Hybrid Computer Network Quality of Service and Experience: Development and Evaluation

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ABSTRACT

Multimedia transmission over wired and wireless (hybrid) networks is increasingly needed as new services emerge and hybrid networks become more diverse and reliable. Quantifying quality of multimedia applications transmitted over hybrid networks is valuable for measuring network performance and its optimisation. For video, the process involves examining the images that make up the video, by quantifying distortion, noise, and complementing them with traffic parameters characterised by packet delay, delay variation (jitter) and percentage of packet loss ratio (%PLR).

Processing all received packets to evaluate the quality of received application is computationally intensive. The study developed a new multi-input adaptive sampling method that allowed a subset of transmitted packets to be chosen according to variations in three synchronised traffic parameters inputs. The method integrated fuzzy logic and regression modelling of traffic parameters and adaptively adjusted the number of packets selected for processing.

Statistical and neural networks methods were developed to evaluate quality of service (QoS) for video streaming and Voice over Internet Protocol (VoIP) transmitted over hybrid networks. The traffic parameters for QoS evaluations were delay, jitter and %PLR. The work involved, Bayesian classification and probabilistic neural network (PNN) based methods to process traffic parameters. QoS. This allocation conformed to the International Telecommunication Union (ITU) recommendations. Overall, the performance of Bayesian method was better than PNN when determining QoS for VoIP. In addition, the developed methods were successfully used in practical tests to analyse QoS in the wireless standards IEEE 802.11ac and IEEE 802.11n.

QoS reflects provides information that indicates the extent the traffic parameters for an application are within the expected bounds. However, the user's perception of the received application is also relevant. This evaluation can be performed through quality of experience (QoE) analysis. For video, QoE considers issues such as image distortion and noise that in this study were quantified by structural similarity index measure (SSIM), peak signal to noise ratio (PSNR) and image difference (ID). A modular fuzzy logic-based system that individually determined QoS and QoE, then combined them to determine the overall quality of a wirelessly transmitted video was developed. The performance of the devised video quality evaluation system was compared against the subjective evaluation performed by 25 participants (i.e. mean opinion scores) and consistent results were observed. A further evaluation of the video quality evaluation system was carried by comparing its results against a recently reported video quality assessment method known as the spatial efficient entropic variation quality assessment. Again, comparable results were obtained between the two methods. The QoE evaluations were carried out both in a network laboratory and over an institutional network.

The study resulted in development a multi-input adaptive sampling method and artificial intelligence and statistical based QoS and QoE evaluation methods. The proposed schemes improved the QoS and QoE assessments for multimedia applications. The devised adaptive sampling model in comparison with random, stratified and systematic non-adaptive sampling methods was more effective as it represented the traffic more precisely. The developed two probabilistic QoS methods showed consistency in their classifications. Both models successfully classified the received VoIP packets into their corresponding low, medium, and high QoS types. Furthermore, QoE with image partitioning approach has improved QoE evaluation as partitioned image approach provided more

accurate results than full image approach. The proposed integration approach of three multimedia parameters SSIM, PSNR and ID improved accuracy of overall QoE assessments compared to single parameter approaches.

DEDICATION

I dedicate this work to:

- My mother and father, for their precious support during all my life, who devoted their life for our success.
- My lovely wife for unconditional love and enormous support.
- My kids Reham, Ehab, Firas and Ranim who make every day beautiful.
- My sister, brothers, and friends for their love, support and inspirations.

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LIST OF PUBLICATIONS

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GLOSSARY TERMS

%PLR	Percentage Packet Loss Ratio
ACK	Acknowledgment
ANN	Artificial Neural Network
AODV	Ad hoc On-Demand Distance Vector
AP	Access Point
ASQ	American Society for Quality
AVCHD	Advanced Video Coding High Definition
AVI	Audio Video Interleave
BC	Bayesian Classifier
CNF	Consistent NetFlow
DDoS	Distributed Denial of Service
DoS	Denial of Service
DSDV	Destination Sequenced Distance Vector
DVD	Digital Versatile Disc
EB	Exa-Byte
ED	Entropy Difference
EDCA	Enhanced Distributed Channel Access
ETSI	European Telecommunication Standards Institute
FE	Fast Ethernet
FIFO	First In First Out
FIS	Fuzzy Inference System
FR	Full Reference
FTP	File Transfer Protocol
GE	Gigabit Ethernet
GLM	Generalised Linear Model
GNU	General Public License
GOP	Group Of Picture
GUI	Graphical User Interface
HD	High Definition
HDTV	High-definition Television
HTTP	Hyper Text Transfer Protocol
ID	Image Difference
IDS	Intrusion Detection System
IEEE	Internet of Electrical and Electronic Engineering
IETF	Internet Engineering Task Force
IoT	Internet of Things
IP	Internet Protocol
IPTV	Internet Protocol Television
ISI	Inter-sampling Interval
ISP	Internet Service Provider
ITU	International Telecommunication Union
ITU-R	ITU Radio communication Sector
ITU-T	ITU Telecommunication Standardization Sector

LAN	Local Area Network
MAC	Medium Access Control
MANET	Mobile Ad hoc Network
MIMO	Multiple-input and Multiple-output
MLP	Multilayer Perceptron
MOS	Mean Opinion Score
MP4	MPEG Layer-4 Audio
MPEG	Moving Picture Experts Group
MSDU	MAC Service Data Unit
MSE	Mean Square Error
MSU VQMT	Video Quality Measurement Tool
NAM	Network Animator
NetEm	Network Emulation
NS2/3	Network Simulator 2/3
NTP	Network Time Protocol
OMNET	Optical Micro-Networks Plus
OPNET	Optimized Network Evaluation Tool
OSD	Distributed of Opinion Scores
OSI	Open System Interconnection
OTcl	Object Tool Command Language
PC	Personal Computer
PNN	Probabilistic Neural Network
PPP	Point to Point Protocol
PSNR	Peak Signal to Noise Ratio
QAM	Quadrature Amplitude Modulation
QoE	Quality of Experience
QoS	Quality of Service
RAM	Random Access Memory
RNN	Random Neural Network
RR	Reduced Reference
RR	Reduced Reference
RSE	Relative Standard Error
RTCP	Real-time Transport Control Protocol
RTP	Real Time Protocol
SID	Sample Interval Difference
SIP	Session Initiation Protocol
SPSS	Statistical Package for the Social Sciences
SSIM	Structural Similarity
SSRC	Synchronization source identifier
TCL	Tool Command Language
TCP	Transmission Control Protocol
UAC	Client's User Agent
UAS	Server's User Agent
UDP	User Datagram Protocol
VINT	Virtual Internetwork Testbed

VLC	Video LAN Client
VOD	Video On Demand
VoIP	Voice over Internet Protocol
VQEG	Video Quality Expert Group
VQM	Video Quality Metric
WLAN	Wireless Local Area Network

Chapter 1 Introduction

An ability to determine the quality of an audio or video sent over a hybrid (wired and wireless) network is valuable as it can assist network engineers to better allocate resources and provide network users with measures that indicate the performance of network services they receive for multimedia applications (Martin et al., 2018). For multimedia (i.e. VoIP and video) transmission, Quality of Service (QoS) is an indicator of conformance of traffic parameters such as delay, jitter, throughput and percentage packet loss ratio (%PLR) to their expected bounds for the applications (Barman and Martini, 2019) and (Díaz Zayas et al., 2018). However, the user perceptions of the quality of the received audio and video applications are also important as they are a more direct indicator of performance (Danish, 2016) and (Nourikhah and Akbari, 2016). Quality of experience (QoE) represents the user's perception of issues related to noise and image distortion during transmission. QoS parameters can be interrelated, for example insufficient bandwidth could increase delay, jitter and %PLR and they do not quantify noise and distortion that negatively affects a user's perception of applications (Tsolkas et al., 2017). According to Perlman and Wechsler (2019) and Kim and Choi (2014), when determining the performance of a hybrid network for multimedia transmission, it can be more effective to combine QoS and QoE into a single overall quality measure. In addition, networks generate a large number of packets and have a dynamic behaviour, especially for multimedia streaming (Hasan et al., 2017). Analysing each packet requires intensive processing and storage. Therefore, solutions to reduce the amount of processing by considering the dynamic changes in the network behaviour are needed (Silva et al., 2017_b, 2017_c, and 2014). The core effort of the study is to propose approaches associated with traffic sampling, determining QoS and QoE, and integrating QoS/QoE assessment processes for multimedia transmission over hybrid networks.

The focus of this chapter is to introduce a summary of the study. The motivation for the study is presented in section 1.1. Section 1.2 outlines the aim and objectives. Section 1.3 provides the main contributions, while section 1.4 outlines the organization of the research thesis.

1.1 Research Motivations

The popularity of multimedia applications supported by the exponential growth in the Internet usage has resulted in the need to improve methods of evaluating QoS and QoE for multimedia applications. According to Goścień (2019) global IP traffic will increase three folds from 2017 to 2022 and by 2022, video will account for 82% of global IP traffic (Nosheen and Khan, 2019). Moreover, mobile data traffic will continue its growth and will reach 396 EB (Exa-Byte is equivalent to one billion gigabytes) per month by 2022 (Nachabe, 2018) and (Cisco, 2019). This data traffic will be compelled by IPTV, video gaming and social networking. Furthermore, online mobile/smart devices continue to grow as the use of these devices increases. This circumstance is associated to the popularity of the Internet of Things (IoT) (Aazam et al., 2018). Service providers' focus will be on value added schemes. This trend needs to be associated with the growth of QoS and QoE assessments and assurances as offering better indicators for user's satisfaction which could lead to more competitive business and enhancing revenue (Janevski, 2019) and (Hamzei and Navimipour, 2018).

In addition, according to (Martinez Ballesteros, 2017) and (De Moor et al., 2015) there are three possible advantages that develop from combining QoE and QoS in the networks operation such as growth in the loyalty curve of the users with reduction customer churn, initiating innovative business operations integrated with customer experience administration services and cutting costs by exploiting the non-linear QoS and QoE relationship. Furthermore, (Nesse et al., 2015) claimed that service providers optimising their network for QoE distinguished services will increase their profit in the region of 10% to 15%. However, variations in QoE implementation make QoE estimate complex and unpredictable (Pokhrel et al., 2016). These trends result in focusing on multimedia QoS and QoE assessments (Pokhrel, 2014). The motivation of this study is to address some important challenges related to evaluating QoS and QoE.

In this study, the extent video and audio applications meet their transmission requirements are determined by analysing their transmission and user perception parameters. As there are challenges associated with quantifying QoS and QoE (Martinez Ballesteros, 2017), the following points summarise the issues that have been addressed in this study:

i. Networks generate a large number of packets, analysing each packet, especially in real time is computationally too demanding or may be impractical. Therefore, suitable traffic sampling techniques were developed to appropriately select representative packets for analysis QoS and QoE. Improvements in QoS and QoE evaluation are important for multimedia networks (Silva et al., 2017_b and 2014) and (Meng et al., 2017). However, networks have a dynamic behaviour and the sampling model must reflect traffic behaviour so that when traffic variations are low, the traffic sampling rate correspondingly increase and vice versa (Clarke et al., 2017), (Afek et al., 2015), (Zhu et al., 2015) and (Dogman et al., 2011, and 2010). Existing non-adaptive sampling methods may produce biased samples which may not reflect the data trend or its behaviour well (Silva et al., 2017_c). In addition, sampling model must consider measuring multiple synchronised network parameters such as delay, jitter and %PLR simultaneously to accurately determine QoS. Lack of a modular approaches such as multi-input in the existing sampling approaches reduces their accuracy in QoS assessment (Silva et al., 2017_b) and (Lin et al., 2014). This is because a single QoS parameter as input to the sampling method would not allow the transmission assessment of different multimedia applications to be considered adequately.

ii. The time sensitivity of multimedia services signifies that when traffic parameters such as delay, jitter, throughput and %PLR exceed their accepted limits, user's experience and feedback can become unsatisfactory (Robitza et al., 2017). These parameters need assessment in an effective way. However, there are several issues in evaluating QoS in multimedia applications. These include dynamic behaviour of the traffic, high traffic throughput, limited resources, variability in transmission requirements of applications and quantifying resources for gathering and processing data (Al-Turjman and Radwan, 2017). The existing QoS evaluation methods operate either by analysis or measurement techniques (Malekzadeh and Ghani, 2019), (Beritelli et al., 2016), (Van Adrichem et al., 2014) and (Jafari et al., 2012). There are limitations in the existing measurement tools, such as the process of monitoring QoS considered as complex, time consuming and do not provide an over-all transmission performance (Hoque et al., 2018), (Bujlow, 2014), (Dogman and Saatchi, 2014) and (Jafari et al., 2012). Some of these methods and techniques used the information that has been collected from headers of transmission packets which may not be enough to obtain precise QoS analysis (Robitza et al., 2017) and (Moore and Zuev, 2005). The approaches reported in (Dogman et al., 2012_a, and 2012_b) use adaptive and neural networks which required computationally intensive learning phase.

iii. The performance estimation of a lossy wireless network requires considering not just the physical network characteristics in the form of QoS, but also how they impact the customer’s applications (Zhang et al., 2018) and (Vega et al., 2014). Adaptation of QoE feedback for multimedia applications would need methods to capture/collect QoE essential information (subjective approaches) and execution of resource management which increase the cost and consume more time (Martinez Ballesteros, 2017), (De Grazia et al., 2017) and (Kim et al., 2012). On the other hand, objective video transmission assessment approaches can reduce the time and cost of the evaluation operation (Zhao et al., 2016). A drawback of existing objective QoE techniques is that, most techniques are based on structural similarity index (SSIM), video quality metric (VQM) or peak signal to noise ratio (PSNR) which do not always provide consistent assessment (Usman et al., 2018) and (Orosz et al., 2014) and (Kim and Choi, 2014). PSNR is the most widely used objective method in image and video transmission assessment. However, it has limited features and biased results (Preethi and Loganathan, 2018), (Pinki, 2016) and (Alvarez et al., 2011). Studies have illustrated that the PSNR is more sensitive to additive Gaussian noise than the SSIM, while the opposite is perceived for jpeg compression (Navarro and Molimard, 2019), (Ece and Mullana, 2011) and (Hore and Ziou, 2010). Both methods have similar responsivity to jpeg2000 compression and Gaussian blur. Furthermore, most objective QoE evaluation methods compare the received image to the original transmitted image to determine QoE. This operation requires availability of image sequence to compare the corresponding transmitted and received images accurately (Maimour, 2018). In addition, transmission impairments, aggravates frame loss which in turn leads to unpaired frame comparisons between the original and distorted images. Therefore, determining a score for an entire sequence become difficult (Sankisa et al., 2016), (Akramullah, 2014), (Pande, 2013), (Soares, 2013), (Feitor et al., 2013) and (Alvarez et al., 2011).

iv. For multimedia transmission, QoS is an indicator of conformance of traffic parameters such delay, jitter and %PLR to their accepted limits (da Hora et al., 2018), (Majedi et al., 2017) and (Alvarez et al., 2011). Nevertheless, the user perception of the quality is also relevant as it is a more direct indicator of quality (Chheda et al., 2018), (Zhang et al., 2017), (Bampis and Bovik, 2017) and (Liu et al., 2015). QoS parameters can be interrelated, for example insufficient bandwidth could increase delay, jitter, throughput or packet loss and but do not express other communication factors such as noise that negatively affects a user's perception of a video (Robitza et al., 2017) and (Fiedler and Hoßfeld, 2010). According to Vega et al. (2014) while operating with wireless networks where wireless interference and other factors impact network applications, QoS assessment on its own is insufficient and mostly inadequate. Consequently, the performance assessment of a lossy wireless network requires considering not only the physical network parameters QoS but also how these impact the customer's service (QoE). In order to assess the performance of multimedia streaming over hybrid network, it is more effective to combine QoS and QoE into a single measure (Zhang et al., 2018) and (Wang et al., 2016).

v. Most previous multimedia transmission evaluation studies developed models based on simulators or emulations testbeds. Network simulations and emulation testbeds have several limitations related to their reliability, validation and scalability limits (Roshan, 2018), (Castillo-Velazquez et al., 2017), (Riliskis and Osipov, 2013), (Petrioli et al., 2015) and (Rampfl, 2013). This study will apply all developed techniques to an institutional network setting.

1.2 Research Aim and Objectives

The overall aim is to devise a multi-input adaptive approach to optimally sample packets from of multimedia traffic and to develop methods to determine QoS, QoE and integrate QoS/QoE for assessing quality of a video transmitted over wireless networks. The objectives of the study are to:

i. Develop a multi-input adaptive sampling technique that can utilise traffic parameters; delay, jitter, and %PLR simultaneously to optimally select packets from a multimedia traffic.

ii. Develop probabilistic and neural network based approaches that utilise Bayesian and probabilistic neural network PNN to classify transmitted multimedia traffic into three corresponding QoS types: low, medium and high. In addition, evaluate the developed QoS classification with IEEE 802.11ac and IEEE 802.11n wireless transmission protocols.

iii. Develop a fuzzy logic-based QoE approach that utilises image difference (ID), Structural Similarity Index Measure (SSIM) and Peak Signal to Noise Ratio (PSNR) to quantify the quality of videos transmitted over hybrid networks.

iv. Develop a fuzzy logic-based approach that combines QoS and QoE to provide an overall quality of videos transmission over hybrid network.

v. Evaluate the developed multi-input adaptive sampling, QoS, QoE and integrated QoS/QoE techniques in a network laboratory setting and over an institutional computer network, critically analysing the results.

Table (1.1) maps the objectives and the method to achieve them to the relevant chapters.

Table 1.1 Objective, network approach and its relevant chapter

Objective	Description	Assessment Approach	Relevant Chapter
(i)	Multi-input adaptive sampling	Simulation NS2 and Emulation testbed	5
(ii)	QoS evaluation	Emulation testbed	6
(iii)	Objective QoE evaluation	Emulation testbed	7
(iv)	Integrated QoS/QoE evaluation	Emulation testbed	7
(v)	• An adaptive sampling • QoS evaluation • QoE evaluation • QoS/QoE evaluation	Large institutional network	8

1.3 Study's Intended Contributions

In relation to the study's objective, the contributions made are:

i. Developed a multi-input adaptive sampling approach that accurately represents multimedia traffic with a subset of transmitted packets according to variations of three synchronised traffic parameters inputs. The method was used to assess QoS for multimedia transmission over a hybrid network. The approach reduced the number of packets required to measure QoS. The effectiveness of the developed approach was compared against non-adaptive sample methods of random, stratified and systematic.

ii. Developed probabilistic methods to determine QoS. A Bayesian based QoS measurement approach with three parallel classifiers and a probabilistic neural network (PNN) based approach to determine QoS in VoIP traffic were developed. They classified traffic packets of VoIP to their corresponding high, medium and low QoS types. The developed QoS assessment methods only needed one iteration to calibrate or train. As they relied on a small number of parameters, e.g. PNN needed just a smoothing parameter and the Bayesian approach required only the prior probabilities for each QoS types, they proved robust and trained quickly as compared to more complex classifiers such as multilayer perceptron. The two methods were used in practical scenarios to analyse QoS in the wireless standards IEEE 802.11ac and IEEE 802.11n.

iii. Developed an objective QoE evaluation that was applied to determine the quality of a video transmitted wirelessly. The approach combined the video parameters PSNR, and SSIM with image difference ID to objectively determine the QoE for a video transmission scenario. It used a Fuzzy Inference System (FIS) that required knowledge of video quality to be coded in a series of IF-THEN rules. As part of the evaluation, image labelling to deal with frame loss, and sampling were adapted to increase accuracy of the measurements and to reduce processing time. A novel approach where the images were partitioned to more precisely localise image distortion was devised. The results obtained were analysed.

iv. Developed an integrated QoS/QoE system to compute the quality of a wirelessly transmitted video. For multimedia transmission, QoS is an indicator of conformance of traffic parameters such delay, jitter and %PLR. However, the user perception of the image quality is also important. For this propose a fuzzy inference system (FIS) was developed that combined the network QoS and objective QoE metrics. The FIS was devised to have a modular structure making its operation more transparent as well as allowing future alterations of its operation for other applications to more convenient. The results obtained when evaluating the approach on a wirelessly transmitted video streaming scenario were studied in details.

v. Evaluated the devised QoS/QoE approaches in determining the quality of video transmission over an institutional network. As simulations and emulation testbeds have several limitations related to their reliability, validation and scalability limits. In this part of the study the earlier developed techniques were applied on a real network to assess their effectiveness. The analysis was conducted by video traffic under different transmission scenarios. The results were used to analysis the relationship between overall QoS based on (delay, jitter and %PLR) and QoE based on (PSNR, SSIM and ID).

1.4 Thesis Organization

Figure 1.1 illustrates the representation overview of the thesis.

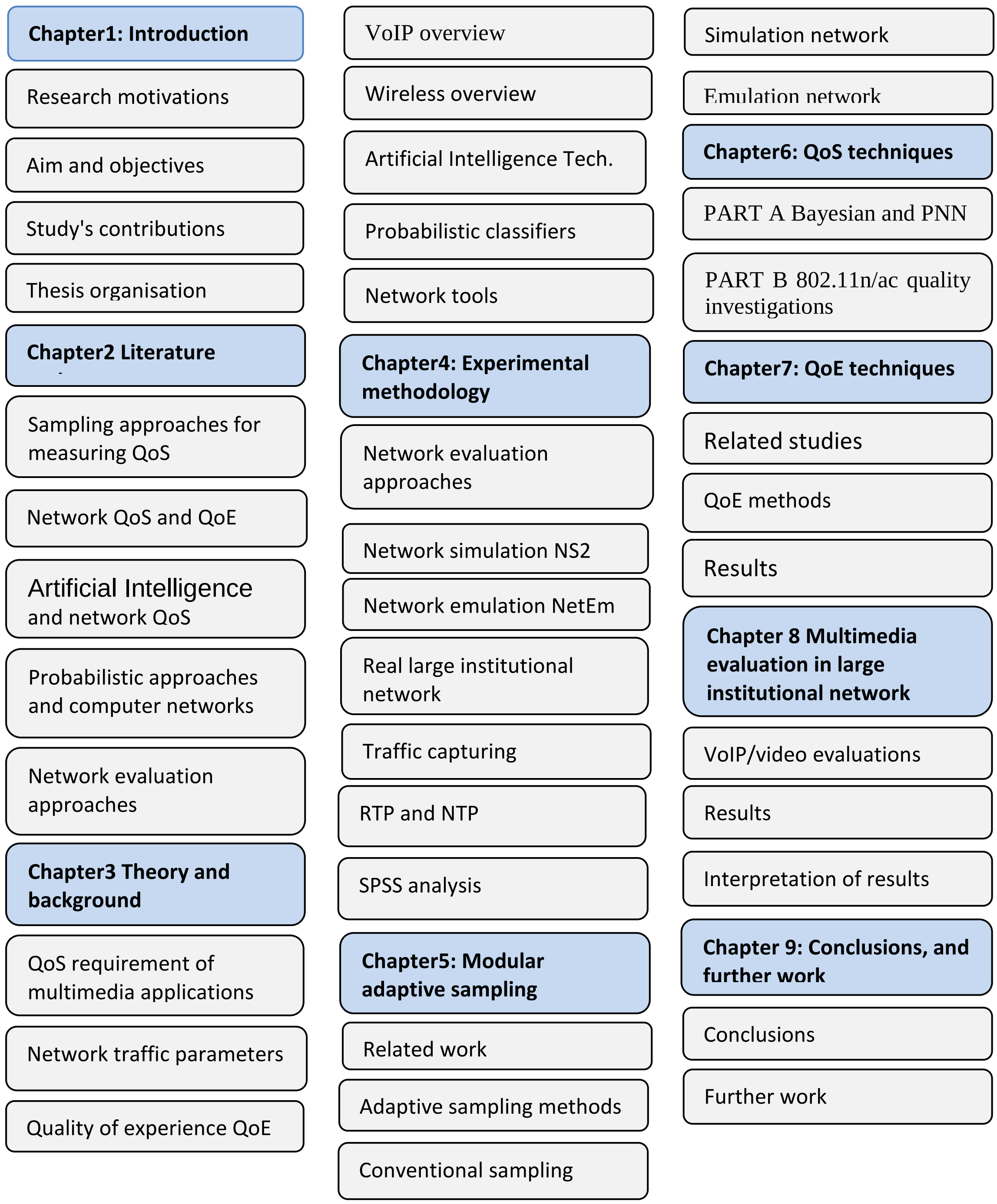


Figure 1.1 The schematic overview of the thesis

Chapter 2 Literature Review

2.1 Introduction

New generation of computing system in the form of the Internet of Things (IoT) have established into people's everyday lives. In addition, the transmission of multimedia packets related with these multimedia services through hybrid networks has created demands on quality of service management and other resources (Roy et al., 2018). Various challenges such as an increase in traffic against network capability and dynamic change in traffic parameters such as delay, jitter and percentage packet loss ratio (%PLR) can decrease the network's performance (Vega et al., 2014). In order to achieve users' expectations in an appropriate manner, functional properties of network services and its quality must be measured. To accurately and efficiently manage these networks for delivering anticipated services, suitable tools to assess their performance are required. System-level features of quality of service (QoS), like packet delay, throughput, jitter and %PLR can be used to compute and increase the QoS (de la Torre Díez et al., 2018) and (Nourikhah and Akbari, 2016). Quality of experience (QoE) can be used to compare the performance from the user perspective. An improved QoE can enhance user experience and thus be beneficial to service providers (Kim et al., 2017) and (Chen et al., 2014). In addition, networks generate a large number of packets with dynamic behaviour. Therefore, performance evaluation of these data requires intensive processing and storage which require packet sampling solutions that can be used for performance evaluation and considering the dynamic change of the behaviour.

In this chapter, the previous studies related to network packet sampling, managing QoS, QoE, and integrated QoS/QoE of multimedia network are reviewed.

The structure of this chapter is: section 2.2 sampling approaches that were used to reduce the number of packets processed to analyse traffic are discussed. In section 2.3 network QoS evaluation approaches are explained. In section 2.4 Subjective and objective QoE analysis and assessment methods are explained. Section 2.5 provides an explanation of artificial intelligence techniques for QoS. Probabilistic approaches for QoS assessment are explained in section 2.6. Network evaluation approaches are explained in section 2.7.

2.2 Sampling Approaches for Measuring QoS

2.2.1 The concept of sampling

Sampling of network packets to analyse traffic behaviour is important to reduce computational and data storage load (Tan et al., 2018), (Robitza et al., 2017), (Hofstede et al., 2014) and (Silva et al., 2013). Though multiple sampling approaches have been reported to support network engineering tasks, these approaches typically use a single traffic parameter such as delay thus not fully meeting the broad needs of multimedia applications.

Probing is an approach for carrying out network measurements, where measurements are performed by considering samples at predefined time intervals. Once the measurements are made, the probe packets are assessed against the traffic metrics (Robitza et al., 2017) and (Chowdhury et al., 2014).

The two types of samplings methods, namely passive and active measurements, have distinct features. Passive measurements adopt a nonintrusive approach, i.e. they only measure the actual network traffic for analysis. Passive probes do not typically disturb the flow of the traffic, but they monitor the traffic of interest (Robitza et al., 2017). A smaller time periods between probing packets provides finer insight into evaluating the traffic behaviour. In general, a larger number of packets provide more reliable probing results (Kaplan et al., 2014). However, producing large number of probing packets may affect the flow of the original network traffic which in turn may reduce the accuracy of measurement results (Silva et al., 2014). Therefore, a high rate of the probing sampling can have a direct effect on the network performance. To overcome this challenge, several techniques have been described for active probing measurements. According to (Silva et al., 2017_b and 2017_c), early proposals for classifying traffic sampling methods (Amer and Cassel, 1989) were advanced and standardized within the Internet Engineering Task Force (IETF), rfc5475 (Zseby et al., 2009). These proposals categorise the methods relating to the packet collection methods in use such as systematic or random sampling but ignore more developed sampling methods (Silva et al., 2017_b). The use of packet sampling for network measurements is not a new research subject. Early efforts addressed sampling methods for statistical analysis that mainly concentrated on communication systems monitoring, traffic evaluation and classification (Tammaro et al., 2012) and (Cozzani and Giordano, 1998). According to Zseby et al. (2009) sampling techniques are categorised in content dependent and content independent techniques. Their differences are related to the manner of gaining access to the packet data to make decision on capture/selection packets (Tammaro et al., 2012).

2.2.2 Non-adaptive sampling

The three conventional (non-adaptive) approaches used by network management for sampling (Meng et al., 2017), (Singh et al., 2013) and (Dogman et al., 2010, and 2011) are:

- **Systematic sampling:** or periodic which samples data at a fixed time interval and sampling triggers are periodic. The first sampled unit is chosen randomly from the first k units in a population. The remainder of the sampling units in the sample consists of every k^{th} element in the population. Sampling can be based on packet position (count based) or packet arrival time or packet contents (content based) (Singh et al., 2013) and (Tammaro et al., 2012). Figure 2.1 (a) presents systematic sampling with time interval (T).

- **Random sampling:** is based on a random procedure to select n subset packets from the original population of N packets. It employs a random distribution function such as probabilistic to define when selection should be taken as shown in Figure 2.1 (b) (Shao, 2016) and (Duffield, 2012). The delivery may be exponential, uniform, or Poisson, etc. The simple random sampling randomly selects a given number of objects from the entire population. Simple random sampling needs to guarantee each member of the population have to have the equal chance to be selected.

- **Stratified random sampling:** is combination of the systematic sampling fixed interval with random sampling by compelling a single sample at a random point during a given time interval. It is a probability sampling method that divides the population into homogeneous subgroups, called strata and selects the sample from each strata separately by applying simple random sampling or systematic sampling. There should be no overlapping data items between any two strata. Figure 2.1 (c) illustrates stratified random sampling (Shao, 2016) and (Meng, 2013).

Despite relative simplicity of non-adaptive sampling methods, they may produce biased samples which may not adequately reflect the data trend or behaviour (Silva et al., 2017_b).

2.2.3 *Adaptive sampling*

An approach for adaptive sampling is to dynamically adjust the sampling time period. When high activity occurs, a smaller period is engaged to compute the behaviour of the network with better accuracy. When a reduced traffic activity occurs, the interval is extended to decrease sampling overhead. Consequently, adaptive sampling allows the network management taking place in a less-intrusive ways by avoiding needless demands (Shao, 2016) and (Silva et al., 2013).

