A Novel Non-intrusive Objective Method to Predict Voice Quality of Service in LTE Networks

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Abstract

This research aimed to introduce a novel approach for non-intrusive objective measurement of voice Quality of Service (QoS) in LTE networks. While achieving this aim, the thesis established a thorough knowledge of how voice traffic is handled in LTE networks, the LTE network architecture and its similarities and differences to its predecessors and traditional ground IP networks and most importantly those QoS affecting parameters which are exclusive to LTE environments. Mean Opinion Score (MOS) is the scoring system used to measure the QoS of voice traffic which can be measured subjectively (as originally intended). Subjective QoS measurement methods are costly and time-consuming, therefore, objective methods such as Perceptual Evaluation of Speech Quality (PESQ) were developed to address these limitations. These objective methods have a high correlation with subjective MOS scores. However, they either require individual calculation of many network parameters or have an intrusive nature that requires access to both the reference signal and the degraded signal for comparison by software. Therefore, the current objective methods are not suitable for application in real-time measurement and prediction scenarios.

A major contribution of the research was identifying LTE-specific QoS affecting parameters. There is no previous work that combines these parameters to assess their impacts on QoS.

The experiment was configured in a hardware in the loop environment. This configuration could serve as a platform for future research which requires simulation of voice traffic in LTE environments.

The key contribution of this research is a novel non-intrusive objective method for QoS measurement and prediction using neural networks. A comparative analysis is presented that examines the performance of four neural network algorithms for non-intrusive measurement and prediction of voice quality over LTE networks. In conclusion, the Bayesian Regularization algorithm with 4 neurons in the hidden layer and sigmoid symmetric transfer function was identified as the best solution with a Mean Square Error (MSE) rate of 0.001 and regression value of 0.998 measured for the testing data set.

Acknowledgements

I wish to express my sincere thanks to my family, for all their support and kindness. I truly owe my success to my parents.

I also would like to express my gratitude to my supervisors, Professor Ian Wells, Dr Kapilan Radhakrishnan and Dr Carlene Campbell for their useful feedback and advice throughout my studies.

I consider it a privilege to be a part of such lovely and kind community at School of Applied Computing. I'm thankful to all members of the Faculty of Architecture, Computing and Engineering for their support and advice when I needed it most.

Declarations

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed Date: *November*, 2018

STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Where correction services have been used the extent and nature of the correction is clearly marked in a footnote(s). Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

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STATEMENT 2

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List of Abbreviations

3GPP	Third Generation Project Partnership
4G	Fourth Generation
ACR	Absolute Category Rating
AMR	Adaptive Multi Rate
AN	Access Network
ANN	Artificial Neural Networks
APN	Access Point Name
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BR	Bayesian Regularization
BSC	Base Station Controller
BSS	Base Station System
BTS	Base Transceiver Station
BVC	Broad Voice Concealment
CCR	Comparison Category Rating
CDMA	Code Division Multiple Access
CELP	Code-excited Linear Prediction
CLI	Command Line Interface
CN	Core Network
CoA	Care of Address

CRS	Cell-specific Reference Signal
CS	Circuit-Switching
CSCF	Call Session Control Function
CSFB	Circuit-Switching Fall-back
dB	Decibels
DCR	Degradation Category Rating
DL	Downlink
eNodeB	Evolved Node B
EPA	Extended Pedestrian A Model
EPC	Evolved Packet Core
EPS	Evolved Packet System
ETSI	European Telecommunications Standards Institute
ETU	Extended Typical Urban Model
E-UTRA	Evolved Universal Terrestrial Radio Access
EVA	Extended Vehicular A Model
FA	Foreign Agents
FDD	Frequency Division Duplex
FER	Frame Erasure Rate
FFT	Fast Fourier Transform
FTP	File Transfer Protocol
GA	Genetic Algorithm

GBR	Guaranteed Bit Rate
GD	Gradient Decent
GERAN	GSM EDGE Radio Access Network
GGSN	GPRS Support Node
GPRS	General Packet Radio Service
GR	Guaranteed Bit Rate
GSM	Global System for Mobile Communications
HA	Home Agents
HSPA	High Speed Packet Access
HSS	Home Subscriber Server
HTTP	Hyper Text Transfer Protocol
IETF	Internet Engineering Task Force
iLBC	Internet Low Bit Rate Codec
IMS	IP Multimedia Subsystem
IMT	International Mobile Telecommunications
IoT	Internet of Things
IP	Internet Protocol
ISP	Internet Service Provider
ITU	International Telecommunications Union
LM	Levenberg-Marquardt
LTE	Long Term Evolution

LTE-A	Long Term Evolution - Advanced
LVQ	Learning Vector Quantization
MGCF	Media Gateway Control Function
MGW	Media Gateway
MIMO	Multiple Input Multiple Output
MME	Mobile Management Entity
MMTel	Multimedia Telephony
MN	Mobile Node
MNB	Measuring Normalizing Blocks
MOS	Mean Opinion Score
MSC	Mobile Switching Centre
MSE	Mean Square Error
NN	Neural Networks
OFDMA	Orthogonal Frequency Division Multiple Access
PAMS	Perceptual Analysis Measurement System
PCEF	Policy and Charging Enforcement Function
PCM	Pulse Code Modulation
PCRF	Policy and Charging Rules Function
PDN	Packet Data Network
PDSCH	Physical Downlink Shared Channel
PESQ	Perceptual Evaluation of Speech Quality

PESQ-LQ	Perceptual Evaluation of Speech Quality - Listening Quality
PGW	PDN Gateway
PLC	Packet Loss Concealment
PLMN	Public Land Mobile Network
PLR	Packet Loss Rate
PMCH	Physical Multimedia Channel
POTS	Plain Old Telephone System
PRACH	Physical Random Access Channel
PS	Packet-Switching
PSQM	Perceptual Speech Quality Measurement
PSTN	Public Switched Telephone Network
QAM	Quadrature Amplitude Modulation
QCI	Quality Class Identifier
QMF	Quadrature Mirror Filter
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
RF	Radio Frequency
RMC	Reference Measurement Channel
RMS	Root Mean Squared
RNC	Radio Network Controller

RNN	Random Neural Networks
RNS	Radio Network Subsystem
Rx	Receiver
RPROP	Resilient Propagation
SAE	Service Architecture Evolution
SCG	Scaled Conjugate Gradient
SDR	Software Defined Radio
SGSN	Serving GPRS Support Node
SGW	Serving Gateway
SIP	Session Initiation Protocol
SMS	Short Messaging Service
SMTP	Simple Mail Transfer Protocol
SNR	Signal to Noise Ratio
SoC	Software on Chip
TDD	Time Division Duplex
TDF	Traffic Detection Function
TTI	Transmission Time Interval
Tx	Transmitter
UE	User Equipment
UL	Uplink
UMTS	Universal Mobile Telecommunication System

UTRAN	Universal Terrestrial Radio Access Network
VoIP	Voice over IP
VoLTE	Voice over LTE
WCDMA	Wideband Code Division Multiple Access
XOR	Exclusive OR

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Chapter 1

Introduction

The fast paced growth of the telecommunication industry has raised end-user expectations. The legacy Internet which was traditionally responsible for transmission of data and pre-recorded multimedia, no longer suffices, due to end-users' expectations of highly available networks with capabilities and features to support real-time communications. Also worth noting that society has outgrown wire-line communications and mobility has become the key to efficiency in every network's infrastructure. Wireless networks are now widely being deployed around the globe using different technologies and for a wide range of purposes. When the evolution of wireless networks is considered attributes such as speed, range, Quality of Service (QoS) and security come to mind.

The purpose of wireless networking is utilization of aforementioned characteristics at their peak. As for Cellular networks, Long Term Evolution-Advanced (LTE-A) 4G and 5G infrastructures can be named as the latest developments in cellular networks. Research on Long Term Evolution (LTE) was initiated in 2004 and first LTE networks were deployed in 2009. This architecture provides much higher speeds (up to 300 Mbps in the Downlink and 75 Mbps in the Uplink) than previous mobile Internet architectures (i.e. 3.5G with HSPA at 600 Kbps to 10 Mbps) [1].

This chapter serves as an introduction to the research. In section 1.1, a brief background on key areas of the research is presented. Section 1.2 highlights the Research Questions of the thesis which are reflected upon and answered by research aims and objectives in section 1.3. Section 1.4 provides an overview of the thesis structure for ease of navigation.

1.1 Background

As illustrated in Figure 1.1, research on LTE was initiated by 3GPP and is basically a set of enhancements to the existing Universal Mobile Telecommunication System (UMTS). Figure 1.2 demonstrates the protocol architecture of the LTE networks in layers 1-3 of the OSI network model.

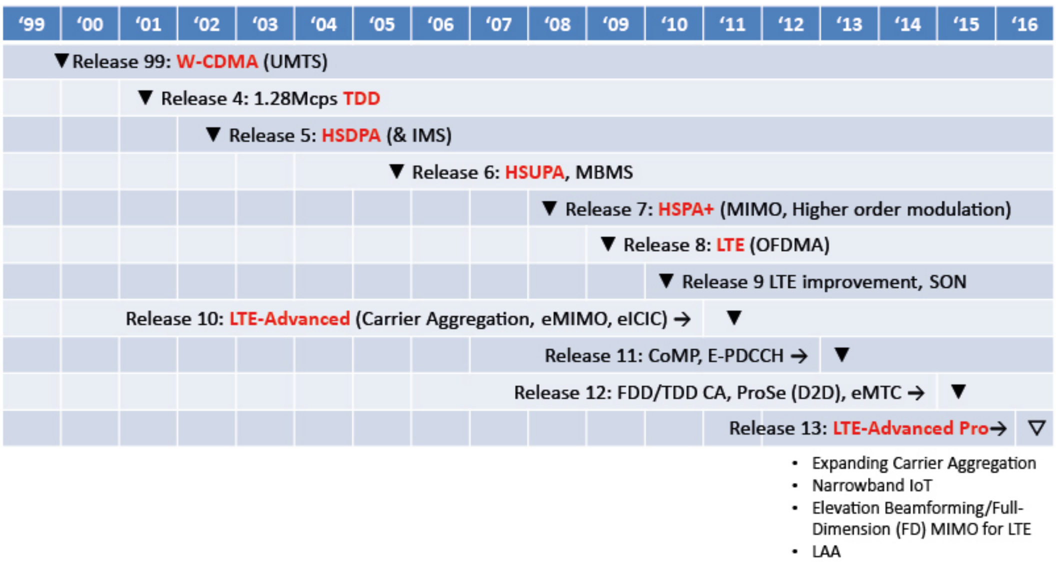


Figure 1.1: 3GPP Milestones [1]

The core purpose of LTE is to increase the capacity and speed of mobile communications. In addition to using multiple antenna techniques, LTE uses different air interface and structure of the packets traversing LTE networks is different to that of its predecessors. Evolved Universal Terrestrial Radio Access (E-UTRA) is used as the air interface in LTE. This interface is based on Orthogonal Fre-

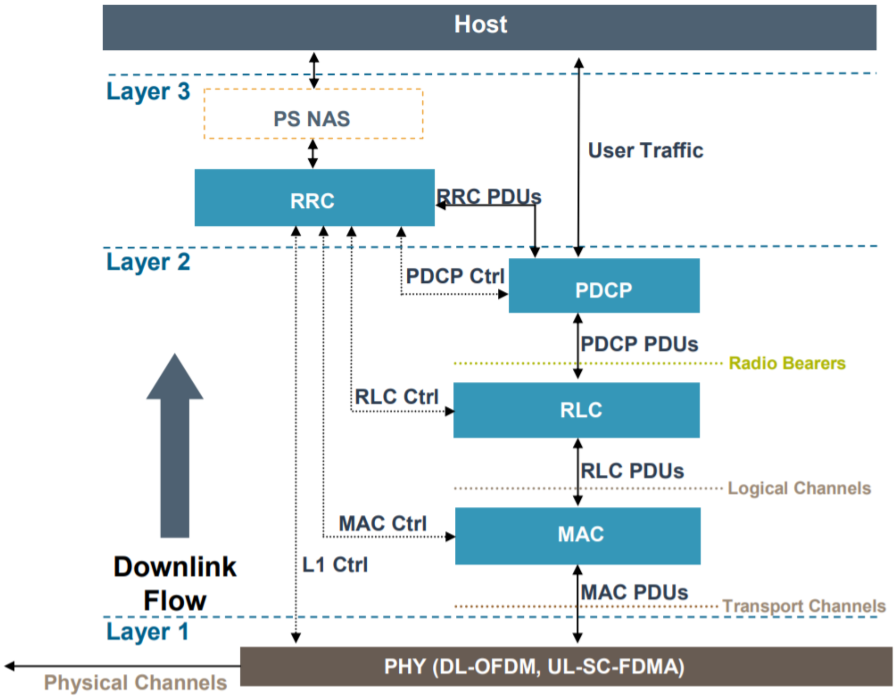


Figure 1.2: LTE Radio Protocol Layers [2]

quency Division Multiple Access (OFDMA) as opposed to Code Division Multiple Access (CDMA) in its predecessors. Instead of packet switching, LTE takes advantage of message switching where instead of breaking down the message to multiple packets, the entire message is routed to the next hop towards the destination host. In a recommendation by Florea et al. [3] it is noted that a flat architecture for LTE improves the core performance by implementing more direct routes from mobile devices to end system.

Reviewing the current relevant literature has illuminated numerous areas in need of further development such as QoS, security, scalability and interoperability between different releases. On the other hand, the real-time nature of communication protocols such as Voice over LTE (VoLTE) is essential to maintain, but could also cause vulnerabilities in the infrastructure which usually remain undetected at early stages. It is crucial to detect such weaknesses and devise countermeasures to overcome these challenges.

Due to the full packet switching core of LTE networks and best effort delivery nature of Internet Protocol (IP), it is necessary to be able to predict and measure QoS scores of voice communications over LTE, based on various factors, such as speed of moving User Equipments (UEs), their distance and trajectory relative to the base station antenna, anticipated noise levels, antenna gains and fading channels.

1.2 Research Questions

1. Which LTE-specific parameters impact quality of voice traffic in LTE networks?
2. How a non-intrusive objective method can accurately measure and predict QoS of real-time voice transmissions in LTE networks, using LTE-specific parameters?
3. What are the applications/limitations of the proposed non-intrusive model using neural networks for QoS measurement/prediction?

1.3 Aim and Objectives

The main aim of this research is to develop a non-intrusive objective method to evaluate and monitor the QoS of voice traffic in LTE networks using neural networks.

To achieve the above aim, the following objective are set to be met:

- Develop a thorough understanding of voice transmission architecture and the factors affecting its quality over IP networks.
- Identify general IP and LTE-specific parameters which have significant impact on QoS of VoLTE.
- Develop a deeper understanding of common LTE simulation techniques and identify a suitable solution to conduct experiments (voice transmission over LTE networks).

- Conduct experiments with voice transmissions over LTE and collect data on key LTE-specific inputs such as SNR and UE travel speed and distance from eNodeB, as well as the resulting MOS output for the voice transmissions.

- Train, validate and test neural networks using the data obtained from experiments, with several algorithms and various architectures to identify the most appropriate method of Voice QoS measurement for on LTE-specific parameters.

- Develop a non-intrusive method to predict and measure QoS of real-time voice transmissions over LTE networks using LTE-specific parameters that would aid Communications Service Providers with network planning and QoS monitoring purposes.

1.4 Structure of the Thesis

This thesis is structured in 6 chapters as explained here:

Chapter 1 offers an introduction to the topic and considers some brief background to support the motivation for this project while presenting the aim, research question and objectives for the research project.

Chapter 2 Collects and examines the fundamental literature which was surveyed before defining the experiment parameters, and also additional relevant updates to the topics considered. Firstly, the Cellular networks are discussed in detail, outlining their improvement from the First Generation networks (1G) to Fourth Generation (4G), by including their technologies, characteristics and architectures. A comparative approach is taken to highlight the improvements in each release of these networks. Voice over IP (VoIP) is then considered, leading to discussions on how voice is handled in LTE networks by implementing IP Multimedia Subsystem (IMS) to support Voice over LTE (VoLTE) efficiently. This chapter also identifies challenges faced by Service Providers while implementing VoLTE in 4G networks, while considering the Quality of Service (QoS) affecting parameters in IP networks. These parameters include radio impairments which are specific to the wireless nature of LTE Access network (i.e. between UE and eNodeB). The chapter offers an overview of intrusive and non-intrusive voice QoS measurement methods. A comprehensive overview of Machine Learning and Neural Networks is also included to link QoS measurement and Neural Networks which are key elements from the scope of research.

Chapter 3 goes on to consider various simulation techniques which are introduced in the research community for the purpose of experimenting on various aspects of LTE networks. This chapter considers the features and functionalities of these tools, to identify the best fit for the requirements of this project. Some Benchmarking tests are also included here to validate the eligibility of the chosen technique.

Chapter 4 discusses the full experiment set-up and deployment, while highlighting the data collection process. The simulation input/output parameters and their ranges are also defined by citing appropriate literature for justifications.

Chapter 5 presents the findings of experiment results and correlates them with the available literature.

Chapter 6 analyses the collected results and proposes a non-intrusive objective approach to measure QoS MOS levels in LTE based on neural networks. Multiple algorithms are tested and the best performance is identified by considering the correlations and squared errors.

Chapter 7 is a summary of the thesis, highlighting the contributions, commenting on suitability of the experiment design, the introduced method and recommending directions for future works in this subject area.

Chapter 2

Literature Review

2.1 Introduction

Commercial deployment of Fourth Generation (4G) cellular communication networks has created many opportunities and challenges especially from the service providers point of view. Introduction of an all-IP core in 3GPP Release 8 is meant to support the increasing level of demand generated by extensive adoption of high quality real-time communications (i.e. voice and video). Typically, users characterize service providers based on the quality of their services and since the common communication technology has evolved from text based to real-time voice and video calls, Quality of Service (QoS) has become a very sensitive aspect of network design and planning for service providers. This chapter offers a survey on key characteristics of Long Term Evolution (LTE) networks (Rel-8 and later releases), Voice over LTE (VoLTE) and a comprehensive study of the most common available QoS measurement methods along with key quality affecting parameters.

2.2 Cellular Communication Networks

Ever since the first experiments with radio communications conducted in the 1890s by Guglielmo Marconi [4], and introduction of mobile telecommunication systems in late 1900s, mobility has had strong impacts on our everyday lives. Initially the First Generation (1G) network architecture was introduced, using analogue signalling similar to that of traditional analogue radios. Due to inefficient utilization in cell sizes and frequencies, 1G's capacity was minimal. High costs of maintenance and the early stages of this technology dictated the researchers to come up with a solution. After a decade of improvement, Second Generation (2G) systems, for the first time used digital technology, enabling them to utilize the radio spectrum more efficiently and providing possibilities for cheaper client-side technologies. 2G was originally designed only for voice transmission, but was later modified to support text traffic through Short Messaging Service (SMS). The most popular system which resided in 2G's domain was Global System for Mobile Communications (GSM). Considering the parallel growth of mobile communications and the Internet, the two architectures were integrated for provisioning of common services. Hence 2.5G systems, based on 2G were implemented by introduction of packet switching at the core and modifications to the air interface. General Packet Radio Service (GPRS), integrated these techniques into GSM [1, 5].

The current project, which has provided the means for collaboration of various national and regional telecommunications standards bodies is the 3GPP [1], otherwise referred to as 3GPP Long Term Evolution. GSM [5], is a second generation cellular system standard which is essentially the predecessor of UMTS [6]. GSM was the first cellular system to specify digital modulation and utilize network level services. UMTS is essentially a term for third generation radio networks developed within 3GPP [7]. LTE evolved from UMTS and due to continuous developments in the field, it still is evolving rapidly [8]. For further information, Figure 2.1 demonstrates the architecture used to implement

UMTS and GSM..

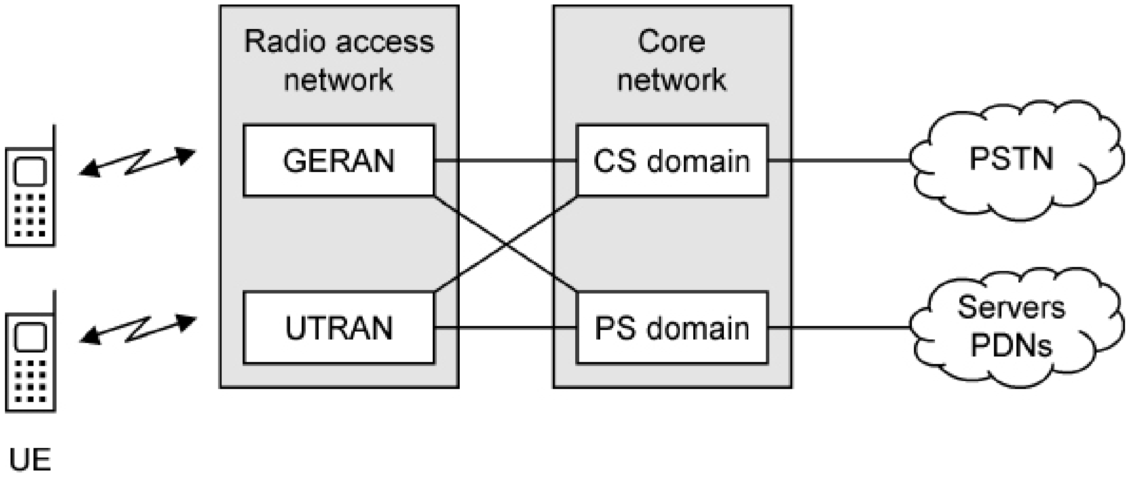


Figure 2.1: High Level Architecture of UMTS and GSM [8]

2.2.1 Radio Communication

Global System for Mobile Communications (GSM)

Originally developed as a European standard, can handle both voice and data traffics. The voice traffic waveform is digitally encoded in GSM before transmission [9].

GSM is a second generation air interface, built to provide voice services in macro cells [10]. This standard was utilized in most mobile phones in 2003 with the goal of making mobile phone communications as secure as Public Switched telephone Network (PSTN) [11].

Universal mobile Telecommunications System (UMTS)

As outlined in [11], work on 3G began in the late 1990s and because of the great deal of money and effort spent on GSM, UMTS was essentially based on the same technology. Hence, UMTS [12] has a very similar structure to GSM in terms of its core network.

Furthermore, in terms of the network architecture, 3GPP uses the terminology of Public Land Mobile Network (PLMN) for a land mobile telecommunications network. This infrastructure is further divided into an Access Network (AN) and a Core Network (CN). Two types of access network are supported by UMTS:

- Base-station System (BSS), GSM's AN
- Radio Network Subsystem (RNS), based on UMTS

UTRAN was included in the RAN specifications in Release 99 which was still heavily based on the core network of 2G implementations [13]. A GSM/EDGE-based RAN, otherwise known as GSM EDGE Radio Access Network (GERAN) was standardized in later releases.

As Etoh [11] further elaborates, CN is comprised of a Circuit Switching (CS) and a Packet Switching (PS) domain. CS is typically used for transmission of real-time traffic and PS is utilized for end to end packet data delivery (i.e. File Transfer Protocol (FTP), Hypertext Transfer Protocol (HTTP), Simple Mail Transfer Protocol (SMTP) and etc.). In [8], an illustration of this architecture, and the relationship between the CS and PS domains formulating the CN in Cellular networks is illustrated and presented here in Figure 2.1.

2.3 Universal Terrestrial Radio Access Network

(UTRAN)'s [14] architecture based on 3GPP Release 11 [15] is shown in Figure 2.2. This consists of few RNS which is comprised of an RNC and one or more NodeBs, connected to the core network via Iu(s). As stated in [10] and observed in Figure 2.2, these RNCs can be interconnected through Iur interface[1].

[1] Iu(s) and Iur are logical interfaces which can be established using direct physical connection between RNCs or via suitable transport networks through virtual networks.

Furthermore the RNCs and Node Bs are connected to each other with an Iub interface.

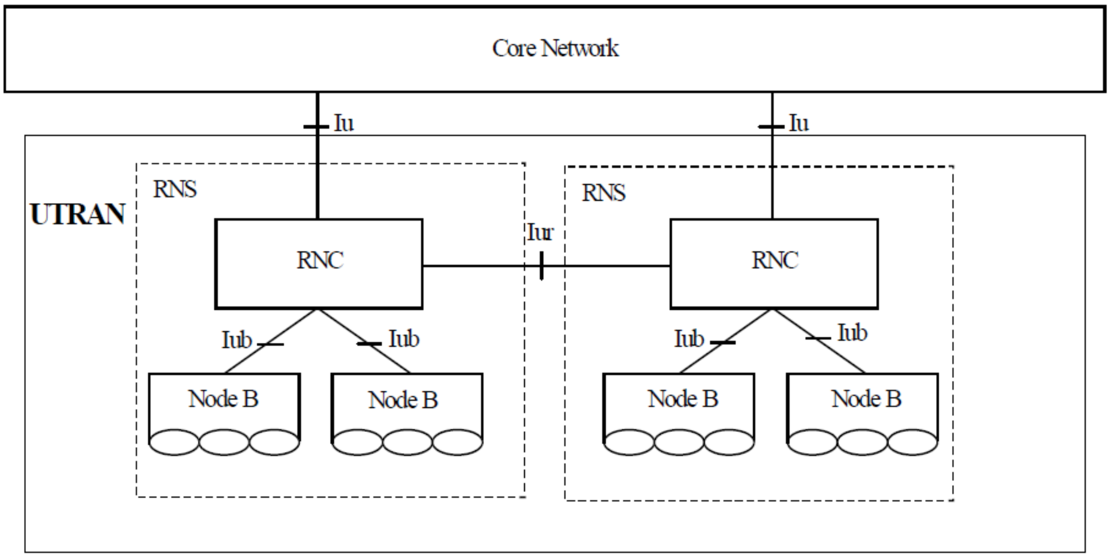


Figure 2.2: UTRAN Architecture [15]

2.4 Second Generation (2G) Networks

Before considering the topology for LTE-A networks, architectures of 2G, 2.5G and 3G are discussed in more details so the need for LTE-A can be illustrated. 2G is essentially the GSM technology and 2.5G was introduced in GPRS leading to development of 3G in Wideband Code Division Multiple Access (WCDMA) [16]. In 2G, there is an RN and a CN as illustrated in Figure 2.3.

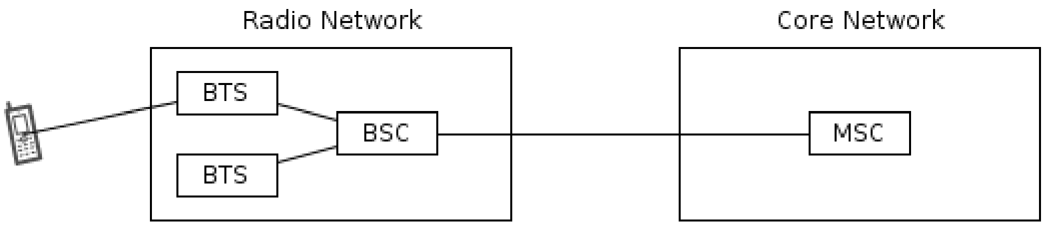


Figure 2.3: 2G Architecture

In the topology, if the end user wanted to use voice service for instance, User Equipment (UE) would contact the Base Transceiver Station (BTS) node which will carry that voice traffic towards a Base Station Controller (BSC), which has the responsibility of acting as an aggregation point and control numerous BTSs. For instance, if the user wanted to move into range of a new BTS, then BSC would be controlling that handover. Now let's look at the core of 2G architecture. The core is comprised of an Mobile Switching Centre (MSC) node which is in charge of controlling call operations and logging usage for user billing. So BSCs would send the call to MSC and MSC would decide upon what action is to be taken in terms of call control options (i.e. Call Setup or Tear-Down). Note that there would be many BSCs that communicate with the MSC.

2.5 2.5G Networks

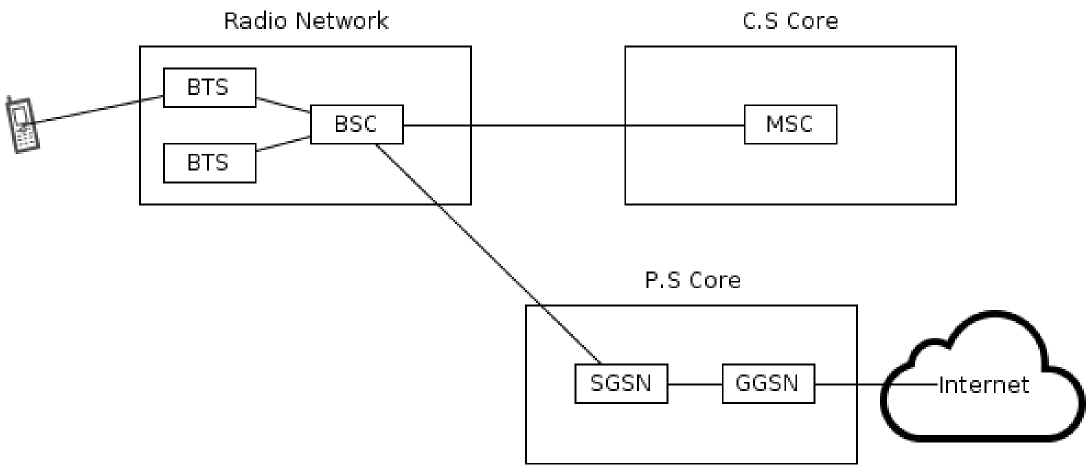


Figure 2.4: 2.5G Architecture

Introduction of 2.5G allowed for provision of data services to users. 2.5G introduced a new PS core to cellular networks. In reference to Figure 2.4, the Serving GPRS Support Node (SGSN) node, included in the PS core of 2.5G had similar role in data networks to that of MSC in voice networks. Another node in 2.5G PS core was the Gateway GPRS Support Node (GGSN) which allowed for interoperability of our data network with outside services such as the Internet. So even though a new core component was introduced to 2G, the user would still have to connect through BTS in the RN in order to access the Data network provided by the new PS core with the difference that BSCs would have to communicate with SGSN in cases where data services was requested by the user.

2.6 Third Generation (3G)

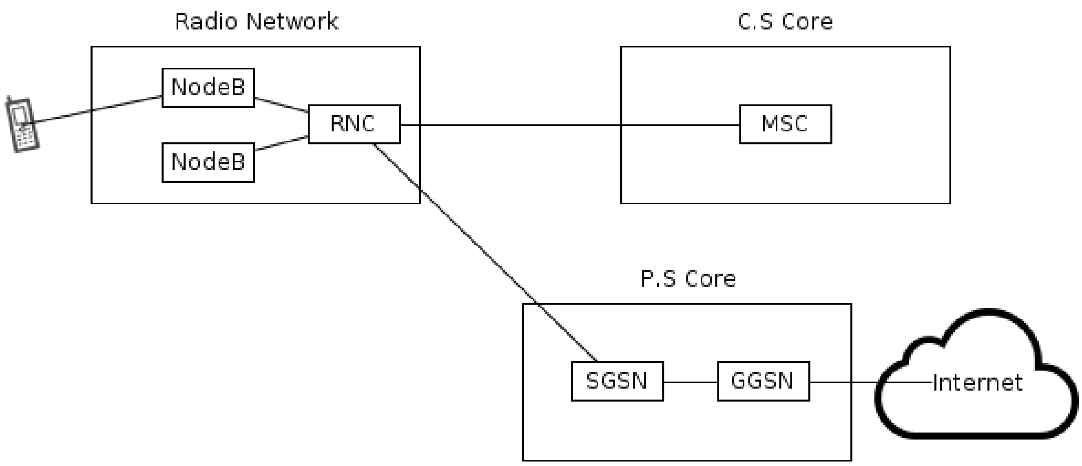


Figure 2.5: 3G Architecture

A key component of 3G standard was the WCDMA. Honkasalo et al. [16], classified the WCDMA evolution from Rel 99 to beyond 3G in three phases; namely, high-speed downlink packet access, uplink high-speed Data, high-speed access for TDD, and capacity improvements in uplink and downlink. As seen in Figure 2.5, a new structure for the RN was devised for 3G, containing a NodeB which is basically the 3G antenna, and an RNC that had same function as the BSC in second generation architectures and subsequently, based on user's request the RNC would forward the traffic towards MSC for voice and SGSN for data. As mentioned before, this new radio network enabled the 3G to allow for much higher data rates.

