the QoE model, we have seen that the QoE model with higher *CM* results into less error percentage as compared to the QoE model with lower *CM*. The reliability of the information depends upon the *CM* of the QoS parameter and we cannot adjust any parameter within the network to control the desired variables because it will affect the other users and cause damage to the MNO. As a result, some QoS parameters cannot be used in the QoE creation and parameter synthesis processes due to low absolute correlation coefficients computed in the pre-processing process. Consequently, these created QoE models with the different datasets for each service with independent parameters. This is more practical than using one model to fit all services because the different services independently need the different parameters to be analyzed. In the implementation of synthesizing QoE, we have tested by entering the defined QoS according to the conditions of parameter synthesis, and we found that this method can make the QoE score higher than the QoE threshold. However, the continuous increment in the number of users may result in the reduction of QoE score. Therefore, the MNOs can utilize the benefits of this research to guarantee the QoE score by improving the network at the right time. As a result, it can help to slow down the investment in terms of improvement in the network quality. In fact, MNOs need their QoE close to 5 but there are some limitations in the network. Thus, the defined QoS threshold from the policy of MNO should be used to find the appropriate QoE threshold from the parameter synthesis process.

V. CONCLUSION

In this paper, we created the QoE model by using the ANN method along with the proposed parameter synthesis based on the objective evaluation method. The QoS parameters are measured by using the end devices to evaluate and synthesize the QoE on the LTE network in a real environment. The QoS parameters have been used to predict the QoE score instead of evaluating the actual user satisfaction, and they are used to synthesize the QoE as a guideline to improve the performance network by maximizing the QoE score for the multimedia services such as YouTube, Facebook, Line and Web browser services. The percentage of errors in the created QoE models come out to be very low (0.70%, 0.45%, 2.01%, and 1.17%) for the services of YouTube, Facebook, Line and the Web browser respectively. In addition, the process of parameter synthesis comes out to be so handy to get the information as guidelines in order to increase QoE by improving the network. This study and the experimental results can be so much beneficial for the operators in order to reduce the time and save the cost of evaluating the network performance by using the Drive or Walk Tests to get the desired QoE score.

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Investigation into User-Centric QoE and Network-Centric Parameters for YouTube Service on Mobile Networks

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ABSTRACT
The number of users on mobile networks has continuously increased due to many attractive multimedia services. According to this reason, the service operators have to regularly improve their networks in order to retain the need of existing users and also attract the expectation of new users. Nowadays, the operators concern Quality of Experience (QoE) metric as the key performance index to evaluate the networks rather than Quality of Service (QoS) metric. However, the QoE metric is based on the viewpoints of domain's experiences which the experiences from users and networks might not be correlated. Therefore, in this paper, the demonstration of user-centric and network-centric viewpoints based on QoS measurement via Drive Tests on mobile networks is presented. The difference viewpoints of QoE derived from user-centric and QoS parameters achieved by network-centric have been investigated through mobile networks of top three operators in Thailand. The results indicate that only some QoS parameters can provide the same trend as QoE. It implies that the operators should set some parameters as the higher priority for improving the network quality if they want to satisfy the experience of users.

CCS Concepts
• **Human-centered computing ➝ Field studies ➝ Mobile devices**

Keywords
User-centric; Quality of Experience; Network-centric; Quality of Service; Drive Tests; Long-Term Evolution.

1. INTRODUCTION
The number of users that access multimedia services on mobile networks has steadily increased [1]. For this reason, mobile