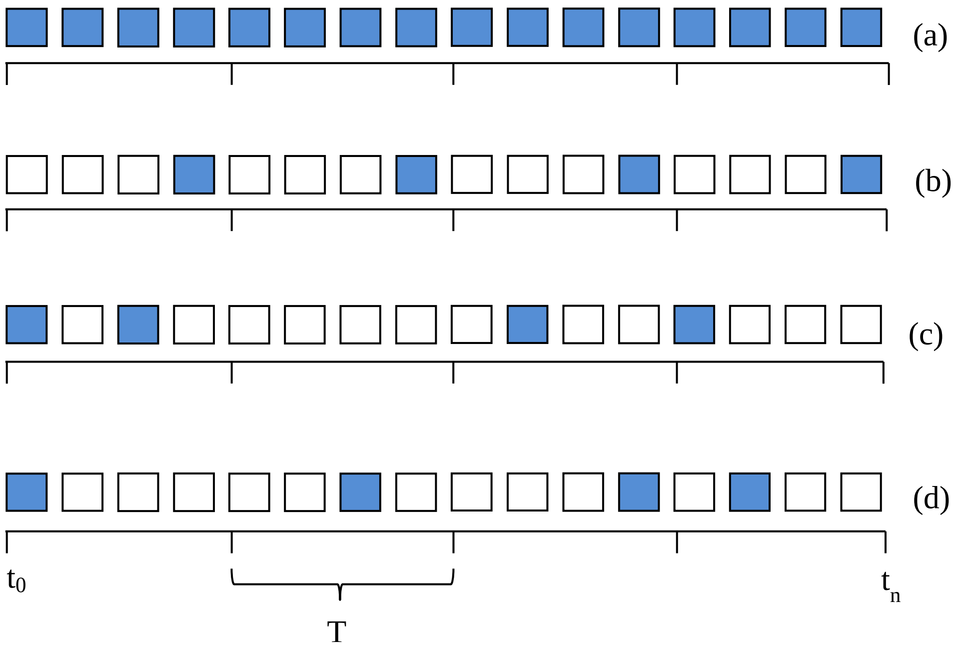


Figure 2.1 (a) Original packets (b) systematic (c) random (d) stratified random sampling with a time interval of T

Under some traffic loads, non-adaptive simple periodic sampling may be poorly suited to the monitoring task (Yoon et al., 2017). To provide enough accuracy at a minimal overhead, adaptive sampling technique has been engaged to dynamically change the interval and to reduce overhead. According to (Silva et al., 2017_b) adaptive approaches usually resort to fuzzy logic, linear prediction, or other strategies which deliberate traffic behaviour, packet data or network status for packet selection mechanism. Dogman et al. (2011, and 2010) developed techniques that adaptively adjusted the interval between two consecutive sampled sections; the developed sampling methods were developed based on simulated network. In both studies the results showed the efficiency of the approach in various scenarios. However, both studies used a single input parameter at a time which reduced its usefulness in measuring QoS.

2.2.4 *Sampling usage in technologies*

Afek et al. (2015), Silva et al. (2013) and Duffield and Grossglauser (2001) summarised sampling involvement in computer networks. The applicability of sampling in computer networks is showed in Figure 2.2.

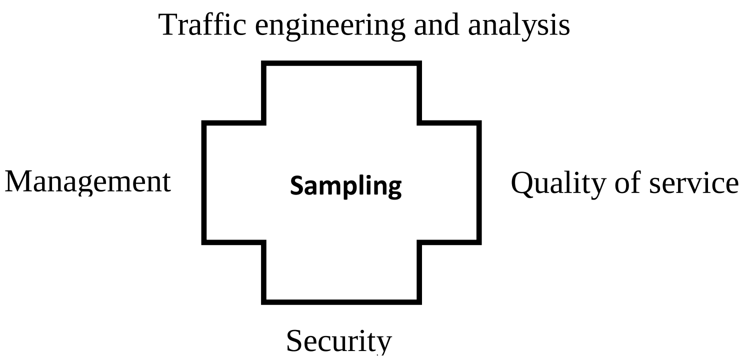


Figure 0.2 Applications of traffic sampling

Traffic sampling supports can be a part of a variety of network traffic analysis tasks. It has been used in traffic engineering to assist traffic characterization and classification (Tammaro et al., 2012). Network security such as intrusion detection, betnet, and DDoS service (Lima Filho et al., 2019), (Zhou et al., 2018), (Zhao et al., 2013) and (Androulidakis et al., 2009). Service level agreement compliance and QoS management for calculating traffic parameters such as delay, jitter, throughput and packet loss ratio (PLR) (Berec, 2019), (Jiménez et al., 2015), (Gu et al., 2009) and (Hu et al., 2008). Sampling has been used for wireless sensors network in (Silva et al., 2017_a) for its ability to analyse traffic behaviour and to reduce overhead of sensing events, without compromising accuracy.

Several studies used sampling for network analysing and measurements (Clarke et al., 2017) and (Shao, 2016). According to Nikolopoulos et al. (2019) network components can deal with sampled packets better. The study proposed packet-sampling algorithm that enabled network assessment estimations with measurable accuracy and was robust to such components prioritization. The proposed algorithm produced receipts for small sampled packets, and an independent monitor collected and used them to estimate the domain's mean packet loss and delay measurements. The algorithm optimised the biased samples to improve its perceived performance. Gu et al. (2009) proposed a new estimation method that did not require any measurement infrastructure or new router features. It relied on use of the sampled flow level measurements that were consistently gathered in operative networks.

Several studies have used sampling for traffic monitoring (Queiroz et al., 2019). For example, Braun et al. (2013) proposed an algorithm for traffic monitoring system and deep packet inspection (DPI) to analyse network traffic. The study proposed an adaptive sampling model that selected maximum number of packets that the DPI system was able to process, the model adapted the sampling rate based on currently observed network traffic and the number of packets that a monitoring application was able to process. The model overcame limitations by dynamic sampling limit. This sampling limit was automatically changed to match real-time events such as packet rate variation or packet consumption rates of the monitoring application. Hu et al. (2008) reported sampling in computation schemes to control memory consumption and reduce overhead processing. The study proposed adaptive sampling for passive measurement to address the issue of outsized gathered errors in analysing small-size flows. The proposed model improved the estimation accuracy while preserving memory and processing overhead. Another study for sampling in network monitoring, Lee et al. (2011) proposed a model Consistent NetFlow (CNF) for quantifying per-flow latency amounts within routers. The proposed CNF used the current NetFlow model that reported the initial and last timestamps of the flow, and it plans hash-based sampling to guarantee that two neighbour routers record the same flows. The proposed model estimates the intermediary delay samples from other related flows to enhance the per-flow delay.

There were several studies to develop sampling in network security related applications such as denial of service attack (DOS). These include, (Wu et al., 2016), (Wu et al., 2015) and (Goldberg and Rexford, 2007). In a study regarding sampling for cyber security, Yoon et al., (2017) considered the practical problem concerning how to attain scalable traffic measurement using Software-Defined Networks (SDN) functionalities. As traditional network traffic monitoring has limited access to core and edge switches while less intrusive traffic monitoring can be done by using a packet sampling model that probabilistically captures packets at switches, then sampled packets is directed toward a traffic analyser like IDS on SDN. The study proposed a centrality quantitative in graph theory for deciding the packet sampling points among the switches. The study of SDN simulated testbed indicated that the proposed sampling point and its decision sampling rate methods improved the intrusion detection performance of IDS for the malicious traffic flows in large-scale networks.

Despite significant research in packet sampling, most existing schemes were intensive on detailed network computation tasks, for optimising accuracy estimation of a single network approach. This scenario impedes the progress of an encompassing computation methods based on traffic sampling that maintain enormous range of network management in a scalable manner. The existing studies on sampling typically consider the effect of packet sampling on numerous network monitoring events (Hofstede et al., 2014) and (Carela-Español et al., 2011). The issues of applying sampling and analysing network measurements has been recognised (Su et al., 2018) and (Zseby et al., 2009) and effectiveness of traffic selection manners were reported (Silva et al., 2017_b), (Tammaro et al., 2012), (Carela-Español et al., 2011) and (Pescapé et al. , 2010). However, they generally do not consider new sampling methods like adaptive, which limit the analysis to the conventional methods. In addition, lack of modular adaptive methods when designating the components of traffic sampling methods also makes it challenging in their analysis. For example (Dogman et al., 2011, and 2010) adaptively sampled one traffic parameter at a time. However, to accurately measured network QoS, at least three synchronized main parameters should be considered, namely delay, jitter and packet loss. Providing a modular vision (such as multi-input) of sampling approaches and categorising their characteristics are therefore to improve the efficiency of the computation systems.

The contribution of this study in this part is developing a multi-input adaptive sampling system that is an advancement of the existing methods. First an adaptive sampling method that deals with one input at a time was developed and published in (Salama et al., 2017_b) and (Salama et al., 2017_c). However, to increase accuracy of the sampling, a multi-input adaptive sampling method was then devised that could consider three synchronized inputs of network parameters simultaneously (i.e. delay, jitter and %PLR) (Salama et al., 2017_a) and (Salama et al., 2018).

2.3 Network QoS and QoE Evaluation Approaches

2.3.1 Concept of quality

Quality in the context of computer networks has been explained by different ways in literature. The most accepted definition is “Quality is the degree to which performance meets expectations" (Mansouri et al., 2016). Another description accepted by the American Society for Quality (ASQ) is, "Quality denotes an excellence in goods and services, especially to the degree they conform to requirements and satisfy customers" (Nguyen, 2013). It can be said that the generally known perception of quality nowadays includes objective mechanisms of determining and guaranteeing dimensional constancy with detailed values, for example for a system, product or a business (Wang et al., 2016). In practical networks, the main parameters associated with the network performance are delay and packet loss (Juluri et al., 2015).

2.3.2 Concept of quality of experience in telecommunications

Over recent years, the term QoS emerged as key description for identifying the transmission quality of packets based switched network such as Internet Protocol (IP) networks and circuit switched networks (Stanojević et al., 2018). QoS classifications have been considered in numerous contexts. However, recently, many new models have been reported for interpreting quality in applicable sense that includes human perceptions (Nguyen, 2013). In general, most QoE explanations indicate that QoE is subjective based on human opinions. According to Information Resources Management Association (2017) "QoE, is a subjective measure of a customer's experiences with a vendor. It is related to, but differs from, QoS, which attempts to objectively measure the service delivered by the vendor." According to the International Telecommunication Union (ITU) "QoE is defined as the user's perception of the acceptability of an application or service" (Wang et al., 2016) and (Baraković and Skorin-Kapov, 2013).

Thus, measurement of QoE may be prejudiced by a user's pre-conceived concepts and expectations. Several studies implicate both subjectively and objectively of a user's observation measurements. For example, European Telecommunications Standards Institute (ETSI), indicates "QoE to be a measure of user performance based on both objective and subjective psychological measures of using an ICT service or product" (Mitra et al., 2014). However, recently many studies provided a more complex QoE description, in which the explanation is associated to specific areas like network transmission, content, device operations, different personality, etc. The view from the Qualinet Group is, "QoE is the degree of delight or annoyance of the user of an application or service. It results from the fulfilment of his or her expectations with respect to the utility and / or enjoyment of the application or service in the light of the user's personality and current state. In the context of communication services, QoE is influenced by service, content, network, device, application, and context of use" (Matulin and Mrvelj, 2013) and (Baraković and Skorin-Kapov, 2013).

2.4 Subjective and Objective QoE Approaches

2.4.1 Subjective approaches

Subjective assessment for visual quality were specified in ITU-R Rec. BT.500 and ITU-T Rec. P.910 (Li et al., 2018) and (Chen and Zhang, 2018) which has suggested standard observing environments, criteria for the selection of viewers and test material, assessment procedures, and data analysis approaches (ITU-T, 2008). According to Mansouri et al. (2016) subjective testing has three major disadvantages. First, it involves high financial cost, time-consuming and manual effort such as computer setup, specific software for video players, carefully select people, and software for gathering the results. In addition, many factors can affect the QoE, depending on the application and users' expectations. To solve the issues of subjective test, objective models were developed.

2.4.2 Objective approaches

Many objective QoS parameters have been used that contribute to the user feedback quality and map the parameters to obtain QoE. Objective testing is conducted by computer software which calculates video quality (Lozano et al., 2015). Common methods are to compute the differences between the transmitted (original) and the received (distorted) video images, and then determine the errors according to temporal and partial features. Many objective quality methods use a subjective approach results to train their models (Lévêque et al., 2019). Most existing studies were achieved objectively based on peak signal-to-noise ratio (PSNR), video quality metric (VQM), or structural similarity index measure (SSIM) (Usman et al., 2018), (Juluri et al., 2015), (Wu et al., 2015) and (Mitra et al., 2014). Several studies assessed QoE using PSNR (Zheng et al., 2015) and SSIM (Zanforlin et al., 2014). A study has shown that the PSNR is more sensitive to additive Gaussian noise than the SSIM, while the opposite was perceived for jpeg compression. Both methods had similar sensitivity to Gaussian blur and jpeg2000 compression (Navarro and Molimard, 2019) and (Ece and Mullana, 2011). SSIM and PSNR are different on their image degradation sensitivity. PSNR is one of the most commonly used objective measures but it often has been criticised for providing results that are not fully consistent with subjective quality assessments (Stanojević et al., 2018) and (Lozano et al., 2015). However, its simple implementation and the ease of interpretation make it valuable (Alvarez et al., 2011). QoE assessment of videos with the SSIM index indicates the extent of the image degradation with regard to apparent structural information changed, thus focusing on the inter-dependence between spatially alike pixels which enclose the data about the objects in the visual scene (Deng et al., 2015) and (Zanforlin et al., 2014). Current methods for obtaining similarity include SSIM, PSNR with mean squared error (MSE). These methods have some limitations: such as reliability, accuracy and computational cost (Hoque et al., 2018), (Bujlow, 2014), (Sadykova and James, 2017) and (Kipli et al., 2012). In the study by Duanmu et al., (2018), a proposal to form a large-scale video database of time-varying quality and scheme, subjective testing to evaluate how humans react to compression amount, spatial and temporal resolution variations for video streaming over HTTP were reported. The study indicated that the proposed model had similar results as those with subjective opinions. First, innovative video quality assessment (VQA) models of SSIM, SSIM plus, MS-SSIM and VQM, all considerably performed better than PSNR measure.

Zhao et al. (2016) used the SSIM to quantify video quality. They reported a SSIM based on error-resilient cross-layer enhancement system and optimised user's perceptual quality for video streaming over wireless. In their model, the optimum elements at each protocol layer were designated by decreasing the SSIM-based decoding distortion according to the transmission latency limit. The study results demonstrated with comparisons of both objective metrics of SSIM and PSNR and subjective measurements.

A flexible video QoE method for determining different types of QoE was reported (Alvarez et al., 2011). It could synchronize the reference sequence with the distorted (received) videos to avoid erroneous match. Their proposed metric was compared with a subjective video images database and correlated with packet loss ratio and subjective quality. Video streaming over Radio-over-Fiber (RoF) networks were studied (Vega et al., 2014). They investigated the sensitivity of QoE to the main network parameters. Their results specified that delay of packets affect video quality less than jitter does and not cause a large reduction on the quality.

A model developed on Random Neural Network (RNN) was proposed to assess the effect of many MAC-level factors on video QoE in 802.11n standard (Paudel et al., 2014). In their proposal subjective assessments were implemented to relate MAC-level elements like queue aggregation and size, load and error ratio with the customer’s perceived video QoE. The developed RNN method was used to estimate the effect of these elements on the video QoE. The RNN model was trained with a subjective database for QoE quantities. The results indicated the estimated QoE were correlated with subjective QoE with realistic accuracy.

However the study did not investigate the impact of network factors such as delay, jitter and %PLR of the QoE.

Most objective QoE evaluation software's and mechanisms compare received images to the original images to determine QoE. The mean opinion score (MSU) Video Quality Measurement Tool (MSU VQMT) is video quality measurements tool. The MSU VQMT supports many video formats (e.g., AVI, YUV, MPEG-4 and MP4) and QoE techniques (e.g., PSNR, VQM, MSE and SSIM) (Vatolin et al., 2019) and (Boavida et al., 2008). However, transmission impairments cause frame losses that lead to non-identical frame comparisons between original and distorted frames. This leads to indeterminate PSNR or SSIM values and therefore obtaining score for an entire sequence became difficult (Sankisa et al., 2016), (Akramullah, 2014), (Pande, 2013), (Alvarez et al., 2011) and (Canadell Pulido, 2008).

According to Stanojević et al. (2018) most video quality parameters use PSNR or SSIM for quality both they could generate different results. Very limited studies considered other video parameters such as image difference (ID) or entropy difference (ED) for video quality. These two parameters could be valuable for QoE measurements.

Image difference (ID) is an image processing technique used to determine changes between images. The difference between two images is calculated by finding the difference between each pixel in each image, and generating an image based on the result. The image difference of two images is defined as the sum of the absolute difference at each pixel.

The concept of information entropy describes how much randomness (or uncertainty) there is in a signal or an image; in other words, how much information is provided by the signal or image. If the uncertainty is measured before and after imaging, the reduction in the uncertainty, i.e., information entropy is a quantitative measure of the information transmitted by the image. The image quality then can be quantitatively compared when the transmitted information provided by the images are known. From the physical measurement's point of view, the more information is transmitted, the better the image quality is. Entropy Difference (ED) is defined as; $sum\ (p \times log_2(p))$, where p contains the normalized histogram counts.

In this study, frame labelling was used for accurate comparison of received frames and transmitted frames. Furthermore, full reference methods require extensive processing and storage to occupy all reference videos for transmission quality. The solution is to use a sampling approach to reduce the processing time and provide accurate quality. In addition, image distortion usually appears on one side of the image, to accurately consider this effect, image partitioning method was introduced in this study. Furthermore, image difference (ID) and entropy difference (ED) was also used to enhance video quality evaluation (Salama and Saatchi, 2019_a).

2.4.3 Integrated QoS/QoE Approaches

According to Barman and Martini (2019) and Alfayly et al. (2012) some work has been done on video QoE performance evaluation from the network parameters (such as delay, jitter and %PLR) but less with parameters such as PSNR and SSIM. Furthermore, the study reported in (Pokhrel, 2014) suggested a mathematical formula to estimate QoE by using QoS parameters like %PLR, burst loss, delay variation, delay, Group of Picture (GoP) length. However, it too did not consider users' perception.

According to Vega et al. (2014) while operating with wireless networks where wireless interference and other factors impact network applications, QoS assessment is insufficient and mostly inadequate as images are affected by noise and distortion. Consequently, the performance assessment of a lossy wireless network requires considering not only the physical network parameters QoS but also how these impact the customer's service (QoE). In order to assess the performance of multimedia streaming over hybrid network, it is more effective to combine QoS and QoE into a single measure (Zhang et al., 2018) and (Wang et al., 2016).

The relation between QoE and QoS has been examined (Nourikhah and Akbari, 2016) and (Dolezal and Kencl, 2012). In those studies, transmission delay was measured and images were evaluated. The models used a sampling approach to record the satisfaction levels of the users on a measure from one to five. The user judgement feedbacks were ordinal; thus, it was not important to deal with the gathered information as metric. To consider this matter, the model used Bayesian examination with a generalised linear model (GLM) to compute the overall approval in the form of the posterior distribution of opinions. The model proposed that the QoE can be represented by probabilistic opinion scores distribution (OSD) alternative to the MOS.

A video QoE assessment technique using delay, jitter, %PLR and bandwidth Internet Protocol Television (IPTV) service has been reported (Hussain et al., 2013). It was found QoS/QoE to be closely associated with video quality degradation. An approach that processed delay, bandwidth, delay variations and %PLR to compute four kinds of degradations on video quality was proposed in (Stanojević et al., 2018). The effect of degradation on subjective impressions was analysed. The proposed method used video dataset with available subjective scores. They showed subjective and objective assessments were consistent.

An integrated QoE and QoS mechanism constructed on the combining fuzzy inference systems (FIS) with fuzzy evidence theory was reported in (Chen et al., 2018) and (Mansouri et al., 2016). The method used QoS as representation of service provider and QoE as the customer view of the service. The proposed approach allocated negative and positive QoE into two different types. A parameter was developed as quality, which is the total QoS according to the subjective and objective perspectives. The parameters mentioned above calculated by FIS. The proposed method assessed the quality of VoIP in three practical cases.

The contribution of this part of the study is that the developed method relied on the combination of objective QoE metrics and network QoS (Salama and Saatchi, 2019_a). However, the relationship between objective QoE and QoS is non-linear, is fuzzy and hard to compute. Therefore, to solve this matter intelligent algorithms (Fuzzy Inference System) have been proposed and used.

2.5 Artificial Intelligence and Network QoS

QoS evaluation and estimation based on analysing traffic factors needs techniques to process and analyse transmission of packets (Ruscelli et al., 2019), (Zhou et al., 2018), (Alanazi and Elleithy, 2015), (Toral-Cruz et al., 2013) and (Moore and Zuev, 2005). An example of a technique that presented prospective for QoS evaluation is artificial neural network (ANN) for real time protocol (RTP) packets has been developed (Dogman and Saatchi, 2014) and (Dogman et al., 2012_a). In both studies the network communication ran over a simulation package (NS2). The network traffic factors were primarily categorised into three QoS categorises by an unsupervised learning, Kohonen neural network. The categorised data was then managed to compute the transmission's QoS using supervised learning multilayer perceptron (MLP). The QoS obtained by the method provided results that correlated with other QoS evaluation approaches which used regression analysis with fuzzy logic (Dogman and Saatchi, 2014) and (Dogman et al., 2012_b).

A comparison of QoS assessments methods of fuzzy c-means (FCM) clustering, Kohonen neural network and FIS and MLP for QoS assessment and estimation was reported, and provided comparable results. FIS based technique needs prepared rules for knowledge base and to decide the parameters and types of membership functions for both inputs and outputs. Kohonen network and MLP based QoS methods require many iterations to train. MLP design needs a careful measurement of quantity of neurons in its pattern layer to reduce overfitting and to guarantee appropriate simplification. Kohonen result is a map that needs analysis by the user to compute groupings.

2.6 Probabilistic Approaches and Computer Networks

Probabilistic techniques have been used for many classifications associated network processes (Gacanin and Wagner, 2019) and (Batalla et al., 2018). Some of these techniques used the data that was gathered from headers of packets may not be appropriate for a precise QoS assessment. Several Bayesian approaches were proposed to categorise internet traffic (Moore and Zuev. 2005) and to estimate QoS assessment for web services. A Bayesian method that collected data about malicious users were developed (Yerima et al., 2014). Bayesian decision theoretic approach for QoE was proposed that deals with the prediction and computational matters of network traffic (Gacanin and Wagner, 2019) and (Batalla et al., 2018). The traffic parameters used for measuring QoE involved location, %PLR, delay, jitter (delay variation) and customer satisfaction feedback. The approach was context aware and estimated QoE with 98.90% accuracy. An adaptive intelligent prioritization has revealed usefulness for QoS variation over wireless (Yuan, 2012). Bayesian classifier networks as prediction systems were developed for intrusion detection (ID) but they indicated some disadvantages (Xiao et al., 2014). The training information for Bayesian classifiers usually uses heuristic techniques. Bayesian classifiers are usually trained by big datasets which causes their learning time to be intense. Though, when the smaller training datasets is used, then the performance of a single Bayesian classifier could considerably decrease due to its incapability to sufficiently signify the input information probability distribution (Xiao et al., 2014). Bayesian methods for monitoring and estimating mobile network irregularity (Lai et al., 2015) and ANNs for network intrusion detection (ID) (Raman et al., 2017) were reported.

A probabilistic neural network (PNN) is principally a classifier that uses a supervised learning to improve probability density functions within a pattern layer (Ahmadlou and Adeli, 2010). The benefits of PNN is that it is often much faster to train as compared to multilayer perceptron network (MLP), PNN accuracy can also be generally high. In addition, PNN networks are reasonably insensitive to outliers (Savchenko, 2019).

Probabilistic methods such as Bayesian and PNN could be valuable in determining QoS for their speed and accuracy. Both methods require one iteration to provide their outputs.

2.7 Network Evaluation Approaches

Evaluation of wired and wireless networks is often performed either by simulation, emulation, or real (actual) world testing. All of these approaches have their particular advantages and disadvantages. Simulations usually adopt simplified models in idealized settings and conditions (Castillo-Velazquez et al., 2017) and (Petrioli et al., 2015). A network simulator replicates a large portion of the network operation in software. Since parts of the experiment are simulated, an experiment can be run without the need of physical equipment necessary to run the same experiment in the real world which reduces the cost. However, the biggest disadvantage of simulation is that the software method is only approximations of their real-world equipment's counterparts. Simulators often provide an inexpensive way to gather high-level views of a wireless networks' operation. Examples include NS2/NS3, GloMoSim and JiST/SWANS (Castillo-Velazquez et al., 2017), (Riliskis and Osipov, 2013) and (Burnett, 2008). In addition, to deal with the actual system's difficulty, the simulation needs simplifications and concepts, that in best-case do not have effect on the result (Gantenbein et al., 2010).

Network emulation is the combination of a modelled network with actual computer hosts and services (Wang et al., 2013). It is a compromise between actual environment and a simulation. Depending on the network evaluation purpose, these methods can be sufficient. Network simulations are generally used for the early development of a new protocol. As soon as the system interaction requirements to be considered, network emulation delivers a more realistic assessment environment, and can often be an alternate to an expensive actual network testbeds (Petrioli et al., 2015). Emulations consider actual networks but allow some controlled traffic parameters such as delay, jitter, %PLR, and throughput. These elements are included in actual tests leading to a difficult environment and can involve labour intensive tests, but the conditions and the results will be practical.

Unlike real-world (actual) networks, simulations imitate all network components, which include the communication channels and hosts in a virtual model. However, the implementations of these components need functional simplifications to decrease the complexity. Table 2.1 provides a comparison between simulation, Emulation and real network testbed (Gantenbein et al., 2010) and (Kropff et al., 2006).

Table 0.1 Real-world vs. emulation vs. simulation testbed (Gantenbein et al., 2010)

	Simulation testbed	Emulation testbed	Real-world testbed
Scenario setup	(+) easy	(+) easy	(-) difficult
Simplifications	(-) high abstraction level	(+) definable	(+) none
Scalability	(+) high	(+/-) depend on the setup	(-) bad
Reproducibility	(+) easy	(+) easy	(-) difficult
Costs	(+) cheap	(-) cheap (software-based) (+) expensive (hardware-based)	(-) very expensive
Duration	(-) variable	(+) soft real-time	(+) real time
Limitations	(+/-) processing power	(+) none	(-) hardware capabilities
Network traffic	(-) modelled	(+) real or modelled	(+) real

In this study, the three evaluation approaches were combined for making the best advantage of each method.

2.7.1 Network NS2 simulation and NetEm emulation testbed

Network Simulator Version 2/3 (NS2/ NS3) is known as open source discrete event simulator developed explicitly for network and communication research (Kabir et al., 2014). NS2 was started and licensed in 1996-1997 for use under General Public License (GNU). It supports both wired/wireless simulation functions and several protocols like UDP, TCP, and RTP etc. NS2 is a very popular network simulator for its flexibility and modularity. It is based on Object-Oriented Tool Command Language (OTcl) and C++ (Rampfl, 2013). C++ defines the interior technique of simulation objects while OTcl is used by users to devise testing simulation scenarios and their events. Both the OTcl and C++ are associated together using TclCL. Tcl simulation script is used to setup a simulation. NS2 executes simulation different issues studies like protocol interface, congestion control, scalability etc. NAM (Network AniMator) tools are used to interpret the output NS2 text-based and provide graphically and interactively output (Kawai et al., 2017) and (Kabir et al., 2014). However, NS2 has many issues such as Credibility and Validation which are considerations using it in simulations. A network simulation considered to be useful only when its shown behaviour and results are equivalent to real networks. Another issue is the simulations scalability limits (Kabir et al., 2014). In addition, when moving from simulation to actual network testing, systems must be practically re-designed, reconfigured and optimised to work with actual hardware. Following such model simulation outputs can be diverse from what achieved through actual network testing (Petrioli et al., 2015).

Several emulation tools have been used to examine many types of networks. For instance, (Le-Trung, 2017) and (Nussbaum and Richard, 2009) studies discussed network emulators that are suitable for different network types and sizes to meet precise needs. Beuran (2012) have discussed three most commonly used network emulators: NISTNet, Dummynet and NetEm. They reported pros and cons of each simulator. Although there were many network emulation tools including the ones shown in (Popescu, 2019) and (Nussbaum and Richard, 2009), it was concluded that the use of NetEm would offer an improved flexibility with the research plans. Therefore, it was decided to use NetEm as the network emulation tool in the network scenarios.

In this study, NS2 was used to develop the multi-input adaptive sampling model. NetEm was implemented in the actual laboratory testbed network to control relevant network traffic parameters, i.e. delay, jitter and %PLR, for sampling, QoS, objective QoE and integrated QoS/QoE assessments. However, as network simulations and emulation testbeds have several limitations related to their reliability, validation and scalability limits (Castillo-Velazquez et al., 2017), (Riliskis and Osipov, 2013), (Petrioli et al., 2015) and (Rampfl, 2013), this study applied the developed multi-input adaptive sampling, QoS, QoE and integrated QoS/QoE techniques to an institutional network setting in practical manner and critically analysing the results.

2.8 Summary

In this chapter an extensive literature review was provided that included prior studies in multi-input adaptive sampling, QoS evaluations of multimedia traffic transmission, QoE methods and techniques and integrated QoS/QoE methods. The issues of multimedia transmission over hybrid networks that require further improvements and investigations were discussed. Artificial Intelligence and probabilistic approaches were discussed. In addition, network evaluation approaches simulation, emulation and real network were reviewed.

Chapter 3 Relevant Theory and Background

The purpose of this chapter is to explain the theories associated to the key challenges related to this study. Section 3.1 gives an overview of QoS requirements of multimedia applications. Section 3.2 includes definitions of delay, jitter and packet loss. Section 3.3 describes issues related to QoE. Sections 3.4 and 3.5 provide details of VoIP and video services, their formats, resolutions, components and signalling. Section 3.6 includes details of IEEE 802.11 as emerging WLAN standards. Section 3.7 introduces the theory of artificial intelligence models used in this study. Section 3.8 introduces the theory probabilistic classifiers. While section 3.9 provides the relevant network tools that have been used in this study.

3.1 QoS Requirements of Multimedia Applications

QoS of multimedia services are considerably unlike other network applications. The services like email, file transfer and web service can be flexible with some network QoS parameter factors such as delay and delay variation (jitter) (Anand and de Veciana, 2016). However, the multimedia services and applications like video streaming and VoIP are very sensitive to traffic factors and needs a quicker reaction by the network components. A longer packet delays or jitter can extremely reduce the performance (Tanenbaum et al., 2018). The provision of usage bandwidth can be hard to compute for these services. This is because of several diverse factors like resolution, transmission activity and usage. In a hybrid network, some parameters limit an acceptable QoS. For example, a large amount of delay, jitter or packet loss can utterly decrease the QoS (Al-Shaikhli et al., 2016) and (Klaue et al., 2003). There are parameters that pose issues to prevent network deliver continuous QoS for transmitting services like congestion that include queueing and signal interference issues. Therefore, the QoS requirements for real time applications such as VoIP and Video need to be measured to deliver adequate QoS for the services. Table (3.1) reviews the QoS requirements for real time applications and insensitive time services as recommended by ITU (Pal and Triyason, 2018), (Khiat et al., 2017), (Dogman et al., 2012_c) and (ITU-T, 2001).