2.7 Fourth Generation (4G) Networks

4G wireless cellular systems received a significant amount of attention in 1997 after 3G system was officially defined by International Telecommunications Union Recommendations Sector (ITU-R). Initially ITU-R defined requirements of 2048 kbps, 384 kbps, 144 kbps and 9.6 kbps respectively for, indoor office, outdoor to indoor pedestrian environments, vehicular connections and satellite connections [17]. 3GPP ran two projects in parallel, LTE and System Architecture Evolution (SAE). These are included in 3GPP Release 8 [15], which is the first specification released by 3GPP for LTE systems. 3GPP-rel8 defines both the access network and the core network of the system. As mentioned in [17], the main incentive for development of LTE was the high demand for mobile broadband with higher data rates and better QoS. Compared to its predecessor, Release 8 is more efficient, provides better data rates, does not include a CS core and is more secure. Development of LTE Rel 8 began before ITU-R had published the requirements for LTE networks, as a result, this release did not comply with ITU 4G requirements [18]. In the access network which is referred to as Evolved Universal Terrestrial Radio Access Network (UTRAN), LTE utilizes Orthogonal Frequency Division Multiple Access (OFDMA) [19] and MIMO. Chan et al. [20], compared the performance of OFDMA over competing technologies and as expected OFDMA was superior in most conditions. Throughout the design, LTE has a flat all-IP based architecture. In LTE, the core network is referred to as the Evolved Packet Core (EPC) and collectively, the UTRAN and EPC are known as Evolved Packet System (EPS). The general architecture of EPS including its key components is presented in Figure 2.6.

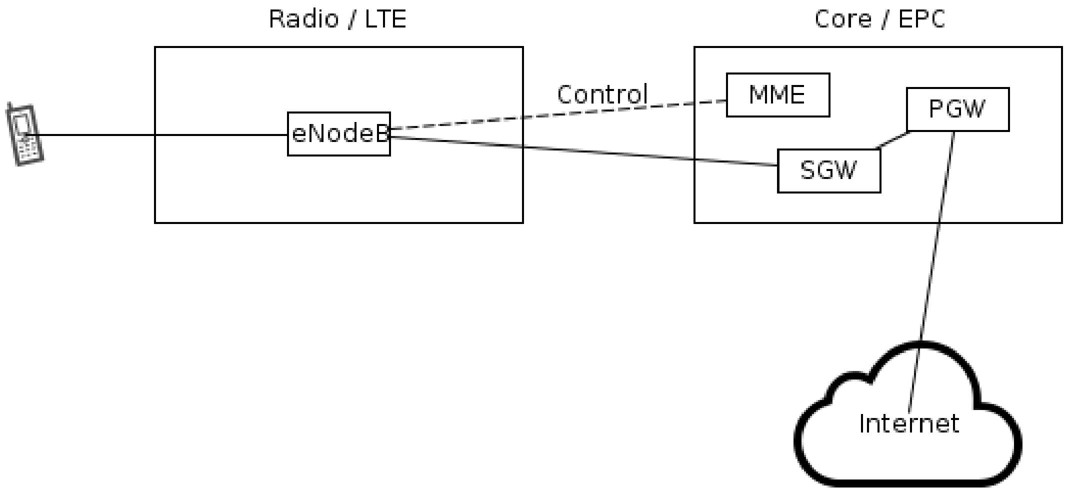


Figure 2.6: 4G Architecture

When compared to its predecessors, 4G abides by the same general structure, however it differs in terms of components. Within the radio network, there is a single eNodeB (the 4G Antenna). The EPC core is a purely PS oriented network which means, the services offered for voice (CS) are no longer available. The access network only contains the eNodeB and there is no need for a control node. Due to this development, the Transmission Time Interval (TTI) is shorter and enables a much smoother handover process. The control node in EPC is called Mobility Management Entity (MME). There is also the Serving Gateway (SGW) which acts as an anchor point for different access networks and there is also a Packet Data Network (PDN) Gateway (PGW) acting as an exit point towards external IP based services (Internet). In regards to LTE-EPC operation, the 4G enabled phone connects to eNodeB, the eNodeB signals the MME, the MME controls access (i.e. call establishment) with help of SGW and when required, the communication vector can be established with various IP based services through the PGW. Due to the absence of a CS core in 4G, there is no support for CS services, subsequently, VoLTE is proposed which is a VoIP type technology implemented in LTE to provide voice and other real-time services over the LTE network. There were some minor improvements in LTE Release 9

[15], which led to development of LTE-Advanced in 3GPP Release 10 [15]. LTE Release 10 met the requirements of IMT-Advanced [18] with the major focus being on the access network. A number of features were introduced in this release, to increase the capacity and data rates of Uplink and Downlink:

- Carrier aggregation: Increased the maximum bandwidth from 20 MHz in Release 8-9, to 100 MHz in Release 10.
- Enhanced multi-antenna support: leading to higher Spectral Efficiency in both Downlink (30 bits/s) and Uplink (16 bits/s).
- Relay nodes: improving coverage and throughput at the cell edge.

LTE release 12 [15], which was frozen in March 2015, adds some key features to LTE. In release 12, enhancements were made to Downlink MIMO, hence increasing the spectral efficiency [21]. Some enhancements were made to Small Cells. Release 12 also benefits from use of higher order modulations up to 256 Quadrature Amplitude Modulation (256QAM) in both Physical Downlink Shared Channel (PDSCH) and Physical Multimedia Channel (PMCH). Some UE receiver enhancements are noted, and new enhancements to Carrier Aggregation, allow Frequency Division Duplex (FDD) and Time Division Duplex (TDD) spectrum to be operated simultaneously. A comprehensive survey of TDD and FDD implementations is offered by [22]. Various enhancements were made to HSPA and also some network and service enhancements is observed. One of the major motivations for 4G's definition was cost efficiency for operators. In 4G, there is still a radio component present which is otherwise referred to as the LTE and there is also a core component which is referred to as the EPC. When compared to its predecessors, 4G abides by the same general structure, however is very different in terms of its components. Within the radio network, there is a single eNodeB (the 4G Antenna). The EPC core is a purely PS oriented network which means, the services offered for voice (CS) are no longer available. The control node in EPC is called MME. There is also the SGW which acts as an anchor point for different access networks and there is also a PDN Gateway (PGW) acting as an exit point towards external IP based services (Internet). In regards to LTE-EPC operation, the 4G enabled phone connects to eNodeB, the eNodeB signals the MME, the MME controls access (i.e. call establishment) with help of SGW and when required, the communication vector can be established with various IP based services through the PGW.

As illustrated in Figure 2.6 the radio network is not as crowded as that of 2G, 2.5G and 3G, which in turn decreases the complexity of the model and also excludes the need for traffic travelling through extra hops. Another advantage associated with this design is that there is no need for two core components and the PS core will handle all communication. 4G does not support the traditional CS, but due to its high speeds, VoLTE has many applications within this architecture.

2.7.1 Bearer Management

As mentioned earlier, LTE is an end-to-end packet switched network. Due to its all-IP architecture, LTE is able to support numerous applications and services. To satisfy QoS requirements of these services, the concept of bearers was introduced at the core of LTEs QoS control [23]. According to [8], one of the most important bearers is the EPS bearer, which can be considered as a bidirectional data pipe. Essentially, this bearer transfers data between UE and the PGW with specific QoS provisions. A number of QoS affecting parameters (i.e. data rate and delay) are used to maintain a healthy level of QoS for each application.

EPS bearers can be classified in two ways; if classified depending on their nature:

- Guaranteed Bit Rate (GBR): Often applied to sensitive real-time services such as voice.
- Non-GBR: Applied to applications with less QoS priority. (i.e. web browsing)

And in terms of their operation within EPS:

- Default bearer
- Dedicated bearer

In a nutshell, every time a UE connects to a PDN, EPC sets up a default EPS bearer. The purpose of this default bearer is to provide the UE with an always-on connection to the default PDN (i.e. the Internet). Once the default bearer is established, an IP address will be assigned to the UE. New IP addresses would only be used if there are connections to different Access Point Names (APNs). Otherwise for a single APN connection, the IP address would remain the same. On top of this, the UE can establish connections to other PDNs (i.e. a company network), in which case another default bearer will be established and a new IP address will be assigned for use in the second PDN. Once a default bearer is in place, one or more dedicated bearers can be established in the same connection. GBR bearer is mainly used for VoLTE or real-time applications to offer a more reliable service, and is not a common configuration used for LTE data channels. Each dedicated bearer will use the layer 3 address of its parent default bearer and will not require a new layer 3 address [8].

The logical EPS bearer spans three different interfaces. Hence, it can be divided into three lower-level bearers as shown in Figure 2.7:

- Radio bearer
- S1 bearer
- S5/S8 bearer

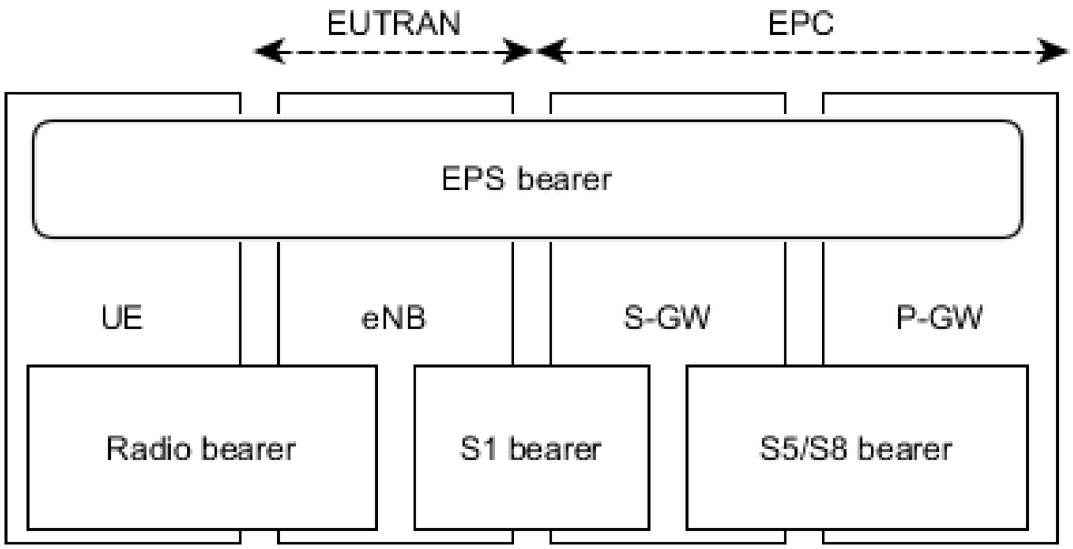


Figure 2.7: EPS Bearer

As further outlined in [23], the introduction of bearers in LTE, allowed for simultaneous QoS management of applications with different QoS requirements.

2.7.2 Time Division Duplexing (TDD) vs Frequency Division Duplexing (FDD)

TDD and FDD are both used in LTE networks to establish full-duplex full-duplex[2] communication channels.

While using FDD, Uplink (UL) and Downlink (DL) channels use different carrier frequencies separated by a band guard. This minimizes the chance of interference between the two channels. FDD offers very low latencies because

[2] UE and eNodeB can send and receive simultaneously

both DL and UL are essentially operating at the same time, with no delay or queues. But this comes at a cost, due to the need for duplexers. Using TDD, both UL and DL can use the same radio carrier frequency. Instead of having separate channels for UL and DL, these transmissions are allowed to use the same channel, using synchronised time intervals. Although the UL and DL transmissions are essentially taking turn (alternating between UL and DL) to use the channel, no delay is experienced by Tx or Rx due to the short interval assignments. There are no guard bands as there is no need to have separate carrier frequencies, but there are guard periods between the timeslots to avoid interference. Generally, in long distance communications, TDD does not perform as efficient as FDD due to enlarged guard periods. But because timeslots are assigned dynamically, more efficient use of bandwidth is observed with TDD implementations. The performance of TDD and FDD in massive MIMO is also evaluated by Flordelis et al. [24].

2.8 Fifth Generation (5G) Cellular Systems

The ever increasing user demand and application requirements at present has caused the rapid development of cellular networks. Since commercialization of 4G, extensive research and development is being carried out on IMT-2020 (5G) network worldwide. It is said that compared to its predecessors, 5G network will be 1000 times greater in capacity and able to connect over 100 billion devices to the network. This will fit nicely with Cisco‘s vision of Internet of Things (IoT), due to the large amount of traffic produced by billions of sensor devices connected the internet. A number of key performance indicators have been defined with their target values for the implementation of 5G [25]:

- “ Peak data rate: $\geq$ 10 Gbps
- Minimum guaranteed user data rate: $\geq$ 100 Mbps
- Connection density: $\geq$ 1M connections/km^2
- Traffic density: $\geq$ 10 Tbps/km^2
- Radio latency: $\leq$ 1 ms
- End-to-end latency: $\leq$ 10 ms
- Mobility: up to 500 km/h ”

Although 5G has received a significant attention from the wireless community recently, the final picture is not yet clear. A number of required breakthroughs were identified in [26] before implementation of a commercial ready 5G such as “Multiple access and advanced waveform technologies, Interference management, Access protocols, Service delivery architecture, Mass-scale MIMO, Single frequency full duplex radio technologies, 5G devices and Virtualized and cloud-based radio access infrastructure”

2.9 Voice over IP (VoIP)

VoIP is another technology which has faced significant demand in SMEs and ISPs. Due to VoIPs cost efficiency, and ease of maintenance when compared to other solutions such as the PSTN, it is being deployed by many organizations and big corporations. VoIP is essentially a replacement for the existing PSTN. PSTN offers reliability, stability and accessibility. Also when VoIP and PSTN networks are compared, VoIP has a great advantage over PSTN in terms of costs. VoIP calls are much cheaper than PSTN. Only an internet connection is required to initiate a VoIP call to any geographical location. There is also a great compatibility between VoIP and the existing PSTN networks. VoIP has many advantages but is very sensitive to packet loss and jitter. Hence, over the years many authors such as [27] and [28] have introduced methods to counter these QoS degrading parameters to some extent. Packet loss is a parameter with a significant impact on voice QoS for any application. This is further elaborated in this thesis. VoIP depends on multiple or at least the minimum of two protocols in order to initiate a session, one of which is a signalling protocol. The most widely used signalling protocol in VoIP is SIP. As defined in [29], a signalling protocol's role is "to manage call setup, modification, and closing".

2.10 Voice over LTE (VoLTE)

VoLTE is a counterpart to VoIP, it defines an architecture which is used for transmission of real-time voice signals over LTE networks. Though the concept seems straight forward, it is essential to first understand IP Multimedia Subsystem (IMS) before getting into operation of VoLTE. It was previously mentioned that EPC can support all IP services.

As outlined in [30], solutions to provide real-time voice services in LTE networks include, IP Multimedia Subsystem (IMS) Multimedia Telephony (MM-

Tel) and Circuit Switched Fallback (CSFB). Currently the preferred solution is MMTel, and CSFB is used to address the migration period from 2G/3G CS services to VoLTE. An in depth analysis of the CSFB can be found in [31]. LTE networks are now being commercially deployed in all regions and as a consequence of LTEs flat IP architecture, Service Providers have to maintain both infrastructures (CS and VoLTE voice services). This has been a strong motivation for transitioning to VoLTE as quick as possible. As noted in [32], over 50% of LTE subscriptions would be using the VoLTE service for real-time voice communications by 2019. Voice and other real-time services can be provided to subscribers in LTE infrastructures by use of IMS. IMS is essentially a service network, defined by 3GPP in Release 8 [15]. Figure 2.8 is an illustration of the interconnection between EPC, IMS and the Internet. IMS is also capable of interconnecting CS core in 2G/3G with the elements presented in the figure. One of the key components of IMS is the Policy and Charging Rules Function (PCRF).

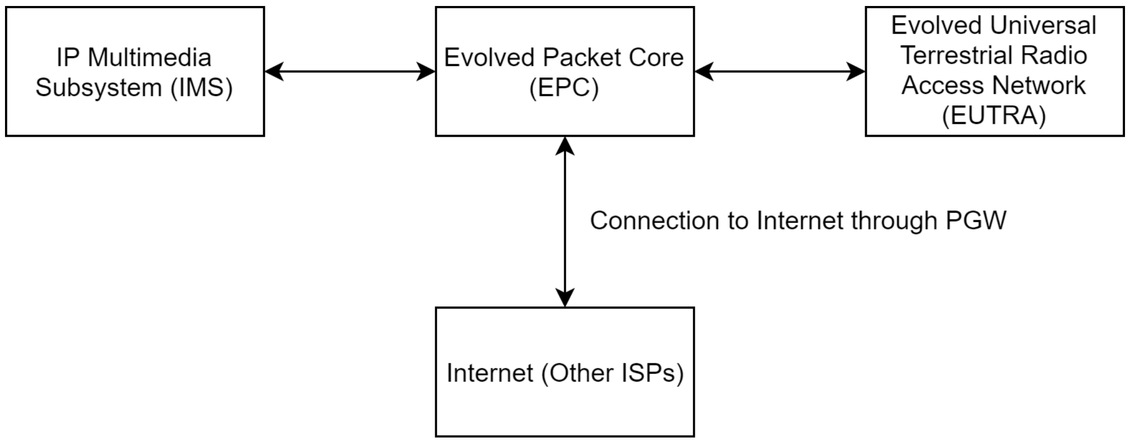


Figure 2.8: EPC, PGW and IMS relationship

The LTE network connects to IMS through this component. Policy enforcement and charging control functions are operations carried out by PCRF. The Call Session Control Function (CSCF) component is responsible for all setup processes, in other words CSCF is in charge of call attributes (similar to MSC in the CS core). CSCF communicates with Home Subscriber Server (HSS) which is basically a subscriber database. If the user wanted to make a call using a

PS voice service to a circuit switched Plain Old Telephone Service (POTS), this would indicate that there is need for another component which could convert the call to and from these two services. To accomplish this, a Media Gateway Control Function (MGCF) and a Media Gateway (MGW) are introduced. As illustrated in Figure 2.9, MGCF and MGW are connected to Public Switched Telephone Network (PSTN). Furthermore, if a more sophisticated service (i.e. third party Video Conferencing server) was required, another network is introduced which consists of application servers. MMTel is essentially a part of these Application Servers.

All aforementioned components are interconnected through an IP network. It is worth noting that IMS and LTE were introduced in different releases of 3GPP and their operation is not dependent on one another. The IMS network can be accessed via different IP Connectivity Access Networks (i.e. WiFi, Cable and ...). However, interconnection of IMS and EPS, provides the means to offer real-

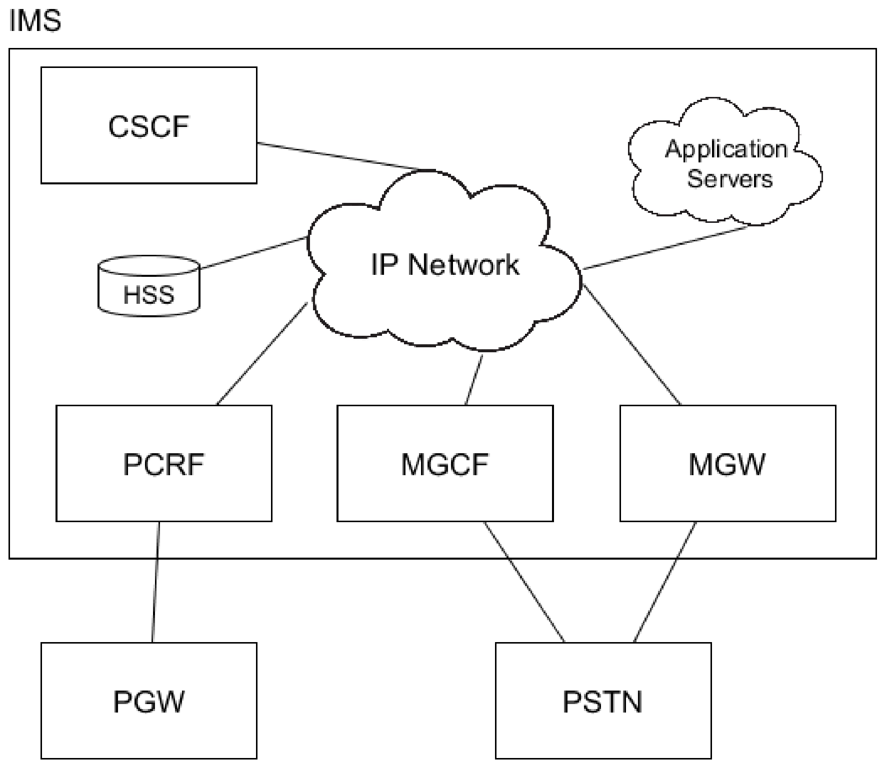


Figure 2.9: IMS Architecture

time services to LTE subscribers. Hence collectively they can be referred to as the VoLTE architecture. This architecture allows for provision of multimedia services across both PS and CS services. Session Initiation Protocol (SIP) is utilized to manage Voice calls in VoLTE. This allows for compatibility with IP Telephony services.

Figure 2.10, is not a fully detailed representation of interconnections between multiple IMS service networks and PSTN networks; only a general illustration, depicting how it enables Service Providers to offer real-time voice services between a UE and a PSTN network. Also worth noting that although HSS is reintroduced in EPS, it was originally defined in 3GPP release 5 [15] and that is why in this thesis it is presented as part of both IMS service network and the EPC respectively in Figure 2.9 and Figure 2.10.

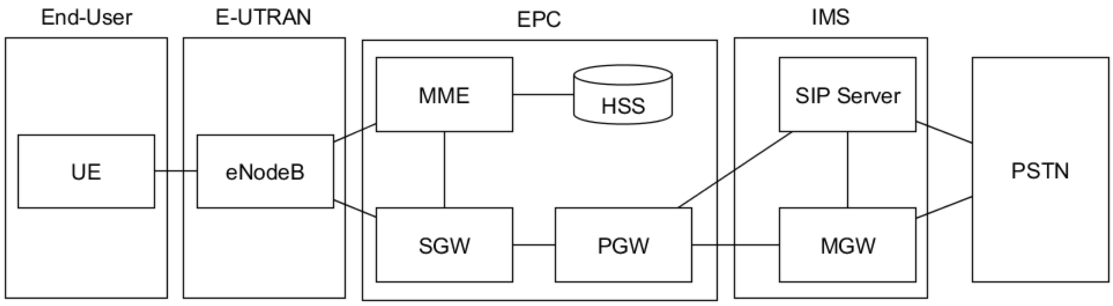


Figure 2.10: IMS, PGW and PSTN relationship

2.11 Challenges

Several challenges are identified and associated with deployment of VoLTE. QoS is a primary concern in any network application, use of Guaranteed Bit Rate (GR) bearers in LTE was noted as a solution in [33]. A default non-GBR bearer is established for IMS signalling and another for general internet traffic. The default bearer associated to IMS signalling has higher priority. Once a call is established a dedicated GBR bearer is assigned to the flow for its duration. Ekstrom [34], elaborates on use of QoS Class Identifiers (QCI) to determine the quality requirements for different applications. The characteristics of 3GPP standardized QCIs can be found in [35]. Additionally, [32] emphasizes the need for a quality feedback mechanism, so that service providers can ensure the calls meet the appropriate QCI requirement. It is further noted that the impact of dedicated GBR bearers on the quality of other flow types should be studied and considered by the service provider. Another major concern in VoLTE implementations is security. As noted in [32], by manipulating the end devices, the user could be assigned a dedicated voice or video bearer and transmit any other type of data; as a consequence the provider could potentially suffer loss of revenue. A possible solution could include use of Traffic Detection Function (TDF) or Policy and Charging Enforcement Function (PCEF). Furthermore, the significant difference between signalling priorities and end-user Quality of Experience (QoE) has been outlined.

2.12 Audio Compression and Codecs

As mentioned in [36], audio signals do not contain much redundant information. Speech coding techniques can be classified into three categories:

- Waveform coding: This process is through sampling quantization and encoding. As [36] describes, "waveform coding is some kind of approximately lossless coding, as it deals with speech signal as any kind of ordinary data." That is why codecs utilizing this kind of coding have very high qualities. PCM is an example of waveform coding.

- Source codecs: As further noted in [36], the basis of source codecs is to understand how the speech signal is produced. The reason for source codecs high compression rate is because only some parameters relating to the speech signal are sent rather than the whole signal.

- Hybrid codecs: As its name suggests, this process is a hybrid of waveform and source coding techniques. AbS is one of the most popular hybrid codecs available.

It is important to consider the codecs used in voice communications, because use of different codecs will have different impacts on the QoS. A number of commonly used speech codecs are discussed here:

- G.711.1: According to [37], G.711 was the most widely deployed speech codec. Defined by ITU [38], G.711.1 is a G.711 embedded wideband speech and audio coding algorithms which operates at 64, 80 and 96 kbit-s/s. Compared to G.711, this new extension has a better quality (7 kHz audio bandwidth), lower delay values and less complexity. G.711.1 has an algorithmic delay of 11.875 ms which is comprised of 5ms for input frame, 5ms lookahead and 1.875 ms for Quadrature Mirror Filter (QMF) analysis-synthesis filterbank.

- G.719.1: This is an 8-32 kbit/s wideband codec, introduced by ITU [39], and is interoperable with G.729, G.729A and G.729B. Compared to G.711.1, G.729.1 has a higher algorithmic delay of 48.9375 ms. This algorithmic delay is accounted for by 20ms for input superframe, 25 ms for lookahead, 3.9375 ms for the QMF analysis. According to [40], the motivation for introduction of G.729.1 was transition from narrowband (300 - 3400 Hz) PSTN to wideband (50 - 7000 Hz) telephony while maintaining backwards compatibility.

- G.722.2: Another ITU recommendation [41], G.722.2 operates within the 6.6 - 23.85 kbit/s range. G.722.2 is otherwise referred to as a high quality Adaptive Multi-rate Wideband (AMR-WB) which is primarily used for 7 kHz bandwidth speech signals. The algorithmic delay for this codec is comprised of the frame size and the lookahead which adds up to 40 ms [42].

- iLBC: Internet Low Bit rate Codec (iLBC), was developed as a freeware solution by Global IP Sound [43]. iLBC operates at the narrowband 13.867

kbits/s. Andersen et al. [43], conducted experiments to measure and compare QoS of iLBC and G.729A against packet loss ratios ranging from 0 to 20%, and according to their findings, iLBC performed significantly better.

- Speex: Based on Code-excited Linear Prediction (CELP), Speex was developed as an open source codec, alternative to costly proprietary speech codecs. Speex can perform voice compression at various bit rates in the range of 2 - 44 kbits/s [44].

- SILK: Designed by Skype, SILK operates at different rates (8 kHz, 12 kHz, 16 kHz and 24 kHz). A comprehensive document is available on Silks operation and design in [45]. As outlined in [46], the frame length and the lookahead for Silk is respectively, 20 ms and 5 ms. This makes up for an algorithmic delay of 25 ms.

2.13 Quality of Service (QoS)

This section aims to offer a comparative analysis of the QoS provisions in ground IP networks and LTE-A networks. In [47], environment quality is labelled as one of the primary factors for differentiating between operators. Worth noting that a major focus of developments in computer networks has been to improve the quality of service. Whether that service is a sent/received e-mail, a requested web page or even an established voice/video call, each of these applications is providing the user with a service, and each of these services requires a minimum level of quality to successfully take place. QoS is defined by ITU as "The collective effect of service performance which determine the degree of satisfaction of a user of the service" [48].

So QoS is derived from the effect of service performance which is made up of numerous factors affecting overall transmission of data. For instance, as

[49] noted, real-time applications are especially very sensitive to QoS parameters such as delay, jitter and ultimately high-capacity bandwidth. To unify the efforts spent on QoS developments, ITU, European Telecommunications Standards Institute (ETSI) and Internet Engineering Task Force (IETF) have standardized terminologies.

In [50], ETSI introduced a number of key performance parameters for different applications to meet end-user performance expectations. In ETSIs specifications for real-time conversational voice services, end-to-end one way delay of 150*ms* is preferred and over 400*ms* is not acceptable. Jitter for such applications should be 1 ms within a call and there is an allowance of up to 3% information loss or as referred to in [50], Frame Erasure Rate (FER).

To better understand the term QoS, viewpoints of various authors have been noted. Gozdecki et al. [49], introduces a number of parameters which are widely known for their impact on network QoS. (Bit rate, delay, jitter and packet loss)

Previous research by [51], introduced a number of quantitative QoS indicators in ground IP networks and described QoS as a group of requirements proposed by various application services. So each application service, depending on the nature of its transmission would require a certain levels of quantifiable attributes, namely delay, jitter, packet loss rate and throughput.

Keeping in mind that Internet's infrastructure revolves around a best effort delivery system, [52] named jitter as the most important parameters of QoS. They further elaborate that attributes such as throughput and average network delay are used for network optimization and cost performance, simply because there is no simple and efficient way of calculating network jitter. To gain a better understanding of jitters impact on throughput and delay, they used an analytical jitter model on pre-WiMax all-IP environments.

In [53], the focus of research has been on QoS of grid computing environments and identified a number of attributes which are believed to impact the QoS in such scenarios. Namely, availability, accessibility, reliability, security, latency, latency fluctuations, throughput, usage and packet loss.

Further studies were carried out by researchers in [54], on QoS of multi-party environments. Within their research, attention was given to IP Performance Metrics (IPPM) attributes, which are believed to be indicators of QoS in one-to-one communications:

- Connectivity
- One-way delay
- One-way loss
- Round-trip delay
- One-way delay variation
- Loss patterns
- Bulk transport capacity

In [55], QoS in mobile environments is considered with IP structure by looking at different mobile entities such as Mobile Node (MN), Foreign Agents (FA), Home Agents (HA), Care of Address (CoA) and Correspondent Node (CN). They introduced a number of QoS parameters which they believed to have the most impact on QoS of such networks namely, data packet load, throughput and packet data dropped.

Due to LTE-As heterogeneous nature, QoS implementations are more complex and a number of parameters are introduced which could potentially impact the QoS experienced by the end-users.

As mentioned earlier, there are two primary components to an LTE network architecture. A radio access network which is referred to as the Evolved UTRAN

(E-UTRAN) and the core network which is called Evolved Packet Core (EPC). According to Forconi et al. [56], E-UTRAN is the most important section of entire LTE mobile networks because of its direct connection to end-user equipment. They base QoS provisioning on the following:

- Packet scheduling algorithm
- Cross layer mechanism
- Service differentiation

In [57], the relation between users, applications and QoS parameters is considered. They compiled a comprehensive list of QoS parameters, prioritized based on their importance on a per layer (Application, Network and Physical) per service (Voice, Video and Data) basis. They note that dropped call rate is the most important QoS parameter for all types of services. They further identified that Bit Error Rate (BER) and Cell Coverage are most important QoS parameters in the physical layer and indicated the Hand-off Success Ratio to be the most crucial in the network layer.

A study on three types of scheduling algorithms in LTE networks is conducted in [58], outlining how each algorithm affects the standard QoS parameters (delay, jitter, packet loss and etc.). Furthermore, they calculated Mean Opinion Score (MOS) based on packet loss ratio and end-to-end delay using a formula provided by Sun et al.[59].

Hu et al. [60], introduce a new method to QoS in LTE networks using a data analytics and statistical modelling approach. They defined a number of performance indicators to evaluate LTE networks in terms of accessibility and performance:

- "Average number of users per cell
- DL physical resource blocks usage
- UL physical resource blocks usage
- Paging resource usage
- Average number of active users in UL buffer per cell
- Average number of active users in DL buffer per cell
- Physical random access channel usage" [60]

As cited in [56], 3GPP technical specification on end-to-end QoS management architecture defines minimum levels for QoS of a particular service in terms of bandwidth, delay, Packet Loss Rate (PLR) and jitter. To this end, these popular QoS parameters have been explained in more detail below:

Delay

Along with Packet Loss and Jitter, Delay is considered as one of the most important impairments in IP networks. Radhakrishnan [61], defines delay as "the average time taken by a packet to pass through from source to destination". As cited by [36], ITU-T defines a range of acceptable delay times for end-to-end speech transmissions in recommendation G.114 [62]. In brief, delays below 150ms are acceptable in general voice transmissions. However, if the distance between source and destination is significant, delays of up to 400 ms could also be acceptable. Any delay more than 400 ms is unacceptable for voice transmissions but potentially unavoidable in some exceptional scenarios (i.e. satellite connections providing service for rural areas). Authors of [36, 63] have noted the following possible cause for delays:

- Packetization delay: As the name suggests, this is the time spent by a system to create a packet and populate it with data and header information.
- Serialization delay: This is the time it takes for an interface to place the packet on the transmission media.
- Propagation delay: The time it takes for a packet to travel from one point in the network to another is called propagation delay.
- Component delay: When a packet is placed on the transmission media, for it to reach the destination, it will have to travel through a number of hops. Each of these devices will cause some delay due to various operations it might have to carry out on the packet (i.e. encapsulation and de-encapsulation). This delay is referred to as the component delay.
- Codec delay or Algorithmic delay: this is the delay incurred by use of codecs to compress the audio. Rango et al. [63] presented Table 2.1 containing some codecs and their associated delay.