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operators must constantly improve their networks to support the increase in traffic for responding users. User-centric is the key for enabling operators to retain existing users and attracting new users which can provide benefits to mobile communication [2]. The operators certainly need to adjust their perspectives by accessing user satisfaction in term of Quality of Experience (QoE). The QoE is the degree of delight or annoyance of user which is resulted from the fulfillment of user expectations with respecting the enjoyment of service on the light of the user's personality [3]. Also, it can be used as a measurement factor to indicate the network success. In the network optimization, operators must rely on QoS measurements to reflect the perspective of network-centric. These data are used as information for engineers to improve the networks. Therefore, QoE and QoS need to map the relationship to create a QoE model. Based on previous research surveys, we have found that the QoE model was created using different methods and different QoS indicators as described in [4]. There is no particular rule for QoE model as it just depends on the requirement of operators who decide the QoS parameters of interest to estimate QoE score. Usually, we can measure QoS from many parts of the networks while, if focusing on user-centric, QoS measurements should be focused on the end-device. It is well known that when operators need to improve their networks, the main process is to measure QoS at the end-device with Drive or Walk Tests [5]. The operators give the importance on many parameters that are the key used for improving the networks. Improving network performance by adjusting Electrical Tilt (E-Tilt) and Mechanical Tilt (M-Tilt) and adjusting the appropriate power antenna has been described in [6][7][8]. These researches aimed at increasing the Signal to Interference and Noise Ratio (SINR) which is the Radio parameter in LTE networks affecting the downlink transfer of information between Evolved Node B (eNodeB) and User Equipment (UE) more efficiently. The SINR is a parameter that operators really concern, which can be used to predict QoE by the model that has been created [9][10]. In fact, Radio parameters may not be able to reach user satisfaction because QoE is an end-user indicator [11]. End parameters are the parameters that users can recognize such as respond time, speed, jerk of video clips, etc. Radio parameters are the parameters that involves air interface. Hence, we use the End parameters and Radio parameters to evaluate the QoE from the model created using the methodology of our research presented previously [12]. It is a QoE modeling with an Artificial Neural Networks (ANN) method which is an effective and flexible way to choose QoS parameters for evaluating QoE.

However, it is the fact that the viewpoints of QoE from users might not be the same as network's viewpoints. Therefore, in this paper, the demonstration of QoE difference between user-centric and network-centric viewpoints is presented. By collecting QoS parameters with Drive Tests for YouTube service on mobile networks, the QoE model can be created and used to evaluate the network performances [12]. The measurements have been performed through the mobile networks of top three operators in Thailand. Then this paper compares the results from three operators to measure the success of network based on user-centric using QoE metric and network-centric using QoS metric. The results are preliminary data for operators to improve the network and be important information for the deeper study of QoE research in the near future.

The remainder of this article is organized as follows: The QoS parameters and QoE model are explained in Section 2. Section 3 presents the design and methodology of the conducted research. The experimental results are discussed in Section 4, and Section 5 concludes the paper.

2. QOS PARAMETERS AND QOE MODEL

2.1 QoS parameters

In this paper, the parameters which can be measured from specific devices to collect data for the use in operations are on focus as shown in Figure. 1 [13]. The QoS parameters are divided into two parts: 1) End parameters consisting of Throughput Download and Buffering Duration and 2) Radio parameters consisting of Reference Signal Received Power and Signal to Interference and Noise Ratio. These parameters can be measured by some specific devices which are described as follows.

- Throughput Download (TD) is a average download throughput from application layer of YouTube session represented in kilobits per second (kbps) unit.
- Buffering Duration (BD) is the sum of buffering duration in YouTube session represented in second (s) unit. The BD should be equal to 0 or close to 0 because it is a measurement of the twitching of clips in YouTube.
- Reference Signal Received Power (RSRP) is a cell-specific signal strength related to metric that is used as an input for cell reselection and handover decisions, which is represented by decibel-milliwatts (dBm) unit.

Figure 1. Application and tools for Drive Tests.

- Signal to Interference and Noise Ratio (SINR) is the ratio of the signal power to the summation of the average interference power from the other cells and the background noise presented in decibel (dB) unit. Operators focus on SINR to increase network efficiency [9].