Table 3.1 QoS requirements for video, voice and data as suggested by ITU (Pal and Triyason, 2018), (Khiat et al. (2017), (Dogman et al., 2012$_c$) and (ITU-T, 2001)

Class	Application	Typical bandwidth	Delay	Jitter	Packet loss ratio
Real-time	VoIP, videoconferencing	16-128 kbps	< 150 ms preferred	< 1ms preferred	< 3 % preferred
	Video streaming	16-384kbps	< 150 ms preferred	< 30ms preferred	< 1 % preferred
Non real-time	E-mail, file transfer, web browsing		Minutes	N/A	Zero

3.2 Network Traffic Parameters

Quality usually describes level of performance with constrained delay, data loss, marginal jitter, and sufficient use of the network resources. Furthermore, quality can be reflected synonymous with predictability and reliability of the application. Santos (2016) has identified essential QoS parameters like bandwidth, application duration, maximum delay, maximum jitter and maximum loss rate.

i. Delay

Delay (D_i) for the i^{th} packet is determined as in Equation (3.1) where R_i and S_i are the time a packet that was received and transmitted respectively (Li and Cui, 2018).

$$D_i = R_i - S_i \tag{3.1}$$

For time sensitive traffic, a short delivery delay is required. A telephone call consumes a delay delivery between 10 or 100 msec which depends on echo cancellation method.

ii. Jitter

Jitter is known as the changes in delay in a period. Jitter (J_i) is determined using Equation (3.2) where D_i and D_{i-1} are the delay measures of the present and prior packets respectively. The use of absolute value to guarantees jitter measurements positive (Callegari et al., 2018).

$$J_i = abs\ (D_i - D_{i-1}) \tag{3.2}$$

Sensitive traffic like video streaming or audio on demand requires that any jitter to be controlled. The application service and the size of their sending buffers will define allowed maximum jitter. The QoS architecture use defined jitter to fix the service class.

iii. Packet loss ratio

The percentage packet loss ratio ($\%PLR_i$) is computed by Equation (3.3) where R_i and S_i are i^{th} packets that respectively received and sent at respective time unit.

$$\%PLR_i = \left(1 - \frac{\sum R_i}{\sum S_i}\right) \times 100 \tag{3.3}$$

The percentage packet loss ratio is an indicator of the maximum tolerable packet loss. Some sensitive applications like VoIP can accept up to 10% of an unrecoverable loss rate. Some services could support certain amount of recoverable packet loss provided that upper layer protocol will retransmit lost packets such as a Real Server streaming. If a receiver measures a recoverable loss then the QoS will be needed in such a way to expand allocated bandwidth requirement a little more so that if application requires 1 Mbps throughput rate with about (10 %) of recoverable packet loss then QoS architecture allow for 1.1 Mbps allocated bandwidth when packet loss occurs (Desogus et al., 2019).

iv. Throughput

Throughput is a network parameter that is used to examine the ability of network to send dataset over certain duration of time (ITU-T, 2016). It is also known as the determined communication speed at a sustained level between two endpoints. It can be defined as the as the amount of received packets successfully in a predefined period (ITU-T, 2016). Equation (3.4) is used to compute the throughput:

$$Th_i\ (t) = \frac{\sum P_i\,(t)}{t_i} \tag{3.4}$$

Where Th_i is the calculated throughput in bps through the i^{th} period, $\sum P_i(t)$ is the complete bits of well received packets through the i^{th} period whereas t_i is the duration time of the i^{th} period.

3.3 Quality of Experience (QoE)

It is important to differentiate between the multimedia computed qualities called QoE with QoS parameters described above. QoE is obtained and measured by end users who have received multimedia streaming in destination side. User perception and measurements depends on many aspects such as resolution and video size, deep colour, brightness, contrast, colour saturation naturalness of pictures, distortion, definition, pixel errors and full or partial lost frames. QoE measurement process is classified to subjective and objective (Pokhrel, 2014) and (Baraković and Skorin-Kapov, 2013).

3.3.1 Multimedia traffic

There are many parameters allied to transmission of multimedia data Santos (2016). They are described in this section. Bit rate is the number of bits processed per second. The videos seen on web are generally 1-2 Mbps while bitrate of a DVD video is between 4-8 Mbps, with a higher quality about four times than a web video (Petrangeli et al., 2019) and (King, 2009). However, a higher quality as a result of higher bit rate requires a larger file size which can be a limitation in some cases. Some related factors are:

i. Encoding: To obtain maximize performance of the streaming signal the encoding system allocates a binary code to each sample. The most used method of encoding is PCM algorithm function which is sufficient at low volume signals (Vukobratović et al., 2013) and (Pulkki, 2007).

ii. Compression: Most codec techniques use compression algorithms to optimize digitized signal and reduce utilized network bandwidth by compressing binary bits. There are considerations in compression such as speed of compression to avoid extra end to end communication delay especially in real time services (Suryakala and Mahesh, 2018) and (Dang and Chau, 2000).

iii. Packetisation: During packet transmission through the network every packet will add its headers. Bandwidth (BW) utilization will increase with more data packets, thus the measured overall delay for a transmitted data packet will be enlarged when the size of the packets increased. In audio streaming, a balance between packet size and its latency is considered due to both the number of packets and the allocated BW can be reduced to low values (Li et al., 2019) and (Benini and De Micheli, 2002).

3.3.2 Subjective QoE

QoS refers to subjective tests performed to determine human perception of a video under the specific laboratory situation. Participants (users) are specified chains of tested video clips; sent (original) and received (distorted) videos presented, and then asked to score values on the video quality. Video Quality Expert Group (VQEG) (Preethi and Loganathan, 2018) and

(Rohaly et al., 2000) has made the recommendations for conducting subjective tests. Subjective categorised into two single stimulus which the viewer is shown only one video at a time and double stimulus, two videos are presented simultaneously on a split-screen environment (Lévêque et al., 2019). The most famous subjective testing method is mean opinion score (MOS).

i. Mean opinion score (MOS)

One of designated subjective QoE approaches is the MOS model. Its testing performed by human perception directly by users' evaluation score values in the specific laboratory conditions. Participants are given chains of video clips, original and distorted ones and then asked to score the quality. The idea of the MOS was produced in 1996 (ITU-T, 1996) and it characterised the first subjective method to the computational of QoE. The approach is applied to real time applications like video, voice, and multimedia such as video streaming and video conferencing (Demirbilek and Grégoire, 2016) for instance, whereas users are viewers, audiences and listeners. For voice assessment, each listener is needed to provide opinion using a five scale point as: 5-Excellent, 4-Good, 3-Fair, 2-Poor, 1-Bad which are stated to "Imperceptible," "Perceptible but not annoying," "Slightly Annoying," "Annoying", and "Very Annoying" (Hoßfeld et al., 2016) and (Microsoft, 2017) as in Table (3.2).

Table 3.2 MOS rating and their description for QoE measurements

Scores	Quality	Impairment
5	Excellent	Imperceptible
4	Good	Perceptible, but not annoying
3	Fair	Slightly annoying
2	Poor	Annoying
1	Bad	Very annoying

3.3.3 Objective QoE

To overcome the higher cost of subjective tests, objective systems can be considered. Many objective QoS parameters have been used that contribute to user perceptual quality (such as PSNR and SSIM) and characterise user QoE. The common methods are to compute the variance between the original and distorted video. Most of existing studies were performed objectively with SSIM, VQM and PSNR (Tsolkas et al., 2017), (Hoßfeld et al., 2017) and (Patil and Patil, 2017).

Objective Reference Data Quality methods are categorised into no-reference, reduced-reference and full-reference based on the size of data needed of the reference (original) video as provided in Figure 3.1 (Lahoulou et al., 2017), (Juluri et al. , 2015) and (Matulin and Mrvelj, 2013). Full-reference (FR) methods process a frame by frame contrast amongst the testing and reference video. Reduced-reference (RR) methods are hybrids between FR and NR methods. Examples used are spatial detail and quantity of motion. The well-known FR method is PSNR and SSIM. However, PSNR only has an approximate accuracy because it is a byte by byte contrast of the datasets without knowing what they really signify (Preethi and Loganathan, 2018).

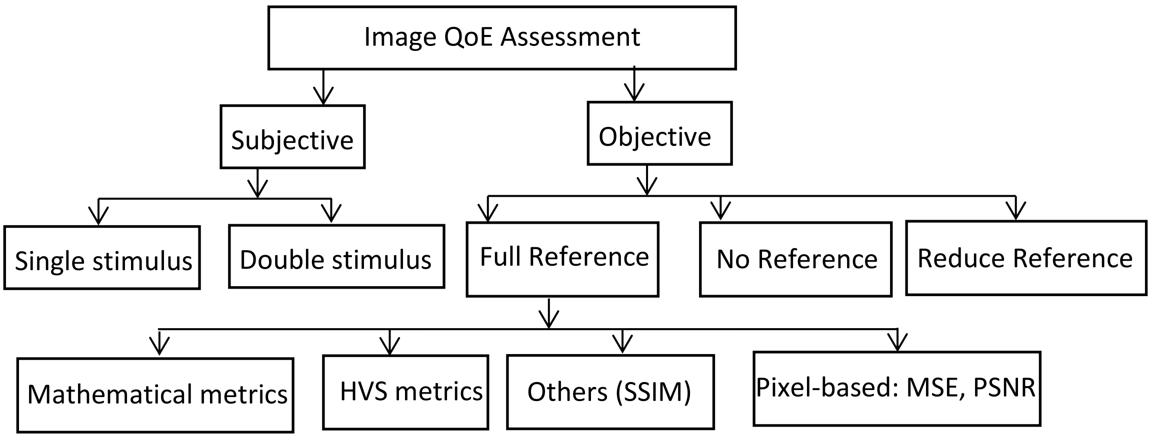


Figure 0.1 An overview of QoE assessment models

3.4 Main Audio and Video Services

i. Voice over IP (VoIP): This is like traditional telephony system but inserted into the IP network. As in traditional PSTN telephony, simply the 0 to 4 KHz period of signal frequencies equivalent to the human voice but digitally encoded. VoIP is a real time two-way directional application that needs a certain requirement of latency and jitter on both ends (Singh et al., 2014).

ii. Video over Demand (VoD): This service is a unidirectional with requirements of high bandwidth relative to number of concurrent users. In VoD audio and video streaming transmitted at same time from a central video server to a client. Every client can connect at any time to the central server and download any available video. It is not a real time service thus the video can be buffered to be represented on the endpoint user side (Van Meggelen et al., 2019).

iii. IP Television (IPTV): It is a unidirectional with requirements of high bandwidth depends on number of concurrent clients. The main difference is that all clients are receiving the same video stream, to save network bandwidth a multicast technique is used (Kua et al., 2017).

iv. Video conference: This is like VoIP service; a real time bidirectional communication which incorporates video signal (Jang-Jaccard et al., 2016).

v. Videogames: Online videogames are new multimedia applications on IP networks. Players in different sites of the world can interact, talk, connect and play. Therefore, these data packets must be treated as real time traffic, like video and audio streaming (Rao et al., 2018).

3.4.1 Video formats/containers and codecs

Videos have technically termed, containers, in various formats. A container contains audio and video data, and other data about the video like codec information to be used to play the video, required audio codec, and possibly metadata such as subtitle information and video title. The file extension of a video usually refers to the container used for the video. Some well-known containers are QuickTime (.mov or.qt) that established by Apple, Flash Video (.flv, .swf) designed by Macromedia, Audio Video Interleave (.avi) which was produced by Microsoft and Advanced Video Coding High Definition (AVCHD) developed in collaboration by Sony and Panasonic. Video codecs is dealing with representing analogue data in a digital form. A codec is referred as compression/decompression. The codec must provide a good quality video with a minimum size whilst utilising a lowest bit rate with keeping the data loss at a minimum (Video Codec, 2016). A codec can be software or a hardware device. Some of the popular codecs are (Imagen, 2019):

- MPEG-1: from Moving Picture Expert Group, mostly used in VCD production.
- MPEG-2: used widely in DVD production, and in HDTV broadcast.
- MPEG-4: very popular with different formats ranging from full HD to the lowest sized mp4 videos.
- H.264 (known as MPEG-4 AVC): used in digital video cameras and camcorders, can compress good quality videos for the web and equally for HD TVs.
- WMA: used in video and audio streaming, supports 720 and 1080 high resolutions.
- DivX (DivX-encoded Movie): offers video compression with a minimal loss in quality, supports high definition resolutions up to 1080.

3.4.2 Video resolution

Resolution is a quantity of pixels, defining the number of pixels present in an image. Pixels are small dots with different colours; these dots make up the whole picture (Morris, 2019). In simple definition, video resolution describes how clear the video will be, once played on a video player. Video resolution is stated as length (in pixels) *x* height (in pixels. Figure 3.2 illustrates picture where the resolution starts with 16x16 pixels and goes up to 512x512 pixels.

Figure 0.2 The concept of image/video resolution illustrated by Vimeo with their logo (Morris, 2019)

The common video resolutions are SD with a resolution of 640x480, HD with a resolution of 1280x720p, full HD with a resolution of 1920x1080, and 4K Videos with resolution in the range of 4000x2160 pixels.

3.5 VoIP Components

VoIP architect includes three key elements which are; Packetize, CODEC (Decoder /Encoder) and buffer. For the communication; the analogue audio voice is transformed into digital, compressed if permitted and then encoded into a format by standard CODEC method (Winkler, 2017). Figure 3.3 shows VoIP architecture. Many CODEC established by ITU-T for VoIP system such as G.729, G.723.1a and G.711 etc. Then, the Packetization method is controlled by fragment the previously encoded audio into packets with identical sizes (Sun et al., 2013) and (Srikanth and Divya, 2013).

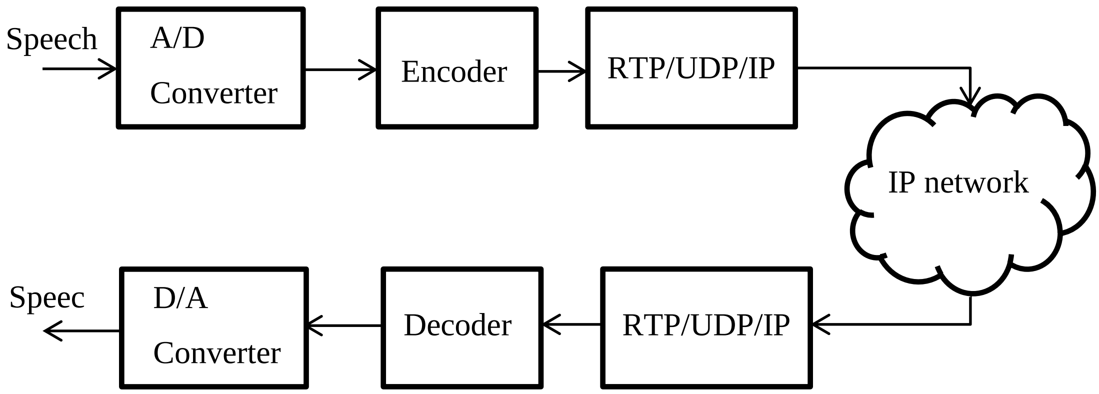


Figure 0.3 VoIP Architecture (Alshakhsi and Hasbullah, 2012)

TCP protocol is appropriate for datasets which need acknowledgment packet (ACK) to be sent by the receiver to the transmitter which causes extra delay as every packet need an ACK packet. Another manner of transmission data packet is using UDP which is more suitable for VoIP service as the receiver not required to report the transmitter of receiving the data (Khiat et al., 2017). During transmission, a changing of packets delay may happen which known as jitter. The playout buffer at receiver is used for smoothening playout and decrease delay variation (jitter) values. VoIP apply combined protocols at different OSI model layers like SIP, media CODECs in presentation layer and RTP in session layer. Figure 3.4 illustrates VoIP, SIP and RTP protocols in OSI model (Medhi and Ramasamy, 2017).

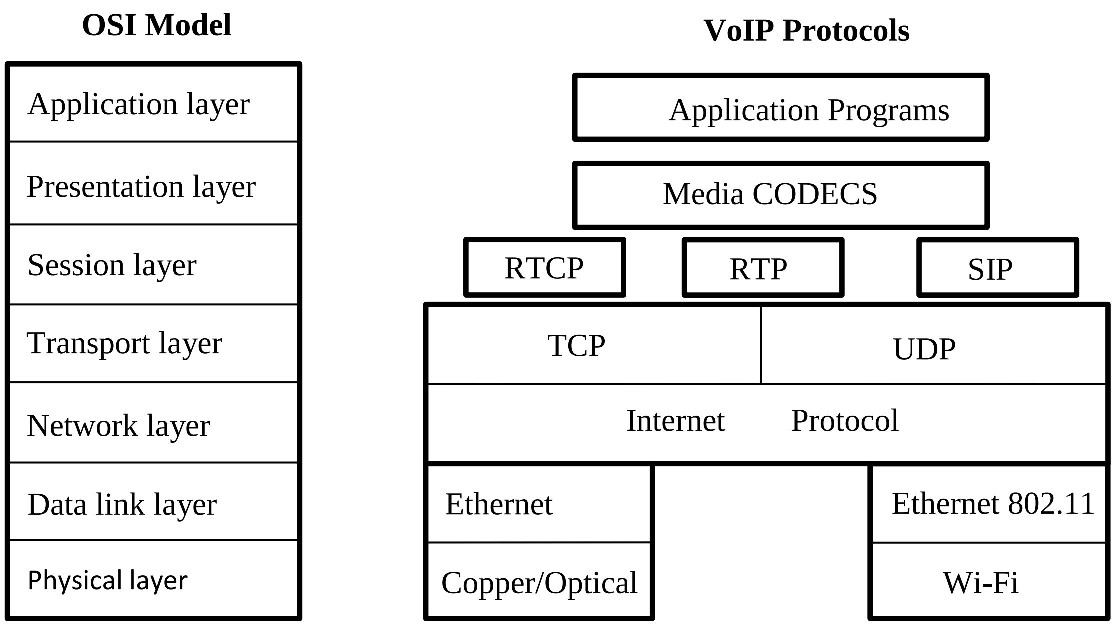


Figure 0.4 OSI model and VoIP Protocol Stack (Srikanth and Divya, 2013) and (Liang et al., 2014)

3.5.1 VoIP signaling protocols

The two known VoIP signalling are H.323 and the well-known Session Initiation Protocol (SIP). The signalling protocols are executed prior to forming the VoIP calls, between two clients, and also at the end to terminate the call and clears the media (Rattal et al., 2013) and (Aliwi and Sumari 2013).

3.5.2 The function of session initiation protocol (SIP)

According to Aliwi and Sumari (2013) "SIP is an application-layer control protocol that can establish, modify, and terminate multimedia sessions (conferences) such as Internet telephony calls." The protocol outlines the rules that manage call start-up, adjustments and terminate. SIP is planned to work on top on RTP that carry voice stream and data. SIP is considered as simpler than H323.

SIP protocol was used in this study for signalling as all experiments using whole IP network. Two network devices that are essential for SIP to form call session as following:

i. SIP end point nodes or called user agents: The two components signify session ends; they can be also hard or soft phones that configured on a computer or smart phones. Two user kinds of SIP agent are known: a server and a client. Client's user agents (UAC) which initiate the call by generate a request whereas a server user agent (UAS) processes and sends a response back confirm the communication (Johnston, 2015).

ii. SIP servers: These devices usually computers that process user agents' requests and send back a response to confirm establishing the call. The processing embraces IP addresses resolving from usernames.

iii. SIP operation and services: The SIP process can be summarized in below six steps (Baset et al., 2012)**.**

1. Register, appropriate initiation and obtain user location.
2. Identify the used media protocol.
3. Define the preparedness of the call to connect (reject or accept).
4. Form the call.
5. Modify and/or handel calls.
6. Terminate the call.

3.5.3 *Real-time transport protocol (RTP)*

RTP is a real time protocol deals with media to form end to end transport. However, it is usually used upon UDP transport protocol. RTP is close to the application layer. RTP is as a framework that VoIP services use for protocol implementation. RTP does not guarantee packets delivery, nor does it retain the packets in sequence (Barz and Bassett, 2016). RTP leaves packet resequencing and recovering lost packets to the application layer. Some applications may tolerate some packet loss during communication. For video or voice, there is no time for retransmissions. Some senders deal with lost packet by providing updated or new data to fix the original loss instead of retransmission. RTP protocol offers: sequence numbering, payload type identification and source identification. RTP Control Protocol (RTCP) delivers feedback of data transmission performance and data about call participants. RTP session is collected of an RTP port number, a RTCP port number and the participant's IP address (Junxiang and Yu, 2019) and (Westerlund, 2014).

In VoIP, RTP sessions are normally formed initially by a signalling protocol like SIP or H.323. RTP uses UDP for transmission method; a stream-oriented transport like TCP can be used (Baset et al., 2012). Figure 3.5 illustrates the SIP and RTP triangular topology, the SIP messages transmission between VoIP Agents and SIP Server, then RTP packets transports between VoIP agents directly.

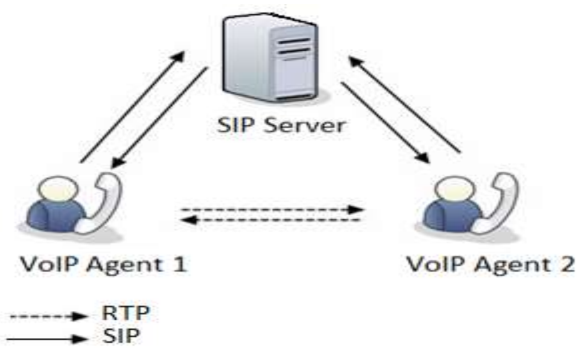


Figure 0.5 RTP and SIP Triangular Topology

The synchronization source identifier (SSRC) is value that generated randomly and individually which recognises the source within a session. RTP was used in this research because of its ability to use timestamps which can be configured so that the transmitter and receiver could synchronise via NTP server. An ability to synchronised time at transmitter and receiver enables an accurate measurement of the actual delay and delay variation (jitter) by extracting the time at timestamp field in RTP (Shannon et al., 2016).

3.6 Wireless LAN (WLAN) Overview

WLAN delivers practically equivalent functions and tasks of the normal wired local area network (LAN), Fast-Ethernet (FE) and Token Ring and Gigabit Ethernet (GE) with no concerns that associated to cable limit (Dordal, 2019). Burbank et al. (2013) in general described the LAN as providing a high throughput by reasonable communication media as related to LAN's copper wires. The communication network WLAN has limitation to its geographic site such as campus building or local office. The simple idea of WLAN creates a connection link between two devices or more without physical cables. The connection link is provided by Access Point (AP) (Comer, 2018) and (Sarkar et al., 2016).

3.6.1 Wi-Fi technology evolution and market status

Wi-Fi is the largest commonly implemented wireless with regard to infrastructure and of devices. Wi-Fi chipsets are standard interfaces parts in computers, laptops and smartphones. Wi-Fi has developed during years to fulfil high speed demands and higher bandwidth to support more applications and features. Wi-Fi is standardized by IEEE with 802 umbrellas of standards for WLANs (Gast, 2013). The newer wireless is IEEE 802.11ah which uses 1 GHz to deliver wider range with less energy consumption that allowing enormous sets of stations or sensors creation which cooperates the signal, associate the conception of the Internet of Things (IoT) (Ravindranath et al., 2016) and (Talari, et al., 2017). In 2009 the 802.11n wireless protocol was published, the new protocol has advantages that recently created in Wi-Fi, known as multiple-input multiple-output (MIMO) that support channels of 40 MHz. The protocol supports frame combination. 802.11n supports three operational modes; High-throughput modes non-HT mode, Greenfield and HT mixed mode.

Table 3.3 Summary of IEEE802.11 standards (Bejarano et al., 2013)

Feature/IEEE standard	802.11b	802.11g/a	802.11n	802.11ac
Maximum data rate per stream (Mb/s)	11	54	>100	>500 (Assuming 80 MHz channels)
Frequency band	2.4 GHz	2.4/5 GHz	2.4 GHz and 5 GHz	5 GHz
Channel width (MHz)	20	20/20	20 and 40	20,40,80, 160, and 80+80
Antenna technology	SISO	SISO	MIMO	MIMO/MU-MIMO
Transmission technique	DSSS	DSSS and OFDM	OFDM	OFDM
Maximum number of spatial streams	1	1	4	8
Beamforming-capable	No	No	Yes	Yes
Date ratified by IEEE	1999	2003/1999	2009	2013

The 802.11n can reach up to 600 Mbps speed rate that considerably 10 times better than the previous 802.11a/b/g standards (Mishra et al., 2015). The newest WLAN is 802.11ac standard that is upgrade of 802.11n. It supplies a high throughput (VHT) reaching 1 Gbps. 802.11ac runs on 5 GHz band as not suitable spectrum is available at 2.4 GHz for high speed. The 802.11ac can support a wider bandwidth that can reach 160 MHz by adjusting 256-QAM. The 802.11ac supports more MIMO spatial that up to 8 to enhance its speed rate. Bejarano et al. (2013) summarized IEEE wireless characteristics as outlined in Table (3.3).

3.7 Artificial Intelligence Techniques

This section of the study explains the concept of two important Artificial Intelligent systems; fuzzy logic, and neural network. Fuzzy logic can perform both numeric and linguistic reasoning and cope with uncertainty in information. Neural networks are adaptive parallel processing systems that can learn by interacting with their operating environment.

3.7.1 Fuzzy logic

Fuzzy logic initially was developed in 1965 by Lotfi Zadeh as computer methods for computing words instead of just numbers. It is widely applied to various services and applications in varied areas like control, evaluating systems and decision making (Egaji et al., 2015) and (Alreshoodi and Woods, 2013). The flexibility and robustness of Fuzzy Logic to handle with inaccurate or uncertain information makes it powerful and excellent technique.

An important feature of fuzzy logic is its capability to process information linguistically. It facilitates modelling of very complex systems efficiently by using advanced level of concepts from human's experiences and knowledge. Below is summary of fuzzy logic process.

i. Fuzzy Inference System (FIS): A fuzzy logic technique to compute input vector values by using predefined rules. FIS allocates measures to the output. It consists of four sections: fuzzification, inference engine base of rules and defuzzification. Figure 3.6 shows a FIS operation (Egaji et al., 2015).

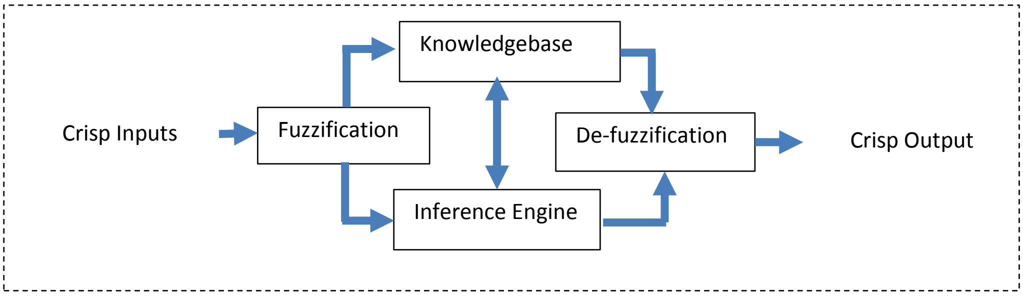


Figure 0.6 Schematic diagram of a fuzzy inference system (FIS)

ii. Fuzzification: In this part of Fuzzy logic the numerical inputs that converted into linguistic forms by determining their extents of belonging to onfe of proper membership functions. Cirstea et al. (2002) explains fuzzy sets that each component (x) in the universe of discourse X is allocated to certain extent of membership μ(x) which is achieved from membership functions. Membership functions allow gradual conversion as full belonging to a fuzzy set to not belonging with intermediary extents of belonging. It is unlike normal classical logic that has very limited borderline between true and false conditions, the fuzzy logic represent a gradient slope of other probable states between true and false.

iii. Rule Base: It is a set of IF-THEN rules which implies linguistic values; the rules and its number are changing according to the number of input's variables, outputs and used many membership functions that are correlated to them. The basic definition form of IF-THEN rules: IF which is (Antecedent), THEN which is (Consequent) (Mendel, 2017).

iv. Inference Engine: It uses fuzzified input data and the defined rules in the knowledge base to deduce new information about the current input case through processes known as implication and aggregation (Lee, 1990). The fuzzified inputs data could be used for multiple rules to identify how effectively every rule defines the current condition. However, implication must apply for every rule whereas the input for the implication procedure is only a number that has obtained by the antecedent of this rule, and the output is considered as a fuzzy set. Then the output fuzzy set from previous implication procedure for every rule is all integrated by aggregation procedure to generate single fuzzy set (Mendel, 2017).

v. Defuzzification: Defuzzification process converts the output linguistic values which are the results of aggregation part to real numeric values. There are many mechanisms that can be used in defuzzification operations like bisector, centroid, smallest of maximum, middle of maximum and largest of maximum (Greenfield and Chiclana, 2013).

3.8 Probabilistic Classifiers

3.8.1 Bayes' theorem

The conditional probability of any event is a possibility attained with the extra data that some other event previously happened. *P(B|A)* refers to the conditional probability for event (B) happening, as that the other event (A) that previously occurred (Parrill and Lipkowitz, 2015) and (Lantz, 2015). The following Equation provides for finding P (B|A):

$$P(B|A) = \frac{P(A \; and \; B)}{P(A)} \tag{3.5}$$

The textbook also involved this "intuitive approach for finding a conditional probability": The conditional possibility of (B) given (A) can be obtained by supposing that event (A) has happened. Bayes' theorem (Bayes' rule) that has been used for studying a probability assessment based on extra data that is later attained. It is important to identify that dealing with consecutive events, whereby new extra data is attained for a consequent event, and that new obtained data is used to revise the probability of the previous event. In this perspective, the terms prior probability and posterior probability are usually used (Mitzenmacher and Upfal, 2017).

Bayes' theorem status that the probability of event (A), as that event (B) has already happened, is in Equation (3.6) (Ambica et al., 2013).

$$P(A|B) = \frac{P(A).P(B|A)}{[P(A).P(B|A)]+[P(\bar{A}).P(B|\bar{A})]} \tag{3.6}$$

Bayesian classifiers (BC) are known as statistical classifiers. BCs can expect class membership possibilities like if given sample belongs to a class. BC is created based on Bayes' theorem. Naive Bayesian classifiers if the influence of an attribute measure for specified class is independent of the other attributes. This assumption is recognised as class conditional independence which make simpler computation considered as "naive" (Junxiang and Yu, 2019) and (Wolstenholme, 2018).