Coding Standards	**Algorithmic Delay (ms)**
G.711	0.125
G.726	1
G.728	3-5
G.729	15

Table 2.1: Popular Codec Delays

Jitter (delay variation)

IETF defines jitter as variation in delay [64]. Comer [65], outlines the cause of jitter as one packet in a sequence being delayed more than another. Because the voice data from one end is divided into multiple packets, each packet could face different delays (i.e. packets experiencing different component delays). Jitter is one of the key parameters affecting QoS of Voice signals and according to [66], VoIP packets are sent out periodically (every 20 ms) with 150 ms budget for delay and according to [67], the ideal target delay variation for two way conversational voice should be $< 1ms$. A simple method of jitter calculation is expressed in equation 2.1 [68].

$$J_N(k) = D_N(k) - D_N(k-1) \tag{2.1}$$

In equation 2.1, $J_N(k)$ represents the jitter of k-th packet in the N-th node, and $D_N(k)$ is the delay of the k-th packet in the N-th node. There are other analytical approaches to calculating jitter using various models created for specific scenarios such as in [69].

Packet Loss

Packet loss is a common theme in IP networks, often due to path unavailability, device errors or even routing problems. Because real-time voice transmission does not allow for retransmission of packets, the users might experience gaps in the conversation which could result in the degradation of voice QoS. As indicated in [67], the performance target for packet loss ratio of two way conversational voice calls has been set as $< 3\%$. Rango et al. [63] mentioned a method called Packet Loss Concealment (PLC), for overcoming the issue of packet loss in voice transmissions. Essentially, when a stream of bits goes missing from the transmission, the decoders will have to use a method to replace the missing bits so that the end-user experiences the least amount of distortion in the audio. In [70], it was noted that although research was being carried out on PLC since 1980s, the current variety of applications, each with different requirements, does not allow for use of only one PLC method. Hence, there are six available algorithms for PLC:

- "BroadVoiceQR 16/32 PLC
- BroadVoice Concealment (BVC)
- Audio-BVC
- ITU-T G.722 Appendix III
- Reduced-Complexity BVC (RC-BVC)
- Low-Complexity PLC (LC-PLC) in Smart AudioTM"[70]

2.14 Radio Frequency Impairments

In this section, some of the most pertinent radio wave impairments are considered. Ultimately, these impairments are often the cause of QoS affecting parameters discussed in the previous section.

2.14.1 White Gaussian Noise (WGN)

There are various types of noise that could affect radio signal transmissions. White noise is one of the first concerns when it comes to these types of impairments. As noted in [71], white noise is comprised of random voltage or current which contains all frequencies of equal amplitude. Figure 2.11, shows a typical white noise voltage plot generated by the *WGN* function in Matlab, followed by Figure 2.12 demonstrating the relative probability of occurring voltages, however this was produced using a finite number of samples, hence slight imperfections are observed in the Gaussian graph, in a situation with infinite values, a perfect Gaussian bell curve is observed. This particular noise matrix had a variance of 1.0031 and a mean of -0.0809.

By referring to Figures 2.11 and 2.12, it becomes apparent that there are many zero crossings and as further stated in [71], there is a chance of infinite peak voltages occurring. As a consequence, it is not possible to measure white noise as peak voltages, hence the Root Mean Squared (RMS) method is used.

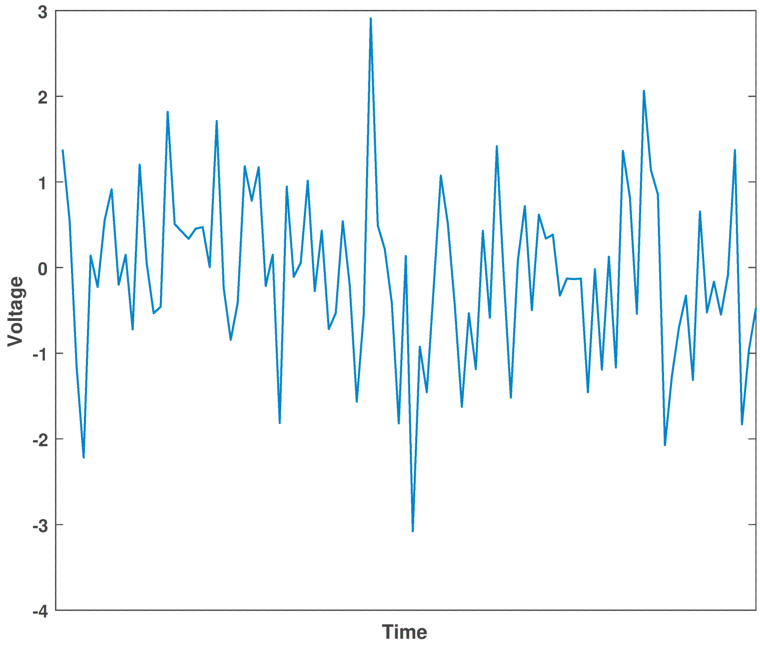


Figure 2.11: White Noise Voltage graph

2.14.2 Multipath Fading Channels

The Fading impairment in wireless channels is not a result of path loss or shadowing. This phenomenon occurs when the multiple versions of the original signal is received by the UE. Essentially, the signal reaches the Rx from multiple paths due to reflection, refraction and scattering effect when radio waves encounter obstacles [72]. This phenomenon is otherwise referred to as the multipath fading channel [73]. Due to the time varying nature of fading channels, this type of impairment will have a more significant impact on radio transmissions when compared to degradation caused by white noise. The most

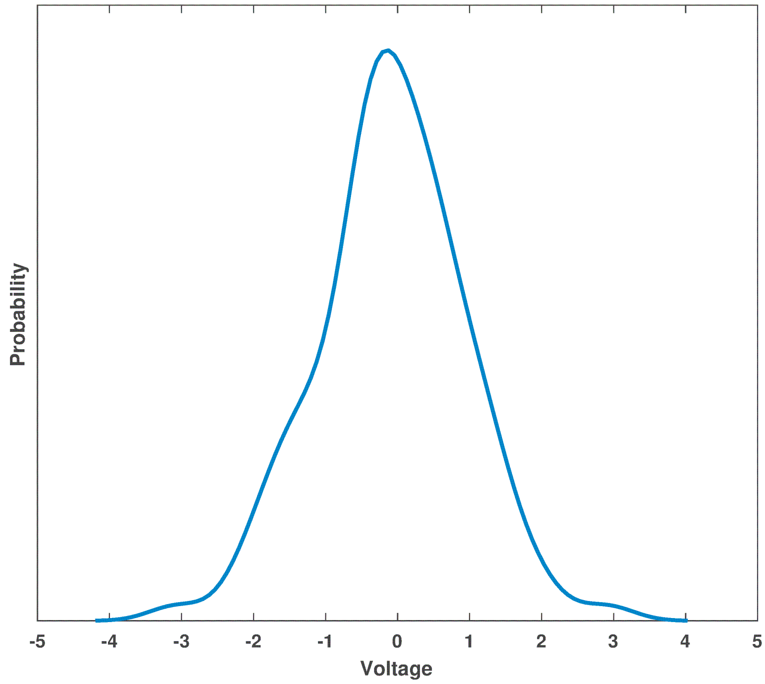


Figure 2.12: White Noise Voltage Relative Probability

common method for dealing with multipath fading is use of diversity technologies. An example of this is transmit diversity, where multiple Tx antennas are used to deliver multiple copies of the signal over separate channels.

2.14.3 Moving Channels

The radio communication channel between a transmitting base station (eNodeB) and a receiving UE becomes more complex as movement is introduced. Especially if the motion results in, high relative velocity (eg. a high speed train scenario).

Doppler Effect

When one or both of Tx and Rx devices are in motion, a phenomenon occurs which is known as the Doppler Effect. The relative motion causes the received frequency to have a different wavelength than that of the original transmission. Doppler shift or doppler frequency is the difference (increase/decrease) in the frequency caused by the moving channel scenario. The resulting frequency can be found by using the formula presented in equation 2.2.

$$f' = \frac{(V \pm V_o)}{(V \pm V_s)} * f \tag{2.2}$$

Where f' is the frequency with increased/decreased wavelength, V is the speed of radio frequency propagation, V_o is the speed of observer (Rx), V_s is the speed of the source (Tx) and f is the original frequency. As seen in equation 2.3, what is known as the doppler frequency or the doppler shift can be found by finding the difference between the original and changed frequencies.

$$\text{Doppler Frequency} = f - f' \tag{2.3}$$

In equation 2.3, f is the original frequency and f' is the frequency with increased/decreased wavelength. Using the aforementioned equations, the doppler frequency value can be derived, using speed and frequency.

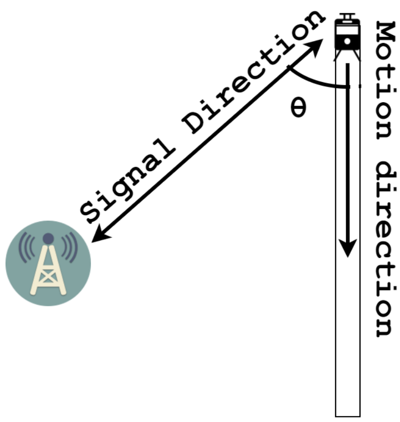


Figure 2.13: High Speed Train Scenario

In a high speed train scenario (Figure 2.13), where there is an angle between the signal propagation and direction of movement, the formula in equation 2.4 is used to find the doppler frequency. In equation 2.4, V_o is the speed of Rx, θ

is the angle of travel between Tx-Rx and λ is the wavelength:

$$\text{Doppler Frequency} = (V_o * \cos(\theta))/\lambda \tag{2.4}$$

2.15 Subjective QoS Measurement Methods

Voice QoS assessment can be considered in two major measurement approaches illustrated in Figure 2.14:

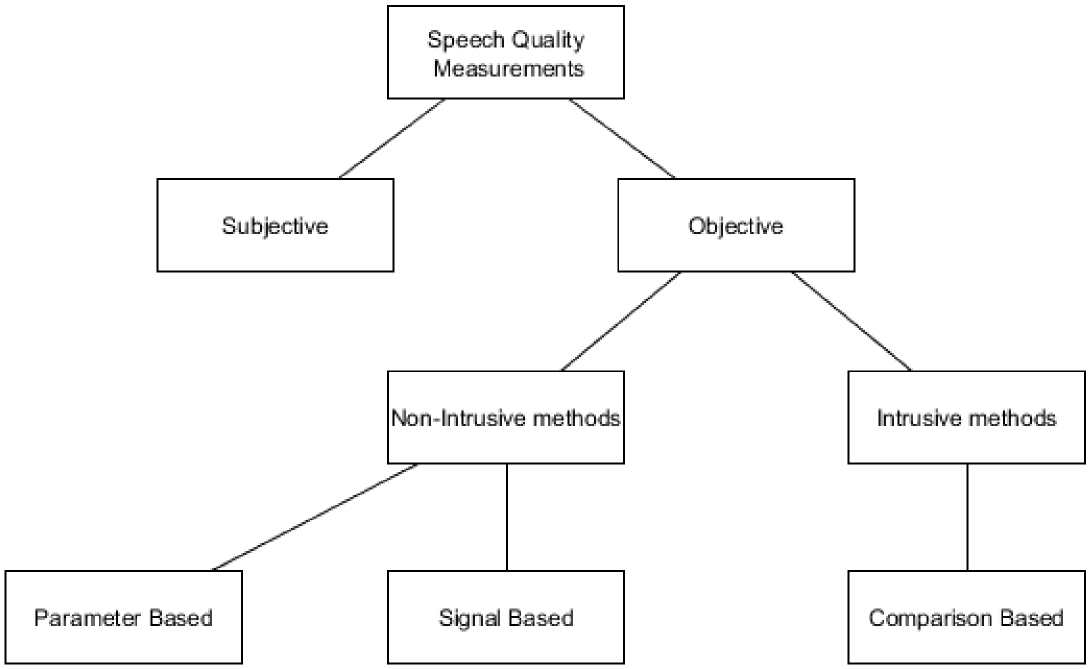


Figure 2.14: Voice Quality Measurement Methods

Subjective methods are carried out by human subjects [36, 74]. There are a number of subjective methods of determining the quality of transmissions, recommended by ITU-T such as conversation-opinion tests and listening-opinion tests. Conversation-opinion tests have been given more credibility compared to listening-opinion tests according to ITU P.800 standard [74] defined by ITU-T. However, conducting subjective tests would take a long time and at a great cost too. For that reason, these methods are not a practical choice for this particular project. From the most popular, Listening-opinion test methods defined by ITU-T [74] Absolute Category Rating (ACR), Degradation Category Rating (DCR) and Comparison Category Rating (CCR) could be referred to.

2.15.1 Absolute Category Rating (ACR)

ACR subjective quality measurement method is the recommended Listening-opinion test method from ITU-T. According to the specifications in [74], this method has been widely applied to analogue and digital telephone connections. ACR utilizes three scales for concluding the voice quality. These are illustrated in Table 2.2.

Score	**Listening quality**	**Listening effort required**	**Loudness preference**
5	Excellent	None	Much louder than preferred
4	Good	Appreciable	Louder than preferred
3	Fair	Moderate	Preferred
2	Poor	Considerable	Quieter than preferred
1	Bad	No meaning understood	Much quieter than preferred

Table 2.2: ACR Quality Scales

2.15.2 Degradation Category Rating (DCR)

Another listening-opinion test method which produces a DCR 5-scale rating by comparison of the system under experiment with a high quality fixed reference. As explained in [74] this method is best fit for scenarios where digital impairment is insignificant. When collectively used with conversation-opinion test and ACR, DCR could be used for optimization purposes. In DCR tests, the subjects are required to rate the conditions using the five point degradation scale illustrated in Table 2.3.

Score	Degradation
5	Degradation is inaudible
4	Degradation is audible but not annoying
3	Degradation is slightly annoying
2	Degradation is annoying
1	Degradation is very annoying

Table 2.3: DCR Category Scales

2.15.3 Comparison Category Rating (CCR)

CCR is essentially a variation of DCR, because of its comparative method nature. Similar to DCR, in this method subjects are presented with two samples per trial. They are asked to compare the unprocessed sample to the processed (degraded) sample. CCR is most suitable for systems improving the speech quality [63]. This type of test is often applied to scenarios when noise degradation is apparent in the samples. The scale point introduced by ITU-T is slightly different to that of ACR and DCR. This is represented in Table 2.4.

Score	CCR Quality Comparison
3	Much Better
2	Better
1	Slightly Better
0	About the Same
-1	Slightly Worse
-2	Worse
-3	Much Worse

Table 2.4: CCR Quality Comparison Scales

2.16 Objective QoS Measurement Methods

Subjective QoS measurement methods are time-consuming and costly, therefore several objective methods were developed that would address these constraints and correlate to the MOS output of subjective methods. Generally, objective methods of QoS assessment, are a more common method of QoS measurement [75, 36], as opposed to their subjective counterparts. However, objective methods too have some disadvantages of their own, such as their lack of correlation with human perception, resource hungry and cannot be applied to real-time communication [36].

As previously noted in Figure 2.14, objective QoS measurements can be non-intrusive or intrusive methods. As stated in [76], the main difference between intrusive and non-intrusive methods, also illustrated in Figure 2.15 is that intrusive methods require both the reference speech (originating from the source) and the degraded speech (received at destination).

It was noted that subjective methods are often not the best test method because

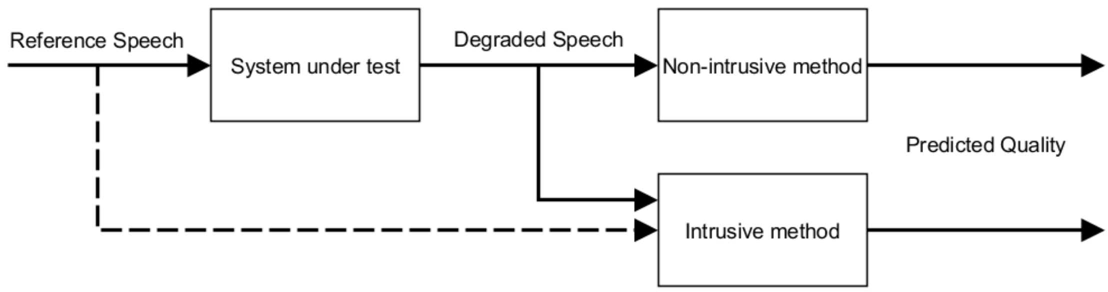


Figure 2.15: Intrusive vs. Non-intrusive Objective QoS Measurement Methods

of their time consuming nature, however the MOS used to evaluate speech quality in subjective methods is used for calibration of objective methods output. A number of popular objective methods are introduced here in brief.

2.16.1 Intrusive Methods

Signal to Noise Ratio (SNR)

SNR is likely to be the most popular and simple intrusive objective method of QoS measurement. SNRs operation is essentially comparison of the original and processed signal to generate an output which can be performed using equation 2.5 [77]:

$$SNR = 10\log_{10}\frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N}\{x(n)-\hat{x}(n)\}^2}[dB] \tag{2.5}$$

In equation 2.5, $x(n)$ is the original speech and $\hat{x}(n)$ represents the processed speech where N is the number of samples to be tested. In [77], this is referred to as the classical definition of SNR. Due to fluctuations between the speech energy and the noise, it was observed that SNR calculations would correlate with subjective QoS measurement significantly more, if the ratio was not the average of the whole speech time. Hence, as presented below in equation 2.6, the Segmental SNR or SNR_{seg} was defined [77]. SNR_{seg} is one of SNRs variations in which SNR is essentially calculated for very small segments.

$$SNR = \frac{10}{M} \sum_{m}^{M-1} \log_{10} \frac{\sum_{n-Lm}^{Lm+L-1} x^2(n)}{x(n) - \hat{x}(n)^2} \tag{2.6}$$

In equation 2.6, L represents the frame length, M is the number of frames. So in reference to equation 2.5, $N = ML$.

Perceptual Speech Quality Measurement (PSQM)

Standardized by ITU-T in 1996, PSQM is an intrusive method for producing a good estimate of the subjective QoS for telephone-band speech codecs (300 Hz - 3400 Hz) [78]. The flowchart presented in Figure 2.16 outlines the general process of PSQM method together with its comparative nature. Essentially, PSQM

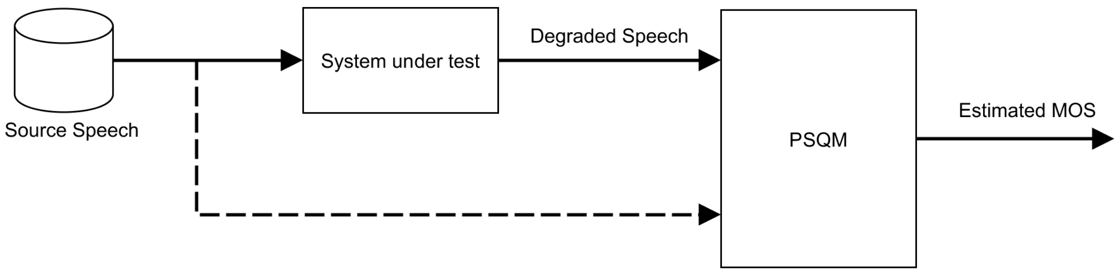


Figure 2.16: PSQM Model

compares the original and processed signal against a number of predefined attributes to closely corroborate the subjective measure of QoS. Ultimately, the output generated from the PSQM algorithm is referred to as the PSQM value which ranges from 0 to 6.5, where 0 indicates the perfect quality and 6.5 is the highest level of degradation. As further noted in [79], the obtained PSQM value is mapped to MOS using equation 2.7 in order to accurately correlate with the subjective perceptual quality of the communication.

$$MOS = \frac{4}{1 + e^{0.66PSQM - 2.2}} + 1 \tag{2.7}$$

However, De et al. [80], observed that when the communication experiences significant delays (longer than 200 ms), PSQMs output is often very low due to a correlation timeout caused by the delay. PSQM considers the following attributes when calculating QoS of voice transmissions:

- Listening level
- Weighting on silent intervals
- Environment noise on the receiving side
- Characteristics of hearing threshold
- Sending and receiving characteristics of handset [78]

Measuring Normalizing Blocks (MNB)

Voran [81] observes that SNR and SNR_{seg} only provide a good correlation in waveform preserving speech systems and are not suitable for use in general coding and transmission systems. It is also noted in [81], that PSQM is limited to higher bit rate speech codecs operating on error free channels. Hence, there was no method in place for objective quality evaluation of highly compressed digital speech which is prone to bit errors or frame erasures. MNB is usually used as an alternative to PSQM. As discussed in [61], using its 2 structure calculation models for Time and Frequency and combining the two outputs, MNB estimates the subjective MOS value for voice QoS. Some attributes like communication channel errors which occur while utilizing lower bit rates (less than 4 kbps) have been incorporated in MNB [74, 76].

Perceptual Analysis Measurement System (PAMS)

As outlined in [47], PAMS was developed by British Telecommunication (BT) Labs, based on models of human senses. PAMS which is also an intrusive method of QoS measurement is not as popular as PSQM, but it is particularly useful when the aim of the test is to include different codecs. As explained in [63], factors such as jitter, packet loss, delay and the distortion caused by codec usage which all have a negative impact on voice quality, are used to calculate outputs such as listening quality score and listening effort score, to better match the human perception of quality. As stated in [82], an auditory transform is applied to the original and processed signals after time alignment, level alignment and equalization.

Perceptual Evaluation of Speech Quality (PESQ) and PESQ- Learning Quality (LQ)

Standardized by ITU-T in 2001 [83], PESQ is an intrusive method which according to ITU, addresses some limitations of PSQM. Due to PESQ taking into account factors such as variable delay, filtering and localized distortions, it is more suitable for end-to-end measurements of QoS. As mentioned in [47], PESQ can be used to objectively assess speech QoS by taking a wider range of network conditions into account. These include, analogue connections, codecs, packet loss and jitter. Hence, PESQ is superior to its predecessors and is more suitable for intrusive objective measurement of speech QoS. Rix et al. [84, 85] note that PESQ has been applied to a wide range of codecs and telephone network tests and its produced output has had a very close correlation with subjective MOS measurements. They calculated the correlation as 0.935 on 22 training and 8 validation experiments. Overall, as illustrated in the outcome of the tests conducted by [79], PESQ has performed much better than PSQM and MNB. PESQ-LQ is the improved version of PESQ. As Radhakrishnan [61] puts it, "PESQ-LQ is a mapping function from P.862 PESQ score to an average P.800 ACR LQ MOS". Similar to ACR LQ, PESQ-LQ also has the maximum range of 4.5 as the MOS. One of the aims in development of PESQ-LQ was for the output to scale from 0 to 4.5, to correlate with ACR LQ. Included in [86] is also the relation between PESQ and PESQ-LQ which is shown below in equation 2.8 where x and y are respectively, the PESQ and PESQ-LQ scores.

$$y = \begin{cases} 1.0 & x \leq 1.7 \\ -0.157268x^3 + 1.386609x^2 - 2.504699x + 2.023345 & x > 1.7 \end{cases} \tag{2.8}$$

Also according to the findings presented in [86] PESQ-LQ is a suitable method for universal mapping between PESQ and average MOS in a wide range of network conditions and languages.

2.16.2 Non-intrusive methods

E-Model

Rango et al. [63], note the E-Model as the most popular objective QoS measurement technique. E-Model was developed as a non-intrusive computational model for use in transmission planning by European Telecommunications Standards Institute (ETSI) with ITUs instructions [87]. E-Model considers 21 input network parameters which are damaging to voice quality and produces an output called the Rating Factor (ranging between 10 and 100). This rating factor can then be mapped to the MOS scale. To obtain the rating factor, the following formula (equation 2.9) can be used [87]:

$$R = R_o - I_s - I_d - I_{e-eff} + A \tag{2.9}$$

In equation 2.9, R represents the rating factor, R_o is the SNR, I_s is essentially all impairments combined which occur at the same time as the voice signal, I_d

represents the delay impairment, I_{e-eff} denotes the impairments of low bit-rate codecs and A is called an advantage factor which allows for user advantages (i.e. mobility [61])

The relation between R factor and MOS are defined in the E-Model standard by ITU-T in equation 2.10.

$$MOS = \begin{cases} 1 & if R \leq 0 \\ 1 + 0.035R + R(R-60)(100-R)7 \times 10^{7} & if 0 < R < 100 \\ 4.5 & if R \geq 100 \end{cases} \tag{2.10}$$

Also, a provisional mapping between user satisfaction and R values is available from ITU-T under recommendation G.107 [87] which is illustrated here in table 2.5:

R-value (lower limit)	MOS_{CQE} **(lower limit)**	**User Satisfaction**
90	4.34	Very satisfied
80	4.03	Satisfied
70	3.6	Some dissatisfied
60	3.1	Many dissatisfied
50	2.58	Nearly all dissatisfied

Table 2.5: Relation between R-value and user satisfaction

Also by definition of E-Model in [87], the input parameters with their default values and permitted ranges can be found. If all parameters would be set to their defined default value, the produced rating factor would correlate to a very high quality (R=93.2).

2.17 Machine Learning

Referring back to the aim of the project, an appropriate method must be identified for prediction of voice QoS based on results collected from the experiment discussed in chapter 4. Effectively the intention is to predict an output based on past experiences. This section considers popular machine learning approaches to identify the most appropriate solution to this research.

Machine learning methods can be categorised as:

- **Supervised methods**: In supervised methods the learner is provided with instances that contain known labels (labels referring to output(s)). Some instances and their labels can be used as a training set, and another portion can be used for validation and testing of the predictions. Supervised methods are suitable for scenarios where some inputs and outputs can be provided but the relationship between them is complex, so supervised methods are used to identify that algorithm.
- **Unspervised methods**: In unsupervised learning methods, instances are given to the learner with no labels. The algorithms used by the learner are then expected to identify and group the instances into useful classes of items. Unsupervised methods are used when instances (inputs) exist, but with no useful classes or labels. Unsupervised methods can classify the inputs into useful sensible categories.
- **Reinforcement learning**: Reinforcement learning is a reward based model. Where the learner is given feedback only from environment as explained by Sutton and Barto [88]. In simple words, the learner is not given instances and labels, but has to go through various actions until the actions with most reward are identified.

2.18 Linear Regression

One of the oldest methods of Machine Learning is Linear Regression. It is essentially a simple line fitting problem by minimizing the sum of square error for training examples. This method is only suitable where the problem is expected to have a simple linear nature. In a survey conducted on machine learning techniques, Burch [89], confirms, while linear regression is simple and easy to understand with a real mathematical rigor, it oversimplifies the classification rule, is difficult to compute and does not at all represent how humans learn.

2.19 Neural Networks

In [90], the most desirable feature of neural networks is described as the capacity to learn from examples. Application of neural networks is a solution to many problems with complex mathematical nature. They can be applied to a wide range of scenarios where the functions between inputs and outputs are unknown or difficult to identify. Recently, Neural Network solutions have been used for prediction of voice and video quality in ground IP networks [91, 92, 93]. Using various training algorithms they can learn and establish relationships between inputs and outputs.

2.19.1 Perceptrons

The simplest type of Neural Networks is use of perceptrons. This section aims to provide a generic overview of how neural networks function by explaining a Backpropagation model. The concept of perceptrons [94], has been around since 1950s, where machines could be taught to perform certain classification tasks based on learning from examples. Figure 2.17 shows a simple design using the perceptron concept, where two inputs are supplied to the perceptron and an output is obtained as a result.

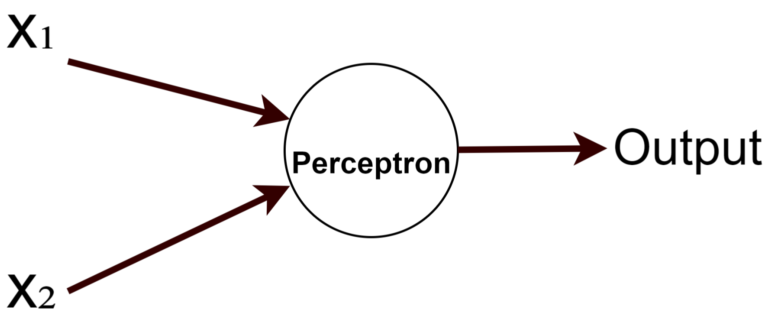


Figure 2.17: Single Perceptron

However, perceptrons are only applicable to classification scenarios that are linearly separable. As a straight forward example, Figure 2.18 AND function used in computer systems can be used (i.e. the perceptron can predict the output based on our input parameters). Note how the outputs are separated by one blue line.

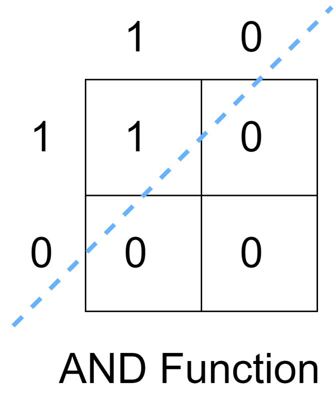


Figure 2.18: AND Function

If we had a more complex problem such as the XOR binary function, single perceptron would not be sufficient to apply for classification. Figure 2.19, shows the Exclusive OR (XOR) function and as presented, the outputs are not linearly separable.

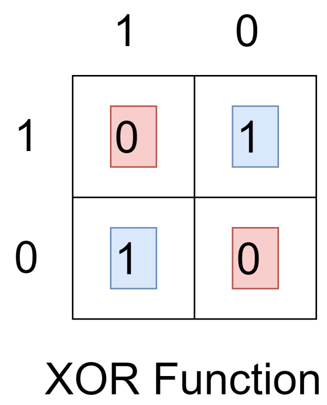


Figure 2.19: XOR Function

So to overcome this we would need to add extra layers and create a multilayer neural network. So in XOR's case, we can use the network presented in Figure 2.20. Inputs (1s and 0s) will be passed to both a NAND (Not AND) function and an OR function. The outcomes of these two functions will be passed to an AND function which will then give us XOR result as output.

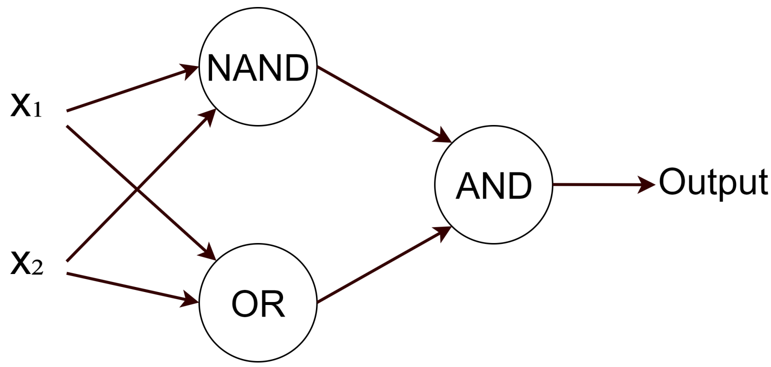


Figure 2.20: Multilayer Neural Network Example

The feedforward terminology simply refers to the direction of calculations in our neural network. Referring back to Figure 2.20, the inputs move forward towards the neurons and ultimately the output. This is a feedforward architecture.

The example considered here, although not linearly separable outputs, it is still easy to classify. With more complex problems, it is important we consider backpropagation. In simple terms, backpropagation refers to the process of passing inputs and bias values through the neurons and once an output is determined by the network, an error value is measured by comparing the network output (predicted value) and the actual target (training data). This error value is passed back through the network in order to adjust and re-adjust the weights as necessary to minimise the error to an acceptable range. Ideally Mean Square Error (MSE) values of less than 1 and as close as possible to zero are optimal.

ANNs are biologically inspired and modelled based on the human brain [95], and due to their wide range of application, ANNs have become very popular in the research community and are utilised in various problems such as classification, regression, modelling, prediction and optimization [96]. ANNs use various algorithms to learn from example and apply the learned pattern to solve new similar problems. The most common type of ANN is a multilayer feedforward neural network which is comprised of an input layer, a hidden layer and an output layer. Each of these layers can have one or more neurons and these neurons are connected to each other with different weights as shown in Figure 2.21.