2.2 QoE model

QoE model was created using the methods from our previous research [12] to be used for predicting QoE from QoS parameters which consist of TD, BD, RSRP, and SINR on YouTube service. For QoE prediction, QoS parameters are entered into (1) and (4) for evaluating the QoE score.

$$y_j = f(x_i \times w_{ij} - \theta_j) \quad (1)$$

$$f(Z) = \frac{1}{(1+e^{-Z})} \quad (2)$$

$$y_k = f(y_j \times w_{jk} - \theta_k) \quad (3)$$

$$QoE = 5 \cdot y_k \quad (4)$$

For w_{ij}, w_{jk}, θ_j, θ_k and x_i which are coefficient values within the QoE model, these coefficients have obtained from the result of modeling process using the collected datasets from the group of defined users with the subjective evaluation method in the real environment. The correlation coefficient of created QoE model was equal to 0.7 which shown a good model. These can be expressed as

$$w_{ij} = \begin{bmatrix} 0.292 & 0.288 & 0.285 \\ 8.241 & 6.458 & 5.159 \\ -0.045 & 0.084 & 0.188 \\ 0.111 & 0.020 & -0.070 \end{bmatrix}, w_{ij} = \begin{bmatrix} 7.642 \\ 7.198 \\ 6.986 \end{bmatrix}$$

$$\theta_j = [3.113 \quad 2.362 \quad 1.746], \theta_k = [0.577]$$

$$x_i = [0.002TD \quad -0.058BD \quad 0.039RSRP \quad 0.236SINR]$$

3. METHODOLOGY

3.1 QoS measurement

For Drive Tests, the specific route is on BTS Sukhumvit Line,

Figure 2. The route for Drive Test measurements.

Bangkok, Thailand for three operators as shown in Figure. 2. The reason to select this route is because there are many people accessing mobile services of three operators everyday while traveling on the train. We used the specific smartphones equipped with applications for collecting the data and travelled with the other passengers on the train to measure QoS parameters throughout the route starting from MO CHIT station to BEARING station.

There are three smartphones to measure QoS parameters. Herein this paper, three operators are named as Operator A, Operator B and Operator C. The measuring smartphones for all operators are set up by Drive Tests applications with the same set of parameters and in the same environment to test the quality of these operators.

3.2 QoE estimation

QoS parameters consisting of TD, BD, RSRP, and SINR are entered into the QoE model in order to predict the QoE scores. The equations in (1)-(4) are converted into (5) for the purpose of easier understanding.

$$QoE = f(TD, BD, RSRP, SINR) \quad (5)$$

The results of the QoE evaluation are ranged from 1 to 5, where 1 means the worst experience and 5 means the best experience according to ITU-T P.800 standards [14].

4. RESULTS AND DISCUSSIONS

By collecting QoS parameters with Drive Tests smartphones on the route shown in Figure. 2., the QoE can be evaluated by using (5). The measured data are filtered first in order to screen only required parameters and then feed into the QoE model to predict the QoE score. The sample data collected from Operator A, Operator B and Operator C are shown in Table 1, Table 2 and Table 3, respectively.

Table 1. The information of Operator A

Points	QoS parameters				QoE
	Throughput Download (kbps)	Buffering Duration (s)	RSRP (dBm)	SINR (dB)	
1	1909	0	-71.82	14.34	4.94
2	1914	0	-70.92	16.43	4.95
…	…	…	…	…	…
240	1920	0	-73.43	18.23	4.95

Table 2. The information of Operator B

Points	QoS parameters				QoE
	Throughput Download (kbps)	Buffering Duration (s)	RSRP (dBm)	SINR (dB)	
1	1906	0	-78.36	9.54	4.93
2	1886	0	-77.07	11.64	4.93
…	…	…	…	…	…
240	1910	0	-83.32	13.04	4.94

Table 3. The information of Operator C

Points	QoS parameters				QoE
	Throughput Download (kbps)	Buffering Duration (s)	RSRP (dBm)	SINR (dB)	
1	1837	0	-90.21	7.78	4.91
2	1839	0	-90.43	10.17	4.91
…	…	…	…	…	…
240	1814	0	-81.69	17.44	4.92

4.1 User-centric result

The results from the collecting data of the QoS parameters on the YouTube service in each operator were entered into the QoE model to predict the QoE score. The measurements took about 40 minutes from MO CHIT station to BEARING station. Each point of measurements took about 10 seconds. Therefore, more than 240 data points are collected for each operator. The results obtained from all points are used to compute the average of QoE value to reflect in the user-centric viewpoint as shown in Figure. 3.

As seen in Figure. 3., the Operator A provides the best experience from the viewpoint of users while Operator B gives the worst experience among three operators. If operators assume that QoE will reflect to every QoS parameter, then the trend of all QoS parameters should provide the same trend as shown in Figure. 3. However, this assumption is not true which the results in the next section will demonstrate the confirmation.