Bayes' Theorem; Let X = {x_1, x_2 ..., x_n} as a sample, whose elements characterise measures made on a set of *n* characteristics. In Bayesian terms, X is known as "evidence". Let *H* be likelihood that the data *X* belongs to a class C. For categorising issues, the aim is to obtain *P (H|X)*, the probability of the hypothesis *H* holds assumed the "evidence", (i.e. the detected data sample *X*). In other words, the probability that sample X belongs to

$$P(H|X) = P(X|H)P(H)P(X) \tag{3.7}$$

3.8.2 Probabilistic neural network

PNN classifies an input dataset to predefined class types. PNN is known as supervised learning feedforward artificial neural network (Raman et al., 2017). It is a classifier using a statistical algorithm which is kernel discriminant analysis. The PNN training needs several examples of identified classes in order to conclude the approximated. PNN has many advantages, its essentially parallel structure, fast training and convergence, and it capability to optimise classifiers by adding training examples.

According to Specht (1990), PNN is linked to Parzen nonparametric probability density function (PDF) and Bayes classification rules. In the algorithm, the PDF of each class is approximated by a Parzen window and a non-parametric function. Then, using PDF of each class, the class probability of a new input is estimated and Bayes' rule is employed to allocate it to the class with the highest posterior probability. PNN structure is shown in Figure 3.7, consists of four layers; input, pattern (hidden), summation layer and output (Raman et al., 2017).

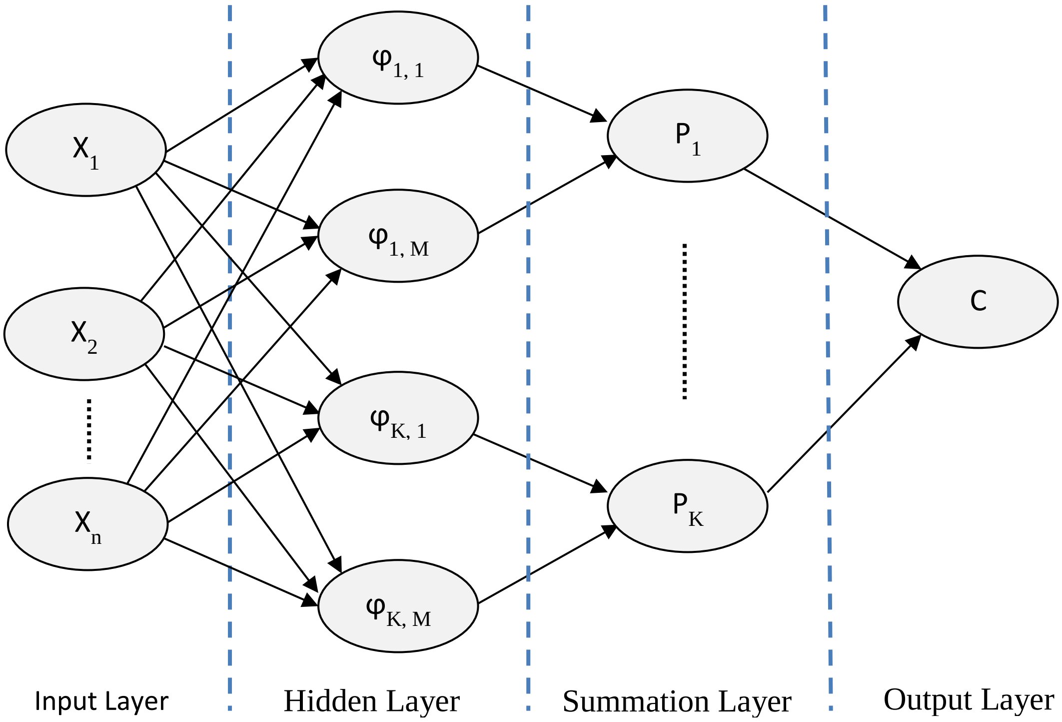


Figure 0.7 Architecture of probabilistic artificial neural network PNN

An input dataset vector is fed to the *n* input neurons. Then, the input layer forwards the data to the neurons in the hidden (pattern) layer which distributed into *k* classes. The neurons in the hidden (pattern) layer process the data using a Gaussian kernel of the form of an input pattern ***x*** from the input layer. There is more explanation about using PNN in chapter 6.
In this study, Bayesian and PNN based methods were developed to classify QoS for their advantages of computational speed and robustness.

PNN is a fast training process and an inherently parallel structure that is guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining. The training time, as measured by number of iterations of the learning algorithm needed for the network to reach its best performance. It is also significantly shorter for the PNN compared to conventional neural networks (CNN) while PNN generally requires more hidden nodes than CNN to reach comparable performance.

3.9 Network Tools

3.9.1 NetEm (Network Emulator)

Network Emulator is a Linux based tool that has the ability to emulate a vast range of network scenarios. Network engineers have used NetEm to emulate wide area network properties to test protocols. By NetEm, it's possible to emulate various networks scenarios whilst having a control over traffic factors like delay, jitter and %PLR, duplication and re-ordering of network data packets (Roshan, 2018) and (Biernacki, 2017).

NetEm runs emulation functionality for required protocols by emulating some of network parameters. The current NetEm emulates delay, packet loss, duplication and re-ordering (Roshan, 2018), (Moe, 2013) and (Beuran, 2012). NetEm allows two delay emulation types. The first type is a fixed delay, as illustrates in Figure 3.8.

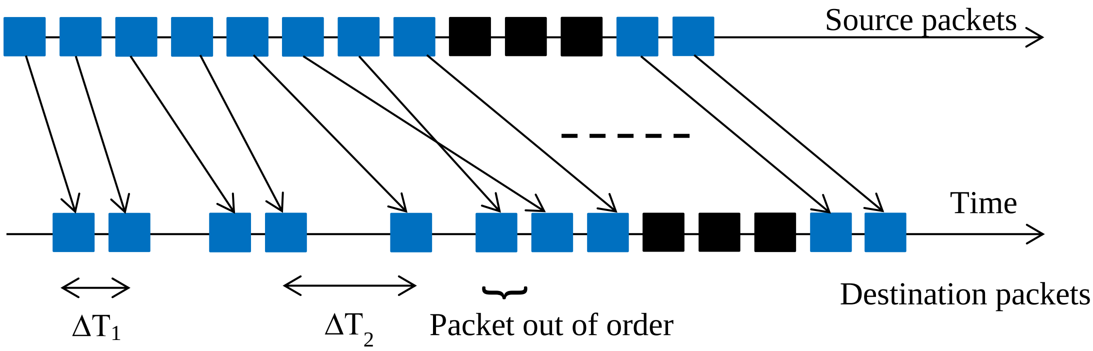


Figure 0.8 NetEm adds a fixed delay to outgoing data packets (Roshan, 2018)

The second type in NetEm to emulate a delay is with the use of a distribution. NetEm has built-in delay distributions called Normal and Pareto which allow added delay to the outgoing traffic based on one of these built-in distributions as illustrated in Figure 3.9.

Figure 03.9 NetEm traffic control logic (Roshan, 2018)

NetEm is a very popular tool used widely by many researchers. It allows testing and design of network related applications in various controllable conditions where the experiments can be repeated for concluding a desired outcome. In this study, the NetEm software was used due its capabilities that allowed control of delay, jitter and packet loss.

3.9.2 Network time protocol NTP

NTP is an Internet protocol used to synchronize the clocks of computers to time reference. NTP is assembled on top of UDP and IP. It is considered to preserve time reliability and accuracy (Douglas et al., 2018). It is constructed for having all devices get correct time close as possible to the - Universal Coordinated Time (UTC). Simple NTP system contains a central server and clients to deliver precise time to the network clients.

The basic NTP operation is to time stamp transported packets between the server and its clients. The process order is: i) the client stamps its time while sends an NTP request packet to the server. ii) The server stamps the time while NTP request packet has received from its client. iii) The server stamps the time while it sends the NTP reply to the client. iv) The network client stamps the time when this NTP reply is received. NTP packet contains four timestamps, where clients use these timestamps to compute the variation between its internal and the UTC time reference then adjusts its local time to synchronise with its server. In addition, the client can measure the latency and apply a correction factor to adjust its internal time, which results in more accurate latency level of synchronization. In this study, to accurately measure multimedia traffic parameters between two PCs, NTP was installed in transmitting and receiving PCs to synchronise time and accurately measured delay, jitter and %PLR.

3.9.3 Wireshark software

Wireshark is identified as packets analyser for hybrid networks, it is "the packet sniffers" capture, and analyse network traffic transmitted between two devices to further study and troubleshoot network problems. Wireshark builds useful statistical information of wireless (Wi-Fi) usage. Wireshark captures and records packets based on many criteria such as protocol number or type UDP, TCP, RTP, RTCP or SIP. In this study the furthermost significant packets that needs to be collected is VoIP packets then calculate some VoIP statistics such as delay, jitter and %PLR (Lamping and Warnicke, 2014).

3.9.4 VLC media Player

VLC, is a media player that produced by Video Lan (VideoLAN, 2019), it operates on Windows, Linux, and MacOS computers. VLC plays a wide range of media files. VLC has controlling streaming capabilities which allow local or network streaming with a large control over the protocols and codecs to meet specific streaming requirements (Panayides et al., 2013). The VOD streaming can be done by VLC using many protocols such as HTTP, RTP and UDP. VLC has capability to display the stream locally to allow check effects of transcoding and rescaling. In this study, VLC have been used for video streaming between PCs.

3.10 Summary

This chapter explained theories that significant to the QoS and QoE of multimedia applications. This covers the descriptions, QoS traffic factors and parameters, QoE visual factors, QoS essential requirements of multimedia services, and multimedia parameters. It introduced the IEEE 802.11n/ac as emerging WLANs standards to provide QoS was explained. This chapter also explained the theoretical background related to Artificial Intelligence (AI). The basic concepts of fuzzy logic, Bayesian classifier, probabilistic Neural Network PNN were explained.

Chapter 4 Methodology

4.1 Introduction

An explanation of procedures that were common in obtaining results presented in the following results chapters is included in this chapter. The procedures that were specific to the results in individual chapters are included in their related chapters to aid clarity and readability. The methodologies were in three parts:

- Simulation approach which was used to generate data that used to develop an adaptive sampling technique covers objective 1. The NS2 simulation-based approach is explained in section 4.3.
- Emulated testbed was used to develop QoS, objective QoE and integrated QoS/QoE techniques, according to needed scenarios, the emulation used NetEm due to its ability to alter delay, jitter and %PLR, this approach covers objectives 2, 3 and 4. The emulation approach is explained in section 4.4.
- Real network of large institution has been used to evaluate multimedia transmission between two computers using all developed techniques which cover objective 5. The approach was explained in section 4.5.

In this chapter, the traffic measurement procedure and SPSS analysis procedure are explained in sections 4.6 to 4.10.

4.2 Network Evaluation Approaches

As described in section 2.7 performance evaluations of wired and wireless networks is often performed either by simulation, emulation or real-world testing. All these approaches have advantages and disadvantages. Simulations typically use simplified models with idealized conditions. Emulations reflect real networks but still allow for controlled network parameters like delay, jitter, %PLR and throughput. These parameters and elements are involved in real world tests leading to a complex environment and can involve labour intensive tests, but the conditions and the results will be practical.

There are many simulation tools for research (Sarkar and Halim, 2011) and (Gantenbein et al., 2010) such as Optical Micro-Networks Plus (OMNET++), Global Mobile Information System Simulator, NS2 by Virtual Internetwork Testbed (VINT) and NS3 from National Science Foundation (NSF). NS2 is an open source and free simulation model. NS2 is wildly used for network research. In this study simulation did not have a major role; it was used to gather network traffic in order to develop an adaptive sampling technique. Therefore NS2 was selected and used for its simplicity in the task required for.

Emulator testbeds only redefine the physical layer instead of redefining many levels of the OSI model, such as the real radios are used. The links between hosts are the only parts modified, not the hosts themselves. Emulation solution offers middle ground between simulators and real network (Angrisani et al., 2017) and (Gantenbein et al., 2010). Because the only issue that needs to be managed is the link, it can be emulated in hardware. At the same time, emulators exclude many of the practical problems that exist in real testbeds by controlling such external factors that may influence the experiment (Petrioli et al., 2015). An example of emulator is the NetEm (Angrisani et al., 2017) and (Petrioli et al., 2015). In this research, the reason for using emulation is to alter network parameters; delay, jitter and %PLR to provide different QoS classification to the multimedia traffic. NetEm software is widely used to control network parameters such as delay, jitter and %PLR (Angrisani et al., 2017) and (Jurgelionis et al., 2011).

Real-world testbeds include computer nodes that are connected through the actual communication media. The entire network contains the original components that able to handle any communication under practical conditions (Attaby et al., 2019). In order to overcome limitations of simulations and small testbed emulation, a real large network is needed for quality performance evaluation.

In this study, simulation and emulation testbed have been used to develop approaches of a multi-input adaptive sampling, QoS and QoE evaluations and Integrated QoS/QoE approaches. However, all developed techniques will be applied on real large institutional network for multimedia. These approaches and the manner they were used are shown in Table (4.1).

Table 4.1 Approaches to test transmission methods

NS2 Simulation	Testbed emulation	Real network
• Multi-input adaptive sampling	• QoS evaluation • QoE evaluation • Integrated QoS/QoE evaluation	• Multi-input adaptive sampling • QoS evaluation • QoE evaluation • Integrated QoS/QoE evaluation

4.3 Network Simulation NS2

NS2 code processing is Object-oriented Tool Command Language (OTcl) and C++ language. While C++ describes the inside the simulation model. The OTcl sets up simulation by configuring the objects and scheduling discrete events (Yu et al., 2018). The simulation process of NS2 is shown in Figure 4.1. NS2 Simulate wired and wireless network functions and protocols. The NS2 is able of stream video like H.264 and MPEG-4 by using Evalvid toolset (Ke et al., 2008). NS2 uses Terminal Command Language (TCl) as scripting language for creating simulation scenario file (for example, sample.tcl). The output of the simulation procedure is saved in two files, trace file and (Network AniMator) NAM file. The trace file contains network packets information such as transmitted packets, received packets, packet types, packet ID, dropped packet, etc. (Katkarand and Ghorpade, 2016). The information in trace file is used to extract relevant information by using script languages such as Perl, Awk and Matlab or script languages such as Xgraph and Gunplot (John and Haroon, 2014).

Network engineers tend to use NS2 for testing new protocols or modifying the existing ones in a controlled environment. Moreover, NS2 can carry out trace-driven simulation using a record of events from a real system and its simple to use; therefore, in this study, NS2 was used to develop the multi-input adaptive sampling model. While, NetEm was implemented in the actual laboratory testbed network to control relevant network traffic parameters, i.e. delay, jitter and %PLR, for sampling, QoS, objective QoE and integrated QoS/QoE assessments.

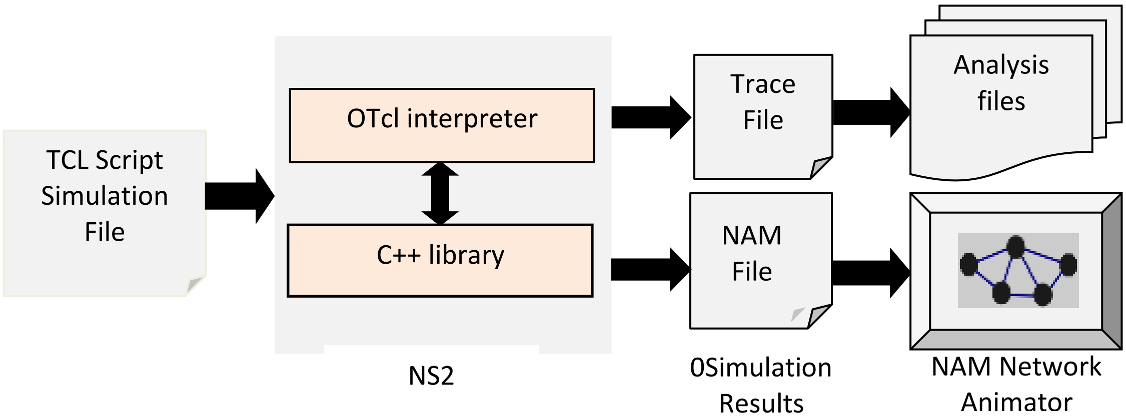


Figure 4.1 The NS2 simulation process (Katkarand and Ghorpade, 2016)

4.3.1 Network topology in NS2

A modular and scalable hybrid network has been implemented using NS2 tool. Figure 4.2 shows the network's design, based on the mentioned hierarchical design which distributed the network into three levels; access, distribution and core. This network structure optimises administration and management (Tan and Fang, 2018), the designed scheme was associated with the Open Source Interconnection (OSI) model (Trabelsi and Barka, 2019). The wireless-cum-wired network was simulated using the NS2. The network nodes in the simulated network were 8 stations. The connections between stations were unidirectional. Each station sent traffic to its counterpart station destination. The network topology area configured of (400×400) m and the stations were positioned randomly. The time period simulation took place varied between 800 seconds to 10 minutes as the scenario requirement.

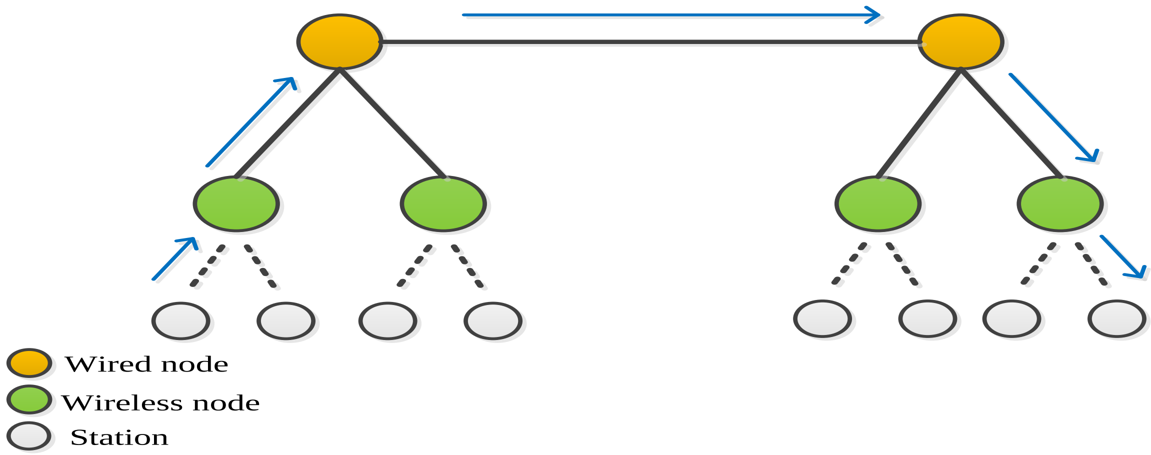


Figure 4.2 Network scheme

The wired side controlled the core layer and assigned 10 Mbps bandwidth. The WLAN part is based on wireless standard of IEEE 802.11e, and it was used the Enhanced Distributed Channel Access (EDCA) with Hybrid Controlled Channel Access (HCCA) approach. In this study the focus was on the IEEE 802.11e EDCA because its easiness (Lee et al., 2011). The default setting for IEEE 802.11e of the main elements modelled the wireless channels is shown in Table (4.2). Data rate was 2 Mbps and basic rate was 1 Mbps (Barolli et al., 2019). The physical part was modelled to work as Lucent Wave LAN DSSS radio interface card at a frequency of 914 MHz. The physical layer parameters are listed in Table (4.2).

Table 0.2 Description of settings of MAC and PHY parameters in IEEE 802.11e

Parameter	Value
Modulation Method	DSSS
Physical Header	24 bytes
MAC Header	28 bytes
The Frequency Band	914x106
Speed Rate	2.0 - 11.0 Mbps
Basic Rate	1.0 Mbps
Preamble Length	144 bits
Capture Threshold	10
Carrier Sense Threshold	1.559x10-11
Receiving Threshold	3.652x10-11
Transmission Power	0.28183815
RST Threshold	3000
PLCP Header Length	48 bits

There are many routing protocols supported in NS2 environment. Destination-Sequenced Distance Vector (DSDV) was chosen for its simplicity as it keeps the routing data for all network nodes and updates the existing routes periodically (Ng, 2018). The queueing technique was First-In-First-Out (FIFO) for all scenarios while the queue size set to 50 packets.

In this study, many traffic types were sent over the network scenarios. These include Voice over IP (VoIP), best effort traffic, video streaming and background traffic. For VoIP, best effort traffic was modelled by constant bit rate (CBR). The G711 coding has been used for audio with 64 kbps. Packet size has been configured for video to 512 bytes (Saraireh et al., 2007). VoIP was configured with 160 bytes. Video streaming frames were configured with MPEG-4 coding scheme and length of 1024 bytes. Following individual simulation, NS2 produced a trace file that included the network status and traffic details like the packet types, packet sizes, received and sent times and delivery status. Matlab© was used to read the data that generated in the saved trace file. Then the traffic parameters; delay, jitter, and %PLR were measured. The generated traffic parameters have been used to develop a multi-input adaptive sampling in chapter 5.

4.4 Network Emulation (NetEm) Testbed

The experiments that have been used to develop QoS, QoE and QoS/QoE techniques were based on multiple scenarios in a network laboratory, size 4 m×6 m, consisting of two access points (APs) and 20 personal computers (PCs) as shown in Figure 4.3. The design established up to 10 PPP connections between PCs that linked to AP-1 and the PCs that linked to AP-2, number of PPP links varied according to the needed scenario and this will be clarified in its relevant chapter. The setup gave flexibility in testing for different traffic conditions. Number of PCs that were attached to the AP-1 and AP-2 were from 1 to 10 depending on the scenarios needed and this will be explained in its relevant chapter.

NetEm is a very common tool used widely by many researchers. It allows the network researchers to emulate network scenarios for evaluating new protocols and application. These environments offer the testing and design of network related applications in controllable conditions where the experiments can be repeated infinitely for concluding a desired outcome or a concrete finding. The common NetEm offered features its ability to control network parameters such as delay, jitter and PLR. Therefore, MetEm was used in this research to control network parameters in such a way to reflect practical scenarios.

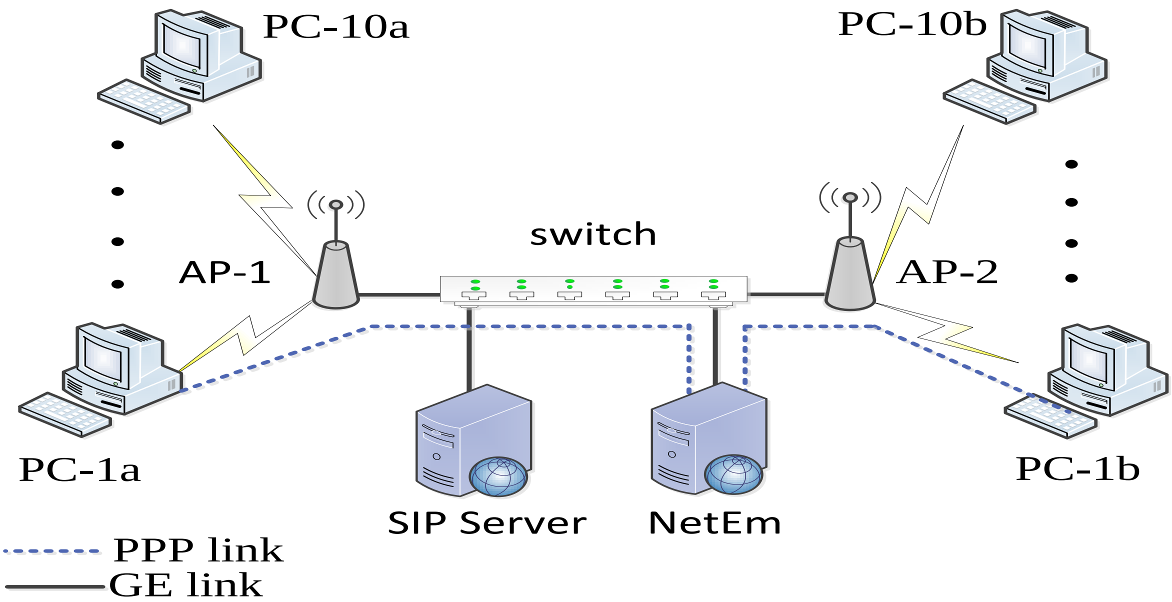


Figure 4.3 Network layout with NetEm

The APs were Cisco© AIR-AP1852E and supported 802.11 g/n/ac protocols. They had four dual-band external antennas. Catalyst switch Cisco© 3560-CX was used to connect the APs and SIP server by 1 Gbps links. On the PC side, wireless adaptors of Linksys AC1200 Dual-Band were used in all scenarios. The data were not encrypted for transmission between PCs' wireless interfaces and APs. As the wireless nodes were at same location, the power of transmission was below 30 mW (15 dBm) (Santos, 2016). NetEm ran over the Windows© PC. SIP Softphones configured on the Windows© PC to provide SIP VoIP sessions. Real Time Protocol (RTP) used packet size of 160 bytes and G711a protocol for audio CODEC. The queuing technique was First-In-First-Out (FIFO) with size of 50 packets for all scenarios.

Initially one to one PPP link was established between PC-1a and PC-1b. The traffic comprised video, VoIP and transmission control protocol (TCP). The traffic was sent simultaneously from PCs connected to AP-1 to PCs connected to PC-2. The manner of traffic transmission varied depended on the scenario and will be explained in the relevant chapter. In addition, NetEm was used in this study for its ability to emulate a setting up the network test scenarios whilst having a control over network parameters; delay, jitter and %PLR. NetEm server was installed in between the PCs as shown in Figure 4.3. The traffic was routed between one end to the other through NetEm. Graphic interface tool was used to access NetEm and change delay, jitter and %PLR in real time manner for QoS and QoE study. In this study, Emulation using NetEm was used in order to develop QoS approach, objective QoE and integrated QoS/QoE approach that covered objectives 2, 3 and 4. Further explanation of the manner of using this emulation is provided in chapters 5, 6 and 7.

4.5 Real Large Institutional Network

In this study, all developed techniques were evaluated on a large institutional network (it is not named for security purposes) that consisted of 35,000 computers, more than 3500 routers, switches and access points. The developed techniques and methods have been used to evaluate multimedia transmission between two PCs over the institution's network, one PC-1 in Campus A and PC-2 in Campus B. The multimedia traffic transmitted from PC-1 to PC-2. The PC-1 connected by wireless Cisco© AIR-AP1852E on Campus A, the traffic passed through Cisco switch 3850UA, then to distribution layer through Cisco 6880X VSS, then to the core routers Cisco 6880X then reverse to Campus B computer passing similar products. On PC-1 the video streaming was done by VLC software and the compression set to MPEG-4 using UDP/RTP protocol. VoIP was handling between the two PCs using softphone called X-Lite using SIP protocol. Wireshark software was installed on both PCs for capturing generated traffic to measure traffic parameters (delay, jitter and %PLR). The time duration of transmission was according to scenario and will be explained in its relevant chapter. The network layout is shown in Figure 4.4.

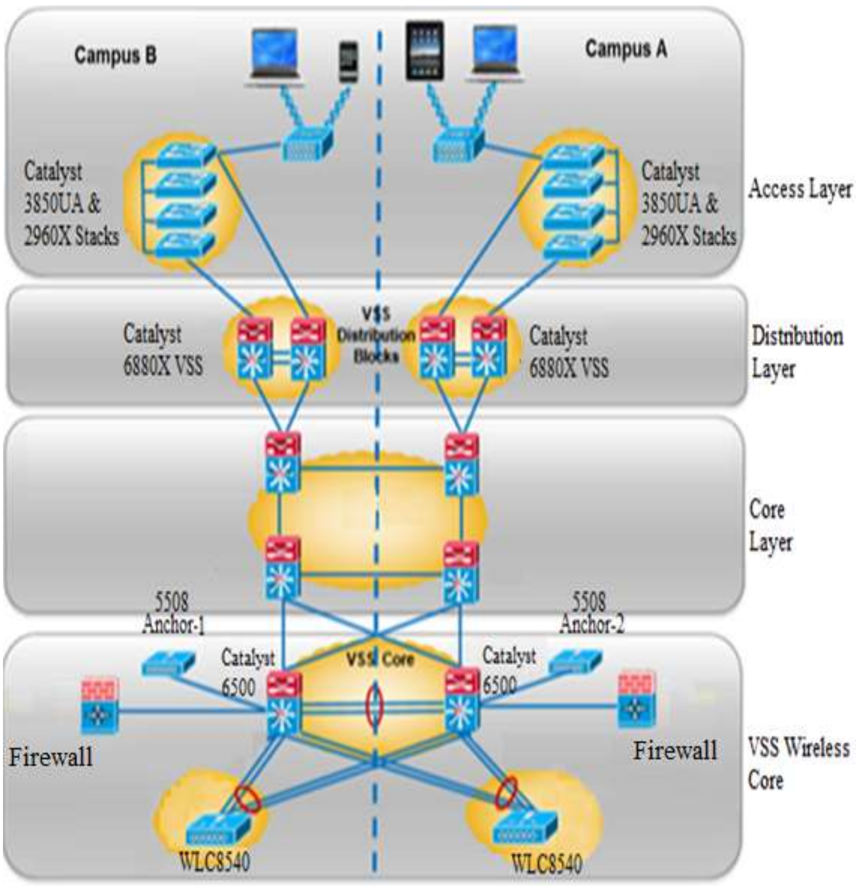


Figure 0.4 Real Institutional Network layouts (partially)

4.6 Traffic Capturing

Wireshark traffic monitoring tool (Banerjee et al., 2010) was installed on PC-1a and PC-1b to capture packets. Wireshark captured packets based on protocol type or number like UDP, TCP, RTP and SIP. The captured packets were processed using Matlab© and a statistical package called SPSS© to compute packets actual delay, jitter and %PLR and used these values to quantify overall QoS for VoIP. Wireshark was used in the testbed emulation and in real network to capture VoIP and video streaming traffic, and then associated delay, jitter and %PLR were determined.

4.7 Real time Transport Protocol (RTP)

In this study, RTP was used to deliver network transport functions suitable for multimedia (video and audio) over unicast or multicast network applications (Perkins and Ott, 2018) and (Duong et al., 2017).

The timestamp was used to place the incoming packets (audio and video) in the correct timing order. The sequence number and timestamp features are main features on RTP headers. Timestamp were used in this study to measure end-to-end delay and delay variation (jitter) accordingly while sequence numbers to detect and measure packet losses. The main two features of RTP are (Perkins and Ott, 2018):

- **Sequence number field:** This is 16 bits. The first value is random and then it increases by 1 in every packet sent. The sequence number feature of RTP is that it can be used to detect any lost or misplaced packets. RTP does not take any actions when it detects a packet is lost.

- **Timestamp field:** This is 32 bits. It identifies the time when the first byte of the RTP packet was constructed. This instant has been configured by clock and increments in a monotonic and linear method.

For the purpose of end-to-end time measurements, time must be synchronized between sender and receiver computers by using NTP.

4.8 Network Time Protocol NTP

The purpose of a time server is to deliver precise time to the clients. In this study, NTP was installed in PC-1a as server and on all other PCs as clients to assure time synchronization.