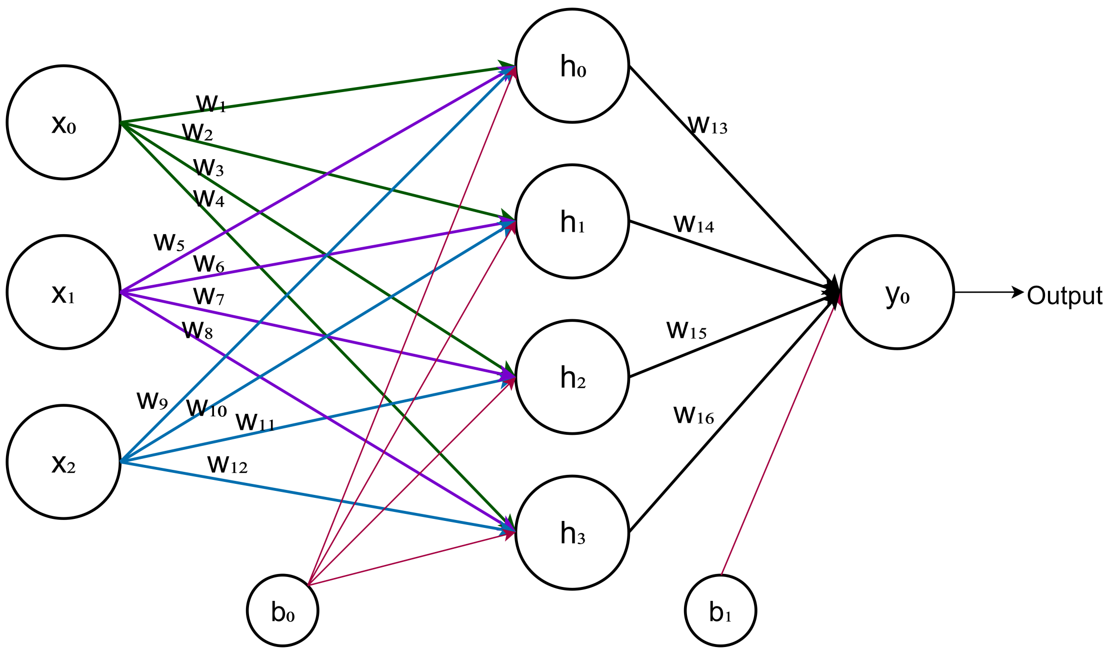


Figure 2.21: Multilayer feedforward neural network

In the multilayer feedforward network example presented in Figure 2.21, the network has 3 neurons in the input layer (x_0, x_1, x_2), 4 neurons in the hidden layer (h_0, h_1, h_2, h_3), and one neuron in the output layer (y_0). Each input neuron is connected to all hidden neurons and the hidden neurons are in turn connected to the output neuron.

So to summarise the procedure: based on the inputs, the weights of the connections between inputs and the hidden layer neurons, and the bias value which is randomly initialised, a value for each hidden neuron is calculated.

i.e.

$$h_0 = (x_0 * w_1) + (x_1 * w_5) + (x_2 * w_9) + b_0 \tag{2.11}$$

With reference to Figure 2.21 and equation 2.11, h_0 is the value of the 0th hidden node, x_0, x_1 and x_2 are input values with weight values of w_1, w_5 and w_9 respectively and b_0 is the bias value for the hidden layer neurons.

Once we have a value for a neuron in the hidden layer, an activation function or a transfer function will be used to calculate the output at the hidden layer and later at the output layer. A common non-linear activation function used in neural networks is the Sigmoid or logistic function given in equation 2.12.

$$f(z) = \frac{1}{1 + e^{-z}} \tag{2.12}$$

Another popular activation function is the hyperbolic tangent or tanh function. The tanh function is defined in equation 2.13:

$$tanh(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}} \tag{2.13}$$

Rectified Linear Units or ReLU is also a commonly used activation function which is defined in equation 2.14:

$$f(x) = max(0, x) \tag{2.14}$$

Variations of the Rectified Linear Units also exist. (i.e. Leaky ReLU and Randomized ReLU)

For the purpose of this example, the sigmoid activation function is used as follows:

Replacing z with the hidden neuron value which was calculated in equation 2.11 will give us:

$$H_0 = \frac{1}{1 + e^{-h_0}} \tag{2.15}$$

Where H_0 is the output of neuron h_0, which will be passed to the output neuron y_0 with the weight w_{13}.

So referring back to Figure 2.21, the resulting y_0 will be calculated as shown in equation 2.16.

$$y_0 = (H_0 * w_{13}) + (H_1 * w_{14}) + (H_2 * w_{15}) + (H_3 * w_{16}) + b_1 \tag{2.16}$$

And using the sigmoid transfer function again, the output of y_0 can be represented as Y_0 and calculated as shown in equation 2.17.

$$Y_0 = \frac{1}{1 + e^{-y_o}} \tag{2.17}$$

At which point, an error value will be calculated and propagated back through the network to the input layer in order to adjust the weights and recalculate the mentioned values if necessary.

The function used to calculate the error is discussed in the next section and given in equation 2.18.

As discussed by Burch [89], the perceptron approach is simple to understand and adapts to new data simply. However is not suitable for application to complex problems, since it is essentially a simple linear combination of inputs similar to the Linear Regression method discussed earlier in section 2.18, but lacks the solid mathematical background.

2.19.2 Artificial Neural Networks

Levenberg-Marquardt algorithm

The specific task of the Levenberg-Marquardt (LM) algorithm is to minimize sum of square error functions with the form illustrated in equation 2.18[97]:

$$E = \frac{1}{2}\sum k(e_k)^2 = \frac{1}{2}||e||^2 \tag{2.18}$$

Where, e_k is the kth pattern's error and e is a vector, and w is the weight vector. The error vector can be expanded to first order by means of a Taylor series if the difference between the previous weight vector and the new weight vector is small:

$$e_{(j+i)} = e_(j) + \partial e_k/\partial w_i(w_{(j+1)-w_(j)}) \tag{2.19}$$

Therefore, by substitution into equation 2.18, the error function can be expressed as:

$$E = \frac{1}{2}||e(j) + \partial e_k/\partial w_i(w_{(j+1)-w_(j)})^2|| \tag{2.20}$$

In the LM algorithm, the error function is minimized, but the step size is kept small, so that the linear approximation can still remain valid. This is achieved by using a modified error function as presented in equation 2.21.

$$E = \frac{1}{2}||e(j) + \partial e_k/\partial w_i(w(_(j+1) - w(j))||^2 + \lambda||w(+1) - w(j)||^2 \tag{2.21}$$

In equation 2.21, λ controls the step size. When minimizing the modified error with respect to $w(j+1)$:

$$w(j+1) = w(j) - (Z^{Tz} + \lambda I)^{-}1Z^{T}e(j) \tag{2.22}$$

Bayesian Regularization algorithm

The paper authored by Foresee et al. [98], demonstrates the application of Bayesian Regularization algorithm in multilayer feedforward neural networks. It is observed that BR shows excellent generalization in non-linear regression. Here, generalization refers to the capability of the network to produce small errors in training set as well as testing set (new instances).

The function used to minimize the sum of squared errors is demonstrated in equation 2.23:

$$E_D = \sum_{i=1}^{n}(t_i - a_i)^2 \tag{2.23}$$

In equation 2.23, E_D is the sum of squared errors, t_i is the ith target, a_i is an index representing the network response, which will later be modified to improve generalization.

The key purpose of BR algorithm is to improve network generalization, and to accomplish this, the weights are kept small to maintain a smooth network response. This process is referred to as regularization.

Naturally, the first objective of a neural network is to minimize sum of squared errors. But with regularization, the objective function also includes the sum of squares of the network weights, as well as two parameters that define whether the emphasis is to reduce errors or reduce the size of weights to obtain a smoother network response. It is important to set the correct values for the objective function parameters to find the optimum balance between the size of errors and weights.

The process of optimizing regularization using Bayes' rule was introduced by MacKay [99]:

$$P(W|D,M) = \frac{P(D|W,M)P(W|M)}{P(D|M)} \tag{2.24}$$

Where it is inferred that D represents the data, M is the network model, W is referring to network weights (a vector), $P(W|D,M)$ is the posterior density function, $P(D|W,M)$ is the likelihood function, $P(W|M)$ is the prior density (the size of weights before data collection) and $P(D|M)$ is a normalization constant to ensure the total probability is 1.

Foresee et al. [98], offers a comparison for a 1-6-1 network trained with and without regularization and demonstrates that without regularization overfitting occurs in Figure 2.22.

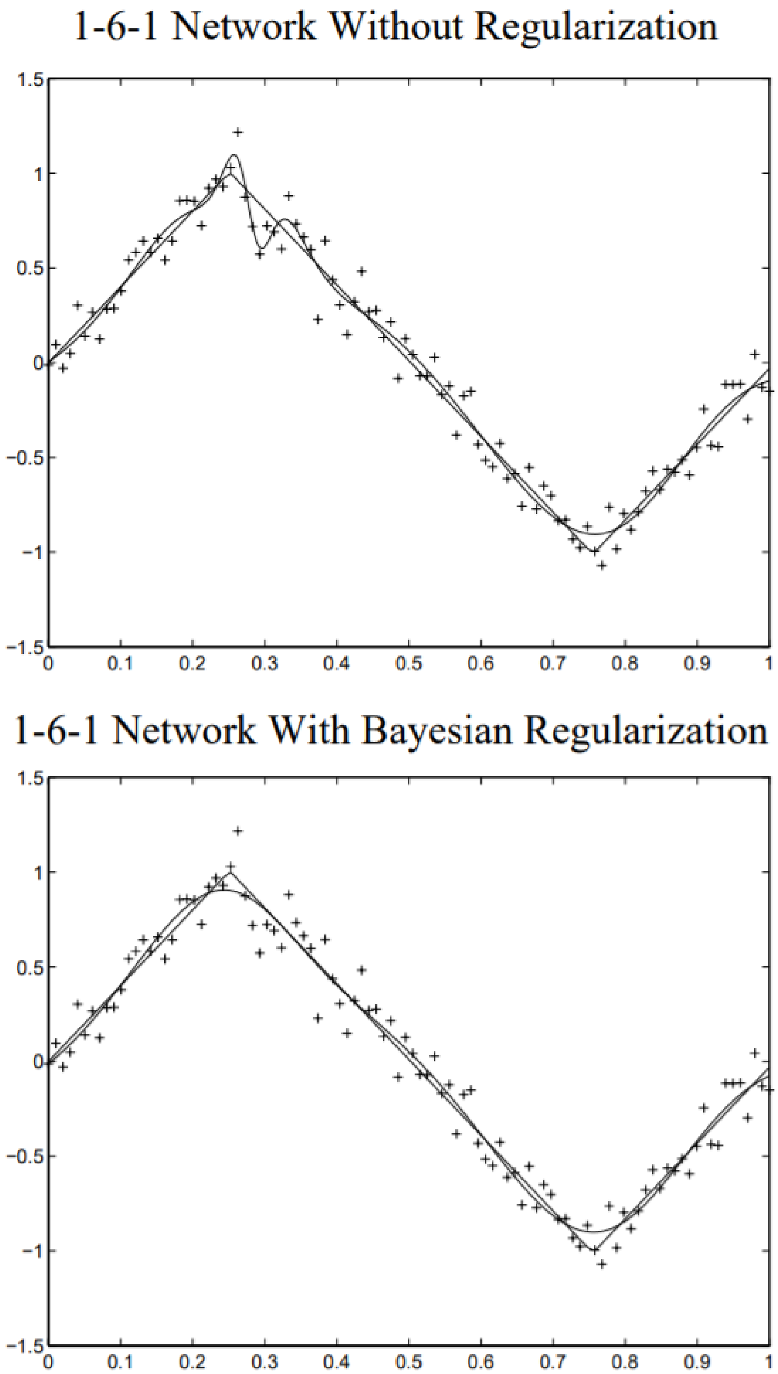


Figure 2.22: Network without regularization vs Network with regularization [98]

In a comparative study that was conducted by Kayri [100], Levenberg-Marquardt and Bayesian Regularization algorithms were put to test for linear and non-linear examples. Sum of Squared Errors and Correlation Coefficient measured for both algorithms indicates that BR outperforms LM in terms of predictive ability.

Scaled Conjugate Gradient algorithm

Scaled Conjugate Gradient algorithm was introduced by Møller [101]. Møller's aim was to automate the process of learning and eliminate the need for user dependent parameters such as learning rate and momentum constants. A major contribution noted in SCG is using a different approach to estimate the step size as opposed to line search. This is accomplished by combining the model-trust region approach from Levenberg-Marquardt with the conjugate gradient approach. As for error minimization, Møller introduction of a quadratic expression of Error in a neighbourhood of a point w is represented in equation 2.25:

$$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w) y \tag{2.25}$$

Where, $E(w)$ is the global error function, $E'(w)$ is the gradient to global error function, $E''(w)$ is the Hessian matrix to global error function and ^{T} identifies the transpose of a function.

Møller further defines the critical points for $E_{qw}(y)$, in order to find the minimum to $E_{qw}(y)$ in equation 2.26.

$$E'_{qw}(y) = E''(w)y + E'(w) = 0 \tag{2.26}$$

In a study conducted by Okut et al. [102], Bayesian Regularization consistently had a higher correlation coefficient than the models trained using Scaled Conjugate Gradient. Okut et al., later comments that although ANNs are useful for predicting complex traits, they also bring complex computing challenges.

2.19.3 Random Neural Networks (RNN)

Random Neural Networks were developed by Gelenbe [103] as a recurrent neural network, in which signals were either negative (inhibitory or -1) or positive (excitatory or +1). In a RNN, there are N neurons, and these inhibitory and excitatory signals are circulated among them. The potential of a receiving neuron is changed and determined by these signals, and a neuron can only fire if its potential is positive. RNNs are derived from the concept of ANN. As described in [61], each neuron in an RNN is represented by +1 or -1. The values of these neurons increase and decrease respectively in reaction to receipt of excitation and inhabitation spikes. Because of RNNs non-linear function calculations for each neuron in the network, its total calculation time is less than that of ANN. However, the training stage is quicker for ANNs. Although the training stage is quicker for ANNs, a common problem is overtraining. When overtrained with a large data set for a particular condition in a scenario, weights of neuron connections are modified based on that specific condition; which in turn degrades the validity of outputs.

RNN mathematical model

In RNN, there are N fully connected neurons that circulate spike signals amongst each other. At the given time t, The state of neuron i is described by $k_i(t)$ as its signal potential. $k_i(t)$ is a non-negative integer and is a result of accumulation of positive signals at the neuron i. So a neuron could be excited if $k_i(t) > 0$ and idle if $k_i(t) = 0$. The excitation probability of neuron i can be represented by $q_i(t) = Pr[k_i(t) > 0] \leq 1$. If neuron i is excited, it can fire with a rate of r_i. After firing, the potential of that neuron will be reduced by 1. The fired signal would reach neuron j either as a positive or negative signal with a probability of respectively $p^+(i,j)$ or $p^-(i,j)$. It is also possible for the spike to depart the network with the probability of $d(i)$ [104]. The aforementioned probabilities must sum up to one:

$$\sum_{j=1}^{N}[p^+(i,j) + p^-(i,j)] + d(i) = 1 \quad \forall i \tag{2.27}$$

So, the rate of firing a positive and negative for an excited neuron i to neuron j is determined respectively by:

$$w^+(i,j) = r_i p^+(i,j) \geq 0 \tag{2.28}$$

and

$$w^-(i,j) = r_i p^-(i,j) \geq 0 \tag{2.29}$$

By combining the equations 2.27, 2.28 and 2.29, the following can be derived for r_i:

$$r_i = (1 - d(i))^{-1} \sum_{j=1}^{N}[w^+(i,j) + w^-(i,j)] \tag{2.30}$$

RNN behaviour in steady state

The network state is described by the vector $k(t) = [k_1(t), ..., k_N(t)]$ at any given time t. The stationary probability distribution of the network can be defined as:

$$p(k) = lim_{t \to \infty} Probability[k(t) = k] \tag{2.31}$$

According to theorem 1 [103], the probability that neuron i is excited at time t is given by:

$$q_i = min\left\{1, \frac{\lambda^+(i)}{r_i + \lambda^-(i)}\right\} \tag{2.32}$$

The total arrival rates of positive signals $\lambda^+(i)$ and negative signals $\lambda^-(i)$ while $i = 1, ...N$ is given by the following simultaneous equations:

$$\lambda^+(i) = \lambda_i + \sum_{j=1}^{N} r_i q_j p^+(j, i), \tag{2.33}$$

and

$$\lambda^-(i) = \lambda_i + \sum_{j=1}^{N} r_i q_j p^-(j, i), \tag{2.34}$$

If a unique non-negative solution exists for non-linear system of equations 2.32, 2.33 and 2.34, where $q_i < 1, \forall i$, then:

$$p(k) = \prod_{i=1}^{N} [1 - q_i] q_i^{k_i} \tag{2.35}$$

The above condition ($q_i < 1, \forall i$), is an indication of the stability condition, which in turn guarantees the excitation level of each neuron remains finite with probability of one. The average steady-state excitation level of neuron i, A_i can be calculated using:

$$A_i = \frac{q_i}{(1 - q_i)} \tag{2.36}$$

RNN learning algorithms

Most commonly used RNN learning algorithm is Gradient descent which was introduced by Gelenbe in 1993. However, due to RNN's popularity in the scientific community, there are alternative supervised learning algorithms introduced by other authors. For instance, Hubert [105] used a modified version of the Resilient Propagation (RPROP) algorithm for RNN supervised learning. In RPROP, weights are updated based on temporal behaviour of the sign of the error function. Or an extension of the gradient descent algorithm can be considered where Aguilar et al. [106], combined genetic algorithms (GA) with the gradient descent RNN learning algorithm. In [107], a technique is introduced for error minimization which is based on quasi-Newton optimization techniques. Quasi-newton methods are more sophisticated for error minimization, however they are more complex and require more processing power. Another example of training algorithm is use of Levenberg-Marquardt (LM) training algorithm in RNNs. Basterrech et al. [108] used the LM procedure with adaptive momentum which is one of its major extensions. This method requires even more memory and is more complex than the quasi-newton method.

Gradient descent supervised learning algorithm

This supervised learning algorithm for recurrent RNNs was developed by Gelenbe [109]. In RNN, the kth input training pattern x_k is represented by the following vectors[109, 104]:

$$\Lambda_k = [\Lambda_{1k,..,\Lambda_N k}] \tag{2.37}$$

and

$$\lambda_k - [\lambda_{1k,..,\lambda_N k}] \tag{2.38}$$

The input training values, x_{jk} are assigned to exogenous arrival rates, such that:

- If $x_{jk} > 0$, then $\Lambda_{ik} > 0$ and $\lambda_{ik} = 0$
- If $x_{jk} \leq 0$, then $\Lambda_{ik} = 0$ and $\lambda_{ik} > 0$

The weights, $w^+(i,j)$ and $w^-(i,j)$ are updated during the learning process. Consequently, the error function to be minimized, is given as:

$$E = \sum_{k=1}^{K} E_k = \frac{1}{2} \sum_{k=1}^{K} \sum_{i=1}^{N} c_i (f_i(q_{ik}) - y_{ik})^2 \tag{2.39}$$

In equation 2.39, E_k represents the error function of the kth input-output pair, $c_i \in 0, 1$ identifies whether i is an output neuron and $f_i(q_{ik})$ is a differentiable function of i.

Using the gradient descent method proposed by Gelenbe [109], training set is sequentially processed and weights are updated, the error function is then calculated each time and this process is repeated until the error function reaches its minimum value.

2.20 Neural Networks for non-intrusive measurement of voice QoS

There are several sources such as Clarkson [110], Patnaik [111] and Ibnkahla [112] that identify neural networks as a suitable machine learning application in communication systems. There are also authors such as Chen et al. [113] that specifically recommend neural networks for application in QoS measurement and assurance problems in wireless communication networks. They further confirm the importance of AI and Neural Networks in the physical layer of LTE systems, which is the exact scope of this research project as per the definition of research questions and objective outlined in chapter 1. Furthermore, there are also several previous works that utilise neural networks with promising results for voice and video QoS prediction and measurement in Ground IP networks such as Samir Mohamed [36], Sun [114] and Radhakrishnan [75].

Reviewing these sources and considering the success of neural networks in their predictability, identifies neural networks as a suitable application in telecommunication problems. As mentioned above, there are several sources that recommend using neural networks for QoS prediction and measurement in ground IP networks, however the input parameters used in those projects are only the key IP quality affecting parameters such as delay, jitter, packet loss and bandwidth. Hence, by applying neural networks to voice QoS problems in LTE networks while using LTE-specific parameters instead of IP parameters, the research is bridging the gap between similar applications in ground IP networks and introducing a novelty which would be of interest to Communication Service Providers. The research intends to use neural networks with physical LTE-Specific parameters and mapping them to QoS, whereas previous works focused on linking parameters from layers 2 and 3 (Data-Link and Network layers) to QoS. Naturally, the next step would be to identify an appropriate platform for simulation of an LTE network which is able to support real voice traffic and can simulate the change of LTE-specific parameters such as noise. Chapter 3 will go on to consider commonly used methods for simulation of LTE networks and will identify the best option by cross-referencing each capabilities‘ against the requirements of the research.

2.21 Summary

The reviewed literature highlights the architecture of LTE 4G networks. Furthermore, importance of voice transmissions in computer networks has been highlighted. Evidently, most authors indicate delay, jitter, packet loss rate, codec and bandwidth as primary QoS affecting parameters. Also worth noting that due to the all-IP implementation of EPC in LTE, the very same parameters could be used to measure and monitor QoS of VoLTE. However, as mentioned in section 5, access to EPC of LTE can be established through numerous technologies and architectures. These access networks introduce a number of new parameters which consequently impact the primary QoS affecting parameters. Ultimately, in LTE networks the objective QoS measurement methods are the same as those used in ground IP networks. But due to the heterogeneous nature of LTE networks, the LTE specific parameters will have impacts on QoS of VoLTE vectors. As mentioned earlier, QCIs are introduced in LTE networks to identify quality requirements for different types of communication applications. Therefore, a model which can predict the QCI and QoS score in a given scenario would be useful for network planning and continuous maintenance.

As part of non-intrusive methods for QoS prediction, neural networks are identified as an appropriate solution. An in-depth literature research on machine learning types and algorithms is conducted to identify the most common methods which tend to have high correlation coefficients and a low squared error rates when applied to complex problems. These algorithms are later used for prediction of QoS in LTE networks using LTE-specific parameters as inputs and the performance of each model is measured and compared against other algorithms to identify the best solution.

Chapter 3

Overview of LTE Simulation Techniques

3.1 Introduction

The objective of this chapter, is to introduce a suitable method for simulation of real voice transmissions over LTE networks. Ideally, this will provide the means of collecting data on the network behaviour during voice transmissions and also makes it possible to capture the input and output voice signals for further analysis. This data can later be processed to develop a new method for accurate estimation and non-intrusive measurement of voice QoS. An overview of the literature relevant to the experiment is presented in section 3.2. The requirements of the experiment for this research and a high level topology are presented in section 3.3. Sections 3.4, 3.5, 3.6 and 3.7 consider various common LTE network simulation tools. In section 3.8, the tools are discussed and analysed to identify an appropriate technique for this particular experiment. Finally, section 3.9 offers a summary of the chapter.

3.2 Background

A particularly important concept to consider is the LTE network topology. The main components of a typical 4G deployments are illustrated in Figure 3.1 and the details of various components are discussed comprehensively in section 2.7. The LTE networks are all-IP based which enables us to access them using a number of different access technologies (heterogeneous). The incentive behind development of an all-IP network was the demand to meet the requirements of growing IP traffic.

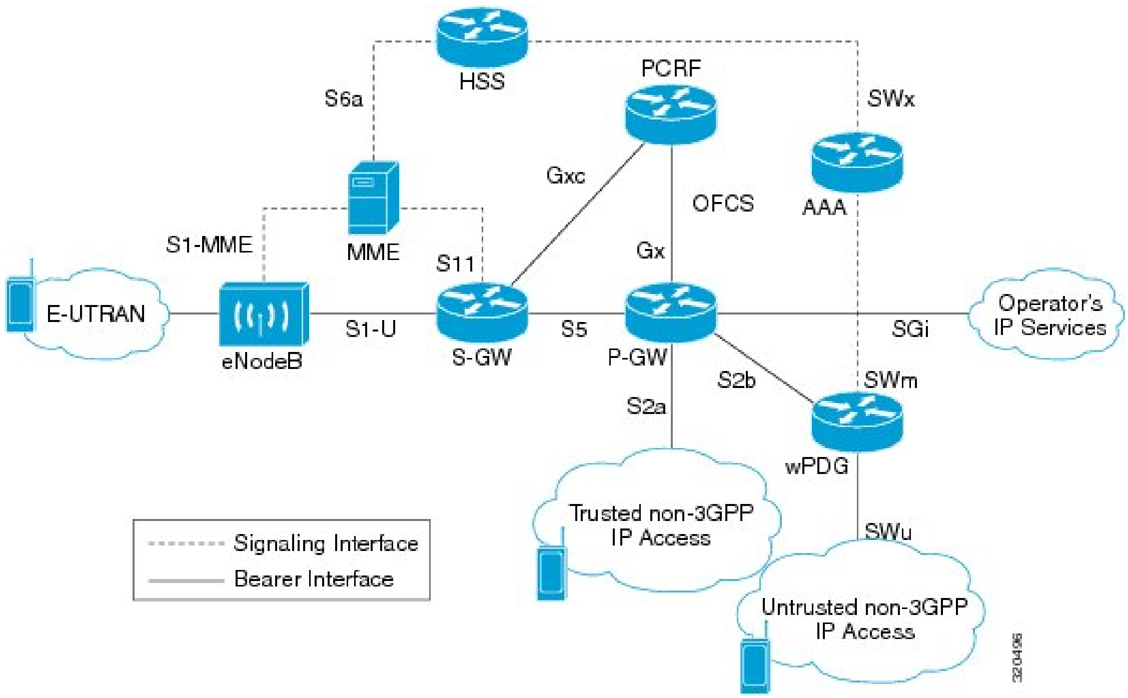


Figure 3.1: Evolved Packet Core - Interconnecting different networks [115]

QoS is a vital aspect of any network, especially when it comes to voice and video transmissions. Generally, the accurate measure of Quality is determined subjectively by users. However, this method is not always feasible due to its time-consuming and costly nature. To address this, objective QoS measurement methods are introduced which are calibrated using subjective methods and correlate closely with subjective outputs. Usually based on a specific criteria related to the specific application under test (i.e. listening quality for voice calls), the subject assigns a value (1-5) that best describes the quality, and this score is referred to as MOS. There are several objective methods available for measuring voice QoS, such as Perceptual Evaluation of Speech Quality (PESQ), Perceptual Speech Quality Measurement (PSQM), Measuring Normalizing Blocks (MNB), Perceptual Analysis Measurement System (PAMS) and etc., out of which PESQ has been the most widely adapted and discussed in the research community.

Section 2.16 can be referred to for an in-depth comparison of intrusive and non-intrusive QoS measurement methods.

Non-intrusive QoS measurement methods are preferred because they are able to measure and predict the MOS without having access to the degraded signal. Ideally, a real-time non-intrusive method would be an attractive candidate for measuring QoS before a session is established. Such a tool can aid in network planning and design, as well as protocol development.

3.3 Experiment Requirements

There are a number of challenges associated with VoLTE deployments when it comes to QoS assurance. Use of Guaranteed Bit Rate (GBR) bearers is one of the solutions for QoS provisioning in VoLTE vectors [116]. There is also mentions of possibly a feedback mechanism to ensure the vector meets minimum requirements of the applications in terms of quality. This can be identified by mapping to the defined Quality Class Identifiers (QCI) assigned for various applications [32]. As stated earlier in section 3.1, the goal here is to introduce a non-intrusive objective QoS measurement method. In order to do that, the following experiment topology (Figure 3.2) was designed to meet the requirements of the project.

As illustrated in Figure 3.2, the reference voice speech will be sent through an emulated LTE environment. Both the reference file and the degraded (output on Rx side) would be saved and compared using an intrusive objective method

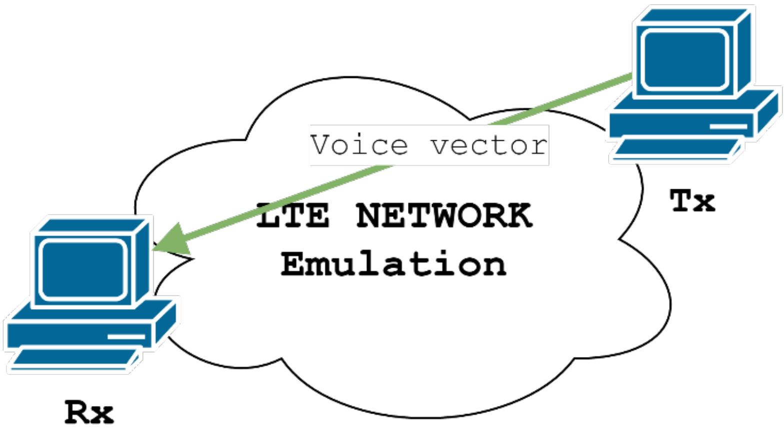


Figure 3.2: Simplified Experiment Topology

(e.g. PESQ). This data set will serve as a reference for future calibration of other non-intrusive measurement methods. Various scenarios can be designed based on real-world implementations of 4G networks and the results can be recorded for each of these scenarios. This would allow for creation of a database with LTE network parameters as inputs and the MOS score as output.

As noted earlier, while some of the data will serve as a reference for calibration, the rest can be used for verification of the new method and consequently for identifying the correlation level (accuracy). Similar experiment design and methodology has been applied to various delay sensitive (real-time) communication streams in other network types [36, 75].

There are a number of popular solutions to LTE emulation scenarios, such as ns 3 [117], OMNeT++ [118], LTE-Sim [119] and hardware in the loop method using Matlab.

3.4 Network Simulator (NS-3)

The ns-3 discrete-event network simulator is a well-maintained framework for computer networks simulations. There is plenty of literature available to offer guidance on using the various features included in ns-3. Also, there is provisions for interaction of real devices with the emulator which makes it a suitable choice when use of real end-devices is necessary. However, due to its open-source nature, NS3 has a community based development and maintenance model. Therefore, when using this tool for specialized projects that do not have a large number of members and organizations involved, one might face difficulties with support with complex protocols and simulation problems.

3.5 OMNet++, Simulte

After some research, it was identified that the suitable solution for voice transmissions over LTE in OMNeT++ is the use of Simulte package [120] from the INET framework. At the time of writing this thesis, the limitations of this model were lack of Control Plane modelling, no support for TDD, no support for EPS bearers and lack of hand-overs modelling. Customization of this simulation software is also more complex due to the high level of programming skills required to modify the simulation. Using Omnet++, it is also possible to have a graphical representation and animation of configured nodes, figure 3.3 is a sample simulation scenario configured in omnet++ by [121].

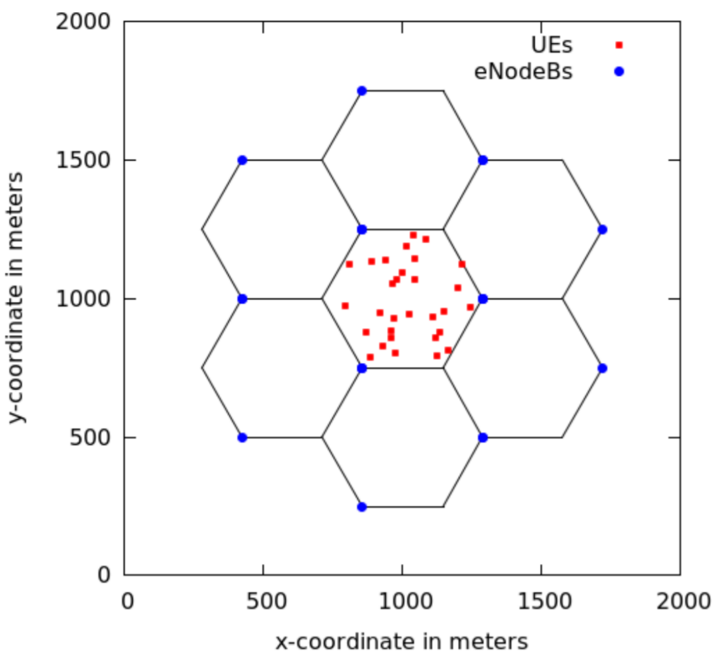


Figure 3.3: Graphical representation of a sample simulation scenario in Omnet++ [121]

3.6 LTE-Sim

LTE-Sim is a user-friendly framework for simulation of LTE scenarios. As shown in Figure 3.4, LTE-Sim is based on Command Line Interface (CLI) and by running the program, the user can input various attributes such as number of cells, radius, number of UEs, scheduling types, frame struct, speed, delay and the number of application vectors such as voice and video. However, this tool lacks the flexibility to allow using real voice traffic and at the time of writing this thesis, the available voice traffic vector was a mathematical model of one.