Figure 3. Average QoE of each operator from user-centric viewpoints

4.2 Network-centric result

For network-centric viewpoints, this paper investigates the conventional key parameters to reflect the quality of mobile networks. These parameters are Throughput Download (TD), Buffering Duration (BD), RSRP and SINR. The operators use these parameters to improve the network quality. The results from the collecting data of QoS parameters in each parameter were used to find the average value for comparing among three operators.

Figure. 4. to Figure. 7. demonstrate the average Throughput Download, average Buffering Duration, average RSRP and average SINR, respectively. As seen in Figure. 4., the average TD of Operator A provides the best performance and Operator B gives the worst. This trend is still happened for Figure.5. and Figure. 6. Operator A provides the best average BD and average RSRP while Operator B gives the worst BD and RSRP. However, interestingly, the results in Figure. 7. does not reveal the same conclusion as the previous figures. In Figure. 7., Operator C provides the best performance of SINR and Operator B still gives the worst SINR.

4.3 Discussions

This paper demonstrates the viewpoints of user-centric via QoE and network-centric via QoS parameters for YouTube services which is one of the most popular service on mobile networks. In Section 4.1, the QoE as user-centric viewpoint is a measurement of entrepreneurial success. The good experience of users is the most importance factor for operators to gain more users.

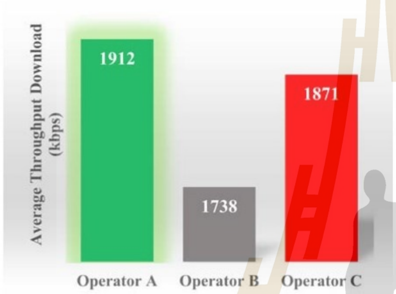

Figure 4. Average Throughput Download of each operator from network-centric viewpoints.

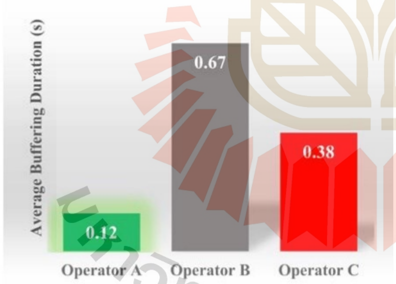

Figure 5. Average Buffering Duration of each operator from network-centric viewpoints.

The results in Section 4.1 indicate that Operator A obtains the highest average QoE and followed by Operator C and Operator B respectively. However, this trend is valid for only some QoS parameters as shown in Section 4.2 when considering the network-centric viewpoints through QoS parameters. It is found that the average SINR of Operator C is the highest and is followed by Operator A and Operator B respectively. This finding is very important to Operator C because if Operator C is happy with the network-centric viewpoints as SINR, then it can mislead Operator C to improve the quality of network.

5. CONCLUSIONS

User-centric viewpoint is an important index used to improve the networks because it can reveal the satisfaction of users via QoE metric. The results of this research have shown that the user-centric and network-centric viewpoints have some consistent layouts. The SINR is a radio parameter that operators must focus on to improve their networks all the time. However, this paper has found that it is inconsistent from ranking the QoE of operators. The average SINR of Operator C is greater than other operators,

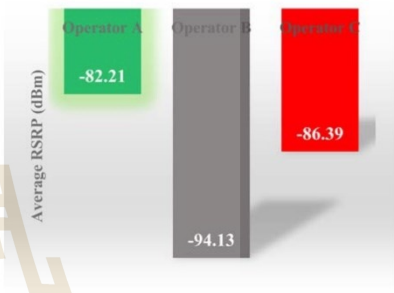

Figure 6. Average RSRP of each operator from network-centric viewpoints.

Figure 7. Average SINR of each operator from network-centric viewpoints.

but the average QoE of Operator C is less than other operators. The configurations within the network of each operator such as bandwidth, frequency, radio resource allocation, etc. may cause these results. This paper suggests that the operators could consider QoE metric as a high priority for improving the network quality if they want to satisfy the experience of users.

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