4.9 Iperf software

It is a command-line network speed measurement. IPerf was installed on the computers at both ends of the connection, PC-1a as a server and PC-1b as client. It was used to measure actual throughput rate by sent TCP packets from the server to the client and return (Bholebawa et al., 2016). TCP throughput was measured for a given TCP packet size that varied from 250 bytes to 64 Kbytes. It was mainly for QoS evaluation that has been carried out in this study to compare VoIP transmission performance over 802.11ac and 802.11n standards.

4.10 Statistical Package for the Social Sciences (SPSS©)

SPSS© is a platform used for statistical analysis and is widely used for computer networks analysis. It has slightly more 'point and click' functionality than some of the other statistical analysis packages, and is easy to learn and to use (Green and Salkind, 2016). SPSS was used in this research for exploring network data. It was used to analysis QoS, QoE and integrated QoS/QoE and their relations to the network and media parameters. The statistical descriptions of data were classified packets, boxplots, histograms and scatter plots. SPSS also used to show the overall performance and its relation to QoS parameters and QoE media parameters.

4.11 Summary

This chapter defined the experiments procedures used to assess and verify the methods developed during this research study. NS2 to simulate network scenarios was provided. The settings include queuing, routing protocols, and wireless parameters were also discussed. The Testbed emulation network was discussed. The manner of NetEm and RTP and capturing packet method were introduced. The real large institutional network was introduced and the manner of how evaluate its multimedia transmission.

Chapter 5 Multi-input Adaptive Sampling Technique for Multimedia Traffic

5.1 Introduction

The transmission of multimedia over hybrid networks generates large traffic loads on bandwidth and other resources (Tan et al., 2018), (Robitza et al., 2017), (Hofstede et al., 2014) and (Manfredi, 2012). Traffic analysis necessitates packet transmission data for the overall network and individual flows to be captured and interpreted. Processing every transmitted packet is not practical in real time because of high processing desires. In addition, network traffic behaviour is dynamic. Therefore, a subset of data packets required to be captured in a way that the subset contains considerably smaller size than the actual number of sent packets while maintaining the total traffic's characteristics and behaviour. The process is called sampling and considers a significant role in assessing multimedia transmission's performance (Salama et al., 2018), (Silca et al., 2014), (Lin et al., 2014) and (AL-Sbou et al., 2008). The contribution of this part is developing a novel multi-input adaptive sampling model based on statistics of the traffic. The method samples multiple traffic parameters simultaneously. It can be used as part of QoS assessment. As stated in the literature, the emulated testbed network is more practical in network evaluation. Thus, the developed model has been initially developed using data generated by a simulated network then the model has been applied practically on emulated testbed network and its results were compared against the conventional sampling techniques.

This chapter is ordered as following: In section 5.2 a review of the latest related adaptive sampling studies that were used for traffic measurements were explained. In section 5.3 a detailed explanation of the proposed multi-input adaptive sampling approach was provided. The details of the implementations of conventional sampling methods are discussed in section 5.4. The measurements of traffic parameters with sampling analysis approaches are discussed in section 5.5. Section 5.6 explains the simulation network topology and its results while actual emulated testbed network topology and its results are introduced in section 5.7. The developed multi-input adaptive model results were compared against non-adaptive sampling (i.e. systematic, random and stratified) in section 5.7.1.

5.2 Related Work

Adaptive sampling based on fuzzy logic has been previously reported where sample rate has been adjusted based on past traffic history and traffic conditions (Tan et al., 2018) and (Silva et al., 2017_b and 2013). Adaptive sampling approaches can be used to represent traffic parameters parameter, such as delay and jitter (Robitza et al., 2017), (Shao, 2016), (Dogman et al., 2010) and (Hu et al., 2008) or packet loss (Serral-Gracia et al., 2010) and (Serral-Gracia et al., 2008). The work reported in (Dogman et al., 2011, and 2010) were based on statistical adaptive sampling methods. They considered the traffic's statistical parameters and adjusted them using fuzzy logic methods. However, the methods lacked sufficient modularity (such as multi-input) as they dealt with a single traffic parameter at a time that reduced the accuracy of determining QoS. According to (Silva et al., 2017_b, 2017_c), existing sampling techniques lacked modularity thus making them less transparent in operation. In this context, this study proposes an adaptive traffic sampling architecture capable of adjusting sampling rate in accordance with multiple traffic parameters that are processed simultaneously to determine QoS. In this part of this study, the main contribution has been to develop a novel multi-input adaptive sampling method that is an advancement of the earlier reported methods. Initially an adaptive sampling method with one input parameter was developed in (Salama et al., 2017_b) and (Salama et al., 2017_c). This was further developed to multi-input adaptive sampling approach that uses multiple network parameters inputs for QoS evaluation (Salama et al., 2017a) and (Salama et al., 2018). The modularity feature allows performance assessment to deal with multiple traffic parameters simultaneously depending on the application requirements. For multimedia transmission; delay, jitter and %PLR are important to sample but if %PLR is not as critical then the approach relies on delay and jitter only. The importance of the multi-input adaptive is that the method dynamically adjusts the sampling interval in accordance with variations in delay, jitter and %PLR.

5.3 Adaptive Sampling Method

A multi-input adaptive sampling approach is proposed in this chapter. The sampling interval was adjusted using the traffic changes that represented linear regression model and fuzzy inference system.

The method samples traffic according to the extent of traffic changed by adjusting a parameter called inter-sampling interval (isi). The parameter provided flexibility in implementation of the sampling method. This design considered delay, jitter and %PLR jointly for the purpose of QoS evaluation. The design can be further adapted to other network measurements with different number of inputs according to the application. The main traffic sampling sections which include packets to be sampled are shown in Figure 5.1.

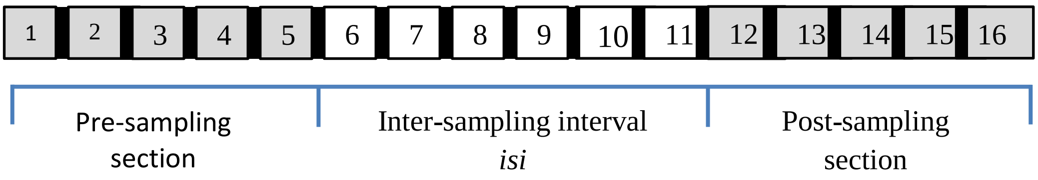


Figure 0.1 The sampling concept

The operating parameters of the developed multi-input adaptive sampling algorithm is shown in Figure 5.2. The parameters of the sampling methods are defined as:

- **Pre- and post-sampling sections:** are defined as the time intervals associated with the selected packets. The duration of these two sections are predefined and do not vary throughout the sampling practice.

- **Inter-section interval (isi):** is defined as the time interval between the pre-sampling and post-sampling sections. In this interval, packets are not selected. The isi interval duration is updated adaptively by FIS based on the change of traffic behaviour (i.e. changes in delay, jitter and %PLR). isi is updated during each sampling iteration.

- **Regression model:** The traffic parameters (i.e., delay, jitter, and %PLR) were represented by an $n \times n$ matrix which allows regression computation between pre-sampling and post-sampling sections, where n is the number of subsections that forms the pre-sampling and post-sampling sections, and n is also equal to number of packets in each subsection.

- **Traffic difference TD:** quantifies the amount of traffic variations between the pre-sampling and post-sampling (intervals) sections by using the Euclidean (traffic difference) measure. In this study, TD_D, TD_J and TD_%PLR represent traffic differences of delay, jitter and %PLR respectively.

- **Fuzzy inference system (FIS):** was used for duration (interval) update of isi based on the vales of TD_D, TD_J, TD_%PLR and current value of the isi.

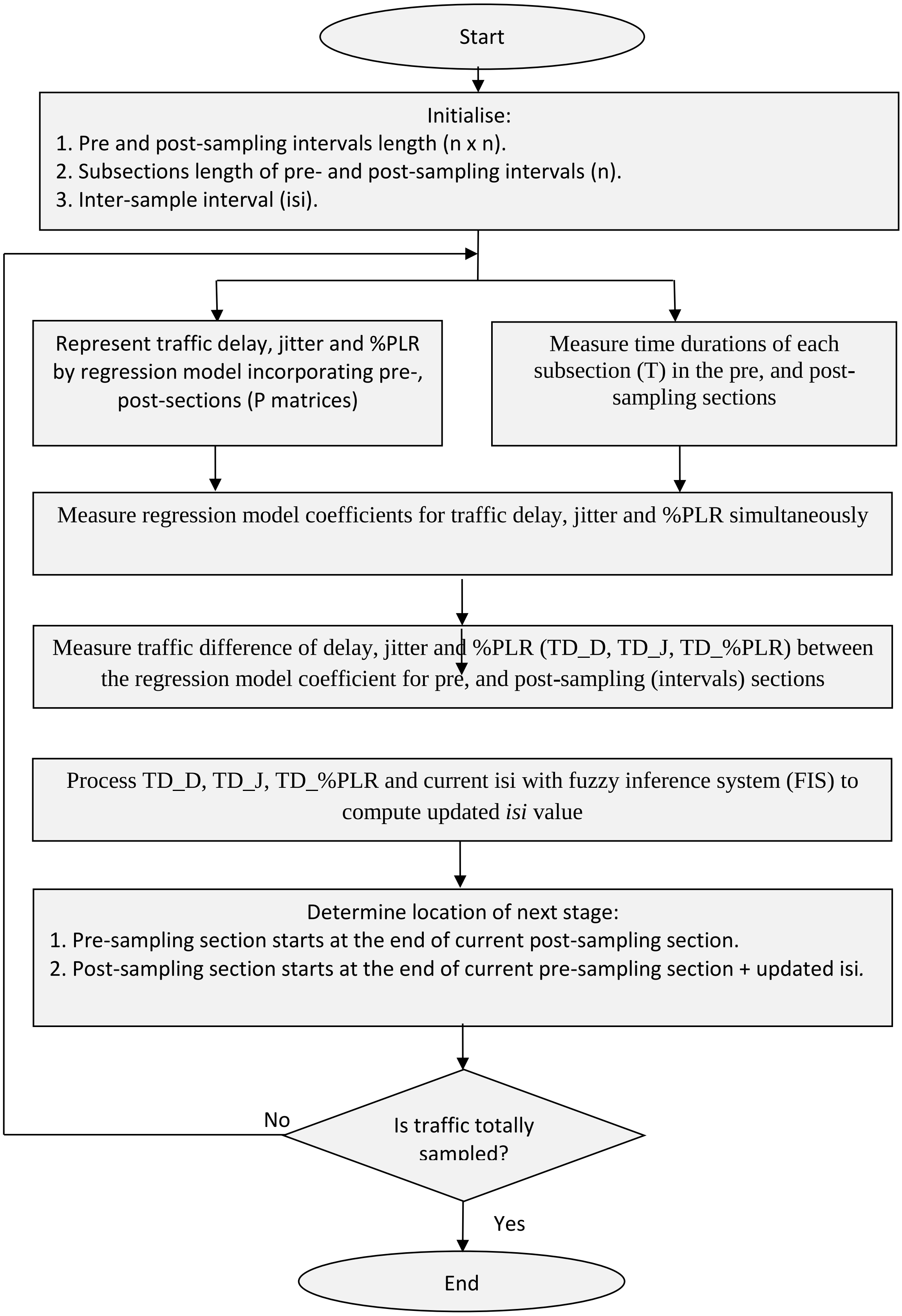


Figure 05.2 The flow chart of the multi-input adaptive sampling algorithm

The method was iterative and at each stage the value of isi was updated. The regression model was used to represent packets included in the pre-sampling and post-sampling (intervals) sections. The traffic factors delay, jitter, and %PLR were the independent measures signifying *p* values in regression model represented in Equation (5.1). The pre-sampling and post-sampling sections were allocated into *n* subsections (s_1, s_2 …, s_n), whereas each subsection had *n* packets as presented in Figure 5.3; the traffic parameters measures of each subsection were characterised by a row of the matrix *P* and the related time interval for every subsection was signified by the vector *T* as specified in Equation (5.1).

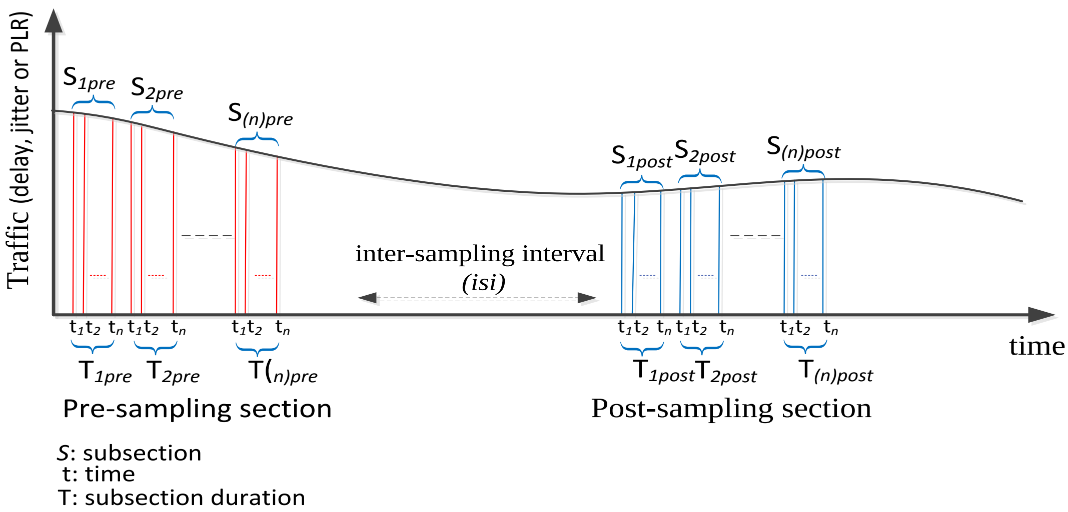


Figure 0.3 A representations of traffic for the regression model (i.e. delay, jitter or %PLR).

In this study the number of pre-sampling and post-sampling subsections (*n*) was 3 and each and each section (*S*) contained 9 data packets. This resulted form of in a 3 × 3 traffic matrix (*P*). The matrix *P* represented one traffic parameter at time (t_1, t_2…, t_n). These produced subsections S_{1pre}, S_{2pre}, while S_{3pre} for the pre-sampling section and S_{1post}, S_{2post}, and S_{3post} for the post-sampling section as shown in Figure 5.3. This representation was repeated for the pre-sampling and post-sampling (intervals) sections. The traffic representation matrices for both sampling sections are shown in Equation (5.1) by linear regression model. The initial *isi* set to zero.

$$T = PC + E = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{bmatrix} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ P_{12} & & P_{2n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \quad (5.1)$$

The time periods related with every subsection's packets (s_1, s_2 ..., s_n) were expressed by T_1, T_2 ..., T_n. These periods were computed by subtracting the arrival time of the last packet from the arrival time of first packet in the equivalent subsection. The vector $E = [e_1, e_2 \ldots, e_n]'$ signifies the computation error which initially was set to zero which led the reduction in the complexity of regression model. The regression coefficients $c_1, c_2 \ldots, c_n$ were measured by Equation (5.2).

$$C = P^{-1}T \tag{5.2}$$

The quantity of change in traffic that related with pre-sampling and post-sampling sections was measured by their corresponding regression model coefficients using the traffic difference (traffic variation), as shown in Equation (5.3).

$$\text{Traffic difference of delay(TD)} = \sqrt{(c_{1\text{pre}} - c_{1\text{post}})^2 + (c_{2\text{pre}} - c_{2\text{post}})^2 + \cdots (c_{(n)\text{pre}} - c_{(n)\text{post}})^2} \tag{5.3}$$

The previous steps, the Equations (5.1) - (5.3) for the delay parameters can be expressed as:

$$T = PC + E = \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{bmatrix} = \begin{bmatrix} D_{11} & \cdots & D_{1n} \\ D_{12} & & D_{2n} \\ \vdots & \ddots & \vdots \\ D_{n1} & \cdots & D_{nn} \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix}$$

where *D*, contains delay values of packets, the first row of the matrix *P* represent the delay values of subsection (1), while, the bottom row represent the subsection (n). This repeated for pre- and post-sections. The coefficients were determined as

$$C_{pre\ or\ post} = D^{-1}T$$

After coefficients of delay parameter were determined, the traffic difference of delay (TD_D) was obtained as

$$\text{Traffic difference of delay(TD\_D)} = \sqrt{(c_{1\text{pre}} - c_{1\text{post}})^2 + (c_{2\text{pre}} - c_{2\text{post}})^2 + \cdots (c_{(n)\text{pre}} - c_{(n)\text{post}})^2}$$

The previous three Equations were repeated for jitter and for %PLR and used in the FIS. FIS received the current interval of the isi and the traffic differences (TD) and accordingly measured the updated isi interval as illustrated in Figure 5.4.

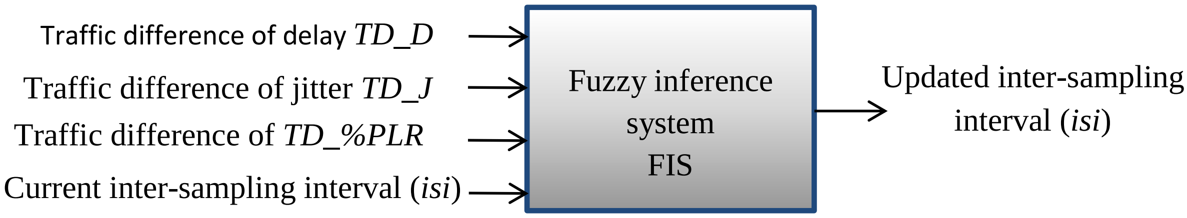


Figure 05.4 Fuzzy logic to update isi interval

The FIS has been used to adaptively change the value of the isi. Four inputs were fed to the FIS. These were the traffic difference for network parameters delay (TD_D), jitter (TD_J), (TD_%PLR) and the current isi. The membership function choice is the subjective aspect of fuzzy logic. The most common membership function is Gaussian which has been most commonly used in literature due its smooth representation of input, and the error is minimized. It allows the desired values to be interpreted appropriately. The amount of overlap and the range of each variable were determined by experimenting with a number of suitable values and selecting the ones that gave best outcomes by trial and error. In this study delay (TD_D), jitter (TD_J), (TD_%PLR) and the current isi membership function have been chosen as Gaussian. The locations, the range, the degree of overlap amongst the produced membership functions, and their equivalent fuzzy linguistics elements are provided in Figure 5.5.

The model inputs and the output have been fuzzified by the Gaussian membership functions that are smooth and have concise notation. The formula expressed in Equation (5.4) signified the Gaussian membership function while c_i and σ_i are the mean and standard deviation for the i^{th} Gaussian fuzzy set A_i (Khalifa et al., 2016).

$$\mu_{A^i}(x) = \exp(-\frac{(c_i - x)^2}{2\sigma_i^2}) \tag{5.4}$$

The inputs to the FIS i.e. the traffic difference measures of delay, jitter, %PLR and current isi were independently fuzzified using five membership functions. The measured traffic difference for delay, jitter, and %PLR were VHigh, High, Medium, Low, and VLow fuzzy sets. While, the input isi was signified by VLarge, Large, Medium Small, and VSmall, fuzzy sets. The output (updated isi) was defuzzified by five membership functions, signified by DH (High decrease), DL (Low Decrease) NC (no change), IL (Low Increase), and IH (Increase High). Figure 5.5 provides these membership functions.

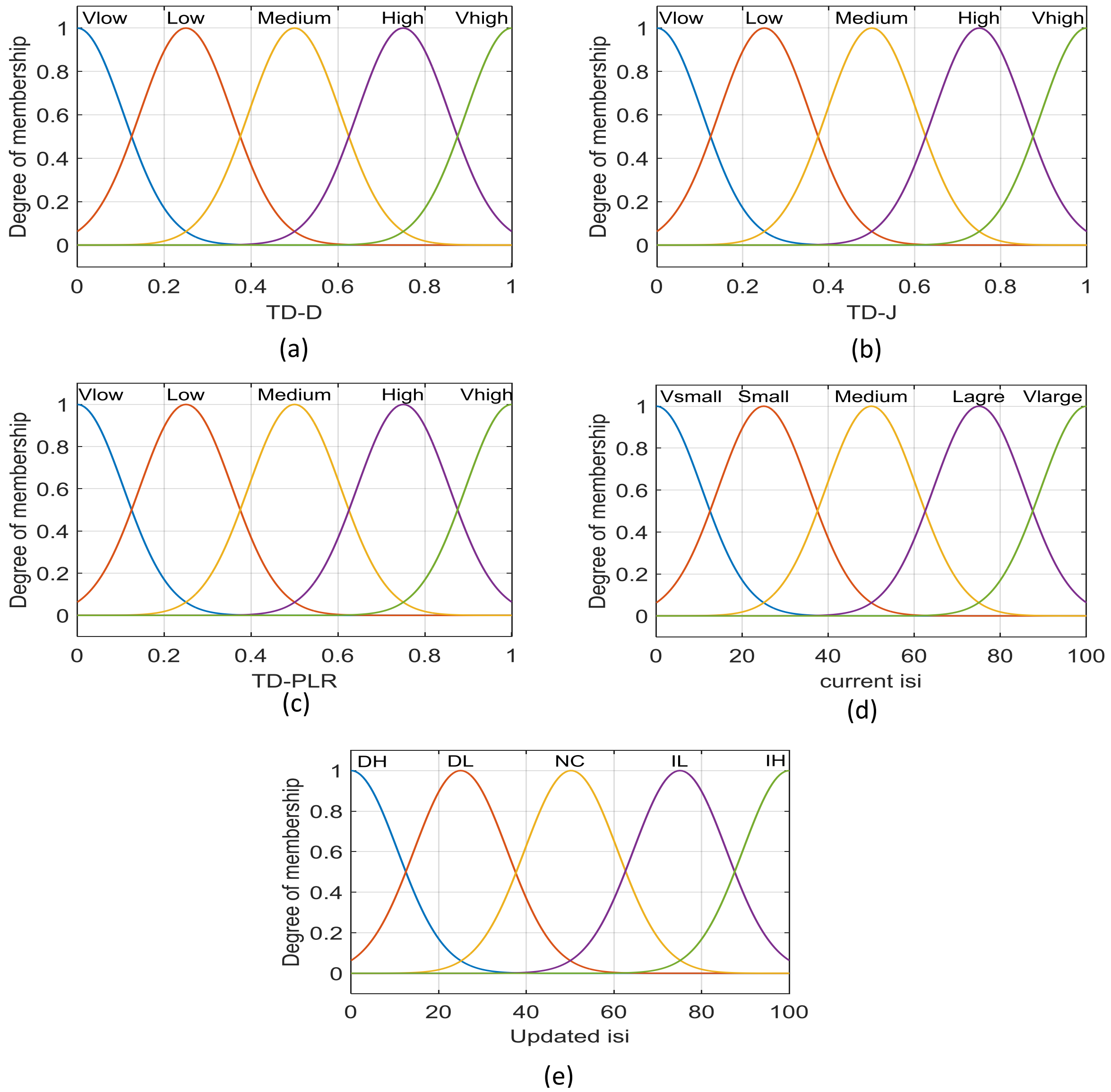


Figure 5.5 The membership functions for (a–c) traffic difference (TD_D, TD_J and TD_%PLR) sets for delay, jitter, and %PLR (d) current inter-sampling interval; and (e) the updated inter-sampling interval

Tables (5.1) - (5.2) provide mean and standard deviation values of the Gaussian membership function parameters for the fuzzy input sets delay, jitter, %PLR, and current isi while, the fuzzy output sets (updated isi) are included in Table (5.3).

Table 0.1 Mean and standard deviation of TD_D, TD_J and TD_%PLR membership functions

Membership functions	Overall statistics	
	Mean	St. dev.
Very low	0	0.10
Low	0.25	0.10
Medium	0.5	0.10
High	0.75	0.10
Very high	1	0.10

Table 0.2 Mean and standard deviation of current isi fuzzy membership functions

Membership functions	Current sample interval isi	
	Mean	St. dev.
Very small	0	10.62
Small	25	10.62
Medium	50	10.62
Large	75	10.62
Very large	100	10.62

Table 0.3 Mean and standard deviation of updated isi output fuzzy membership functions

Membership functions	Updated sample interval isi	
	Mean	St dev.
Very small	0	10.62
Small	25	10.62
Medium	50	10.62
Large	75	10.62
Very large	100	10.62

The association between the inputs and the output was defined by a set of fuzzy rules. The number of fuzzy rules was set based on the number of inputs and their related fuzzy sets. The method to define a fuzzy rule base for fuzzy logic controllers was based on experience knowledge. In this case, trial and error has been a choice to design fuzzy rules. The rules are expressed in linguistically forms and the size of the rule base is small enough to allow modelling of the systems to be easily interpreted and analysed. In this part 25 rules have been chosen based on experience and best outcome results. The rules are explained in Table (5.4).

Fuzzy reasoning was based on (minimum and maximum) inferencing. Each rule was individually associated by the membership functions and their minimum was mapped into related output membership function. While, the output fuzzy set from the implication operation for each rule was joined via the aggregation method to create one fuzzy set. The FIS output was produced from aggregated fuzzy set (defuzzification) by the centroid method.

The centroid method indicated the centre of area under the curve of the aggregated membership functions according to Equation (5.5) (Kovac et al., 2013).

$$Y = \frac{\sum_{i=1}^{m} y_i \cdot \mu_i}{\sum_{i=1}^{m} \mu_i} \tag{5.5}$$

Where *m* is the fuzzy sets achieved after implication, y_i is the centroid of fuzzy region *i*, and μ_i is the of degree membership measure.

Table 0.4 The fuzzy rules used by FIS to adjust isi

Rule	TD Delay	TD Jitter	TD %PLR	Current isi	Updated isi
1	Very low	Very low	Very low	Very large	No Change NC
2	Very low	Very low	Very low	Large	Increase Low IL
3	Very low	Very low	Very low	Medium	Increase High IH
4	Very low	Very low	Very low	Small	Increase High IH
5	Very low	Very low	Very low	Very small	Increase High IH
6	Low	Low	Low	Very large	No Change NC
7	Low	Low	Low	Large	No Change NC
8	Low	Low	Low	Medium	Increase Low IL
9	Low	Low	Low	Small	Increase Low IL
10	Low	Low	Low	Very small	Increase Low IL
11	Medium	Medium	Medium	Very large	Decrease Low DL
12	Medium	Medium	Medium	Large	No Change NC
13	Medium	Medium	Medium	Medium	No Change NC
14	Medium	Medium	Medium	Small	No Change NC
15	Medium	Medium	Medium	Very small	Increase Low IL
16	High	High	High	Very large	Decrease High DH
17	High	High	High	Large	Decrease High DH
18	High	High	High	Medium	Decrease Low DL
19	High	High	High	Small	Decrease Low DL
20	High	High	High	Very small	No Change NC
21	Very high	Very high	Very high	Very large	Decrease High DH
22	Very high	Very high	Very high	Large	Decrease High DH
23	Very high	Very high	Very high	Medium	Decrease Low DL
24	Very high	Very high	Very high	Small	Decrease Low DL
25	Very high	Very high	Very high	Very small	No Change NC

5.4 Implementations of Conventional Sampling

Non-adaptive sampling methods based on systematic, stratified and random sampling were measured according to the count-based method. These sampling methods were selected due to their easiness (Silva et al., 2017_b and 2013), (Robitza et al., 2017) and (Shao, 2016). The implementation of conventional sampling methods involved:

i. **Systematic sampling:** for every *n* packet, the n^{th} packet was chosen. In systematic sampling operation, a counter was set at beginning to *n* and it is decreased by 1 at receiving every new packet. Once the counter become zero, the packet chosen. The operation represented selection of one packet. In the next step, the counter was reset, and the computational method was repeated.

ii. **Random sampling:** for a sample size of *n* obtained from a population of *N*, the *n* is random number require to be produced for a range 1 to *N*, and then the packet chosen process is achieved according to the packet's positions in the data flow. For every run, a new *n* would be produced in order to get multiple sets of samples at same size.

iii. **Stratified sampling:** For each *N* packets, random numbers *n* is produced in the range [1, *N*], and packets are chosen based on their position. For every run, a new *n* is obtained for the same sample size.

In this study *n* was given different values for different sample fractions (selected sample fractions are shown in Tables (5.5) - (5.7).

5.5 Measurements of Sampling Traffic Parameters and Sampling Analysis

The network traffic parameters delay, jitter and %PLR were determined as explained in chapter 3 section 1. The sequence number of the packets at the receiver side which is a unique number for every packet was used for this purpose. Then the timestamp in RTP header for the VoIP traffic was used to measure these parameters based on Equations (3.1) - (3.3). The traffic parameters (i.e. delay, jitter, and %PLR) of the sampled traffic that were computed using adaptive sampling model.

To assess the efficiency of the proposed sampling model, the actual traffic's population and its sampled were compared. According to Wan et al. (2014) assessments of mean and standard deviation of the sampled traffic and original traffic may not be adequate to assess the accuracy of the sampling consequently, further assessments were used to evaluate the efficacy of the proposed model. The parameters used were:

i. **Bias:** It specifies how distant the mean of the sampled version deception from the mean of its actual data (Wan et al., 2014). The bias is the average of variance of all samples as indicated in Equation (5.6) was used to measure biasness:

$$\text{Bias} = M_i - \text{M} \tag{5.6}$$

Where, M_i and M are the means of the actual data and its sampled form.

ii. **Relative Standard Error (RSE):** The RSE is an additional method that was used to evaluate the accuracy of the sampling. The RSE determined the consistency of sampling (Sileshi, 2015). RSE is described as a percentage and can be computed by Equation (5.7), the standard error (SE) divided by the sample size of (*n*):

$$RSE = \frac{SE}{n} \times 100 \tag{5.7}$$

Where *n* is the sample size, and SE is the standard error values of the actual and sampled data.

iii. **Curve fitting:** is an additional computational technique used to determine the sampling behaviour for its representation of the actual population. It determines the data trends of the actual population and its sampled version by the process of curve fitting. The curve fitting is a convenient approach for representing data in linear, polynomial and quadratic formats (Guruswami and Venkatesan, 2016) and (Fraundorf et al., 2012). Equation (5.8) shows the general formula for a polynomial:

$$f(x) = a_0x^N + a_1x^{N-1} + a_2x^{N-2} + \dots\dots + a_{N-1}x + a_N \tag{5.8}$$

The curve fitting polynomial calculates a least squares polynomial for a set of data *x* and determines the coefficients of the polynomial that demonstrates a curve to fit the data giving the quantified degree (*N*). Whereas, the polynomial degree is equivalent to the maximum number of the exponents (*N*), and (a_0, a_1... a_N) is a set of polynomial coefficients. The polynomial assessment function determines a polynomial for *x* and then generates a curve to fit the data depend on the coefficients that have been obtained using the curve fitting (Guruswami and Venkatesan, 2016) and (Fraundorf et al., 2012). In this study *N* was selected to be 4.