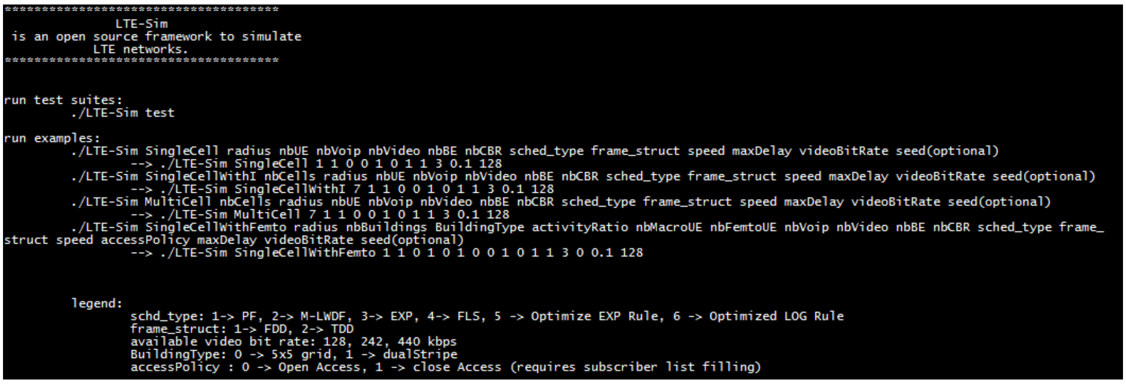


Figure 3.4: LTE-Sim framework

3.7 Hardware-in-the-loop using Matlab

Another method that can be used to send voice data and produce a degraded voice file for analysis is using a hardware-in-the-loop solution with Matlab. MathWorks offers an LTE system toolbox [122] which can be used for simulation of LTE systems. The toolbox is focused on simulation of layers 1 and 2. This toolbox can be used to simulate and analyse end-to-end communication links. Using the LTE Downlink RMC Generator [123], it is possible to generate and modify Downlink Reference Channel Options based on the standards defined in TS 36.101, Annex A.3 [124]. Figure 3.5, is a demonstration of how the network can be setup to establish and end-to-end communication link between

Figure 3.5: Hardware-in-the-loop using Matlab Zedboards and SDRs

the Tx (transmitting) and Rx (Receiving) machines. The data which in our case is an audio reference file with a .wav format, is prepared on the Tx machine, encoded and converted into binary. Then a baseband LTE signal is generated with fully customizable channel parameters. These parameters can be modified for QoS testing under various conditions and scenarios. Ultimately, the signal will be prepared for transmission by converting it to the native format for the SDR hardware and is sent through the channel to the other side. After receiving the signal using the SDR device on the Rx machine on which similar LTE parameters are configured, the Radio Frequency (RF) is captured, the received signal is down-sampled, A cell search is carried out to obtain cell ID and timing offset and after demodulation and decoding the data can be put back together as a .wav file. This will be our degraded file. The two files could later be used for an intrusive objective QoS measurement. It is also possible to simulate RF impairments such as Rayleigh fading channels and introducing Gaussian additive noise. These parameters are well known for affecting QoS in LTE networks. The output parameter of the experiment would be the MOS Score calculated using PESQ. However, before progressing into the simulation results, the reference .wav files included with PESQ software were used to benchmark the measurement method [83]. Five reference files were used to perform the benchmarking task. First, these files were tested using the PESQ software without going through a communication channel, then the same files were used in the test-bed without introducing any impairments. The resulting MOS output from these tests were compared and demonstrated in a line graph as seen in Figure 3.6. The correlation between the tests is very high, which is an indication that the test-beds setup is appropriate for using PESQ objective measurement method. To demonstrate the success of the experiment, the following

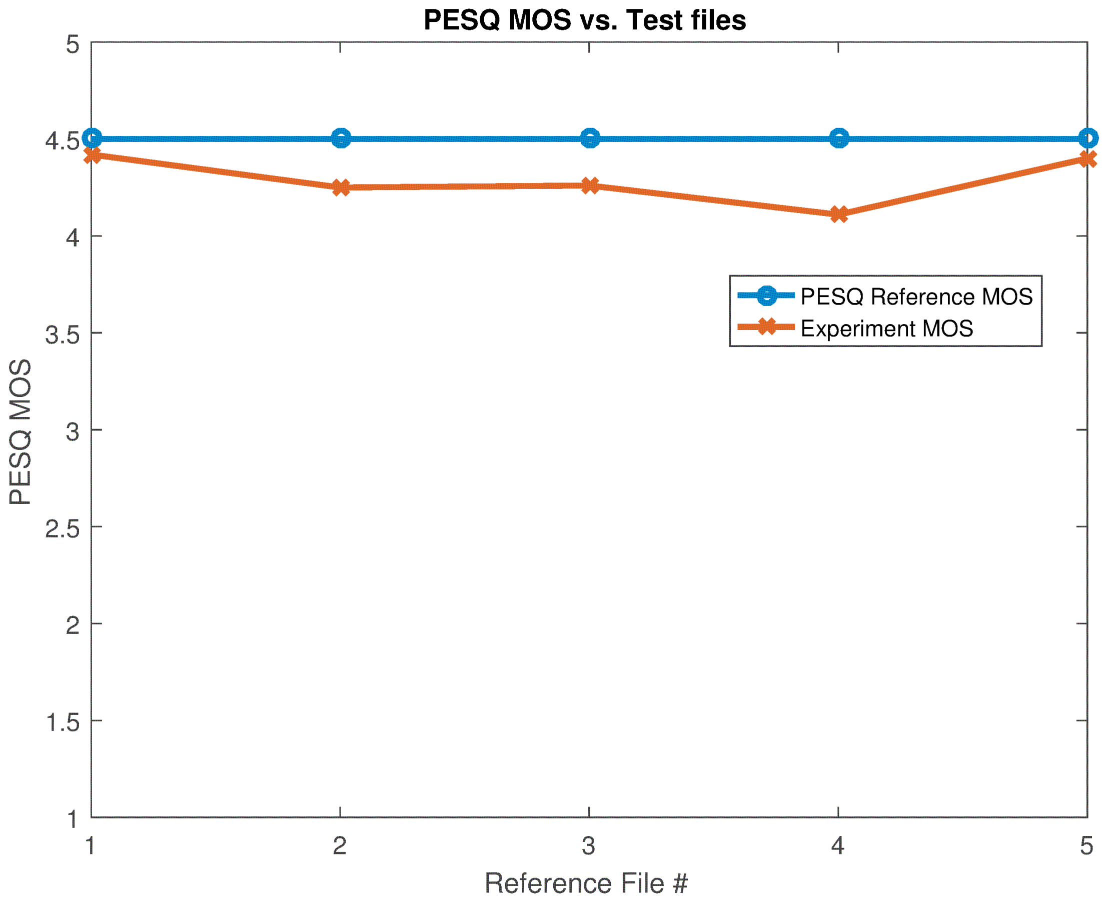


Figure 3.6: Benchmarking Test Conditions

scenarios were created:

- Scenario A: SNRdB = 10;
- Scenario B: SNRdB = 30;

The resulting MOS score for A and B was 1.75 and 4.27 respectively. To illustrate the difference in the received data, the 64QAM constellation diagram was produced for each scenario and is illustrated in Figure 3.7.

As demonstrated in the constellation diagrams, compared to scenario A, the organized distribution of symbols for scenario B shows the data was successfully demodulated at the Rx side and also justifies the high MOS score of 4.27.

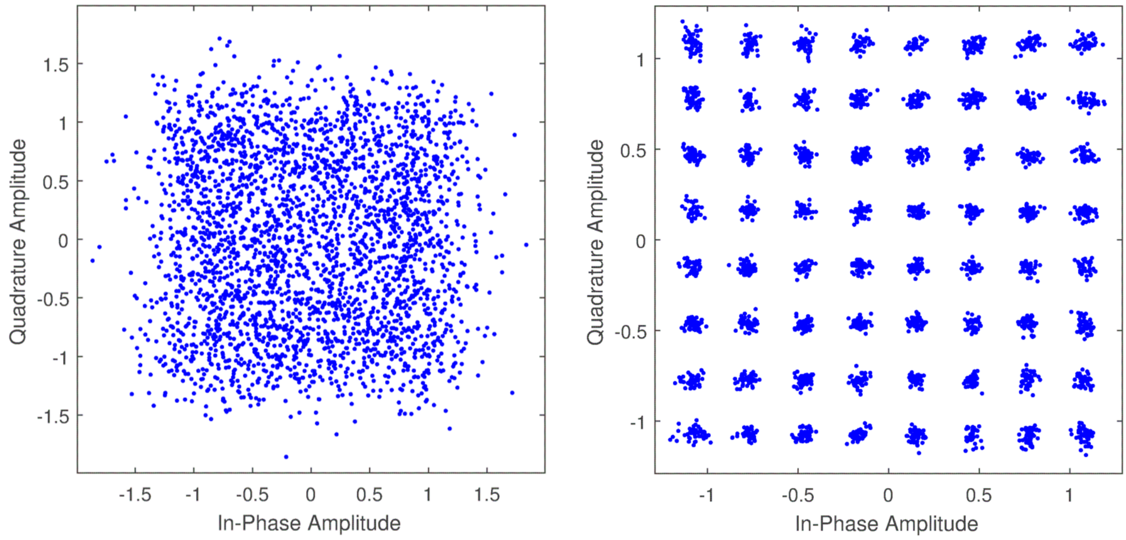


Figure 3.7: (left-to-right) 64QAM constellation for Scenario A and B

These experiments were executed with the R6 Reference Measurement Channel (RMC) configurations (25 Resource Blocks, 64 QAM) and additive Gaussian noise levels mentioned earlier.

3.8 Discussion

After considering the experiment requirements based on the research scope, it was identified that there are various solutions to simulating Voice transmissions in LTE networks. However, using each of these methods will potentially impose different limitations on test scenarios. For intrusive objective measurement of voice QoS, ns3 could be an ideal choice, however it requires an in-depth knowledge of programming languages especially when trying to define complex scenarios. Having attempted all the mentioned methods, the hardware-in-the-loop method has been relatively easier to implement and configure. The flexibility of this method to incorporate real voice transmissions encoded using Matlab makes it a suitable solution for this research. In addition to that, due to utilisation of real radio interfaces, the voice transmission is as close to real-time as possible. Success of this method was evaluated by conducting PESQ benchmarking tests and as demonstrated in Figure 8, these tests show a very close correlation to the output obtained from PESQ reference files. This simulation setup can serve as a starting point for analysing the impact of LTE communication channel impairments such as various fading channel models, moving channels (Doppler effects) and different noise levels. Since there is a PESQ package written for matlab, using this method eases the process of output (MOS) generation. Also, upon successful implementation of the test-bed, it is possible to use basic programming functions in MATLAB to automate batch-tests to run continuously by incrementing various input parameters and re-running the simulation. The inputs and outputs of these tests can be inserted into Excel or csv files for further analysis. By considering the researched literature, and testing various solutions to the problem outlined in Section 3.1, the hybrid (hardware-in-the-loop) approach was chosen to carry the experiment forward. It is worth noting that the Transmitter and Receiver functions can be easily deployed at end devices using Matlab. Audio coding and decoding using various codecs can also be performed calling various functions. Once decoded at the Receiving device, the audio can be recorded for later comparison to the reference signal, which is a requirement for intrusive objective QoS measurement. The most important advantage however, is the ability to simulate the LTE radio network using real LTE antennas and generating LTE baseband signals. There is also provision for an interactive mode which is a very close match to real eNodeB to UE communication vectors.

3.9 Summary

This chapter offers an analysis of common methods used to simulate/emulate LTE networks. The chapter revisits some background on LTE network topologies, QoS of voice traffic and QoS measurement methods. This brief background was included for easier navigation through the document. The chapter then discusses the requirements of experiment by highlighting a simplified topology. To build this topology, various tools were tested and considered. After considering the limitations and advantages of these tools, the hardware-in-the-loop method was identified as an appropriate solution. In 3.8, this choice is justified by considering the practicality, complexity and relevance of the various discussed solutions.

Chapter 4

Experiment Design and Implementation

4.1 Introduction

This chapter provides in-depth discussion of the experiment setup, tools (hardware and software), processes and parameter selection/configurations.

As discussed earlier in section 3.3, a Hardware-in-the-loop method has been selected to conduct the experiments. The LTE System ToolBox from Matlab [122] was used to provide the necessary signal processing support.

FMCOMMS3 from ADI ANALOG [125] was used as the SDR (Figure 4.1). FMCOMMS3 is an integrated Radio Frequency (RF) transceiver which was specifically designed for use in RF applications such as 3G and 4G base stations. It supports Multiple Input Multiple Output (MIMO) configurations and very useful in implementation of point-to-point communication systems. It supports up to 2 direct conversion RF receive channels in both Rx and Tx. FMCOMMS3 can interact with Matlab or Simulink via an all Programmable Software on Chip (SoC).

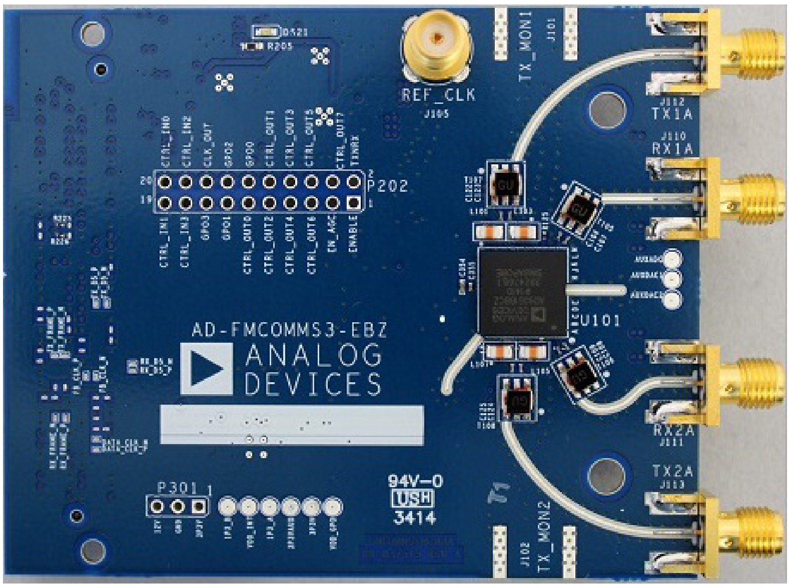


Figure 4.1: FMCOMMS3 Software Defined Radio (SDR)

Using the libiio library with SDR, the SoC and Matlab, the following can be accomplished [126]:

- Streaming data to/from a target.
- Target settings configuration.
- Target parameters monitoring.

Figure 4.2 is a top level representation of an architecture of a system utilizing Matlab/Simulink, all Programmable SoC and FMCOMMS3 SDR.

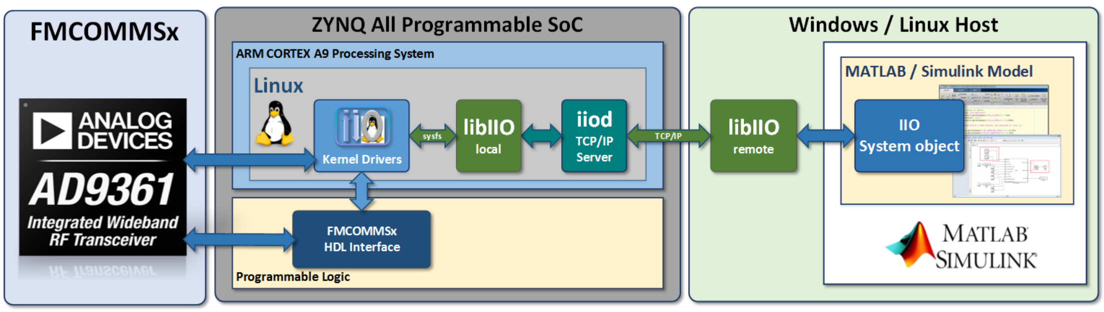


Figure 4.2: Interaction of FMCOMMS3, all Programmable SoC and Matlab/Simulink [127]

ZedBoard [128] Development kit, which is a suitable All Programmable Software on Chip (SoC), with targeted applications such as Voice/Video processing and SoC prototyping, was used as an interface between the Software Defined Radio (SDR) and the Transmitter/Receiver machines (Figure 4.3).

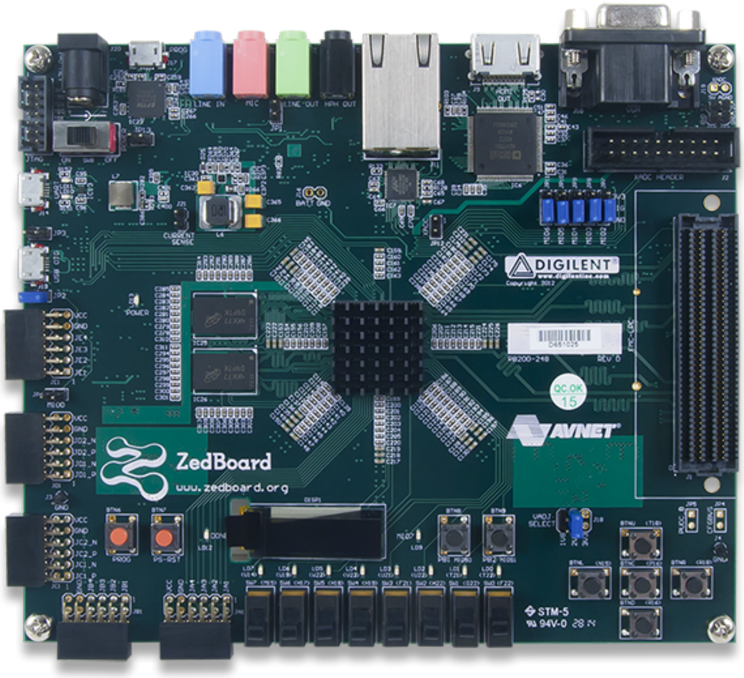


Figure 4.3: ZedBoard

Figure 4.4, further illustrates the interaction of hardware and software in experiment setup.

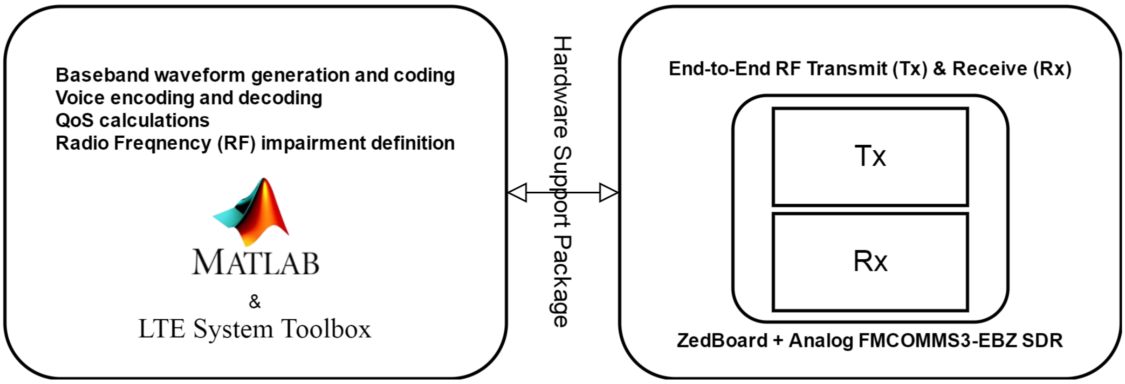


Figure 4.4: High-level layout of the experiment setup

The purpose was to send a voice signal from one device to another through an LTE environment. This would essentially simulate a voice communication session between an eNodeB and a UE. To accomplish this, reference voice files available from ITU were used as the reference signal, LTE network parameters were configured on the ZedBoard SoC and the SDRs via the LTE System Toolbox on Matlab, the voice signal is sent across to the receiving device and recorded as the degraded signal. This degraded signal is then used in conjunction with the reference signal using the PESQ Matlab wrapper to measure the MOS value. As shown in figure 4.5, the transmitting PC is connected to the SoC through a UART mini USB cable for control purposes and an ethernet connection (Cat6) for data transmission purposes. The SDR is assembled on the SoC and interacts with the software through the SoC. While fine-tuning this technique (Hardware-in-the-loop), initially Dipole 4G antennas were used. But after running some tests, it was identified that due to interference from other mobile devices and other wireless frequencies present in the room, the results were inconsistent. To overcome this, Submarine Type A (SMA) cables were used to directly connect the corresponding Tx and Rx connectors on the 2 SDRs. Further tests proved that this controlled approach provided consistent results. So the only interference would be that which is introduced intentionally by the software.

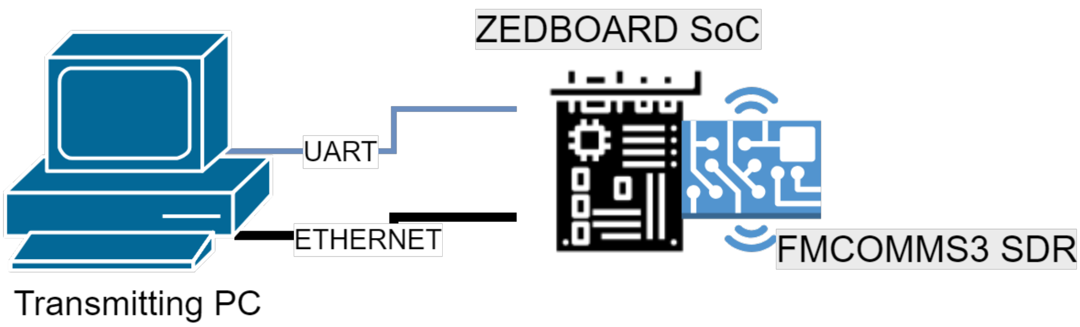


Figure 4.5: Transmitting (Tx) system architecture

To simplify, the steps/objectives identified in figure 4.6 needed to be met in order to accomplish the purpose of the defined experiment:

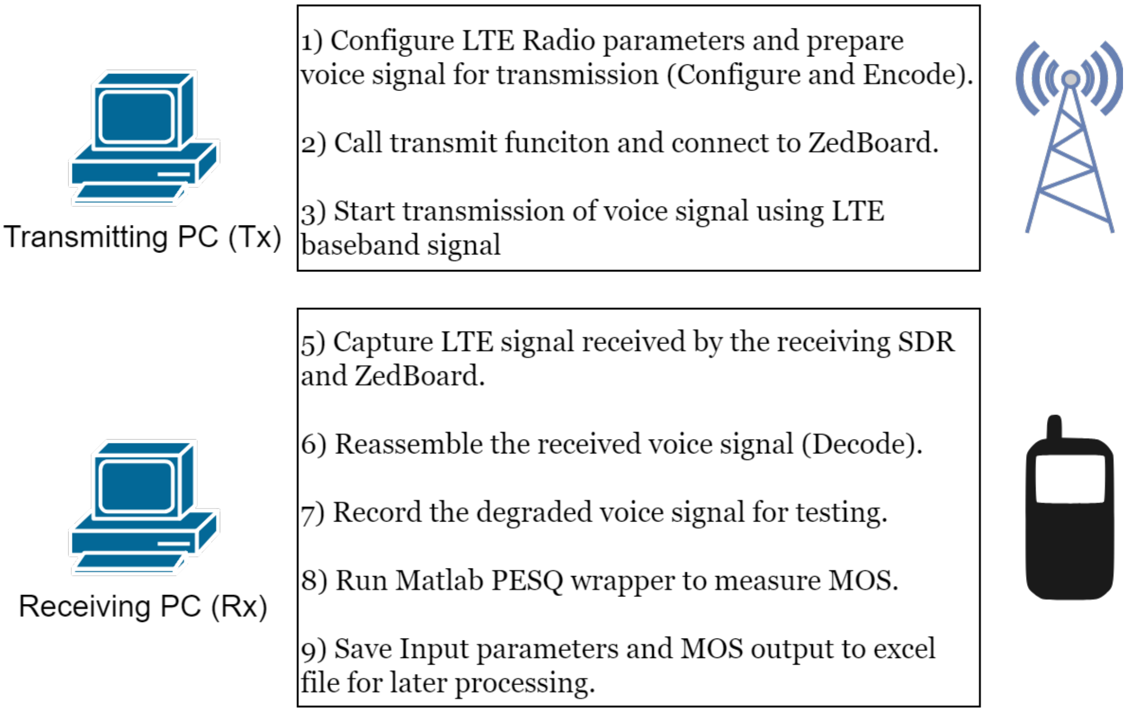


Figure 4.6: Simulation Steps / Objectives for the Hardware-in-the-loop technique.

4.2 Transmitter and Receiver Configuration

The important operations of Transmitter and Receiver designed for this experiment are identified here. These functions and processes all take place in the two PCs which are acting as Tx and Rx (eNodeB and UE). For reference, the topology was illustrated in Figure 3.5 and discussed briefly in section 3.3.

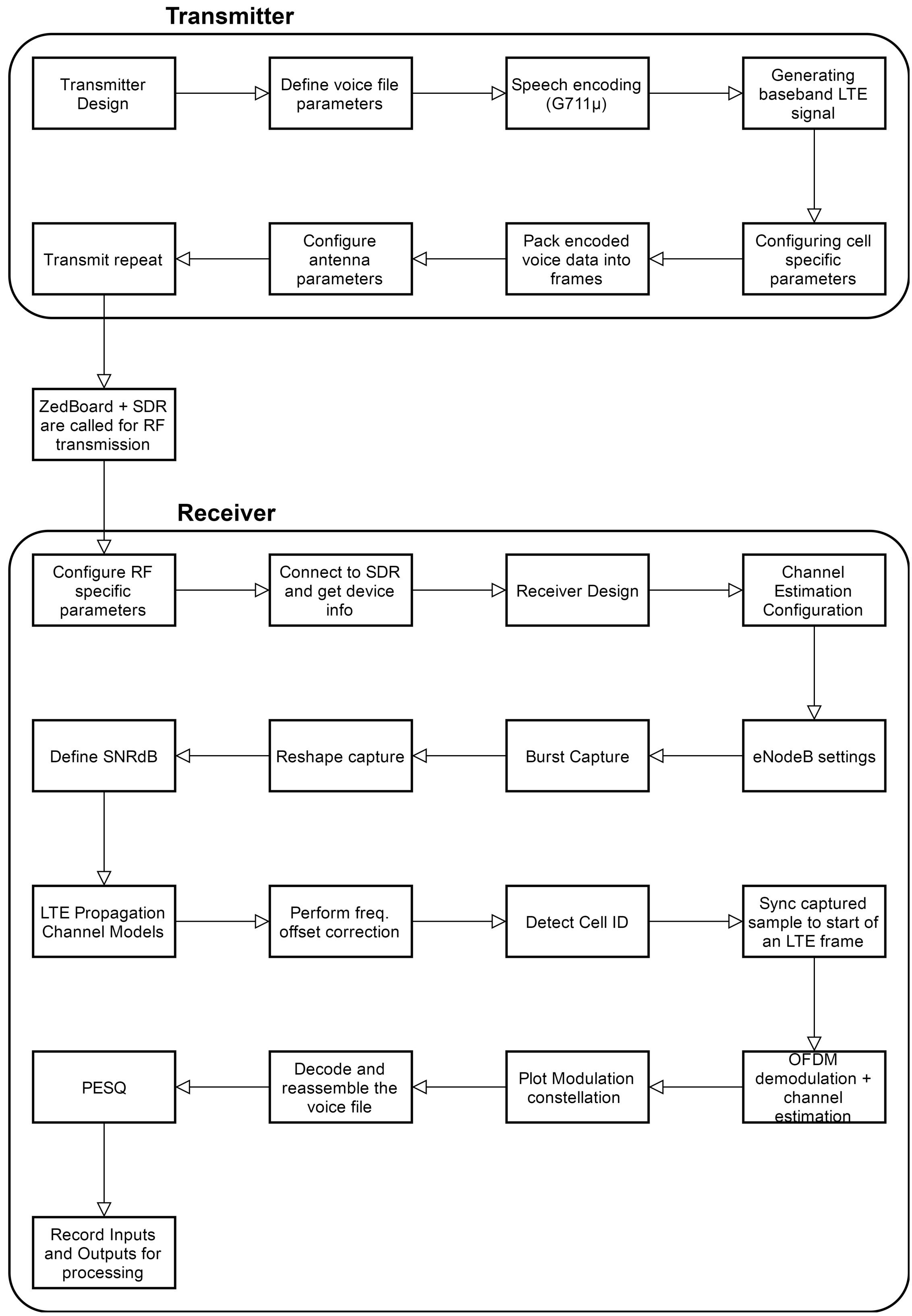


Figure 4.7: Full Experimental Process

Figure 4.7, outlines the important procedures used during the process of transmission and reception of RF.

Since the two systems of Transmitter and Receiver presented in figure 4.7 are implemented in separate systems as individual Matlab scripts, tic-toc function was used to synchronise the running time of simulation and provide a platform to run the simulations in a loop and increment input variables for each instance. This is illustrated in listing 4.1.

Listing 4.1: Simulation Synchronisation

```
n= 1;
for n = 1:51;
tic;
fprintf('Running simulation number: %d',n);

%%%%%%%%%% Contents of Matlab Script Rx/Tx%%%%%%%%%%

n = n+1;
T=toc;          %total time of simulation
pause(180-T);
```

4.2.1 Transmitter (Tx)

This section discusses in detail the processes identified in the Transmitter entity represented in Figure 4.7.

Transmitter Design: As observed in listing 4.2 an empty struct is created in Matlab, using the LTE system toolbox [129], which contains specific parameters related to eNodeB. Attributes such as Reference Measurement Channel (RMC) configurations, Number of frames to generate, Centre frequency and number of transmit antennas are defined here. Since the most common bandwidths of Release 8 LTE deployments were 5*MHz* and 10*MHz*, the RMC was chosen with a 10*Mhz* bandwidth. Cell ID is a value that uniquely identifies the cell within the Public Land Mobile Network (PLMN). And 2 transmit and 2 receive antennas have been configured to utilize the MIMO capabilities of the SDR to represent a realistic LTE radio network.

Listing 4.2: Transmitter Design

```
txsim = struct;           % Transmitter Struct
txsim.RC = 'R.7';         % Base RMC configuration, 10 MHz bandwidth
txsim.NCellID = 17;       % Cell identity
txsim.NFrame = 700;       % Initial; frame number
txsim.DesiredCenterFrequency = 2.45e9; % Center frequency in Hz
txsim.NTxAnts = 2;        % Number of transmit antennas
```

Define voice file parameters: depending on characteristics of the reference voice file, this information can be modified if necessary. The Sampling rate, Frame size and duration of the speech are configured here. The parameters defined in listing 4.3 are passed to SpeechToBits function for speech coding.

Listing 4.3: Voice File parameter selection

```
Fs=8000;
FrameSize=427;
SecondsOfSpeech= 8;
[trData, txpcm] = speechToBits(Fs, FrameSize, SecondsOfSpeech, Interactive);
```

Speech coding: G711μ law codec was used to convert the speech signal to bits. At this stage, the speech signal is encoded and converted to bits (1s and 0s). The resulting stream of 1s and 0s is decoded again at the transmitting PC and saved as a separate file to serve as the reference signal. This reference file is later copied to the receiving PC separately to be used for the purpose of intrusive PESQ QoS measurement.

Generate baseband LTE signal: Using the configured Tx parameters and some default preset information, by calling the lteRMCDL function shown in listing 4.4, a baseband LTE signal is generated using RMC R.7 as described in [122].

Listing 4.4: Reference Measurement Channel Creation

```
rmc = lteRMCDL(txsim.RC);   % Creating the reference measurement channel
```

Configure cell specific parameters: As shown in listing 4.5, several parameters are configured and communicated (attached to frames) to Rx (UE), such as Cell ID, frame indexing, number of antennas and Redundancy Version sequence (RVSeq).

Listing 4.5: Cell Specific Parameters

```
rmc.NCellID = txsim.NCellID;
rmc.NFrame = txsim.NFrame;
rmc.TotSubframes = txsim.TotFrames*10; % Number of subframes per frame
rmc.PDSCH.RVSeq = 0;
```

Configure antenna parameters: Antenna parameters such as antenna configuration, Transmit scheme and duplex mode (FDD/TDD) are defined in listing 4.6.

Listing 4.6: Antenna Parameters

```
rmc.PDSCH.TxScheme = 'TxDiversity';
rmc.PDSCH.DuplexMode = 'FDD';
rmc.PDSCH.NLayers = 2;
```

Transmit repeat: Using the above information, the software interacts with the

ZedBoard to interface with the SDR which then starts transmitting the data in a loop towards the receiving SDR.

Listing 4.7: Transmit Function

```
eNodeBOutput = int16(eNodeBOutput*2^15);
tx.transmitRepeat(eNodeBOutput);
```

4.2.2 Receiver (Rx)

This section discusses in detail the processes identified in the Receiver entity represented in Figure 4.7.

Configure RF-specific parameters: As illustrated in listing 4.8, Radio front-end sample rate, centre frequency, frames per burst, number of bursts to capture and number of receive antennas are configured using the LTE System Toolbox [129]. To account for potential timing offset requirement, an extra frame than the number of transmitted frames is captured.

Listing 4.8: Receiver Struct

```
rxsim = struct; % Creating an empty struct for Rx
rxsim.SDRDeviceName = 'ZedBoard and FMCOMMS2/3/4'; %
    choosing the device in use
rxsim.RadioFrontEndSampleRate = 15360000;
rxsim.RadioCenterFrequency = 2.45e9; % adjusting center
    frequency (Hz)
rxsim.FramesPerBurst = 5;    % Frames to capture at each
    burst
rxsim.numBurstCaptures = 1;
rxsim.NRxAnts = 2;           % number of rx antennas
samplesPerFrame = 10e-3*rxsim.RadioFrontEndSampleRate;
```

Connect to SDR and get device info: Using the code shown in listing 4.9, the SDR device object is created and Matlab is prompted to establish a connection to the SDR and obtains information such as channel mapping and configures the SDR with the aforementioned parameters (i.e. samples per frame, centre frequency and etc.)

Listing 4.9: SDR device object

```
hdev = sdrdev(rxsim.SDRDeviceName);
devInfo = hdev.info;
```

Receiver Design: As presented in listing 4.10, the parameters configured here are derived from those defined on the Tx side in the Transmitter struct as discussed in listing 4.2. (i.e. RMC R.7, TxScheme and Antennas)

Listing 4.10: Receiver Design

```
rmc = lteRMCDL('R.7'); % identifying the rmc which was
   earlier set at the Tx
rmc.PDSCH.TxScheme = 'TxDiversity';
rmc.PDSCH.NLayers = 2;
rmc.CellRefP = 2;
```

Channel estimation configuration: As shown in listing 4.11, a 9 by 9 averaging window is used with cubic 2D interpolation type to perform the channel estimation. In order to estimate channel characteristics, LTE uses pilot symbols which are inserted in time and frequency. By aid of interpolation, the channel properties can be estimated across several subframes.

Listing 4.11: Channel estimation configuration

```
cec.PilotAverage = 'UserDefined';
cec.FreqWindow = 9;                % Frequency window
   size
cec.TimeWindow = 9;                % Time window size
```

```
cec.InterpType = 'Cubic';            % interpolation type
cec.InterpWindow = 'Centered';       % Interpolation
   window type
cec.InterpWinSize = 3;               % Interpolation
   window size
```

eNodeB settings: As shown in listing 4.12, parameters such as Duplex Mode, cyclic prefix and Number of Downlink Resource Blocks.

Listing 4.12: Rx eNodeB Settings

```
enb.PDSCH = rmc.PDSCH;
enb.DuplexMode = 'FDD';
enb.CyclicPrefix = 'Normal';
enb.CellRefP = 2;
enb.NDLRB = 50;
%%%%%
enbDown = struct;                     % configuring the
   base station with the struct
enbDown.DuplexMode = 'FDD';           % FDD duplexing
enbDown.NDLRB = 50;                   % Number of RBs
ofdmInfo = lteOFDMInfo(enbDown);      % getting the
   sampling rate
```

Burst capture: As shown in listing 4.13, the number of desired frame captures are identified for each burst and this is dependent on the number of frames transmitted in this case.

Listing 4.13: Burst Capture

```
burstCaptures = zeros(samplesPerFrame,rxsim.NRxAnts,
   rxsim.FramesPerBurst);
```

Define SNRdB: After reshaping the capture, SNRdB level is identified to account for the desired Additive White Gaussian Noise (AWGN). The code in listing 4.14 is used to introduce AWGN, into the received signal based on the formula discussed in section 4.3.1.

Listing 4.14: SNRdb

```
SNRdB = 15;
SNR = 10^(SNRdB/20);
rng('Default');
%
N0 = 1/(sqrt(2.0*enb.CellRefP*double(ofdmInfo.Nfft))*SNR
   );
noise = N0*complex(randn(size(rxWaveform)),randn(size(
   rxWaveform)));
rxWaveform = rxWaveform + noise;
```

LTE Propagation Channel Models: Using a number of functions included in LTE System Toolbox, various RF impairments such as Multipath fading propagation conditions, High speed train conditions and Moving propagation conditions can be emulated. Within the Multipath fading propagation conditions, Extended Pedestrian A model (EPA), Extended Vehicular A model (EVA) and Extended Typical Urban model (ETU) can be configured to simulate delay profiles with various tap delays which correspond with different levels of relative power (dB). Also, different channel models are defined that implement different levels of Maximum Doppler Frequencies.

Perform frequency offset correction: To account for frequency mismatches in Tx and Rx SDRs, frequency offset correction is performed using the code in listing 4.15.

Listing 4.15: Frequency Offset Corrrection

```
frequencyOffset = lteFrequencyOffset(enbDown,downsampled);
downsampled = lteFrequencyCorrect(enbDown,downsampled,frequencyOffset);
rxWaveform = lteFrequencyCorrect(enb,rxWaveform,frequencyOffset);
```

Detect Cell ID: The lteCellSearch function allows for performing a blind cell search in the down-sampled signal for a Cell ID which was configured and transmitted from Tx (eNodeB) and the timing offset.

Listing 4.16: Cell ID Calculation

```
[NCellID,downOffset] = lteCellSearch(enbDown,downsampled);
frameOffset = downOffset*round(sr/ofdmInfo.SamplingRate);
enbDown.NCellID = NCellID;
```

Synchronise captured sample to start of an LTE frame: Here, Frames are individually identified and any samples that are part of an incomplete frames are trimmed off. Although this experiment setup simulates realtime LTE voice transmission, it is not real time in nature, only an emulation in fact. Hence, due to the possibility that Rx might start capturing in the middle of a frame, this synchronisation is necessary.

Listing 4.17: Synchronise the sample to start of frame

```
rxWaveform = rxWaveform(frameOffset+1:end,:);
tailSamples = mod(length(rxWaveform),samplesPerFrame);
rxWaveform = rxWaveform(1:end-tailSamples,:);
```

OFDM demodulation and channel estimation: 64 QAM is used as the modulation scheme in most LTE implementations. After OFDM demodulation of received waveform, using the lteDLChannelEstimate, allows for estimation of channel characteristics for the received resource grid. This resource grid is a three dimension array of complex numbers which is specified as [130]:

$$N_{SC} \times N_{Sym} \times N_R \tag{4.1}$$

where;

$$N_{Sym} = N_{SF} * N_{SymPerSF} \tag{4.2}$$

In equation 4.1, N_{SC} is the number of subcarriers and N_R is the number of antennas. In equation 4.2, N_{SF} is the total number of subframes and $N_{SymPerSF}$ is the number of Symbols (OFDM) per subframe.

Listing 4.18: OFDM demodulation

```
rxGrid = lteOFDMDemodulate(enb,rxWaveform);
```

Plot Modulation constellation: A constellation diagram is plotted for the demodulated OFDM symbols. An example of this was presented in Chapter three Figure 3.7.

Listing 4.19: Plot Constellation Diagram

```
step(hcd,rxEncodedSymb{:});
```

Decode and reassemble the voice file: The received bits are decoded using the same codec and the speech file is reassembled. This output is the degraded voice file, since it has been passed through the emulated LTE radio network with preconfigured RF impairments. As a result, some degradation is expected in the resulting voice file.

Listing 4.20: Decode and reassemble the voice signal

```
decodedRxDataStream = decodedRxDataStream(1:8000*8*8);
Fs=8000;
DataType='int16';
FrameSize=427;
numBitsPerSample = 8;
LawG711='Mu';
params = initializeSpeechCoding(LawG711);
```

PESQ: PESQ matlab driver [131] was used after the reassembly process in order to compare the original speech file with the degraded version.

Listing 4.21: PESQ Matlab Wrapper

```
MOS=pesq2_mtlb( 'or246.wav', 'RxSpeech.wav', 8000, 'nb',
    'pesqa2.exe' , 'C:\Users\R2D2\Documents\MATLAB');
fprintf('\n PESQ MOS Score = %0.2f \n',MOS);
```

Record Inputs and Outputs for processing: The mentioned inputs and MOS output are populated in a csv file.

Listing 4.22: Write Input/Output to file

```
close(figure(1)); % Closing the figure because it takes
   too much space.
fileid=num2str(n);
outpath = ('C:\Users\R2D2\Desktop\RX\hst\dg246');
outfolder = ['hst' fileid];
mkdir([outpath filesep outfolder]);
outdest = [outpath filesep outfolder];
csvwrite('PESQ-MOS.dat',MOS);
save([outdest filesep 'matlab.mat']);
copyfile('C:\Users\R2D2\Documents\MATLAB\RxSpeech.wav',
   outdest);
```

```
copyfile('C:\Users\R2D2\Documents\MATLAB\PESQ-MOS.dat',
    outdest);
excelout=[num,dopplerfrequency,MOS];
xlswrite('hstdoppler4_Dmin3000_Ds10000_V350_test_246.xls
    ', excelout , 'Velocity', strcat('A',num2str(num)));
n=n+1;
```

4.3 Input Selection

This section discusses the selected QoS affecting input parameters and offers justification on their ranges applied to the experiment.

4.3.1 Additive White Gaussian Noise (AWGN)

As discussed in section 2.14.1, white noise is one of the first concerns when it comes to RF impairments. The introduced AWGN is measured in SNRdB. The higher this value, the stronger the signal and consequently, the higher the quality of voice. SNR is given by Equation 4.3:

$$SNR = E_s / N_0 \tag{4.3}$$

Where E_s is the signal energy and N_0 is the power of noise. The noise needs to be scaled and noise gain can be calculated using Equation 4.4.

$$N_0 = 1/(\sqrt{2.0 * CRP * FFT_s}) * SNR \tag{4.4}$$

Where CRP is the number of cell-specific reference signal (CRS) antenna ports and FFT_s is the size of Fast Fourier Transform (FFT). In Equation 4.5 using above information, the additive noise matrix is generated by:

$$noise = N_0 * C_M \tag{4.5}$$

Where C_M is a random complex matrix with the size of generated waveform. The generated noise matrix is added to the waveform. As highlighted by [132], according to their tests which were carried out on 2.4 GHz wireless channels, the following findings were published (Table 4.1).

Signal	**SNRdB**
Excellent	$> 40dB$
Very good	$25dB$ to $40dB$
Low	$15dB$ to $25dB$
Very low	$10dB$ to $15dB$
No signal	$05dB$ to $10dB$

Table 4.1: Relationship between SNRdB and Signal quality

According to [133], any signal with SNRdB of ≥ 20 corresponds to an excellent RF condition.

To ensure the entire SNRdB spectrum is covered, for the purpose of this experiment, the **minimum** and **maximum** levels of AWGN SNRdB were chosen respectively as **0dB** and **40dB**.

4.3.2 Multiple Input Multiple Output (MIMO) channel settings

As set out in [134], and [135] a MIMO channel is emulated by passing the waveform through a multipath Rayleigh fading channel model. The following three profiles are defined and implemented for emulation of various real-world scenarios. Effectively, these three profiles correlate with Low, Medium and High delay spread environments respectively:

- Extended Pedestrian A Model (EPA)
- Extended Vehicular A Model (EVA)
- Extended Typical Urban Model (ETU)

As per definition of multi-path fading propagation conditions, the tap delay to relative power correlation for EPA, EVA and ETU profiles are defined in [135].

4.3.3 Antenna Gain

A key performance indicator for wireless antennas is represented as antenna gain. This factor describes how well an antenna converts electrical power into radio waves and vice versa. Generally, external LTE antennas have a gain range of $2.2dBi$ to $10dBi$.

4.3.4 High Speed Train Conditions

The number of high speed trainlines is increasing globally and LTE aims to support the communication aspect with UEs moving at speeds as high as 350km/h and 500km/h. In various publications, these scenarios are referred to as High Speed Train conditions [136, 137]. The typical cell size for LTE release 10 would be between 1 to 5 kilometres to preserve compatibility with 2G and 3G networks, however, this size can go up to 100(km) or 62 miles in wider deployments [137]. In order to have a comprehensive overview of all possibilities concerning the cell size, the following variables are defined with their ranges to match the maximum and minimum values defined by 3GPP standards [136].

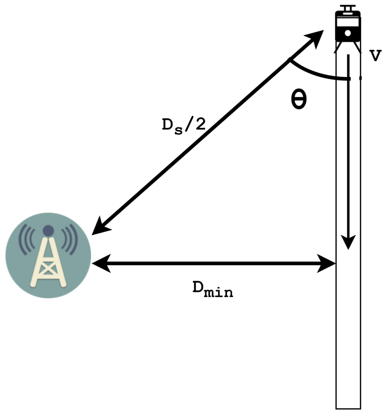


Figure 4.8: High Speed Train Scenario Input Parameters

Considering the scenario depicted in Figure 4.8, Doppler shift can be found using Equation 4.6 [138]:

$$f_s(t) = f_d cos\theta(t) \tag{4.6}$$

In equation 4.6, $f_s(t)$ and f_d are respectively the Doppler shift and the maximum Doppler frequency. To find the $cos\theta(t)$, equation 4.7 is used below [138]:

$$cos\theta = \begin{cases} \frac{D_s/2 - vt}{\sqrt{{D_{min}}^2 + (D_s/2 - vt)^2}} & 0 \le t \le D_s/v \\ \frac{-1.5D_s + vt}{\sqrt{{D_{min}}^2 + (-1.5D_s + vt)^2}} & D_s/v < t \le 2D_s/v \\ cos\theta(t \, mod(2D_s/v)) & t > 2D_s/v \end{cases} \tag{4.7}$$

In equation 4.7, $D_s/2$, D_{min} and v are illustrated in Figure 4.8, and t is time in seconds.

- Initial distance to eNodeB - $D_s/2$ (m): Ranging from $3,000(m)$ to $100,000(m)$
- Distance between eNodeB and Track - D_{min} (m): Ranging from $3,000(m)$ to $100,000(m)$
- Velocity - V (kph): Ranging from $50(kph)$ to $500(kph)$

4.4 Summary

Based on the requirements of the experiment explained in section 3.3, chapter 3 examined several solutions for emulation of an LTE environment to examine QoS of voice vectors. Each method was thoroughly discussed along with advantages, disadvantages and limitations. Based on the findings, use of hardware-in-the-loop method which utilizes Matlab, Zedboards and FM-COMMS3 SDRs was recommended. This recommendation was justified to be in alignment with the experiment requirements. A high-level layout of the method was provided and all processes and procedures (software and hardware related) included in the recommended method were explained by aid of visual representations. Code snippets were included to aid with comprehension of experiment development technique. The various supported LTE-specific input parameters related to the experiment are also discussed in detail, highlighting the ranges of those parameters by cross-referencing to the relevant literature. The findings of this chapter are a combination of literature available from 3GPP [1], and Coding support from Matlab [139]. The introduced hardware-in-the-loop configuration with the current setup can serve as a platform for further testing with a wider range of parameters and future releases of 3GPP LTE networks. This research strongly recommends use of this technique by Communication Service Providers to aid with network planning and design in a wide range of scenarios.

Chapter 5

Results and Discussions

5.1 Introduction

This chapter presents the results obtained from the experiment discussed in chapter 4. Section 5.3, contains the complete table of inputs and outputs used in the experiment, explanations about the contents of the table as well as discussion on procedures used to obtain the values. Sections 5.4, 5.5 and 5.6 respectively discuss individual impacts of SNRdb, distance and speed on MOS with aid of plots.

5.2 Result Collection

The procedure for result collection and processing using the experiment technique discussed in chapter 4, is illustrated in figure 5.1. For easier navigation, the figure is numbered and each process/part is described in the following list:

1. Reference speech files from ITU were used as input for Matlab at the Tx end.

2. The transmission parameters are configured here and the channel is prepared.

3. The reference speech file is passed through the encoding process and is decoded to produce the reference voice signal which will later be used in step 8.

4. The frames generated by the Transmitting system at step 2 is sent towards the Receiving system through the hardware (ZedBoard SoCs and FMCOMMS3 SDRs).

5. The data is taken off from the hardware channel and before being processed, the inputs from step 6 are introduced.

6. The selected inputs (SNRdb to represent AWGN, Velocity of UE in kph and Distance of UE from eNodeB in meters) are introduced into the receiving system.

7. After reassembly of the degraded data stream, the receiving system generates and records a degraded voice signal.

8. The reference voice signal from step 3 and the degraded voice signal from step 7 are both passed to the PESQ Matlab driver [131] for QoS assessment.

9. The inputs introduced in step 6, along with the MOS value generated in step 8 are saved in an excel file. Ultimately, these results are combined and represented in section 5.3.

The above process is repeated for different input values and with several reference files to produce a complete database of inputs and outputs which is later used as discussed in 3 to propose a non-intrusive objective method for QoS prediction/measurement in LTE networks.

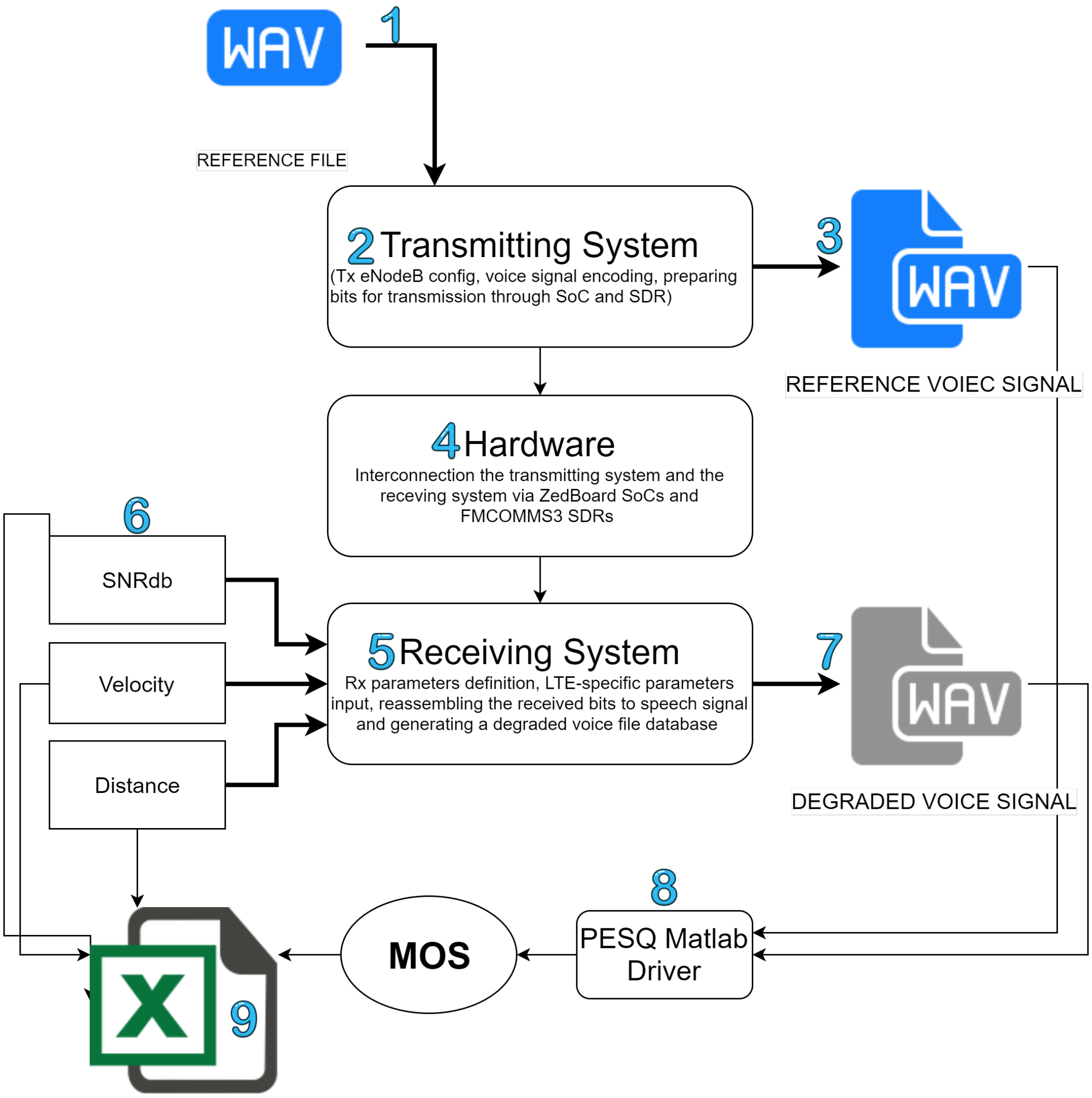


Figure 5.1: Result Collection Procedure

5.3 Representation of Results

Table 5.1, contains the outcome of the experiment in 125 test conditions. The first column contains the condition number, followed by SNRdb in the second column, then the distance which is represented in metres, followed by speed in kph and finally the fifth column contains the MOS value for each of those conditions. The justifications for choosing these inputs was discussed in chapter 4. To briefly recap, the SNRdb is the signal to noise ratio value arising from channel noise, the distance parameter refers to the distance of an eNodeB from the moving User Equipment (UE) path (i.e. Train track), the speed variable is referring to the speed at which the user is travelling and the MOS value is calculated using the PESQ matlab wrapper. To ensure the outcomes are valid, each condition was tested with two different reference files (supplied by ITU), and each test was repeated 3 times. The average of these outputs was recorded and presented in table 5.1, below. These results were later used for neural network training, validation and testing which is discussed in chapter 6.

A sample of test conditions and results are extracted from table 5.1 explained below:

- In test condition 11, at an SNRdb value of 0, distance of $30000m$ and speed of $100kph$, a MOS value of 1.27 was obtained using PESQ matlab driver. The output voice file for this test condition was completely inaudible and all static. It was noted that the PESQ matlab driver's lowest output throughout the experiment was 1.27. This value is associated with test condition 11 due to the low value of SNR. The noise level here is so high that it completely masks the original signal and really the other inputs here (speed and distance) become irrelevant, therefore such low value of MOS is obtained.
- In test condition 28, An SNRdb of 10, at distance of $5000m$ and a speed of $100kph$ outputs a MOS value of 1.35. Even at this value of MOS, the

voice is inaudible and this represents a very high level of degradation. Clearly, a very small level of improvement is observed in MOS, but it was observed that with SNRdb values of $< 13 - 14$, a very high level of degradation occurs at the Rx.

- In test condition 51, An SNRdb of 20, from a distance of $5000m$ and at a speed of $50kph$, a significant improvement in MOS was observed from 1.35 in previous lower SNRdb values to 4.235. Comparing to previous conditions discussed in this sample, a huge improvement is observed. In fact, this was the highest value obtained for MOS using PESQ software. This maximum value was also observed in Figure 3.6 in chapter 3. Looking at the inputs for test condition 51, it is observed that speed and distance are at their lowest tested values, and the SNRdb is > 13 which produced such high MOS output. This is further justified by considering the relevant literature, such as [140] and [141].

- In test condition 80, with an SNRdb of 30, at a distance of $5000m$ and a speed of $450kph$, a MOS value of 3.812. In this test condition, SNRdb of 30 represents minimal level of noise in the channel which would be associated with high QoS, the distance of 5km is very small as long as appropriate amount of power is used at the eNodeB and although the travel speed of UE is set to $450kmph$, a small amount of degradation is observed in MOS. This correlates with the literature discussed in chapter 4, that LTE was designed to supports speeds of upto $500kph$ [136, 137].

- In test condition 114, with a high SNRdb value of 40, at a distance of $30000m$ and a speed of $300kph$ an acceptable MOS value of 3.784 was obtained. As discussed earlier in chapter 4, LTE cell ranges can range from 5km to 100km according to [137]. For this test condition, the SNRdb value represents a minimal amount of noise, relatively high speed of 300kmph and a high distance of 30km. Although some degradation is observed, even at this distance, the voice quality is acceptable with a MOS of 3.7.

Condition	SNRdb (db)	Distance (m)	Speed (kph)	PESQ MOS
1	0	5000	50	1.27
2	0	5000	100	1.27
3	0	5000	150	1.27
4	0	5000	300	1.27
5	0	5000	450	1.27
6	0	15000	50	1.27
7	0	15000	100	1.27
8	0	15000	150	1.27
9	0	15000	300	1.27
10	0	15000	450	1.27
11	0	30000	50	1.27
12	0	30000	100	1.27
13	0	30000	150	1.27
14	0	30000	300	1.27
15	0	30000	450	1.27
16	0	50000	50	1.27
17	0	50000	100	1.27
18	0	50000	150	1.27
19	0	50000	300	1.27
20	0	50000	450	1.27
21	0	75000	50	1.27
22	0	75000	100	1.27
23	0	75000	150	1.27
24	0	75000	300	1.27
25	0	75000	450	1.27
26	10	5000	50	1.35
27	10	5000	100	1.35
28	10	5000	150	1.35

Condition	SNRdb (db)	Distance (m)	Speed (kph)	PESQ MOS
29	10	5000	300	1.35
30	10	5000	150	1.35
31	10	15000	50	1.35
32	10	15000	100	1.35
33	10	15000	150	1.35
34	10	15000	300	1.35
35	10	15000	450	1.35
36	10	30000	50	1.35
37	10	30000	100	1.35
38	10	30000	150	1.35
39	10	30000	300	1.35
40	10	30000	450	1.35
41	10	50000	50	1.35
42	10	50000	100	1.35
43	10	50000	150	1.35
44	10	50000	300	1.35
45	10	50000	450	1.35
46	10	75000	50	1.35
47	10	75000	100	1.35
48	10	75000	150	1.35
49	10	75000	300	1.35
50	10	75000	450	1.35
51	20	5000	50	4.235
52	20	5000	100	4.189
53	20	5000	150	4.034
54	20	5000	300	3.965
55	20	5000	450	3.931
56	20	15000	50	4.212

Condition	SNRdb (db)	Distance (m)	Speed (kph)	PESQ MOS
57	20	15000	100	4.156
58	20	15000	150	4.015
59	20	15000	300	3.932
60	20	15000	450	3.906
61	20	30000	50	4.153
62	20	30000	100	4.109
63	20	30000	150	3.986
64	20	30000	300	3.885
65	20	30000	450	3.809
66	20	50000	50	3.974
67	20	50000	100	30865
68	20	50000	150	3.801
69	20	50000	300	30768
70	20	50000	450	3.674
71	20	75000	50	3.621
72	20	75000	100	3.43
73	20	75000	150	3.236
74	20	75000	300	3.157
75	20	75000	450	3.064
76	30	5000	50	4.227
77	30	5000	100	4.107
78	30	5000	150	3.989
79	30	5000	300	3.86
80	30	5000	450	3.812
81	30	15000	50	4.269
82	30	15000	100	4.15
83	30	15000	150	4.093
84	30	15000	300	3.967

Condition	SNRdb (db)	Distance (m)	Speed (kph)	PESQ MOS
85	30	15000	450	3.921
86	30	30000	50	4.189
87	30	30000	100	4.165
88	30	30000	150	1.046
89	30	30000	300	3.93
90	30	30000	450	3.741
91	30	50000	50	3.98
92	30	50000	100	3.865
93	30	50000	150	3.759
94	30	50000	300	3.715
95	30	50000	450	3.671
96	30	75000	50	3.637
97	30	75000	100	3.61
98	30	75000	150	3.574
99	30	75000	300	3.531
100	30	75000	450	3.468
101	40	5000	50	4.27
102	40	5000	100	4.267
103	40	5000	150	4.153
104	40	5000	300	4.015
105	40	5000	450	3.986
106	40	15000	50	4.214
107	40	15000	100	4.13
108	40	15000	150	4.035
109	40	15000	300	3.896
110	40	15000	450	3.752
111	40	30000	50	4.187
112	40	30000	100	4

Condition	SNRdb (db)	Distance (m)	Speed (kph)	PESQ MOS
113	40	30000	150	3.895
114	40	30000	300	3.784
115	40	30000	450	3.753
116	40	50000	50	3.891
117	40	50000	100	3.87
118	40	50000	150	3.761
119	40	50000	300	3.718
120	40	50000	450	3.68
121	40	75000	50	3.648
122	40	75000	100	3.781
123	40	75000	150	3.574
124	40	75000	300	3.55
125	40	75000	450	3.476

Table 5.1: Experiment results

Table 5.1, expresses the outcomes of experiments which were passed through the PESQ wrapper for MOS calculation. This is a commonly used intrusive objective method for measuring QoS and not ideal for application to real-time scenarios, or scenarios in which time is an asset. Therefore, these results are later used in chapter 6 to train, validate and test neural network models which would be suitable for real-time applications.

5.4 Impact of SNRdb on MOS

After conducting the experiments, it became obvious that the amount of noise has a significant effect on quality of service. Of course, this is common to all communication systems and is also backed up by literature. The experiments shows that the degraded voice file is inaudible while $SNRdb \leq 13$, and excellent

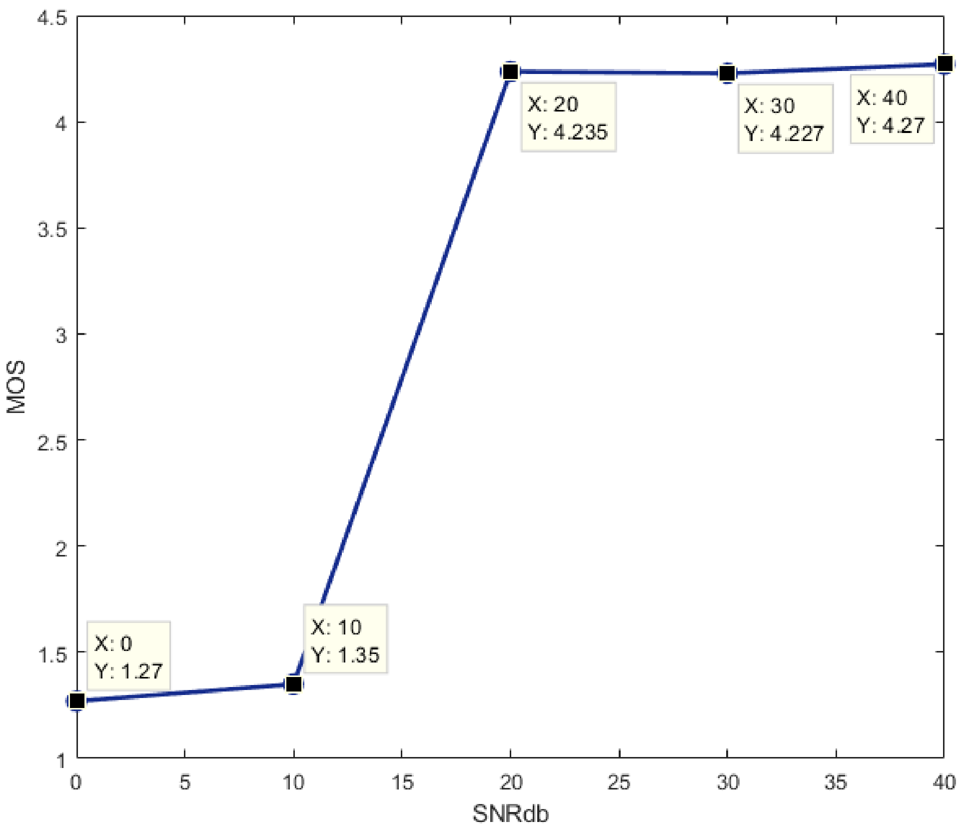


Figure 5.2: SNRdb vs MOS

quality while $SNRdb > 13$ with marginal increments in MOS up to $SNRdb = 40$. This is also evident in the graph of Figure 5.2. A great increase in MOS is observed between the second and third entry, yet only marginal differences between the 3rd, 4th and 5th values of SNRdb.

Overall increase of SNRdb results in increase of MOS which is also backed up by the literature as demonstrated by Mukherjee et al. [142], and shown in figure 5.4. It was observed that increase in SNR decreases BER which equates to a better overall quality in the network, hence supporting the argument that higher SNRdb values correlate with higher MOS QoS values.

Overall increase of SNRdb results in increase of MOS which is also backed up by the literature as demonstrated by Prasad et al. [140], and shown in figure 5.3. It was observed that increase in SNR decreases BER which equates to a better overall quality in the network. The modulation scheme used in the experiment design discussed in chapter 4, utilises 64QAM, and the graph in Figure 5.3 supports the argument that higher SNRdb values correlate with higher MOS QoS values.

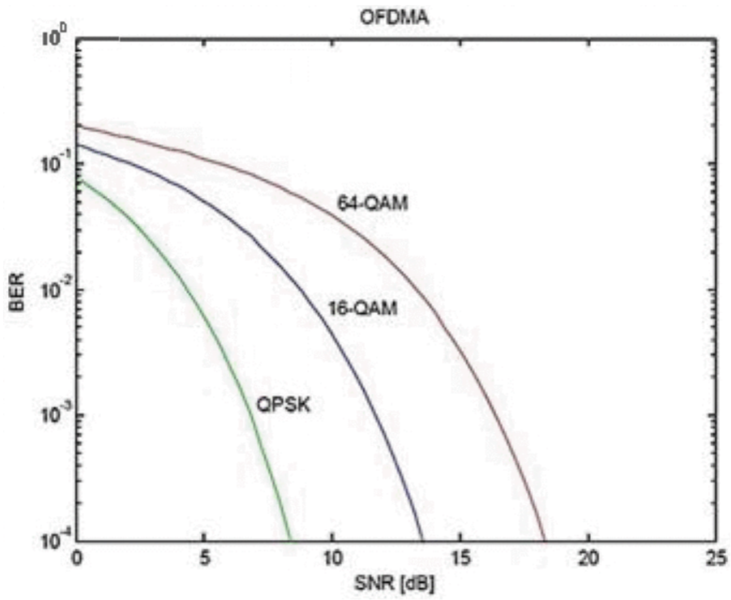


Figure 5.3: SNRdb vs BER for different Modulation Schemes [140]

This is further verified by examining the graphs presented in [141], as seen in figure 5.4.