The sampling fraction is a part of data that will be calculated. The sampling fraction is the ratio of the sampled size (*n)* divided by the data size.

5.6 PART A: Simulation Network Topology

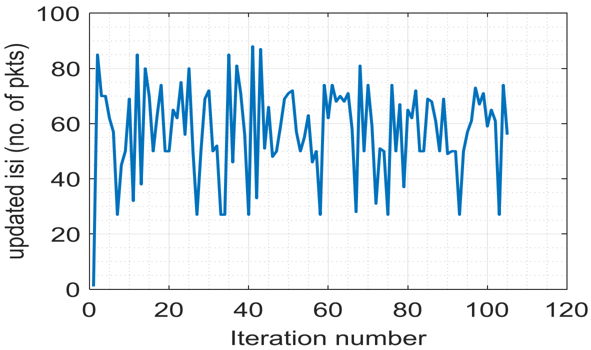
A hybrid and scalable network design was implemented using NS2 simulator. The designed scenario is explained in section 4.3 and shown in Figure 4.2.

The core layer was the wired part of the network with a capacity of 10 Mbps. The wireless channel capacity was configured to 2 Mbps. The queuing model for the testing scenario was First-In-First-Out (FIFO). The traffic included HTTP, FTP video streaming and VoIP. G711 was adapted as audio coding. The NS2 sampling evaluation scenarios ran for period of 800 seconds. After the simulation was completed, a trace file was generated that included packet transmission details like the packet types, sent and received times, packet sizes and delivery status. Traffic parameter measurements been quantified based on Equations in section (3.1) - (3.3). VoIP results were extracted; delay, jitter and %PLR were calculated for the VoIP to be sampled.

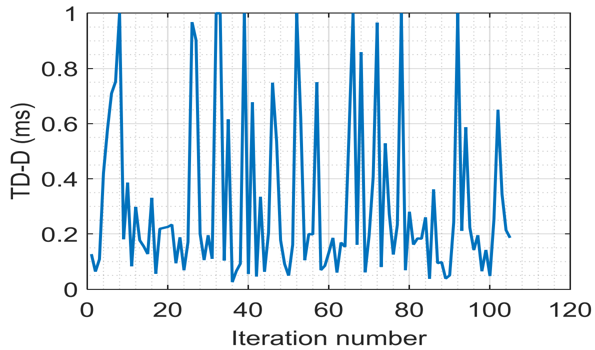
5.6.1 Simulation network results and discussion

Figure 5.6 (a) provides the updated isi based on the differences in TD_D, TD_J, TD_%PLR, and current isi. Figure 5.6 (b) indicates the manner the Traffic difference of TD_D. When differences are large, isi value declined and vice versa. Figure 5.6 (c) illustrates the actual delay and its trend. Figure 5.6 (d) provides the sampled delay and its trend. The trends for the actual delay and its sampled form were very close. The updated value of isi changed dynamically. For each iteration, isi changed the packet count which included the number of packets that isi increased or decreased for the next iteration.

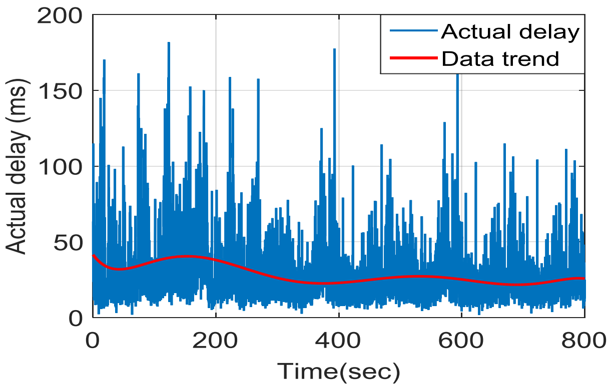
The scenario repeated several times to best normalise TD of delay, jitter and %PLR. Initially, the maximum and minimum values were defined and then the data were normalized between 0 and 1 for membership simplicity, and this was for delay, jitter and %PLR. However, the same normalised numbers (maximum and minimum numbers were used for the simulation and the real testbed scenario which make the designed method suitable for networks.



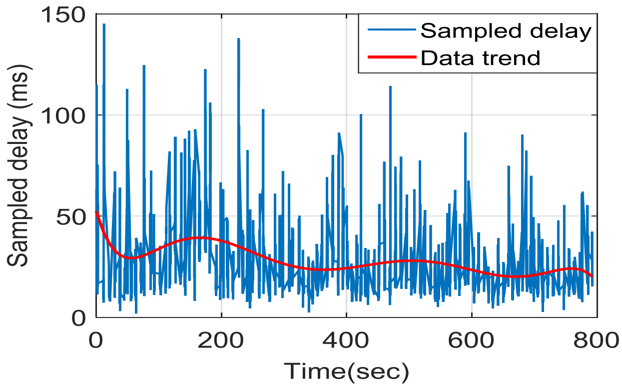
(a)



(b)



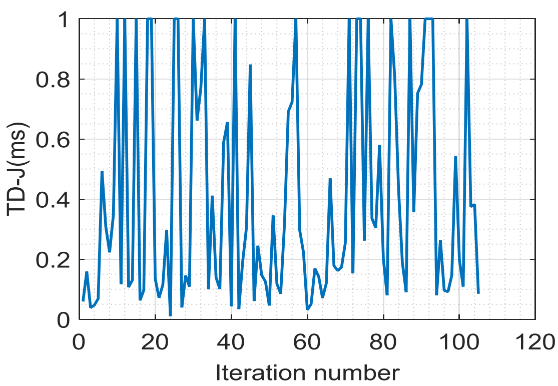
(c)



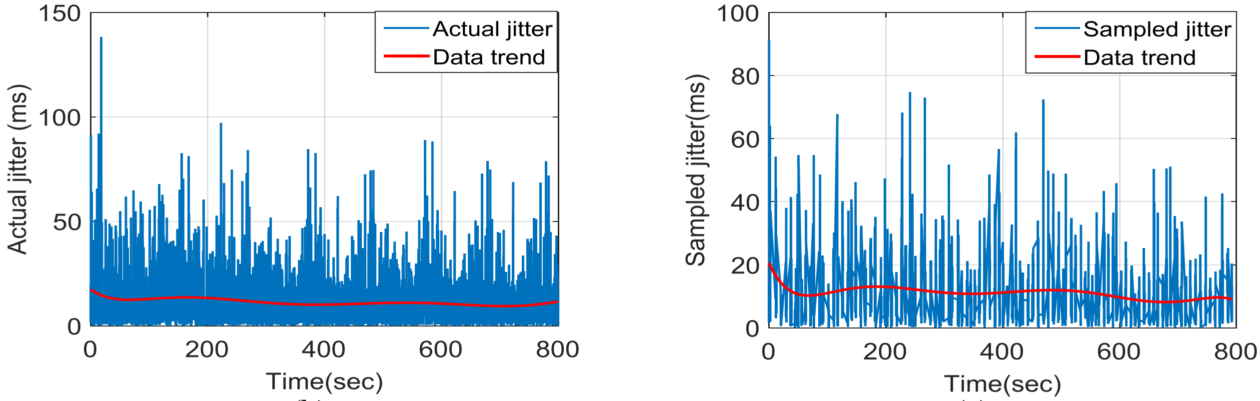
(d)

Figure 05.6 Typical results obtained from the developed adaptive technique (a) FIS output for updated isi (b) traffic difference for delay TD_D (c) actual traffic delay (d) sampled traffic delay

In Figures 5.7 (a) - (c), the way the developed sampling method tracked the jitter is shown. In Figure 5.7 (a) the traffic difference of jitter TD_J is shown. In Figures 5.7 (b) - (c) the actual jitter and their sampled traffic are shown. For traffic jitter, the trends for the actual traffic are similar to the sampled form. In Figure 5.8 (a) the traffic difference for %PLR (TD_%PLR) is shown. Figures 5.8 (b) - (c) the actual %PLR and its sampled version are shown. For %PLR, the trends for the actual traffics are very close to the sampled form.

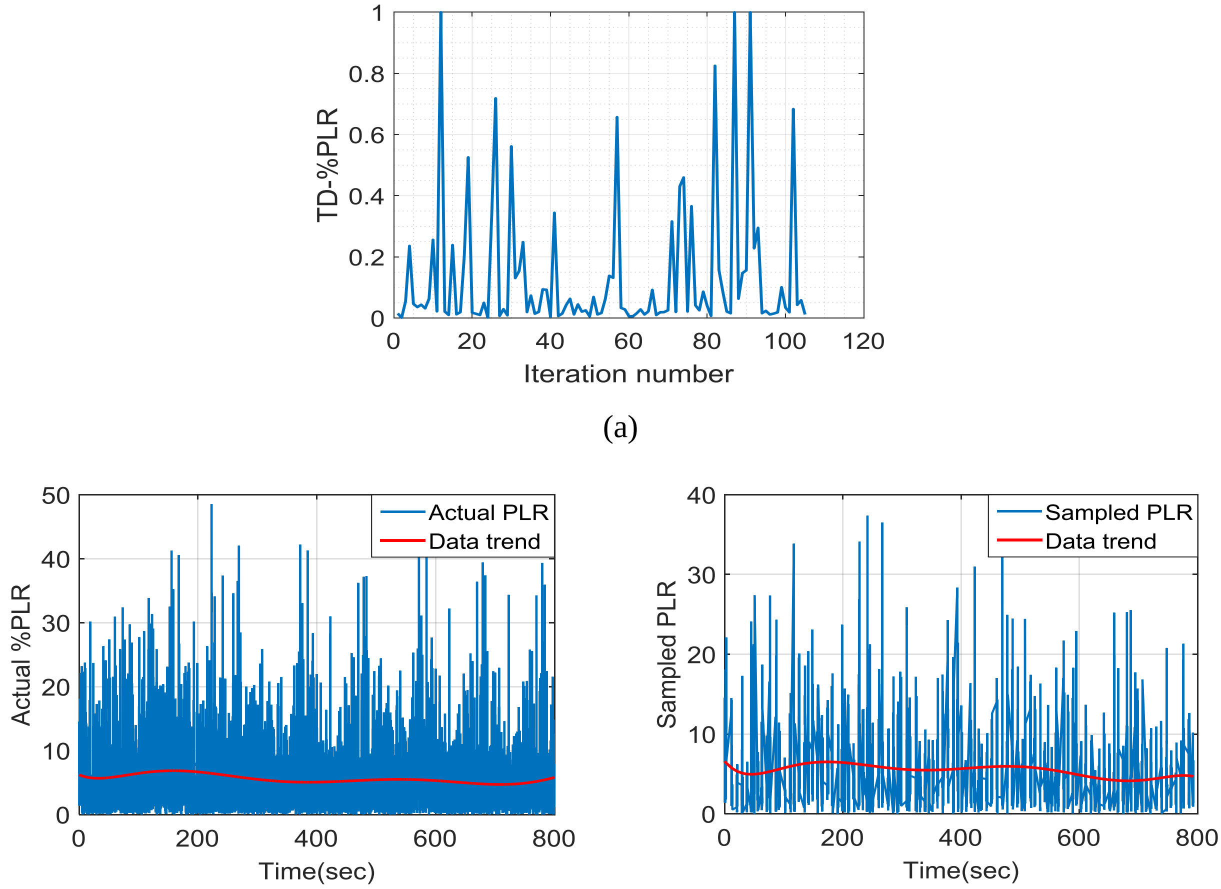


(a)



(b) (c)

Figure 5.7 Typical results obtained from the developed adaptive technique (a) traffic difference for jitter TD_J (b) actual jitter (c) sampled jitter



(a)

(b) (c)

Figure 5.8 Typical results obtained from the developed adaptive technique (a) traffic difference for %PLR (TD_%PLR) (b) actual traffic %PLR (c) sampled traffic %PLR

5.7 PART B: Emulated Testbed Network Topology

As stated in literature review, the actual emulated network represents network traffic conditions more practically than the simulations. Therefore, the developed sampling technique was applied on an actual emulated network in this section. The results of this section will be compared against conventional sampling techniques. Hybrid computer network was used to evaluate the developed adaptive sampling model. The design is explained in section 4.4 and shown in Figure 4.3. The network was implemented and configured in a network laboratory with 6 m × 4 m area. Details of the hardware description are explained in methodology chapter 4, section 4.4.

The traffic transmission continued for up to 900 seconds and includes of VoIP, video streaming using MPEG-2, and normal data using the TCP. VoIP call was initiated by SIP and UDP/RTP.

The process of initiated PPP connections between the PCs that connected to AP-1 and the other PCs that connected to AP-2. The traffic sent included VoIP call which was captured by Wireshark that was installed in PC-1a and PC-ab.

NetEm was used for its capability to emulate traffic factors (Roshan, 2018). In this part of the study NetEm was configured to alter delay, jitter, and %PLR between PC-1a and PC-1b. The scenario ensures that VoIP packets sent between PC-1 and PC-2 were sufficiently large to allow accurate sampling for QoS assessment.

5.7.1 Emulated testbed results and discussion

The packets for VoIP were selected and their parameters, i.e., delay, jitter and %PLR were measured using Equations (3.1) - (3.3). Linear regression Equation (5.1) was used to model traffic packets. The traffic difference (TD_D, TD_J and TD_%PLR) shown in Equation (5.3) was used to measure the traffic variation behaviour related with the pre- sampling and post-sampling intervals. The FIS output produced the updated isi for every iteration based on the FIS inputs values and the fuzzy rules. As an example, Figure 5.9 (a) shows the adaptive updating of isi based on variation of TD_D, TD_J and TD_%PLR and current isi. Figure 5.9 (b) shows the way the variation of traffic difference of delay TD_D. Figure 5.9 (c) provides the actual delay with its trend and Figure 5.9 (d) provides the sampled delay and its trend. Both actual delay packets and its sampled packets are very close. When traffic differences were large, *isi* reduced and vice versa. Figures 5.9 (c) - (d) show the curve fitting model applied for both the actual and sampled forms of the network traffic parameters. The fitted curve shown in red confirms that actual traffic and its sampled version are very close. It can be observed from the Figure that trend of the sampled traffic using the adaptive sampling technique characterised the trend of its actual data very closely. The updated inter-sampling interval (*isi*) changed adaptively.

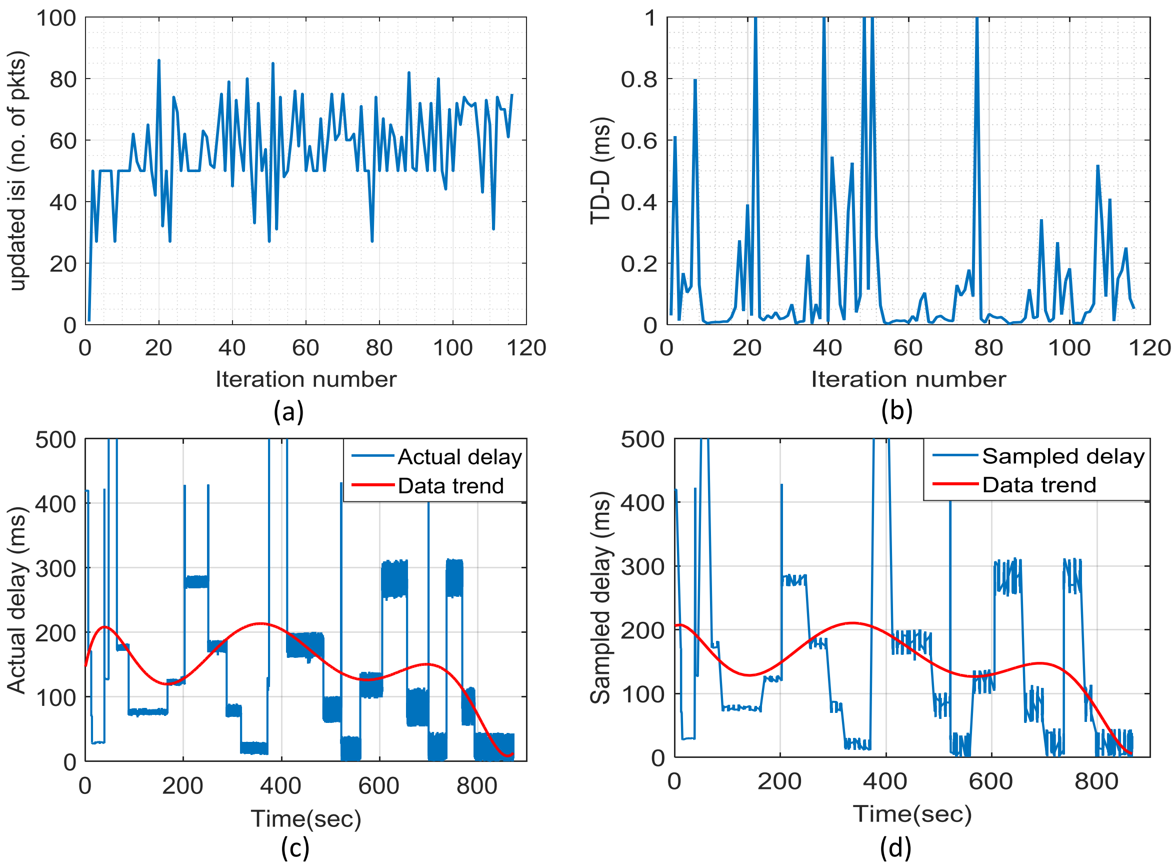


Figure 5.9 Typical results obtained from the developed adaptive technique (a) FIS output for the inter-sampling interval (isi) (b) traffic difference for delay (c) actual traffic delay (d) sampled traffic delay

Figure 5.10 (a) shows the traffic difference for jitter, TD_J. Figures 5.10 (b) - (c) show the actual, sampled jitter and their trends. The trends for the actual jitter and its sampled form are very close. A similar observation is for %PLR. In Figures 5.10 (b) - (c) the curve fitting model was applied for both the actual and sampled jitter. It is shown in red which confirmed that actual population traffic and sampled version were very close. To produce the results, the same minimum and maximum numbers of delay, jitter and %PLR from the simulation test (previous section) were used and these were relied upon to normalize data between 0 and 1.

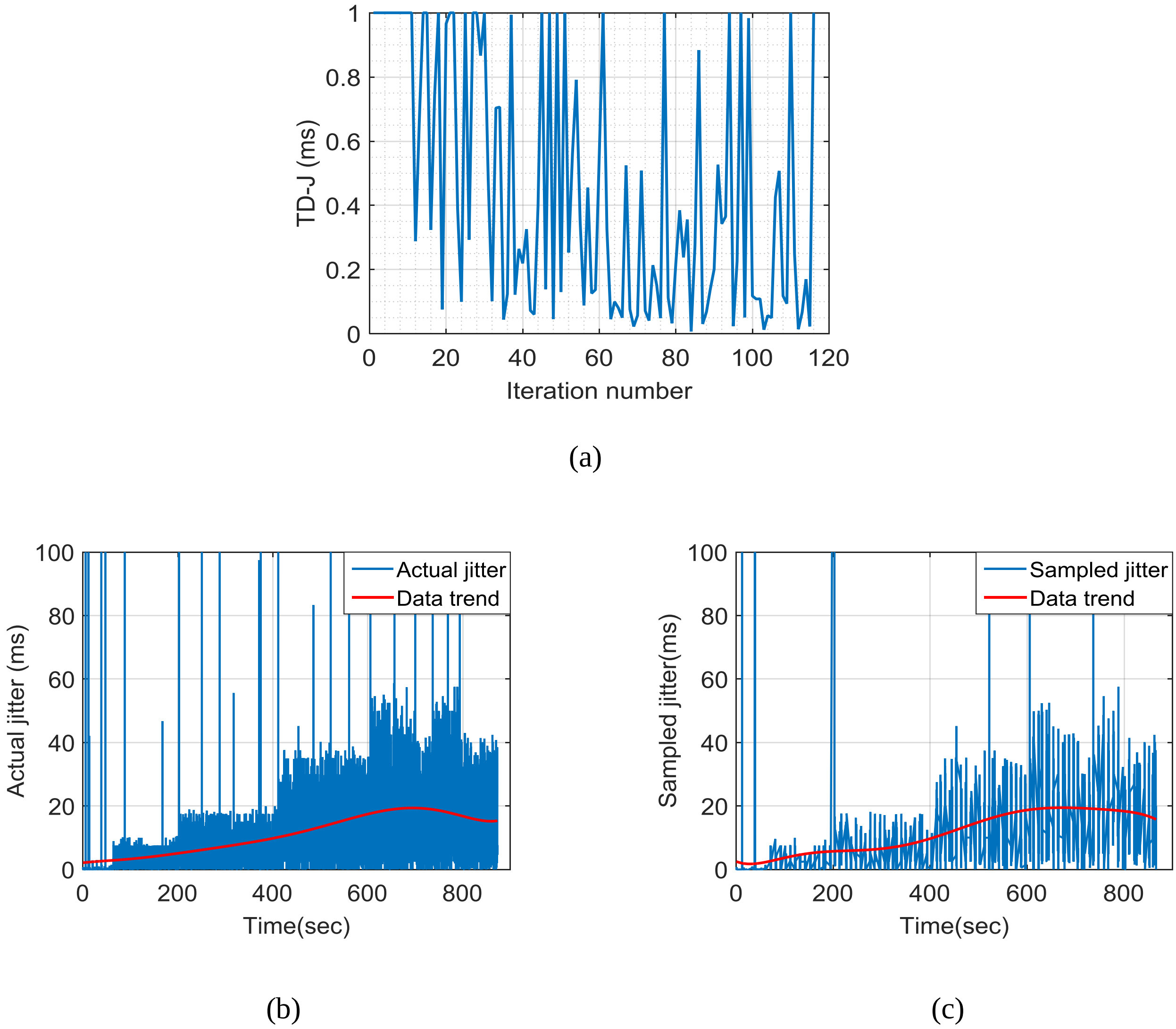


Figure 5.10 Typical results obtained from the developed adaptive technique (a) traffic difference for jitter (b) actual traffic jitter (c) sampled traffic jitter

Figure 5.11 (a) show traffic difference of %PLR (TD_%PLR). Figures 5.11 (b) - (c) show the actual, sampled %PLR and their trends. In Figures 5.11 (b) - (c), curve fitting was applied to both the actual and sampled %PLR. It indicated that actual population traffic and sampled version are very close.

In order to compare the proposed sampling against non-adaptive techniques, the bias and RSE were calculated. These comparisons were performed using an emulated testbed as it is based on a real network laboratory. This provided a suitable accuracy as explained in the literature review.

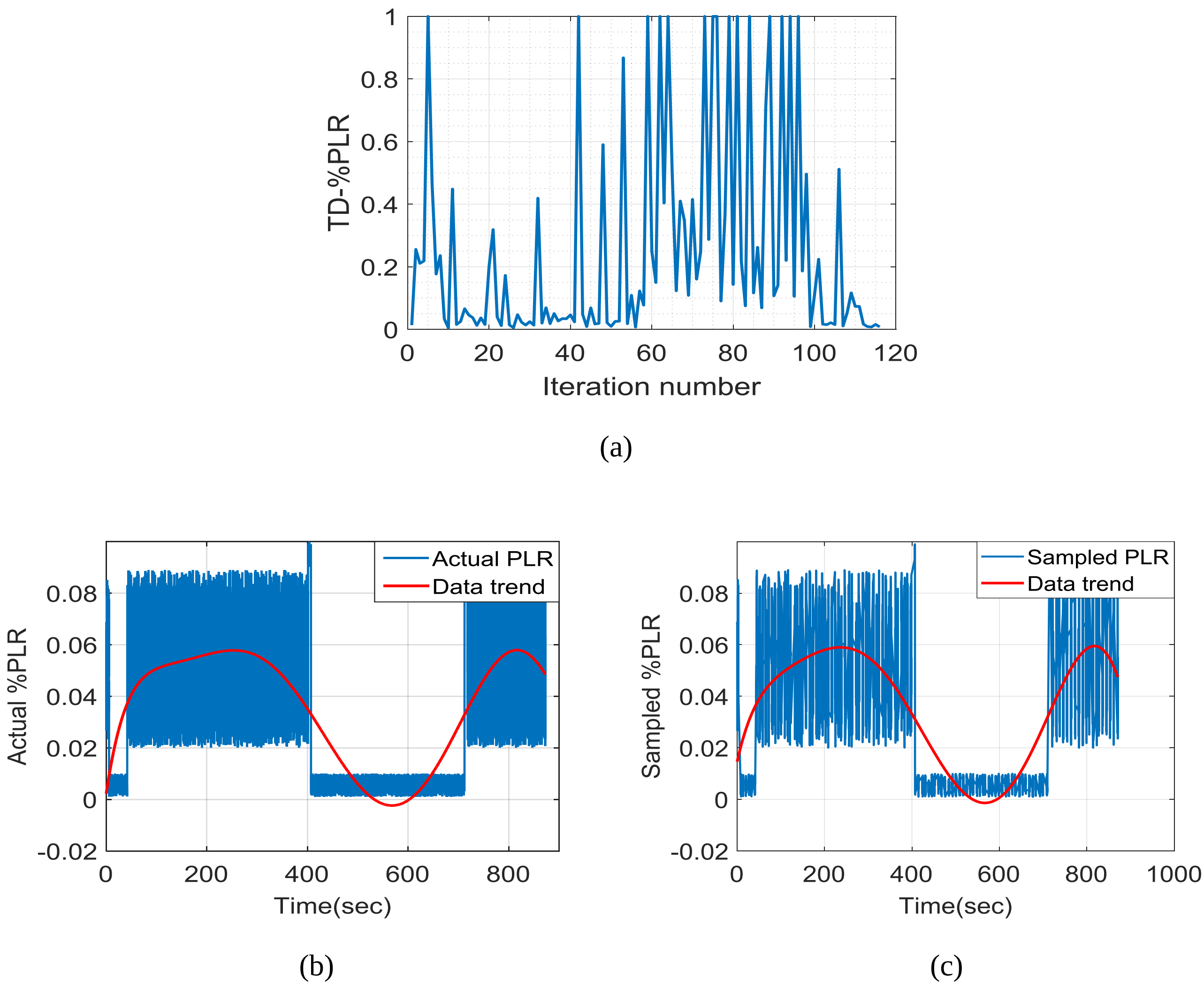


Figure 5.11 Typical results obtained from the developed adaptive technique (a) traffic difference for %PLR (b) actual traffic %PLR (c) sampled traffic %PLR

Table (5.5) shows the comparisons of the mean, standard deviation, biasness and RSE for the actual and sampled delay at many fractions using the proposed model and non-adaptive techniques. In all approaches, as the sample size was increased, the deviation of the mean and RSE reduced consequently as a large sample size included a larger number of packets that improved representation of the actual population. The mean and standard deviation of the actual delay traffic (at 0.0 sample fractions) were 146 ms and 141 ms, respectively. At sample fraction of 22.9%, the sampled delay achieved from the proposed model had a mean of 147 ms and standard deviation of 141 ms, respectively. The mean and standard deviation of the actual sampled delay obtained by systematic, random, and stratified sampling, at sample fraction of 22.9%, were (143 and 138 ms), (150 and 142 ms) and (149 and 139 ms) respectively. The results indicated that the delay measures of sampled traffic by proposed technique represented the actual delay traffic more accurately. Tables (5.5) - (5.7) indicate that the proposed model has the lowest relative error and bias measures in most of the sample fractions as compared against the non-adaptive approaches, indicating a better performance.

Table 0.5 Measurement results for delay using different sampling methods: adaptive, systematic, random, and stratified

Measured	Sample Fractions %				
	0	6.1	10.2	13.0	22.9
Adaptive sampling method					
Mean	146	147	147	147	147
Std.	141	141	141	142	141
Bias	0	0.875	0.683	0.067	−0.262
RSE	0	0.90	0.40	0.30	0.11
Systematic sampling					
Mean	147	145	146	148	143
Std.	141	146	142	141	138
Bias	0	1.974	0.725	−1.279	3.960
RSE	0	0.99	0.52	0.38	0.15
Random sampling					
Mean	147	176	157	149	150
Std.	141	165	152	149	142
Bias	0	−28.551	−9.741	−1.401	−2.432
RSE	0	1.13	0.50	0.29	0.14
Stratified sampling					
Mean	147	146	150	150	149
Std.	141	143	149	142	139
Bias	0	1.093	−2.740	−2.977	−2.184
RSE	0	1.20	0.46	0.38	0.26

The measurements provide a similar jitter trend, as specified in Table (5.6). The mean and standard deviation of the actual jitter (at 0.0 sample fractions) were 11.116 ms and 17.493 ms respectively. While, the sampled jitter version quantified by the developed model had a mean of 11.073 ms and standard deviation of 17.493 ms, respectively, at sample fraction of 22.9%. Though, the mean and standard deviation of actual jitter using systematic, random, and stratified sampling at sample fraction 22.9% were (10.855 and 12.120 ms), (10.608 and 14.770 ms) and (11.389 and 18.681 ms) respectively. These indicated that the sampled jitter by the proposed model characterised the actual jitter more closely.

Table 0.6 Measurement results of jitter using different sampling methods: adaptive, systematic, random, and stratified

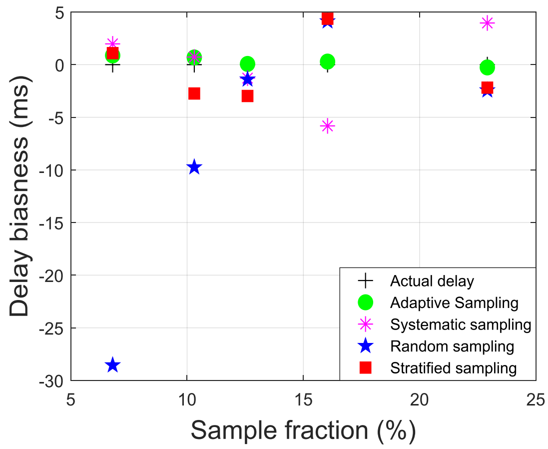
Measured	Sample Fractions %				
	0.0	6.1	10.2	13.0	22.9
Adaptive sampling method					
Mean	11.116	11.235	10.638	11.185	11.073
Std.	17.493	17.479	11.636	14.073	17.493
Bias	0	−0.118	0.478	−0.068	0.043
RSE	0	0.11	4.31×10^{-2}	2.69×10^{-2}	1.5×10^{-2}
Systematic sampling					
Mean	11.116	12.612	11.133	12.732	10.855
Std.	17.493	23.778	21.049	26.650	12.120
Bias	0	−1.495	−0.016	−1.615	0.261
RSE	0	0.16	6.97×10^{-2}	7.40×10^{-2}	1.66×10^{-2}
Random sampling					
Mean	11.116	11.733	10.325	10.691	10.608
Std.	17.493	23.990	13.723	21.510	14.770
Bias	0	−0.616	0.790	0.425	0.508
RSE	0	0.16	4.53×10^{-2}	4.34×10^{-2}	1.55×10^{-2}
Stratified sampling					
Mean	11.116	13.127	11.357	11.202	11.389
Std.	17.493	23.601	19.236	18.428	18.681
Bias	0	−2.011	−0.241	−0.085	−0.272
RSE	0	0.20	6.08×10^{-2}	5.05×10^{-2}	3.5×10^{-2}

Table (5.7) provides a similar %PLR trend. The mean and standard deviation of the actual population of %PLR (0.0 sample fractions) were 0.035 and 0.029 respectively. The sampled %PLR version quantified by the developed model had a mean of 0.035 and standard deviation of 0.029, respectively, at sample fraction of 22.9%. The mean and standard deviation of the actual of sampled %PLR by systematic, random, and stratified sampling at sample fraction 22.9% were (0.035 and 0.029 ms), (0.035 and 0.028 ms) and (0.036 and 0.028 ms) respectively. This also indicated that the sampled %PLR by the proposed model represented the actual %PLR more precisely.