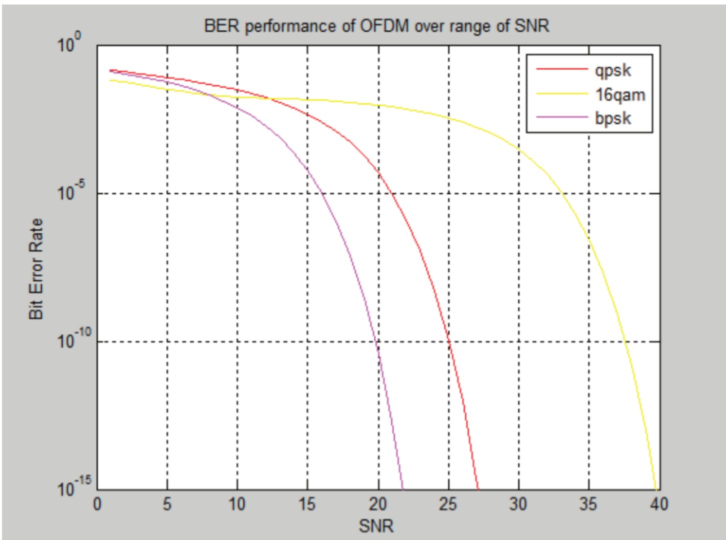


Figure 5.4: BER performance of OFDMA over range of SNR [141]

5.5 Impact of Distance on MOS

An eNodeB in the 4G network is designed to have a range of 100 km. However, this would depend on the Physical Random Access Channel (PRACH) setup and also the UE hardware. In this experiment, the PRACH preamble format of 1 is implemented which would provide for a maximum cell range of 78km. A 5.9% drop in MOS is observed between 15km and 50km range, which is the biggest drop seen in Figure 5.5. However, considering that even the value of 3.986 for MOS at 75km range is still an acceptable quality, it is evident that as long as the UE has sufficient transmit power, cell range will not have a significant impact on QoS. This is perhaps partially backed up based on the lack of literature available linking distance with MOS or other performance parameters of LTE networks such as SNR and BER.

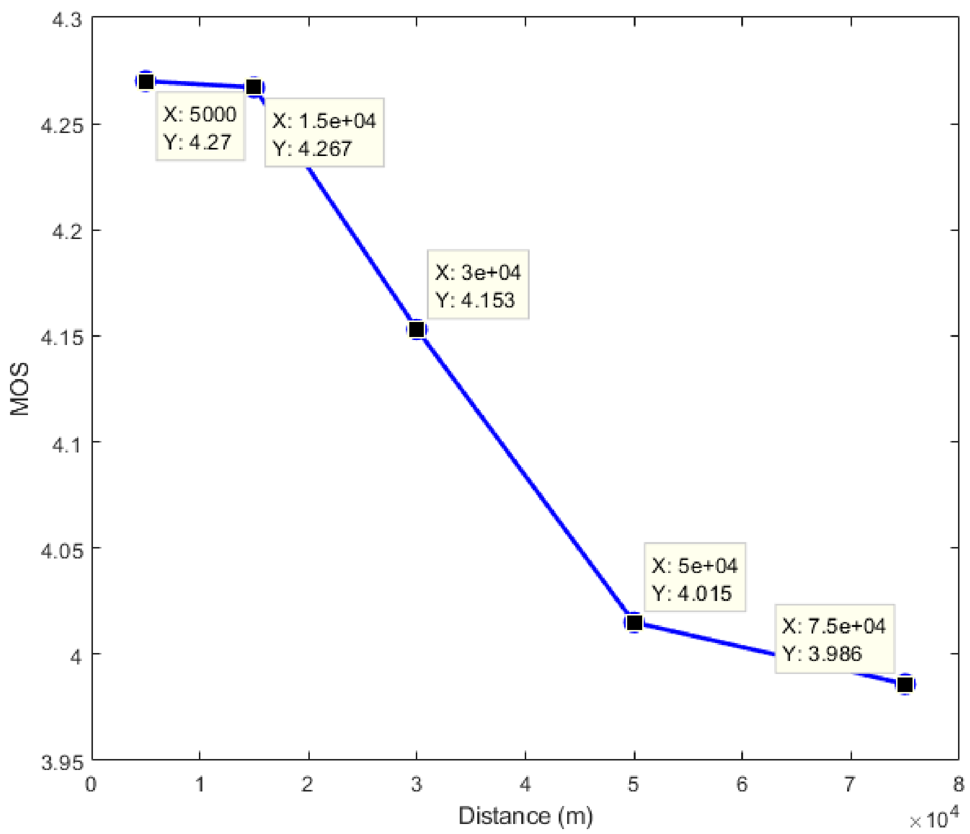


Figure 5.5: Distance vs MOS

5.6 Impact of Speed on MOS

In recent years, the High Speed Train (HST) condition has become more popular, and LTE was designed to operate at speeds of up to 500 kmph [136, 137]. Referring to Figure 5.6, negligible drop in MOS is observed in speeds of upto 100 kmph. There is a more significant drop in MOS in speeds above 100 kmph upto 300 kmph and marginal difference from 300 kmph to 450 kmph. There is no previous work that links UE travel speed to voice QoS, hence it is difficult to measure the correlation of this to literature.

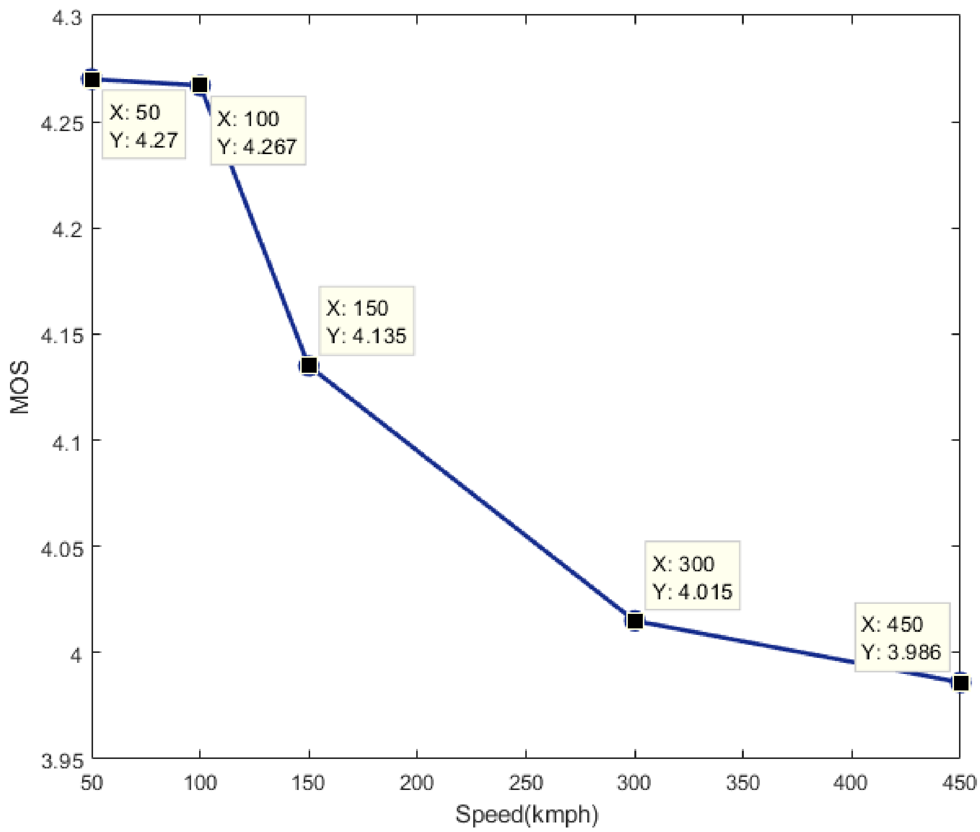


Figure 5.6: Speed vs MOS

There is no previous work directly mapping velocity in LTE networks to QoS MOS. However as identified by Meesa-ard et al. [143], examining figure 5.7 it was observed that the increase in velocity of UE was linked to degradation of both SNR and Bit Error Rate (BER) in the channel.

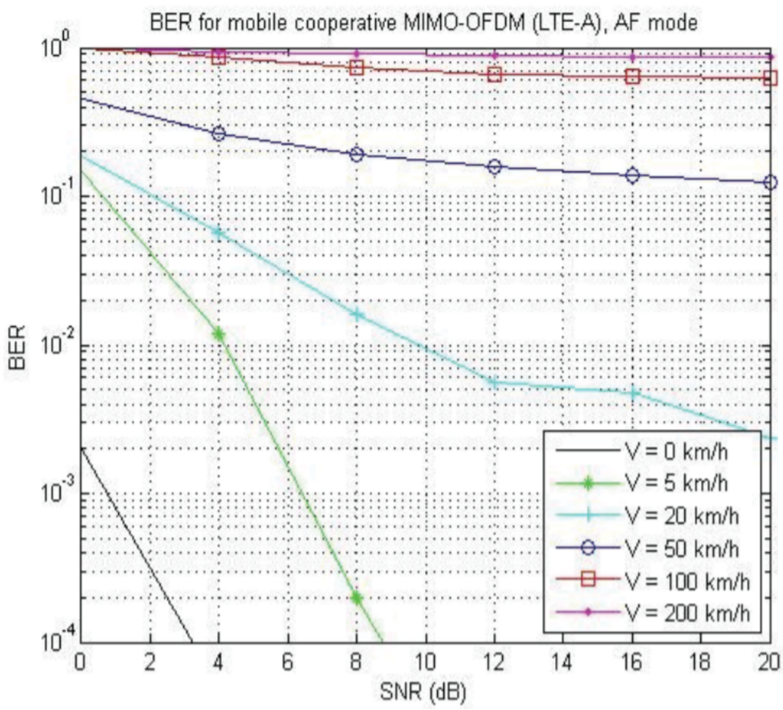


Figure 5.7: Mobile LTE-A performance; Relation between Velocity, SNR and BER [143]

5.7 Summary

Considering the outcomes of the experiment, it was observed that AWGN had the most significant impact on MOS which was expected, since SNR has a severe impact on any telecommunications system. Examining the researched literature presented in Chapter 2, it becomes clear that generally delay, jitter, throughput and packet loss are parameters that have the most impact on MOS. There is ample literature confirming this and some have even created models to measure QoS based on these parameters. This is accepted as a general consensus, for any type of network, whether LTE radio networks or ground IP networks. However, there is no previous work considering the impact of LTE-specific parameters on MOS, such as those discussed in this thesis, and no model exists to link them to QoS.

Chapter 6

Use of Neural Networks for non-intrusive objective measurement of QoS

6.1 Introduction

In chapter 2, common methods of QoS measurement were introduced accompanied by a comparative analysis of the said methods. Also, in section 2.13, importance of QoS monitoring was highlighted and important voice QoS affecting parameters were identified based on extensive literature research. Given the nature of the experiment defined in Chapter 4, and literature findings presented in 2.17, since the experiment provides us with inputs and outputs, a supervised machine learning solution would be an appropriate choice. By considering relevant literature on neural networks in section 2.19, Artificial Neural Networks (ANNs) and Random Neural Networks (RNNs) were identified as suitable solutions to non-intrusive prediction of MOS in LTE networks. Application of these methods in traditional VoIP networks has shown promising results and therefore made it an appropriate choice for measuring QoS of voice vectors in LTE networks. To develop a neural network based on the obtained results (presented in chapter 5), ANNs with the Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms, and RNN with Gradient Decent algorithm were used. This chapter discusses the mentioned methods, offers plots that contain training, validation and testing results and also presents a comparison of the used algorithms. Each of these algorithms was trained using 4, 10, 20 and 100 hidden layers. Mean Squared Error (MSE) plots for each of these scenarios was recorded and presented here for comparison. Also in order to make a valid comparative analysis between the methods, in all scenarios, 62 test conditions out of the 125 were used for training and 63 were used for validation and testing. Finally in the summary section, the most suitable algorithm and setup is identified based on comparison.

The procedures by which neural networks are used to generate a model for QoS prediction illustrated in Figure 6.1. The data is used for training, validation and testing, using different algorithms and several architectures (variations explained in this chapter). This would create a model and is then evaluated based on MSE and regression.

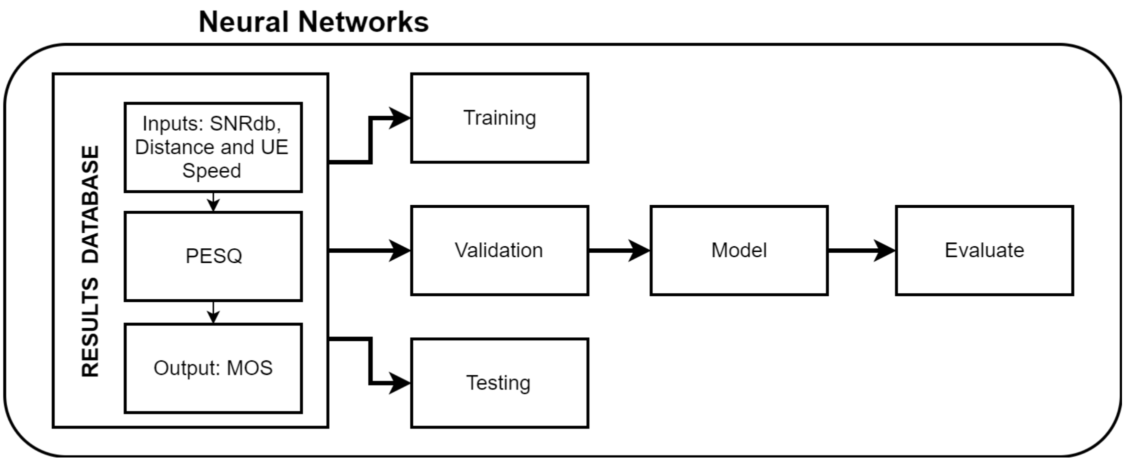
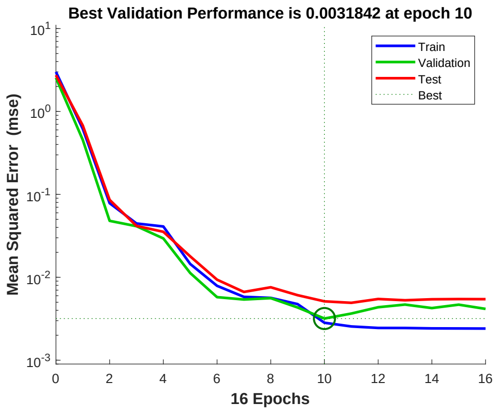


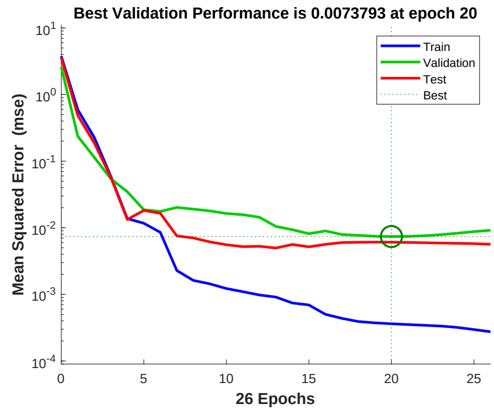
Figure 6.1: Data Processing and Model generation using Neural Networks

6.2 Artificial Neural Networks (ANN)

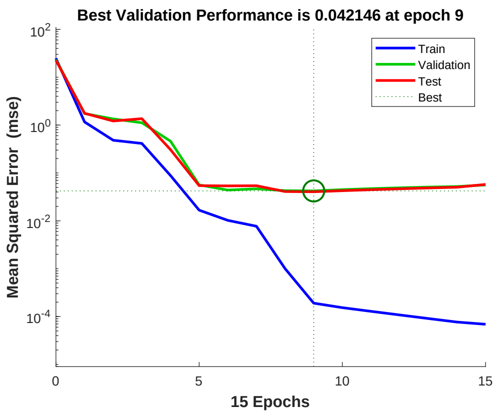
In Figure 6.2, the Mean Squared Error (MSE) plots for the 4 scenarios are shown. The best performance of training, validation and testing with the LM algorithm was observed in the scenario with 4 hidden nodes (Figure 6.2a).



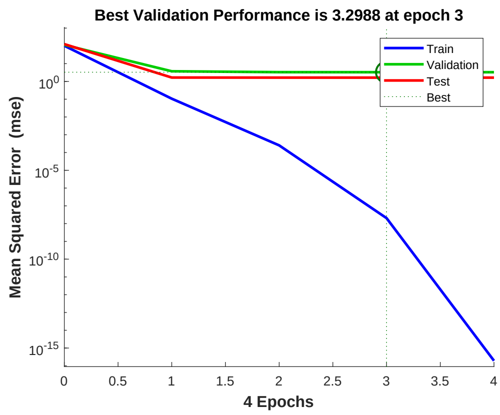
(a) LM with 4 hidden neurons



(b) LM with 10 hidden neurons



(c) LM with 20 hidden neurons



(d) LM with 100 hidden neurons

Figure 6.2: Collection of MSE plots for LM training with 4, 10, 20 and 100 hidden neurons

In reference to Figure 6.2a, at epoch 10, the best validation performance was reached at 0.0031842. It is also evident that the MSE value for training, validation and testing data sets is marginally close throughout all 16 epochs as well as epoch 10. Looking at Figure 6.2b, LM with 10 hidden neurons had its best performance at epoch 20 with 0.0073793, which is slightly higher than the performance in Figure 6.2a. In Figure 6.2c, the best performance was reached only after 9 epochs, but an MSE of 0.042146 is considerably higher than those observed in Figure 6.2a and 6.2b. It is generally expected that $0 < MSE < 1$, and the ideal would be to have an MSE value as close to 0 as possible. Therefore, the MSE of 3.2988 calculated for LM implementation with 100 hidden neurons represents a very high level of error and hence not an acceptable model. Further examinations on Figure 6.2, identifies that due to over-training, in Figure 6.2b 6.2b and 6.2c, the MSE for the training dataset is close to 0, but the validation and testing data sets show a much higher MSE when compared to the training set.

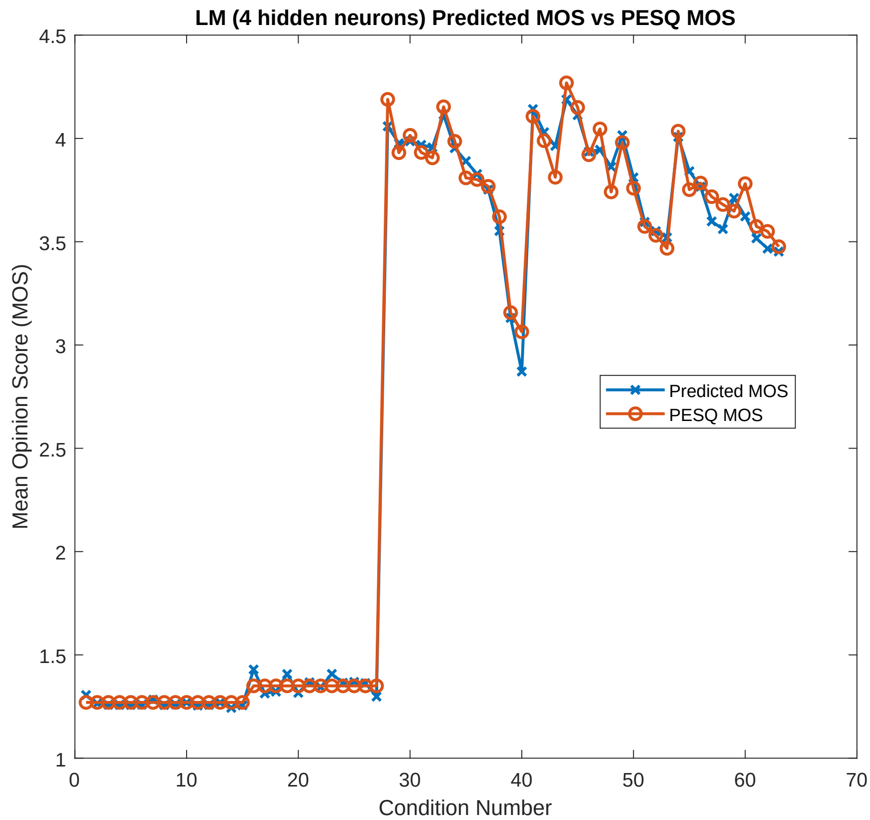


Figure 6.3: LM Predicted MOS vs PESQ MOS (4 neurons in hidden layer)

In Figure 6.3, the red line represents the MOS value calculated using PESQ (from the experiment) and the blue line with cross markers represents the test values calculated by the LM neural network with 4 neurons in the hidden layer.

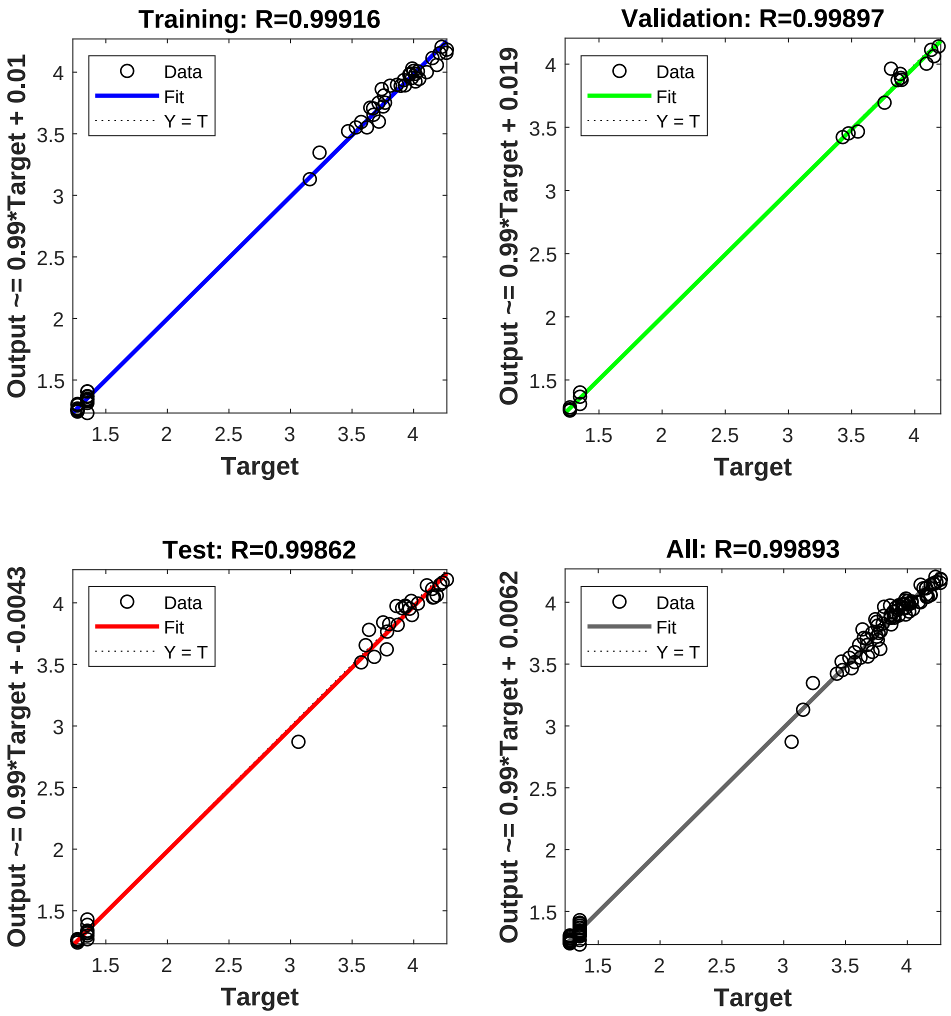
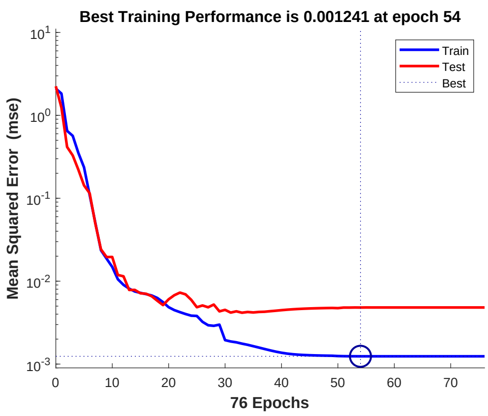


Figure 6.4: LM regression plots (4 neurons in hidden layer)

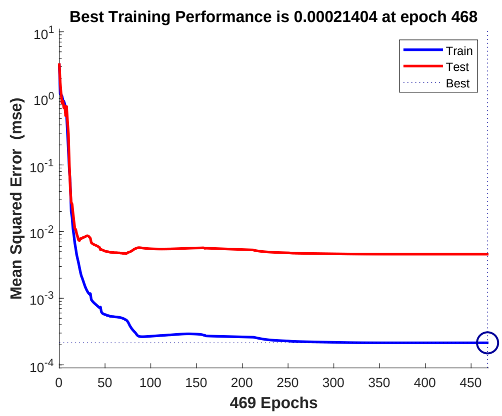
As seen in Figure 6.3 and confirmed by examining the regression values given in Figure 6.4, the LM algorithm with 4 neurons in the hidden layer has proved a suitable choice for the solution with an overall (Training + Validation + Testing) regression value of 0.99893.

6.2.1 Bayesian Regularization (BR)

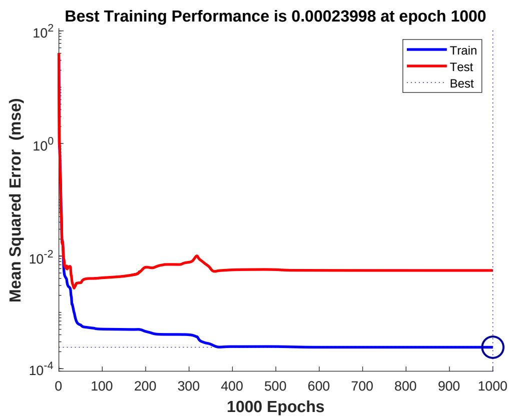
Figure 6.5 is a collection of MSE plots for the 4 scenarios trained with BR algorithm and sigmoid symmetric transfer function. in Figure 6.5a, with 4 hidden neurons, the best MSE for the training data is reached at epoch 54 as 0.001241. Here, a relatively larger gap is observed between the training and testing MSE, when compared to the same scenario using LM. Figures 6.5b, 6.5c and 6.5d respectively have performances of 0.00021404, 0.00023998 and 0.000063738 which are theoretically, better than the MSE value observed for Figure 6.5a, however further examining Figure 6.5, identifies a large gap between the testing and training data sets, which suggests over-fitting.



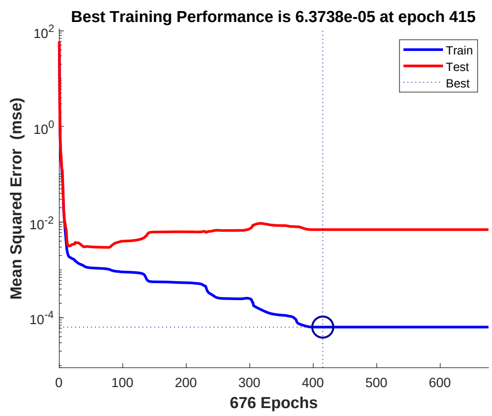
(a) BR with 4 hidden neurons



(b) BR with 10 hidden neurons



(c) BR with 20 hidden neurons



(d) BR with 100 hidden neurons

Figure 6.5: Collection of MSE plots for BR training with 4, 10, 20 and 100 hidden neurons

Also looking at the first spike in the testing MSE line (red line) in Figure 6.5c, over-training could be a possibility. The training MSE plot in Figure 6.5d, had the best performance at epoch 415 (0.000063738), however, the testing MSE at epoch 415 is considerably higher, and closer to the same values of Figures 6.5b and 6.5c. It is evident from the information obtained by examining the MSE plots, and maintaining that less number of hidden neurons equates to less time-consuming and complex calculations, BR with 4 hidden neurons in the hidden layer is an appropriate candidate for the solution.

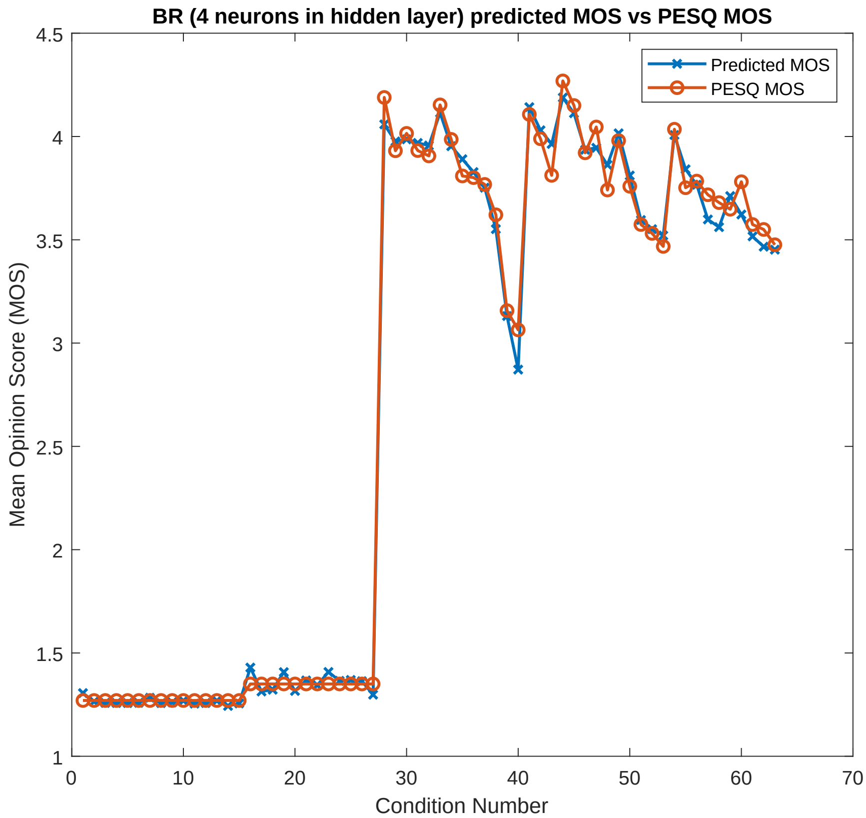


Figure 6.6: Bayesian Regularization with 4 neurons in the hidden layer, Predicted MOS vs PESQ MOS

While examining Figure 6.6, and comparing it to Figure 6.3, there is no noticeable difference.

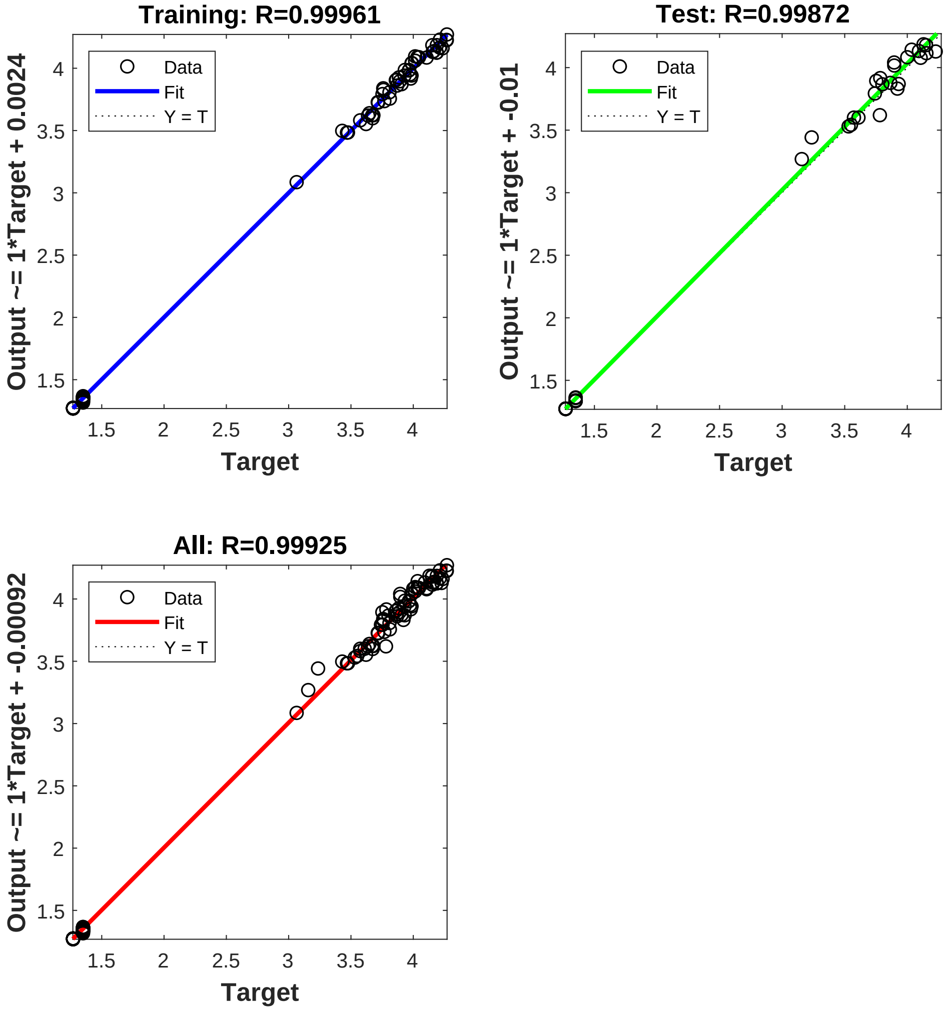
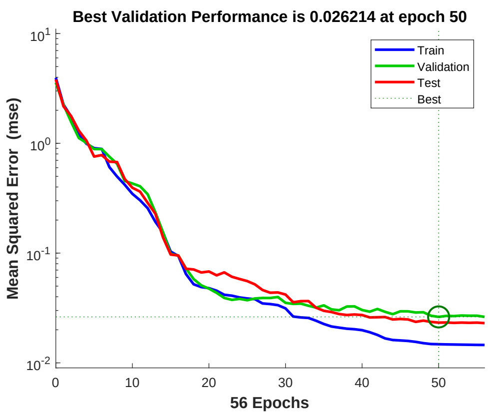


Figure 6.7: BR regression plots (4 neurons in hidden layer)

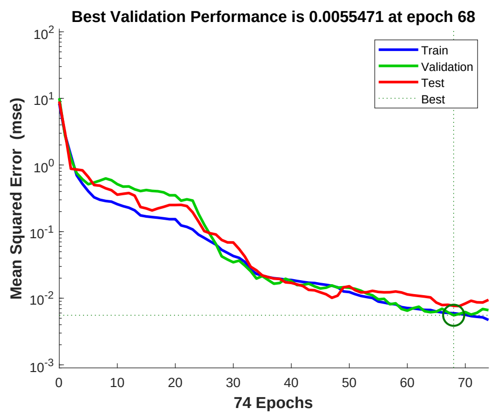
This is also confirmed by observing Figure 6.7. Comparing the R value for all data sets in LM and BR respectively gives 0.99893 and 0.99925. This comparison shows only a 0.03% improvement in using BR.