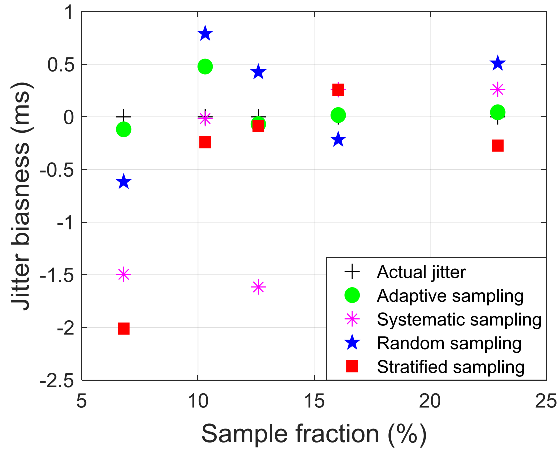
Table 0.7 Measurement results of packet loss ratio using different sampling methods: adaptive, and non-adaptive (systematic, random, and stratified)

Measured	Sample Fractions %				
	0.0	6.1	10.2	13.0	22.9
Adaptive sampling method					
Mean	0.035	0.035	0.034	0.036	0.035
Std.	0.029	0.029	0.029	0.029	0.029
Bias	0	6.23×10^{-6}	0.0016	-5.96×10^{-4}	-7.22×10^{-5}
RSE	0	1.88×10^{-4}	3.05×10^{-5}	5.93×10^{-5}	2.08×10^{-5}
Systematic sampling					
Mean	0.035	0.037	0.035	0.035	0.035
Std.	0.029	0.029	0.029	0.028	0.029
Bias	0	−0.0014	5.20×10^{-4}	7.95×10^{-6}	-2.72×10^{-4}
RSE	0	2.06×10^{-4}	9.62×10^{-5}	8.05×10^{-5}	3.99×10^{-5}
Random sampling					
Mean	0.035	0.035	0.034	0.034	0.035
Std.	0.029	0.029	0.027	0.028	0.028
Bias	0	1.65×10^{-5}	0.0013	8.07×10^{-4}	-2.90×10^{-4}
RSE	0	1.98×10^{-4}	1.03×10^{-4}	7.94×10^{-5}	3.30×10^{-5}
Stratified sampling					
Mean	0.035	0.034	0.035	0.037	0.036
Std.	0.029	0.028	0.029	0.029	0.028
Bias	0	0.0013	1.03×10^{-6}	−0.0014	-6.45×10^{-4}
RSE	0	2.55×10^{-4}	9.35×10^{-5}	8.13×10^{-5}	5.47×10^{-5}

Figures 5.12 (a) - (c) indicate the bias of sampled delay, jitter and %PLR respectively at several sample fractions using the developed model and non-adaptive sampling methods. The measurements indicated that the bias was near zero for all used techniques for a large sample size. Additionally, the proposed model has a smaller bias as compared against non-adaptive methods. For example, at 22.9% sample fraction, the absolute value of the bias of sampled delay was 0.262 ms, whereas, the absolute values of bias measures for systematic, random, and stratified sampling were 3.960 ms, 2.432 ms, and 2.1844 ms, respectively. When the sample fraction was 6.1%, the lowest bias was obtained by the proposed model (i.e. 0.875 ms), followed by the stratified sampling method (i.e. 1.093 ms), then systematic methods at 1.974 ms while the highest absolute value of bias was for the random method was at 28.55 ms.



(a)



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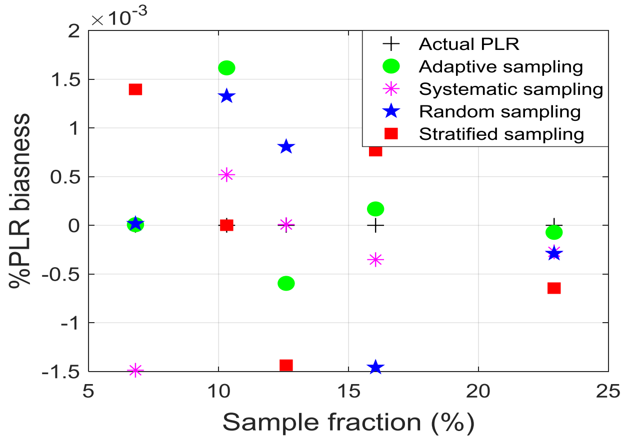
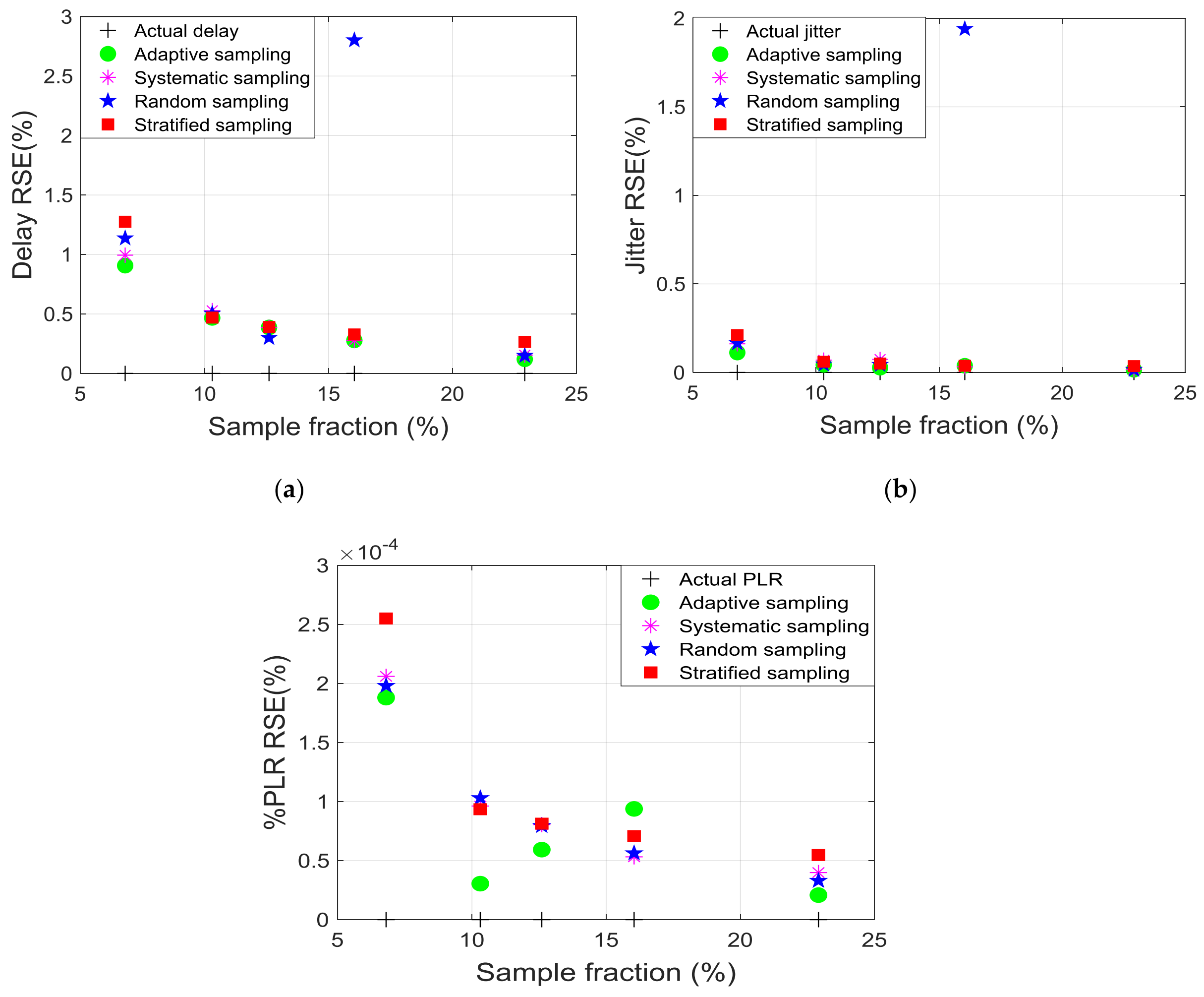


(c)

Figure 0.12 Comparisons of biasness of (a) delay, (b) jitter, and (c) %PLR between the developed technique and non-adaptive methods

In Figures 5.13 (a) - (c) the RSE for the sampled delay, jitter and %PLR for non-adaptive techniques were compared with the quantified RSE for the developed adaptive model. The measurements indicated that the developed adaptive model has the lowest RSE as compared with the non-adaptive methods. For example, at a 22.97% sample fraction, the RSE of the sampled delay traffic was 0.11%, while the bias measurements for systematic, stratified, and random sampling were 0.19%, 0.14%, and 0.26%, respectively. It can be concluded that RSE measurements reduced and became nearer to zero for all used techniques when sample size was increased.



(a) (b)

(c)

Figure 0.13 Comparisons of RSE of (a) delay, (b) jitter, and (c) %PLR between the developed technique and nonadaptive methods

The improved performance of proposed sampling method over conventional non-adaptive sampling methods was due to its capability to select packets based on traffic variations, while the packet selection process in the non-adaptive methods depended on a predefined or random manner.

5.8 Summary

A novel multi-input adaptive sampling approach that sampled multimedia traffic parameters was proposed and assessed. It processed network traffic parameters: delay, jitter and %PLR simultaneously for its analysis. The developed approach performance was assessed and compared with the non-adaptive approaches of systematic, random, and stratified. The proposed approach adaptively increased the inter-sampling interval (isi) causing an increase in the number of selected packets when the traffic variations decreased and vice versus. The adaptive sampling approach expressed the actual traffic more precisely than the non-adaptive techniques. The adaptive sampling method successfully sampled three network parameters simultaneously (i.e. sampled three traffic parameters at same time delay, jitter and %PLR) which increased its accuracy for sampling multimedia traffic. The proposed adaptive sampling approach was successfully applied to simulated and emulated testbed laboratory computer networks that carried VoIP traffic. In both networks the developed method shows better performance against non-adaptive sampling methods.

Chapter 6 Development of Quality of Service Evaluation Methods for VoIP

6.1 Introduction

There is growing dependence on wired and wireless networks for transmitting numerous types of time sensitive applications such as VoIP and video streaming. QoS has significant role in hybrid networks as it can simplify assessment of their performance and deliver approaches to their operation optimisation (Li et al., 2018) and (Chen et al., 2018). Thus, to successfully manage networks to deliver desired services, appropriate tools to evaluate their performance are required. The contribution of this part of the study is to propose two probability-based techniques that combine measurements, evaluation and assessment for overall QoS in multimedia transmission over a hybrid network in an effective manner. Probabilistic neural network (PNN) and Bayesian classification were proposed to process traffic parameters delay, jitter and %PLR and determine Quality of Service (QoS) for VoIP. Both approaches successfully categorised the VoIP packets into their corresponding high, medium and low QoS types. The devised approaches were tested with IEEE 802.11ac (80 MHz) wireless protocol in different traffic load scenarios. The results were compared with IEEE 802.11n (20 and 40 MHz) protocols. In addition, statistical means by SPSS were used to interpret QoS results and their relationships to the traffic parameters.

This chapter is divided into two parts, part A describes the developed performance evaluation models based on actual emulated testbed network in section 6.3. While, part B covers a practical use of developed models by investigate QoS of VoIP over Wi-Fi protocols 802.11ac (80 MHz) and 802.11n (20 and 40 MHz) under different traffic load conditions and their analysis 6.4.

6.2 Related Works

The definition of QoS assessment with the recent related studies was discussed in detail in section 2.3. QoS evaluation according to analysing traffic parameters is measurable but needs tools to compute and interpret traffic transmission (Kim and Choi, 2014). An example of such tool that was used to evaluate QoS in wireless networks is artificial neural network (ANN) (Dogman et al., 2014, 2012_a). Fuzzy c-means (FCM) clustering, Kohonen neural network, multilayer perceptron (MLP) neural network and fuzzy inference system (FIS) was also applied for QoS assessment (Salama et al., 2017_d). A restriction in FCM is that its results can be influenced by the initial setting of its variables. The FIS based technique needs the user to prepare the rules for its knowledge base and to measure the parameters and the membership types for its inputs and outputs. MLP and Kohonen network based QoS assessment approaches can require much iteration to train (1000 iterations in (Salama et al., 2017_d)). MLP designed approach needs careful determination of the number of neurons in its pattern layer to avoid overfitting and to guarantee appropriate generalisation. Kohonen results output is a map that needs analysing by the user to establish distinct groupings.

A number of probabilistic methods were reported to determine QoS in computer networks. For example, Bayesian methods were proposed to classify internet traffic (Namdev et al., 2015) and to analysis QoS for Web applications (Liu et al., 2015) and (Xu, 2012). A Bayesian method that collected data about malicious users was developed Chorppath et al. (2015). A Bayesian decision theoretic approach for QoE modelling was proposed that dealt with computation and estimated problems related to network transmission traffic (Mitra et al., 2014). Bayesian network classifiers as predictive approaches were developed for intrusion detection but they had limitations (Xiao et al., 2014). A technique that addressed the restrictions of Bayesian networks was reported, it was referred to as Bayesian Network Model Averaging (BNMA) (Xiao et al., 2014).

Based on the literature, Probabilistic based methods such as Bayesian and PNN could be used for QoS evaluation for their simplicity and accuracy. Both methods require a single iteration to provide their output. A contribution of this study is proposing two QoS evaluation approaches for VoIP traffic (Salama and Saatchi, 2018). The performance of the developed probabilistic classification approaches were tested in Wi-Fi 802.11n and 802.11ac wireless protocol settings (Salama and Saatchi, 2019_b).

6.3 PART A: Probabilistic Classification of QoS in Using Emulated Testbed

6.3.1 Bayesian classification

Bayesian classification is a supervised learning approach that deals with uncertainty by probabilities with services such as classification, modelling and prediction. Bayesian classification allows *apriori* about data to be used as part of classification (Rappel et al.,

2019) and (Taroni et al., 2007). Bayes' theorem uses the knowledge that prior events as part of quantifying future events, i.e.

$$P(h|e) = \frac{P(e|h)P(h)}{P(e)} \tag{6.1}$$

Where *p(h)* is the prior probability of hypothesis *h*, *p(e)* is the prior probability of evidence *e*, *p(h|e)* is the probability of *h* given *e*, *p(e|h)* is the probability of *e* given *h*. Using Bayes' theorem, the probability that a feature vector $\boldsymbol{X}$ with parameter vector $\boldsymbol{\theta}$ is assigned to a type t_1 is given by

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)P(\boldsymbol{X}|t_1,\boldsymbol{\theta})}{P(\boldsymbol{X})} \tag{6.2}$$

Where $p(t_1)$ is the prior probability of type t_1, $p(X|t_1,\boldsymbol{\theta})$ is the probability density function of $\boldsymbol{X}$ for a given type t_1 and n is number of types. The total probability is

$$P(\boldsymbol{X}) = \sum_{t=t_1}^{t=t_n} P(\boldsymbol{X}|t,\boldsymbol{\theta})\, P(t) \tag{6.3}$$

Equation (6.2) can then be written as

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)P(\boldsymbol{X}|t_1,\boldsymbol{\theta})}{\sum_{t=t_1}^{t=t_n} P(\boldsymbol{X}|t,\boldsymbol{\theta})P(t)} \tag{6.4}$$

$\boldsymbol{\theta}$ is unknown but the calibration data set ($\boldsymbol{Z}$) is known and so $p(\boldsymbol{X}|t,\boldsymbol{\theta})$ can be replaced by $q(\boldsymbol{X}|t,\boldsymbol{Z})$ Saatchi et al. (1995), where

$$q(\boldsymbol{X}|t,\boldsymbol{Z}) = \int_{\boldsymbol{\theta}} P(\boldsymbol{X}|t,\boldsymbol{\theta})\, P(\boldsymbol{\theta}|\boldsymbol{Z})\, d\boldsymbol{\theta} \tag{6.5}$$

So, Equation (6.4) becomes

$$P(t_1|\boldsymbol{X},\boldsymbol{\theta}) = \frac{P(t_1)q(\boldsymbol{X}|t_1,\boldsymbol{Z})}{\sum_{t=t_1}^{t_n} P(t)q(\boldsymbol{X}|t,\boldsymbol{Z})} \tag{6.6}$$

Equation (6.6) is the predictive density function for an observation $\boldsymbol{X}$ on a case of type t measured on the calibration data $\boldsymbol{Z}$. The right-hand side of Equation (6.5) can be rewritten by Saatchi et al. (1995).

$$q(\boldsymbol{X}|\mathrm{t},\boldsymbol{Z}) = \boldsymbol{St}_d(v_t, \boldsymbol{m_t}, \left\{1 + \frac{1}{n_t}\right\} \boldsymbol{S}_t) \tag{6.7}$$

Where there are n_t cases of type t with observation vectors $\boldsymbol{x}_1$, $\boldsymbol{x}_2$..., $\boldsymbol{x}_{nt}$; v_t is the degrees of freedom (given by n_t - 1), $\boldsymbol{m}_t$ is the vector of the means of the input features and $\boldsymbol{S}_t$ the covariance matrix of the inputs. $\boldsymbol{St}_d$ is a d-dimensional student-type density function defined by

$$\boldsymbol{St}_d(v, \boldsymbol{b}, c) = \frac{\Gamma[0.5(v+1)]}{\pi^{0.5d}\{[0.5(v-d+1)]\}\,|vc|^{0.5}}\, x\, \frac{1}{[1+(\boldsymbol{X}-\boldsymbol{b})^T(vc)^{-1}\,(\boldsymbol{X}-\boldsymbol{b})]^{0.5(v+1)}} \tag{6.8}$$

Where Γ is the gamma function. Thus using Equation (6.8) the required values of $p(\boldsymbol{X}|t,\boldsymbol{\theta})$ can be computed for the case of known type. To compute the probabilities for the test or evaluation data set, Equation (6.8) uses the observation vector $\boldsymbol{X}$ for the cases of known type but retains the mean and covariance matrices (i.e. calibration information) for the classification of cases whose types are not known.

In order to further interpret the Bayesian classification results, the atypicality index can be calculated. This is between 0 and 1. Higher values (i.e. values close to 1) of this index for a case indicates that the case is not typical of that type. The atypicality index for a type t and an observation vector $\boldsymbol{X}$ is given by Saatchi et al. (1995) as

$$A(t) = \beta\{\frac{d}{2}, \frac{n_t-d}{2};\ \frac{w_t(\boldsymbol{X})}{w_t(\boldsymbol{X})+\frac{(n_t^2-1)}{n_t}}\} \tag{6.9}$$

where

$$w_t(\boldsymbol{X}) = (\boldsymbol{X}-\boldsymbol{m}_t)^T\boldsymbol{S}_t^{-1}(\boldsymbol{X}-\boldsymbol{m}_t) \tag{6.10}$$

β designates the incomplete beta function computed based on the algorithm of Majumder and Bhattacharjee (1973) and n_t is the number of individuals of type t.

6.3.2 Probabilistic neural network

PNN is a supervised learning, feedforward presented artificial neural network that maps an input to predefined output types (Raman et al., 2017). It is principally a classifier based on a kernel discriminate statistical analysis algorithm. PNN training needs example sets of classes to infer the approximated functions that best define its input (Kowalski and Kulczycki, 2017). The main benefits of PNN are its basically parallel model and fast training convergence to optimum classifiers by aggregate training data. PNN is related to Bayes classification rules (Raman et al., 2017) and (Georgiou et al., 2004) and nonparametric probability density function estimation theory (Kowalski and Kulczycki, 2017).

The neurons in the pattern or hidden layer measure the outputs of an input pattern $\boldsymbol{x}$ from the input layer by executing a Gaussian kernel of the model:

$$\varphi_{k,i}(x) = \sum_{i=1}^{M_k} w_{ki}\, \varphi_{k,i}(x) \quad k = 1, \ldots, number\ of\ groups\ (classes) \tag{6.11}$$

$$\varphi_{k,i} = \frac{1}{(2\pi\sigma^2)^{n/2}} exp\left(\frac{\|x - x_{k,i}\|^2}{2\sigma^2}\right) \tag{6.12}$$

Where $x_{ki} \in R^n$ is the centre of the kernel, and σ is identified as the smoothing (spread) parameter which states the size of the kernel's receptive field. The second layer (the summation layer) sums the outputs separately for each group and provides the probabilities for the input to fit to the predefined clusters by joining the earlier added densities as,

$$p_k(x) = \sum_{i=1}^{M_k} w_{ki}\, \varphi_{k,i}(x) \quad k = 1, \ldots, number\ of\ groups\ (classes) \tag{6.13}$$

Where M_k is the number of neurons in the pattern (hidden) layer of type k and $\boldsymbol{w}_{ki}$ are positive coefficients satisfying $\sum_{i=1}^{M_k} w_{ki} = 1$.

The neuron at the output layer defines the class or type of the input vector **($\boldsymbol{x}$)** based on Bayes' decision rule and the information from the neurons in the summation layer, i.e.

$$c(x) = \arg\ max_{1 \ll k \ll K}\, (p_k) \tag{6.14}$$

The smoothing parameter needs to be specified as part of PNN's training.

An input vector is fed to the n input neurons. Then, the input forwards them to the neurons in the hidden layer where they are distributed into k classes which is equal to 3 classes in our study (i.e. k=1, 2 and 3 represent high, medium and low respectively) which are coloured as pink, green and blue in the Figure 6.1. The structure of a PNN indicating its four layers i.e., input, pattern (hidden), summation and output layers is provided in Figure 6.1.

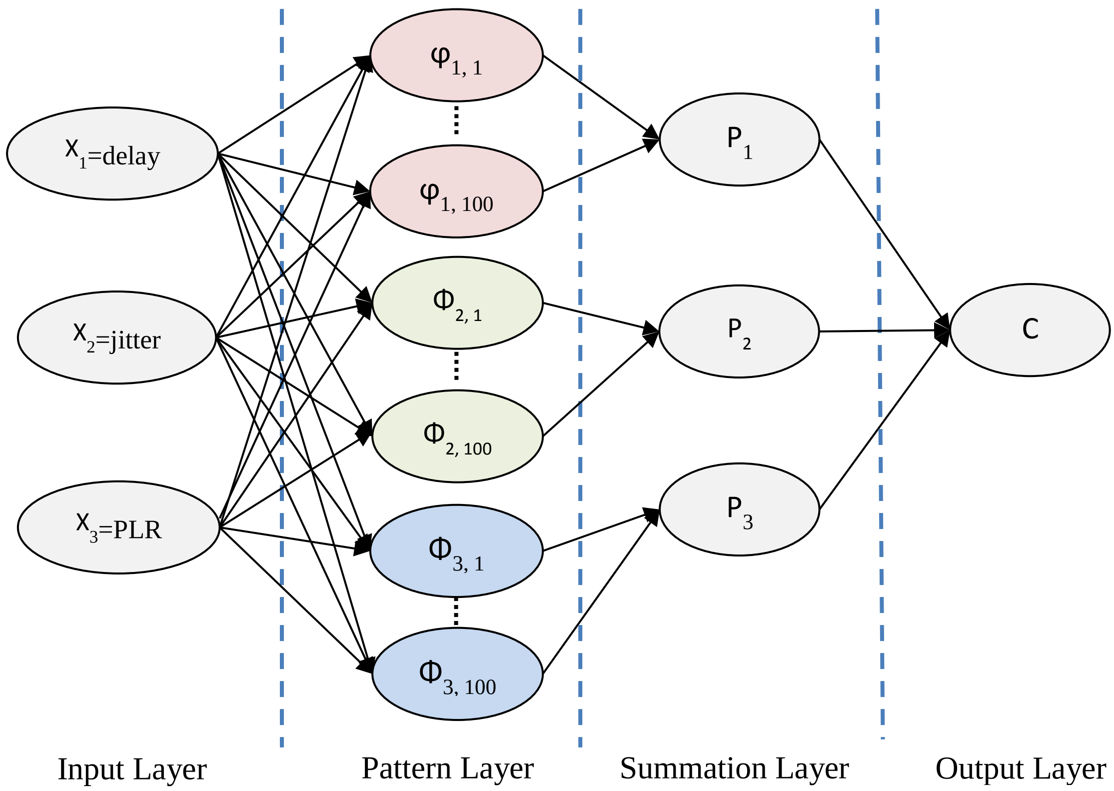


Figure 6.1 A probabilistic artificial neural network

6.3.3 Methodology

In this part of the study the devised approaches of Bayesian classification and probabilistic neural network (PNN) have been applied practically in a computer network laboratory. The proposed traffic transmission classification approaches were assessed on a hybrid network in the laboratory. Figure 6.2 shows the network design. The network equipment details are discussed in chapter 4. The computer network switch device connected the APs, the SIP and NetEm server via 1 Gbps. The equipment's details are explained in chapter 4.

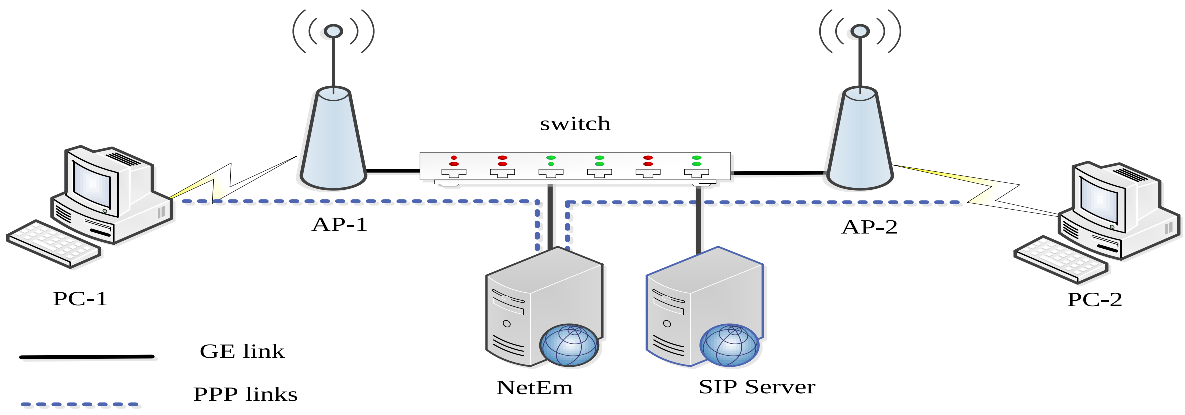


Figure 0.2 Network design

The testing procedure establishes PPP connection between the PC-1 that connected to AP-1 while PC-2 that connected to AP-2. NetEm was configured at the middle of the PPP link to enable adjusting delay, jitter and %PLR measures and consequently to produce high, medium and low QoS classes for the traffic to be evaluated. The traffic packets were transmitting over PPP connection in like that traffic from PC-1 sent to PC-2 through NetEm server and vice versa. The traffic includes TCP, video streaming, and VoIP traffic. The VoIP and the RTP packets were evaluated and analysed. SIP server was used to establish, and control VoIP transmission and the streaming period was about 10 minutes. Wireshark were installed on PC-1 and on PC-2. The captured packets by Wireshark were used to compute delay, jitter and %PLR for VoIP packets (due to RTP features of their sequence numbers and timestamps) based on Equations (3.1) - (3.3). The resulting delay, jitter and %PLR measurements were then used by the classification approaches Bayesian and PNN. Training examples of 300 entries have been used for both Bayesian and PNN methods were extracted from recorded data and its pre-classification based on ITU recommendations specified in Table (6.1).

Table 0.1 VoIP QoS requirements (Dogman and Saatchi, 2014)

QoS range	Delay (ms)	Jitter (ms)	%PLR
High	<150	<1	<2
Medium	150-400	1-3	2-4
Low	>400	>3	>4

Both developed methods classified the received packets into the corresponding high, medium or low QoS types. The implementations of these methods are defined next.

6.3.4 *Bayesian method*

The Bayesian based method processed input data that included the traffic parameters for received packets and formed an output specifying the QoS type for the packets. The approach for the Bayesian model contained three parallel routes as shown in Figure 6.3 that related to high, medium and low classes.