6.2.2 Scaled Conjugate Gradient (SCG)

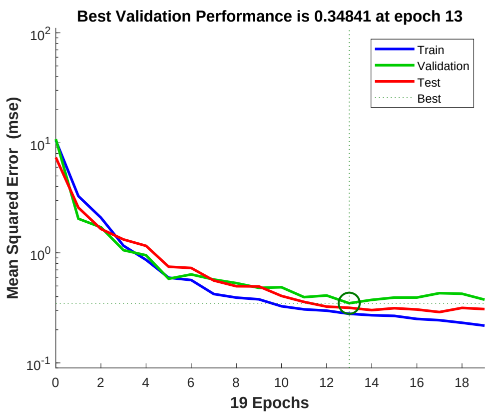
The last ANN algorithm discussed in this chapter, SCG, had the worst overall performance out of the three. Referring to Figure 6.8, a closer correlation of MSE plots is observed between training, validation and testing data sets. Out of the four scenarios, SCG with 10 neurons in the hidden layer had a better performance with the minimum MSE of 0.0055471 at epoch 68. SCG with 4 hidden neurons in Figure 6.8a, also had a desirable MSE of 0.026214. The validation and testing data sets at epoch 50 have similar MSEs, the training data set shows a much lower MSE (close to e^2), which could potentially be due to over-fitting.



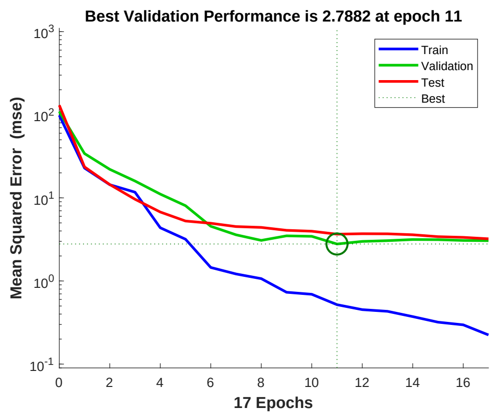
(a) SCG with 4 hidden neurons



(b) SCG with 10 hidden neurons



(c) SCG with 20 hidden neurons



(d) SCG with 100 hidden neurons

Figure 6.8: Collection of MSE plots for SCG training with 4, 10, 20 and 100 hidden neurons

Although the obtained results from SCG's performance were not as favourable as those of LM and BR, Figure 6.9, shows a close correlation between the MOS calculated using SCG's neural network and PESQ MOS.

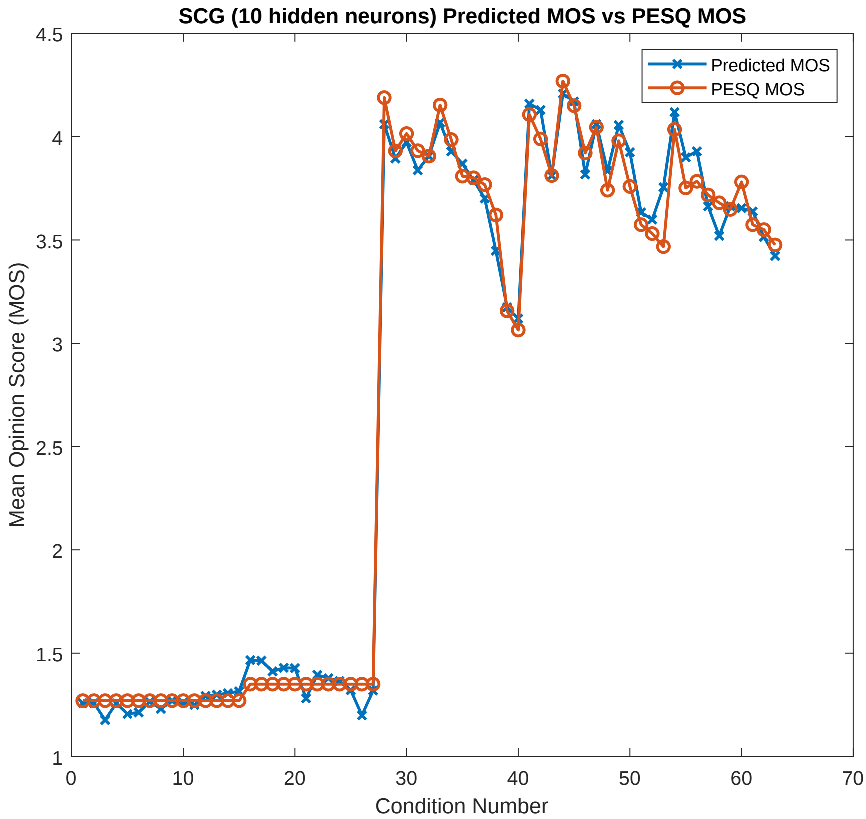


Figure 6.9: Scaled Conjugate Gradient with 10 neurons in the hidden layer, Predicted MOS vs PESQ MOS

Also to corroborate this, the regression plots for SCG with the 10 hidden neuron scenario is presented in Figure 6.10. The combined (training, validation and testing datasets) R value for this scenario is $R = 0.998$, which is only marginally different from the R values associated with the selected LM and BR scenarios.

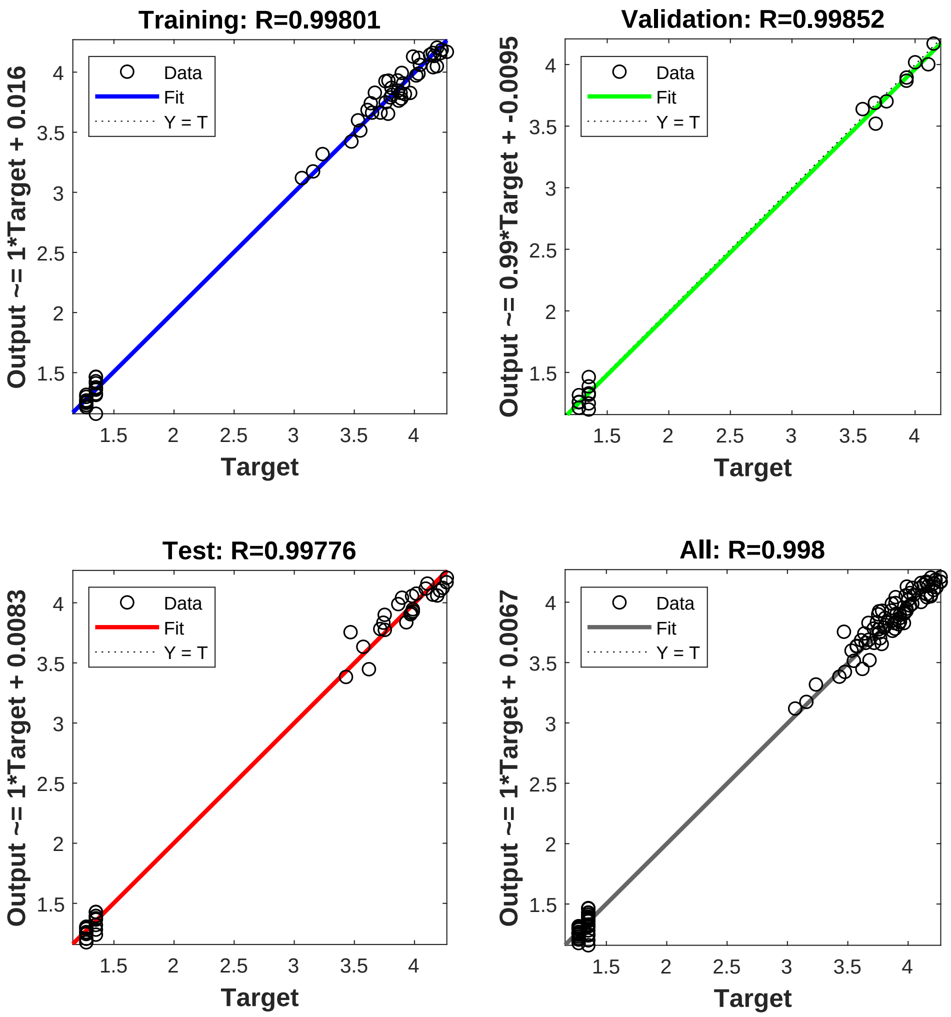
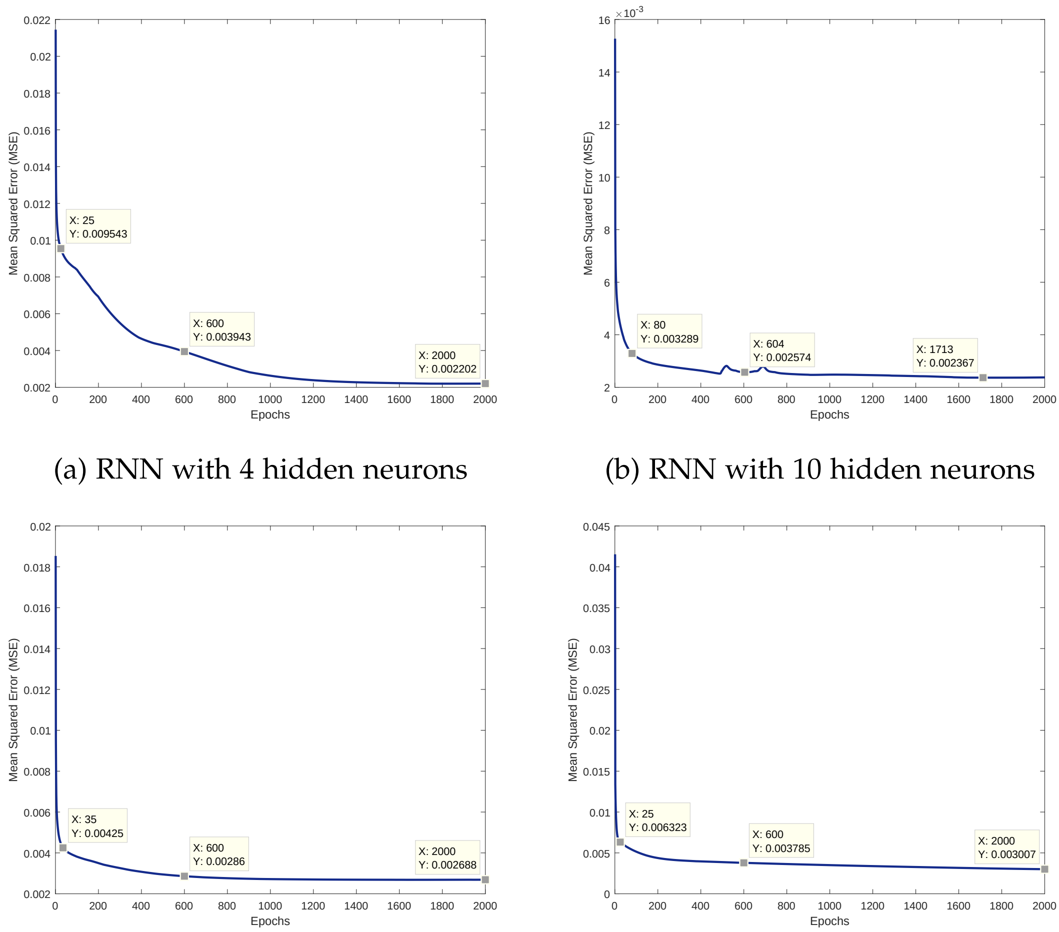


Figure 6.10: SCG Regression plots (10 neurons in hidden layer)

6.2.3 Random Neural Networks (RNN)

The RNN method with Gradient Decent (GD) algorithm was used to train networks with the same scenarios as those used in LM, BR and SCG (discussed in section 6.1). Figure 6.11, illustrates the MSE plots for each of these scenarios. Although, the MSE values are very close in all scenarios, examining the plots identifies that RNN has been most effective when running with 4 neurons in the hidden layer.



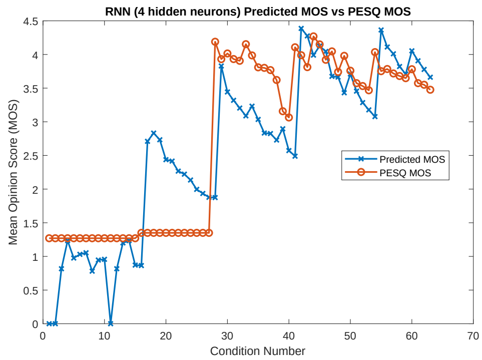
(a) RNN with 4 hidden neurons (b) RNN with 10 hidden neurons

(c) RNN with 20 hidden neurons (d) RNN with 100 hidden neurons

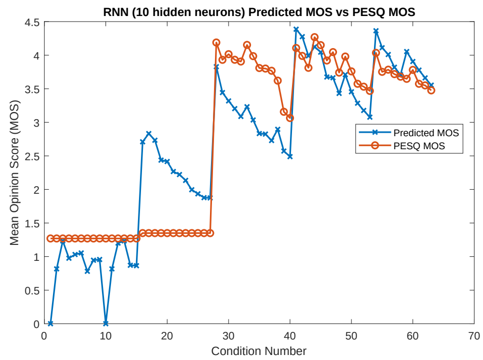
Figure 6.11: Collection of MSE plots for RNN training with 4, 10, 20 and 100 hidden layer neurons

It becomes clear that compared to LM, BR and SCG, RNN is an unfitting choice for this problem. Although the MSE value presented in Figure 6.11a seems somewhat appropriate at $MSE = 0.002202$, this is only the MSE for the training data set. The MSE for the testing data set was separately calculated at $MSE = 0.3254$, which is too high, especially relative to the training data set MSE.

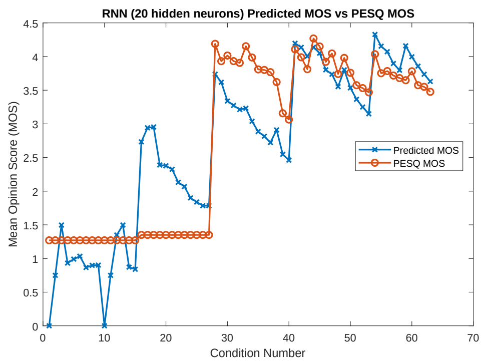
Referring to Figure 6.12, substantiates the above finding further. It is clear that in all four scenarios, the performance has been somewhat similar, however, in the first 30 conditions, there is very little correlation observed.



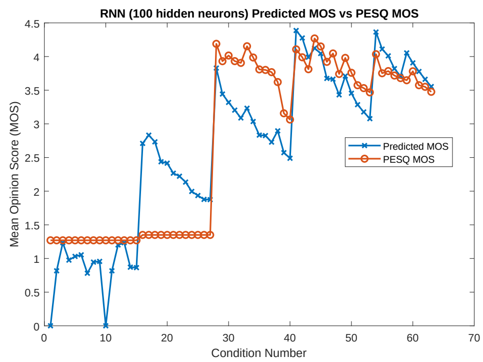
(a) RNN vs PESQ (4 hidden neurons)



(b) RNN vs PESQ (10 hidden neurons)



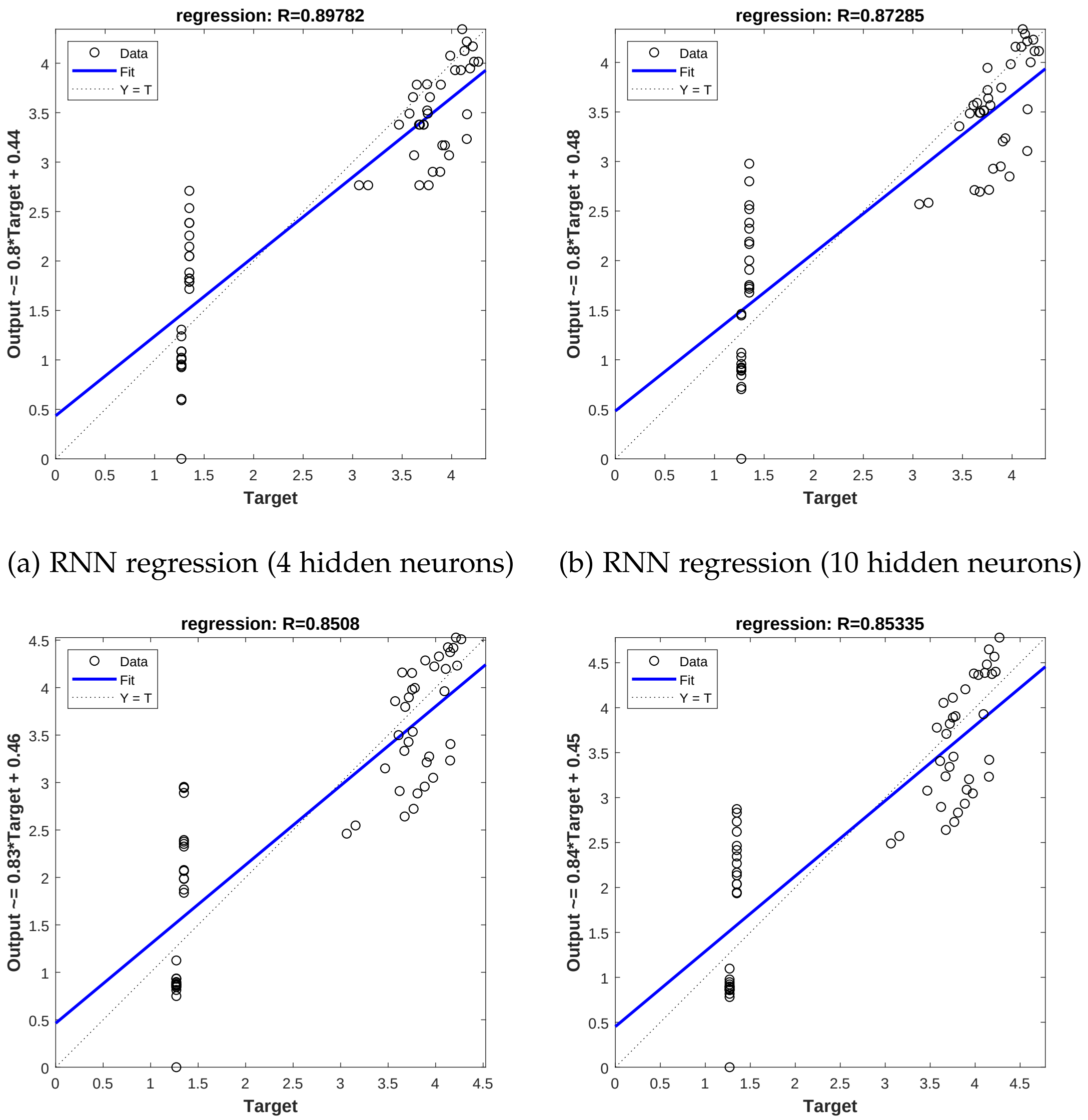
(c) RNN vs PESQ (20 hidden neurons)



(d) RNN vs PESQ (100 hidden neurons)

Figure 6.12: Comparison of RNN MOS vs PESQ MOS in four scenarios

To perform a thorough comparative analysis, the regression plot has also been presented in Figure 6.13. The best R value observed has been $R = 0.89782$, which is significantly lower than that of ANN solutions.



(a) RNN regression (4 hidden neurons)

(b) RNN regression (10 hidden neurons)

(c) RNN regression (20 hidden neurons)

(d) RNN regression (100 hidden neurons)

Figure 6.13: Collection of regression plots for RNN training with 4, 10, 20 and 100 hidden layer neurons

6.3 Performance comparison of tested NN algorithms

To make it easier for the reader, and to sum up the chapter's findings, Table 6.1 is presented as follows:

NN Type/Algorithm	Testing Data Set MSE	Testing Data Set Regression
ANN/Levenberg-Marquardt	0.0031842	0.99862
ANN/Bayesian Regularization	0.001241	0.99872
ANN/Scaled Conjugate Gradient	0.0055471	0.99776
RNN/Gradient Descent	0.3254	0.89782

Table 6.1: Comparison of Neural Network Types'/Algorithms' Performance

Referring to Table 6.1, Bayesian Regularization has the best performance out of the four algorithms. However the difference between BR and LM is marginal and both are strong candidates for use in such fitting problem. When choosing the algorithm, it would be advisable to consider that BR goes through more complex calculations and usually takes longer to train than LM. SCG's performance is also suitable, but RNN had a very high MSE in the testing data set, making it unfit for the purpose of this project.

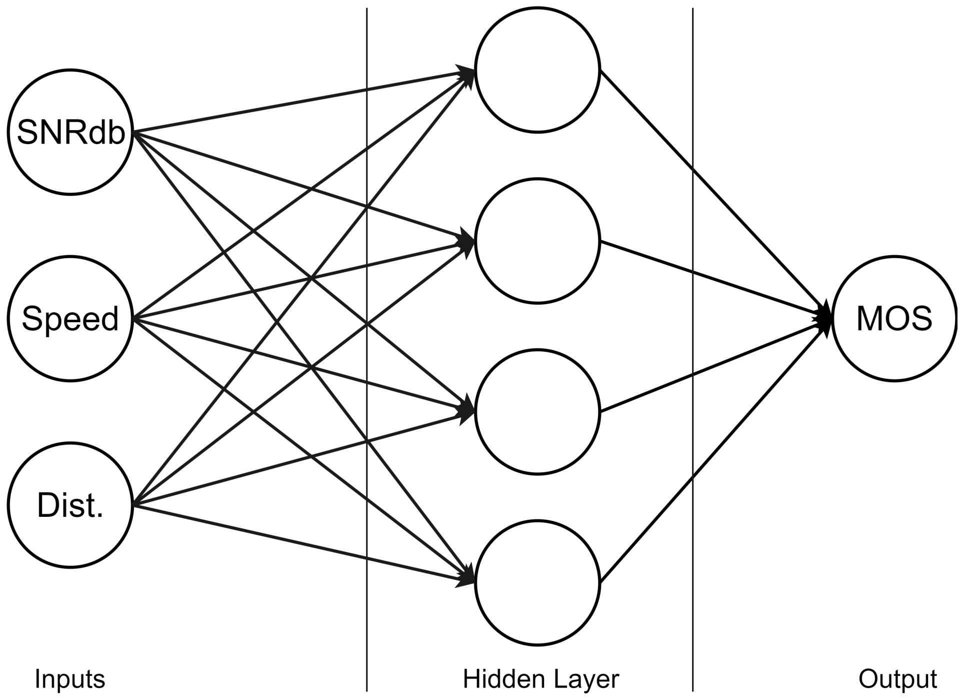


Figure 6.14: Proposed Neural Network Configuration for Bayesian Regularisation algorithm

Using the analytical approach, based on the outcomes presented in this chapter as summarized in table 6.1, it is proposed that the model which was created using the Bayesian Regularization algorithm with the architecture outlined in figure 6.14 is suitable for measuring QoS of voice vectors in LTE networks in real-time or for prediction of QoS to be used by Service Providers in infrastructure planning and deployment.

6.4 Summary

This chapter examined four NN architectures (3 ANNs and an RNN) for the purpose of introducing a non-intrusive method for measurement of QoS MOS in LTE networks. The data which was used to train, validate and test these NN architectures was comprised of three input values (SNRdb, Speed, Distance) and one output (MOS). This is also presented in Figure 6.14. ANNs were considered with Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient as well as an RNN approach using the standard Gradient Descent algorithm. The chapter offered some background on each of these algorithms and presented performance plots (MSE vs epochs), Correlation plots (predicted MOS vs PESQ MOS) and Regression plots for each of the chosen algorithms. These graphs were interpreted and comparisons were made to understand which algorithm is best suited for the solution. Ultimately, Bayesian Regularization with 4 neurons in the hidden layer proved to be superior to other considered algorithms and architectures, which led to development of a non-intrusive objective method for predicting and measuring QoS of voice transmissions in LTE networks. This method capable of predicting and measuring voice QoS accurately using only non-IP LTE-specific parameters and is suitable for use by service providers for the purpose of network planning and design as well as network maintenance once deployed.

Chapter 7

Conclusions and Future Work

7.1 Introduction

Voice traffic makes up a major portion of computer networks traffic. LTE is an emerging technology which includes standards for 4G and post-4G cellular networks. The primary method for measuring voice QoS is use of subjective MOS. However due to the time-consuming and costly nature of subjective tests, various objective methods have been developed over the years that calculate MOS by comparing the received voice signal to the reference signal and measuring the degradation. These objective methods highly correlate to subjective MOS results, however due to their intrusive nature, they are not suitable for monitoring live traffic. The main aim of the thesis was to identify key parameters that affect QoS and to develop a non-intrusive method to evaluate and monitor the QoS of voice traffic in LTE networks using neural networks based on LTE-specific parameters.

Section 7.3 presents a summary of contributions and conclusions based on the thesis findings, and possible future works are highlighted in section 7.4.

7.2 Contributions

1. **A detailed analysis of LTE network architecture and how voice transmissions are handled in LTE environments.**

   Chapter 2, critically evaluates the available literature related to LTE networks, voice transmissions in LTE networks and QoS fundamentals. Section 2.10 examines the architecture of LTE networks and demonstrates how voice is handled in this new all-IP environment. Challenges faced by communication service providers, related to how voice is handled in LTE networks are highlighted in section 2.11.

2. **A thorough analysis of the impact of IP parameters and LTE-specific parameters on voice QoS in LTE networks.**

   Before highlighting QoS measurement methods, section 2.13, gathers literature from numerous sources and critically evaluates a thorough list of possible parameters which have significant impact on QoS in general and QoS of voice traffic in computer networks which is followed by introduction of LTE-specific parameters that would impact the key common IP parameters (such as delay, jitter, packet loss and bandwidth).

3. **Design and implementation of a hardware-in-the-loop setup for testing voice QoS using two PCs, two ZedBoards and two SDRs. This design is highly customizable with LTE variables and suitable for testing voice vectors over LTE network.**

   Chapter 3, examines common LTE simulation techniques, along with their advantages and limitations. Based on these findings, in chapter 4, an appropriate method is proposed and developed to satisfy the requirements of the experiment. Detailed graphical presentations are provided to explain the full experiment processes along with transmitter and receiver designs. Chapter 4 also finalizes the input selection for the experiment based on the literature and importance of these parameters to the service provider.

4. **Produce a degraded voice database which was used for generating the data presented in chapter 5. This data was used for NN training, validation and testing.**

   A database is produced that contains the selected inputs and their corresponding PESQ MOS values in chapter 5. This database contains 125 test conditions. Each condition was tested with two different reference files and ran twice, the average of the output (PESQ MOS) was then calculated and presented as the final result.

5. **Training, validating and testing neural networks with several algorithms and identifying the best performance, which led to proposing a novel method for predicting and measuring QoS of voice vectors in LTE networks.**

   In chapter 6, the results are used for training and validating ANNs with Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient SCG, as well as RNNs with Gradient Descent algorithm. The performance of these algorithms are measured using MSE and regression plots. A comparative analysis is conducted and the appropriate algorithm is used to propose a novel method for non-intrusive measurement/prediction of voice QoS in LTE networks.

7.3 Summary of Conclusions

This thesis considered QoS of voice traffic in general, QoS affecting parameters and voice QoS parameters in traditional ground IP networks and ultimately, non-IP LTE-specific parameters that affect QoS of voice traffic in LTE networks.

A comprehensive study was conducted on common voice QoS measurement methods, investigation of their models and a thorough comparative assessment of their advantages, limitations and applications in various network types. Examining the more recent literature, and recommendations made by researchers, led to proposing a non-intrusive model for measuring QoS of voice traffic in LTE networks which overcomes the limitations of its predecessors.

To propose an appropriate model for QoS testing, several simulation techniques were identified and implemented. The most appropriate solution which was a hardware-in-the-loop model was chosen due to its superiority, based on comparisons made between the various available techniques. The proposed model was tested against the most commonly used QoS measurement method and was analysed through testing and validation using a comprehensive data set which was produced using a hardware-in-the-loop procedure.

The main contribution of the thesis is definition of a new non-intrusive method to accurately estimate the quality of voice transmissions over LTE networks. This model only uses a few LTE channel-specific parameters to predict the Mean Opinion Score (MOS) score for a given scenario, without having access to the original reference file. This is a very useful tool for Communication Service Providers for network planning and design.

Other contributions of the thesis include a comprehensive survey on QoS measurement methods, particularly the quality affecting parameters that apply to LTE networks.

A thorough understanding of voice transmission architecture and its IP and non-IP QoS affecting parameters was established by surveying the available literature which is presented in chapter 2.

A comparative study on most common solutions to simulation of voice transmissions in LTE networks, helped design a hardware-in-the-loop experiment to meet the requirements of most projects with the objective of researching voice QoS measurement methods in LTE networks.

Experiments were conducted using a hardware-in-the-loop method to collect data on a range of SNRdb, distance and speed values and the resulting MOS values in each test condition.

This data was then used to train three artificial neural network types and a random neural network. Each of these algorithms were trained with four different architectures. The performance of these models were then compared and the most appropriate method was chosen for development of a non-intrusive objective method for predicting and measuring QoS of voice transmissions over LTE networks.

The conclusion supports the aim of thesis presented in chapter 1, that it was possible to develop a non-intrusive method to measure the QoS of voice vectors in LTE networks using LTE-specific parameters as inputs.

Based on the validation and testing performed in chapter 6, the proposed method in section 6.4, is suitable for measuring/predicting QoS of voice vectors in LTE networks. The novelty of the proposed method is the input selection, network type and the model itself. There is no previous work that provides a non-intrusive method to measure voice QoS in LTE networks based on LTE-Specific parameters. This would be particularly useful for communication service providers, to aid with network planning and design.

The proposed model/solution was tested against the PESQ MOS scores and showed very high correlation as illustrated in figure 6.6.

7.4 Future Work

- **Video Traffic.**

  There has been some research in QoS prediction of video traffic in IP networks. Perhaps the same methodology used in this thesis can be applied to Video traffic over LTE networks. This would be useful due to the increasing demand of real-time video services. The applications of such model would benefit real-time video service providers (i.e. the video conferencing software) and the communication service providers.

- **A wider range of inputs for further training, validation and testing.**

  Based on the environment in which the LTE network is being deployed/extended, more LTE-specific QoS affecting parameters (such as, Tx/Rx antenna gain, Urban areas and etc.) can be considered for further training, validation and testing. In addition to a wider range of inputs, the impact of handover on MOS can also be investigated and various handover mechanisms could potentially serve as some type of input.

- **A mapping between LTE voice QoS, LTE Quality Class Identifier (QCI) and selected LTE-specific parameters.**

  As discussed in chapter 2, QCIs are used to identify suitability of network for various applications. A mapping between voice QoS and LTE network QCI could be useful for communication service providers. Possibly a number of LTE-specific parameters could be used as inputs and both the QoS and QCI values could be the outputs of the neural network model.

- **Real-time application of the proposed method**

  As elaborated earlier, the proposed objective non-intrusive QoS measurement/prediction method using neural networks is suitable for application to real-time scenarios. A possible future work would be to actually implement this solution as part of a real-time solution, potentially a hardware implementation or a software one could be considered.

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