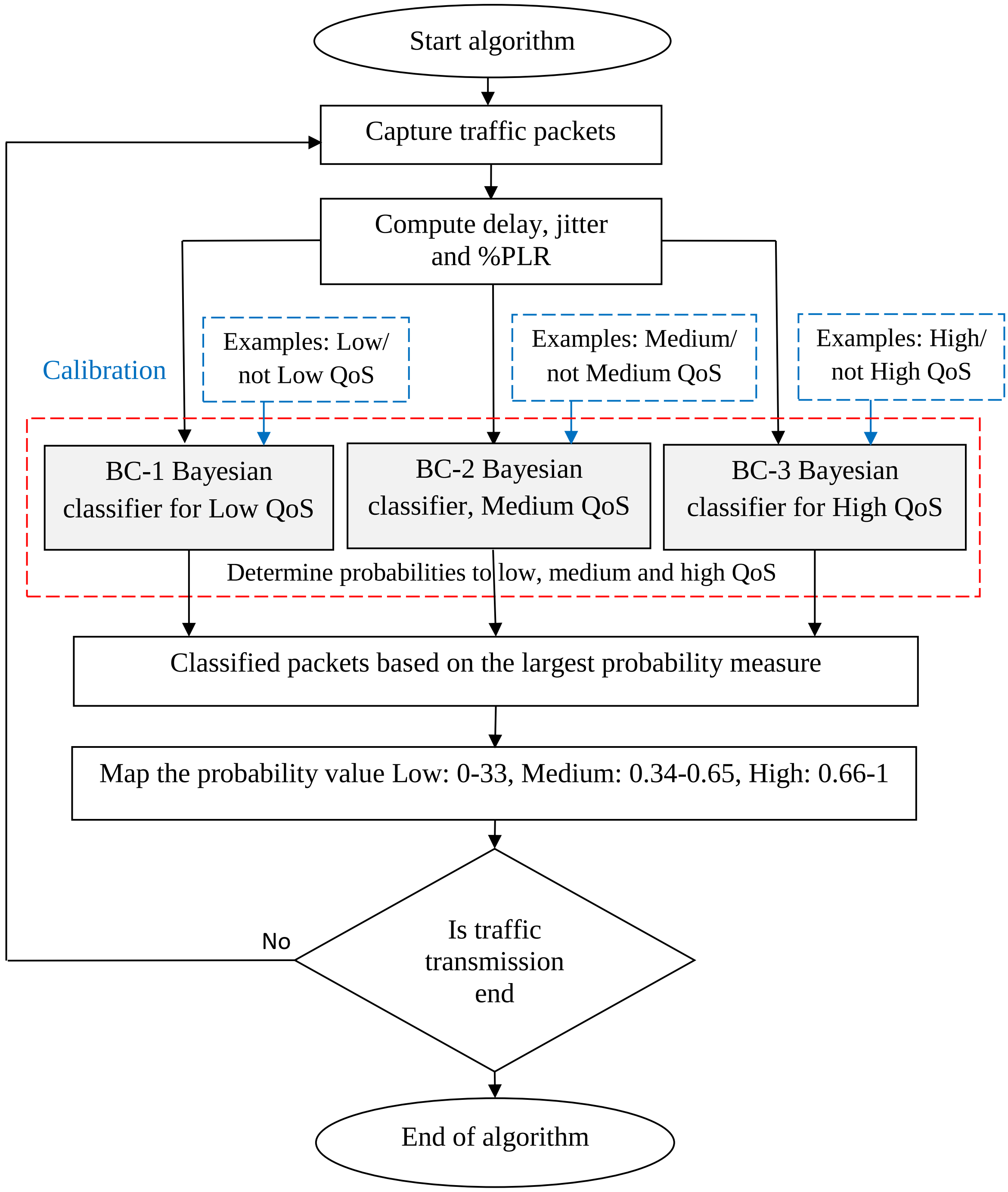


Figure 0.3 Flow chart for the Bayesian approach

Three lists of training (calibration) data examples were organised from recorded data according to Table (6.1) that contains 300 predefined entries which indicated different levels of delay, jitter and %PLR measures identify for high, medium and low qualities. Figure 6.3 illustrates the method traffic computes were connected to each class. If a packet highly belonged to a QoS class type (e.g. low, represented by BC-1 route) then the related probability was close to 1. The same methods were processed for BC-2 (medium) and BC-3 (high). In BC-1, the training data from the low and not low QoS entries in calibration list (training file) were used. Whereas, BC-2 used the examples from the medium and not medium QoS entries and BC-3 used the examples from the high and not high QoS entries. Each path produced a probability value between 0 and 1. High measures of probability stated QoS associated with that path. In order to have a constant range between 0 and 1, for the three paths, the outputs from the paths were mapped as: 0 to 0.33 for low QoS that classified through BC-1 path, 0.34 to 0.65 for medium QoS packets that through BC-2 path and 0.66 to 1 for high QoS packets classified through BC-3 path. The test file contained VoIP transmission parameters $\boldsymbol{X}$= (x_1=*delay*, x_2=*jitter*, x_3=*%PLR*) in Equations in section 6.3 for traffic that continued for 10 minutes.

6.3.5 Probabilistic neural network PNN method

The PNN architecture is shown in Figure 6.1 for three inputs of traffic parameters. The (calibration) training file included 300 entries that associated a range of delay, jitter and %PLR values for many QoS classes (i.e. good, medium and low). For every entry in the training file the equivalent QoS type: 3=high, 2=medium or 1=low, were thus identified. In this study the spread (σ) parameter in Equation (6.11) value was selected as 0.01. The test file (calibration) includes VoIP traffic parameters $\boldsymbol{X}$= (x_1=*delay*, x_2=*jitter*, x_3=*%PLR*) in Equations (6.11) - (6.14).

6.3.6 Results and discussion

Figures 6.4 (a) - (c) show the results for the network delay, jitter and %PLR of VoIP packets. The associated traffic variations were established by NetEm. Figures 6.4 (d) - (e) indicate the QoS results for both Bayesian and PNN models individually. Initially the QoS was high as delay, jitter and %PLR measures were lower. Then, at minute 1.2, QoS became medium. Then, at minute 2.8, the QoS become high again. At time minute 5.5, the QoS fluctuated between low, medium and high in relation to the variations in the delay, jitter and %PLR.

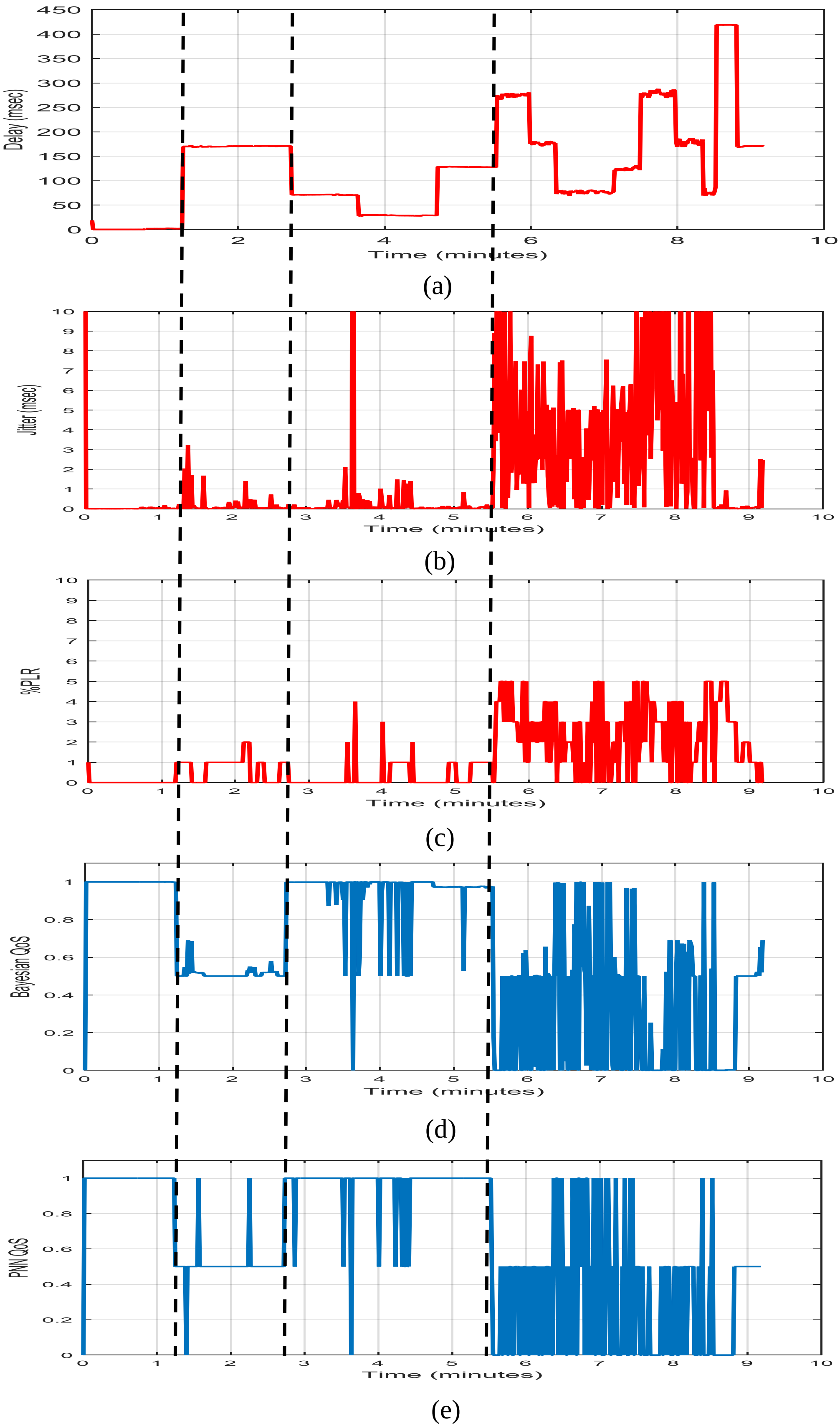
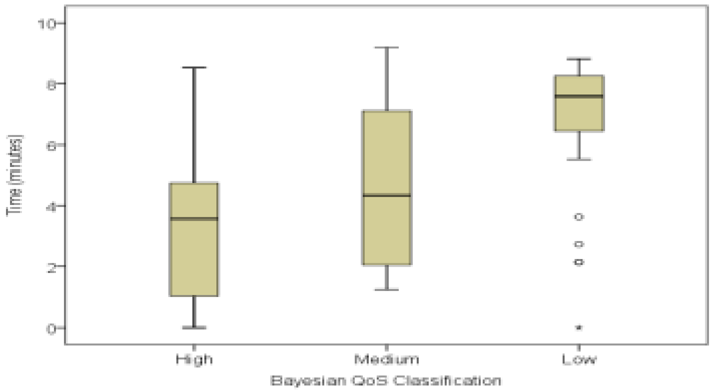
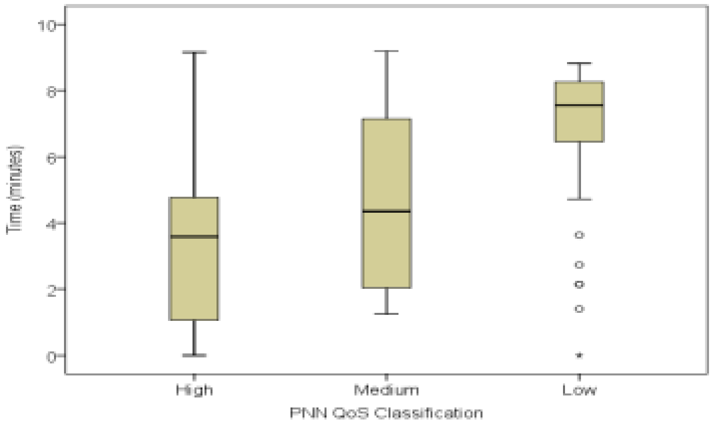


Figure 0.4 (a) Delay, (b) jitter, (c) %PLR, (d) QoS classification Bayesian and (e) QoS PNN classification

To examine the efficacy of the proposed methods SPSS© statistical analysis package was used. Figures 6.5 (a) - (b) illustrate the QoS categorisation boxplots for both Bayesian and PNN models. The measured median (the bar inside each box) for the two methods were very close. Initially the QoS was high. Then, at minute 1.2, packets were classified as high or medium with more packets classified as medium. Then, at minute 5.5, most packets start to be classified as low or medium. The median measure for the high QoS was at minute 3.5, the median measure for the medium QoS was at minute 4.2. Whereas, the median measure for the low QoS was at minute 7.8. Both approaches had some outlier's data for the low QoS between 0 and 4 minutes.



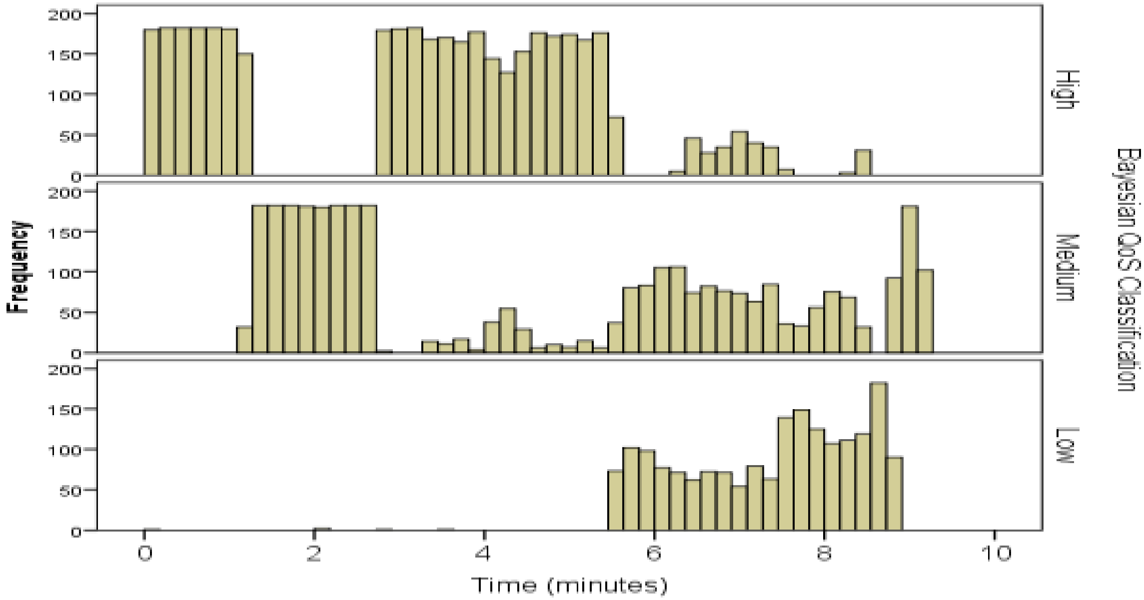
(a)



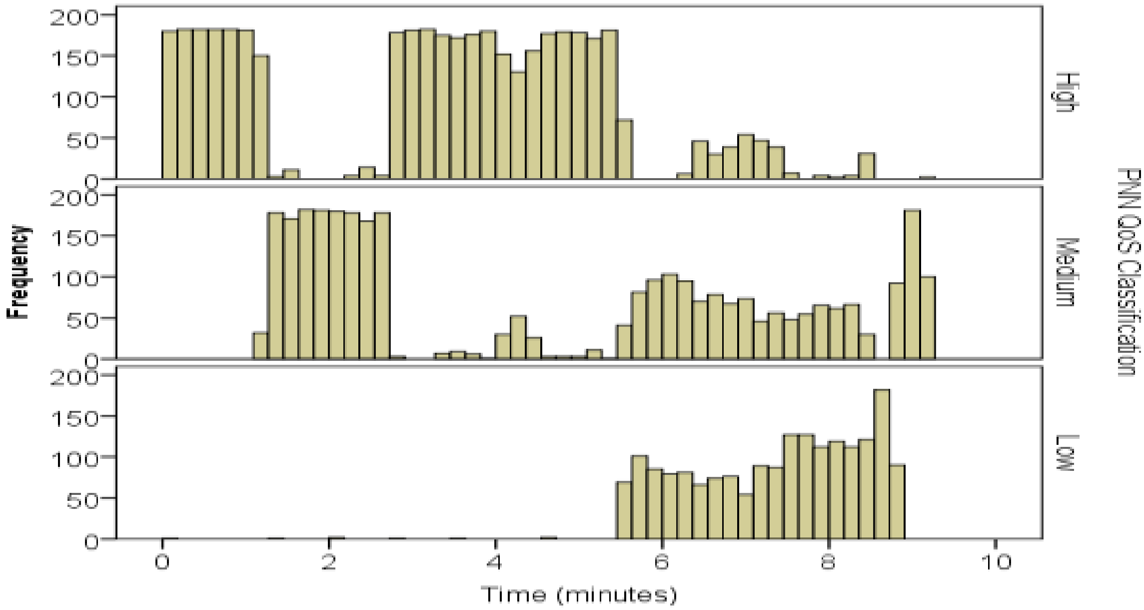
(b)

Figure 6.5 QoS boxplots for (a) Bayesian (b) PNN

Figures 6.6 (a) - (b) show additional information about the packet's classification for both Bayesian and PNN models. Both methods indicated consistent classifications however there are some variances, e.g. between 1.5 and 2.5 minutes, Bayesian has categorised them as medium QoS while PNN has classified some packets into high class.



(a)

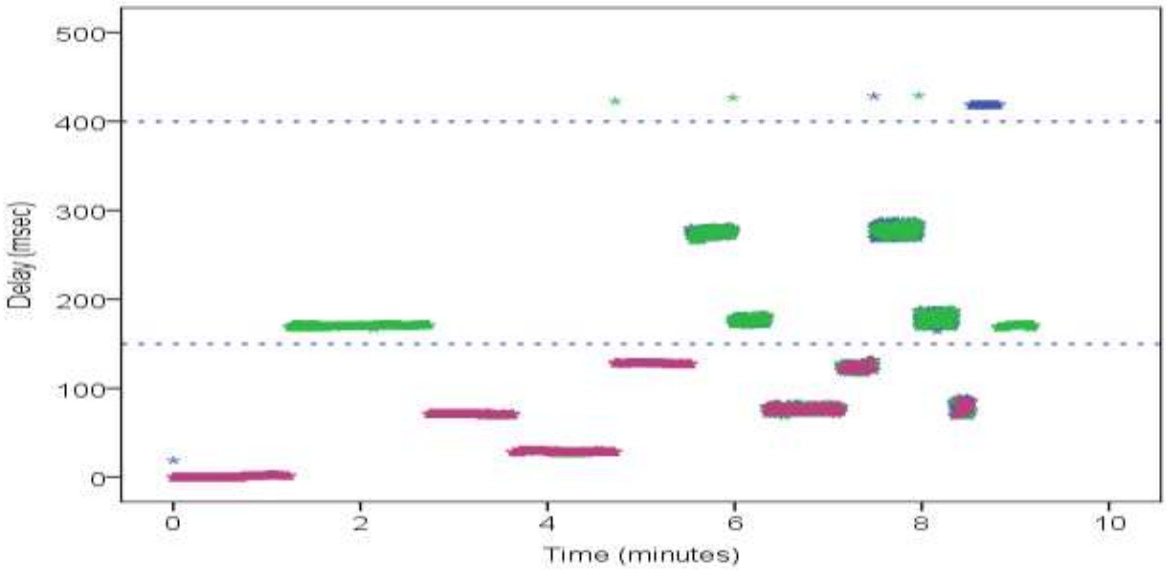


(b)

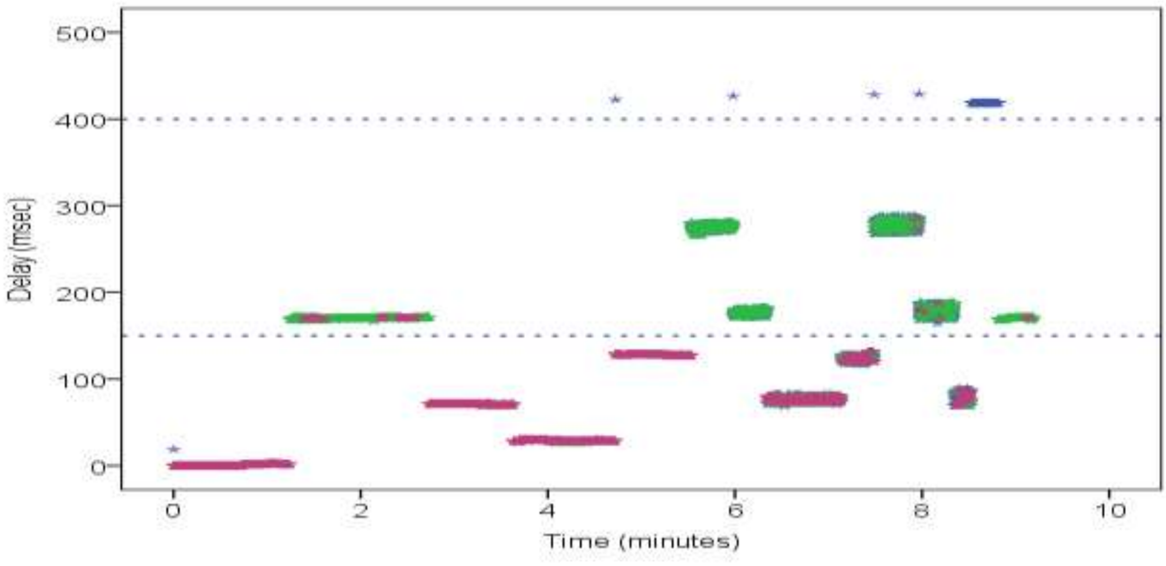
Figure 0.6 Packet classifications for (a) Bayesian (b) PNN

6.3.7 Interpretation of results

Figures 6.7 (a) - (b) show an interpretation of results related to the categorisation, the causes for packets being categorised as low, medium or high quality by the Bayesian and PNN methods. Blue, green and red colours in the Figures indicate low, medium and high QoS respectively. The blue dotted line is at 150 and 400 msec indicates the recommended delay values (indicated in Table 6.1). Several packets were assigned to the medium (green) QoS that have delay less than 150 msec due to their jitter or %PLR exceeding the ITU recommended values. There are some packets between transmission time 1.5 and 2.5 minutes and between 7.8 and 9 minutes that were classed by PNN as high quality (red) but that their delay measures exceeded 150 msec.



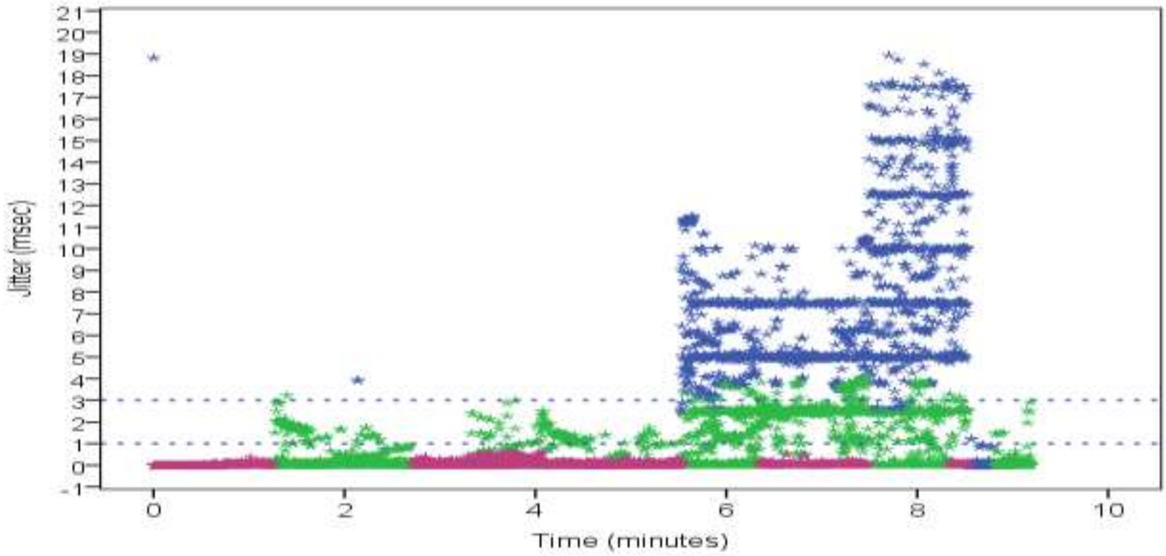
(a)



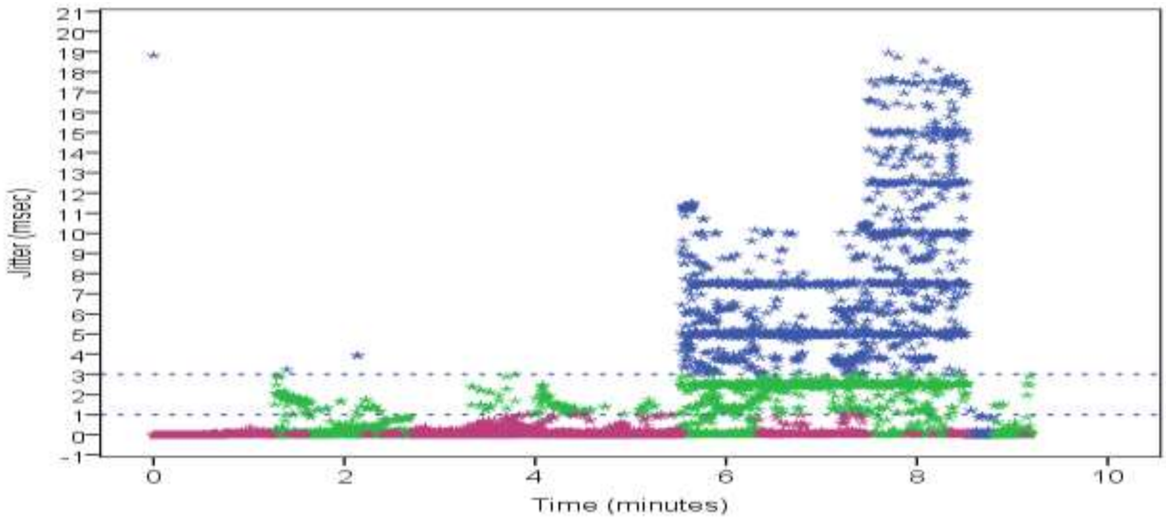
(b)

Figure 6.7 Relationship between packet delay and QoS classification for (a) Bayesian (b) PNN approaches

Figures 6.8 (a) - (b) show an interpretation of the categorisation, the explanations for packets that categorised as low, medium or high quality by both the Bayesian and PNN methods according to their jitter values. Blue colour indicates low QoS, green specifies medium QoS and red indicates high QoS. While, the blue dotted line is at 1 and 3 msec according to recommended jitter values in (Table 6.1). The Figures indicate that there were several packets that were classed into medium (green) QoS that have jitter less than 1 msec, but %PLR is high. There were several packets between (1.5 and 2.5 minutes) and between (7.8 and 9 minutes) that were categorised by PNN as high (red) QoS despite that their jitter measures exceeing 1 msec.



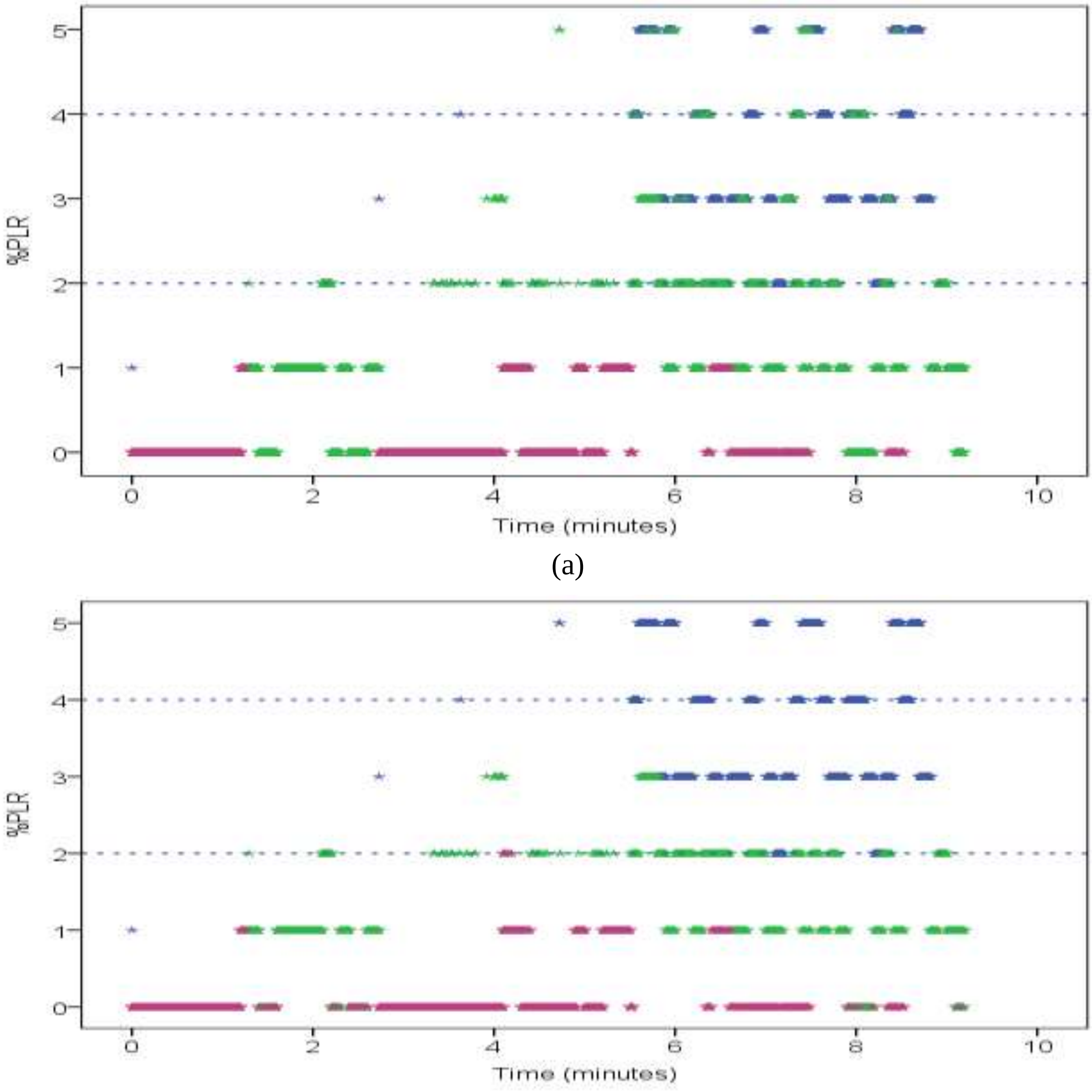
(a)



(b)

Figure 0.8 Relationship between packet jitter and QoS classification for (a) Bayesian (b) PNN approaches

Figures 6.9 (a) - (b) show an interpretation of the categorisation, the causes for packets were categorised as low, medium or high QoS by both Bayesian and PNN models individually according to %PLR parameter measures. Blue colour in the Figures specifies low, green specifies medium and red illustrates high QoS. The blue dotted line is at 2% and 4% that according to %PLR recommendation values in Table (6.1). In general, Figures 6.7, 6.8 and 6.9 show that both methods classified packets similarly.



(a)

(b)

Figure 6.9 Relationship between %PLR and QoS classification for (a) Bayesian (b) PNN approaches

Table (6.2) provides the percentage of packets categorised as high, medium and low quality by both Bayesian and PNN methods by considering recommended values in Table (6.1) as reference. The measures indicate that the Bayesian method had a better precision for classification than to PNN. This is because the three paths associated with the Bayesian method assisted in sorted the packets in their groupings.

Table 6.2 Percentage of packets classed as high, medium and low QoS by PNN and Bayesian methods

QoS category	%Classification accuracy	
	Bayesian	PNN
High	99.7	97.9
Medium	98.6	97.3
Low	100	94.9

Atypicality parameter is another measure to examine the accuracy of the Bayesian and PNN classification results. Figures 6.10 (a) - (c) provide the atypicality index (formula provided in Equation 6.9) for the Bayesian classifier for the traffic in the testing file connected with paths BC-1, BC-2 and BC-3 respectively. It also relate to the flow chart provided in Figure (6.3). The index specified the extent the traffic data represented by delay, jitter, and %PLR, and expressed a QoS category, i.e. high, medium and low. A high atypicality index specified that traffic parameter was not typical of that QoS type. Thus misclassification could be attributed not to the classifier's failure but to the relevance of the input itself. The blue coloured circles in Figures 6.10 (a) - (c) represent packets that belong to BC-1, BC-2 and BC-3 respectively (i.e. low, medium and high QoS). These packets have high probability and low atypicality index representing correct classification. The red coloured circles in Figures 6.10 (a) - (c) show packets that do not belong to BC-1, BC-2 and BC-3 respectively. They have low probability and high atypicality index. The black coloured circles in Figures 6.10 (a) - (c) represent packets that were misclassified. These had high probability and high atypicality index. Combining the blue coloured circles in Figures 6.10 (a) - (c) with their related times, show consistent results to those in Figures 6.4 (d) - (e).

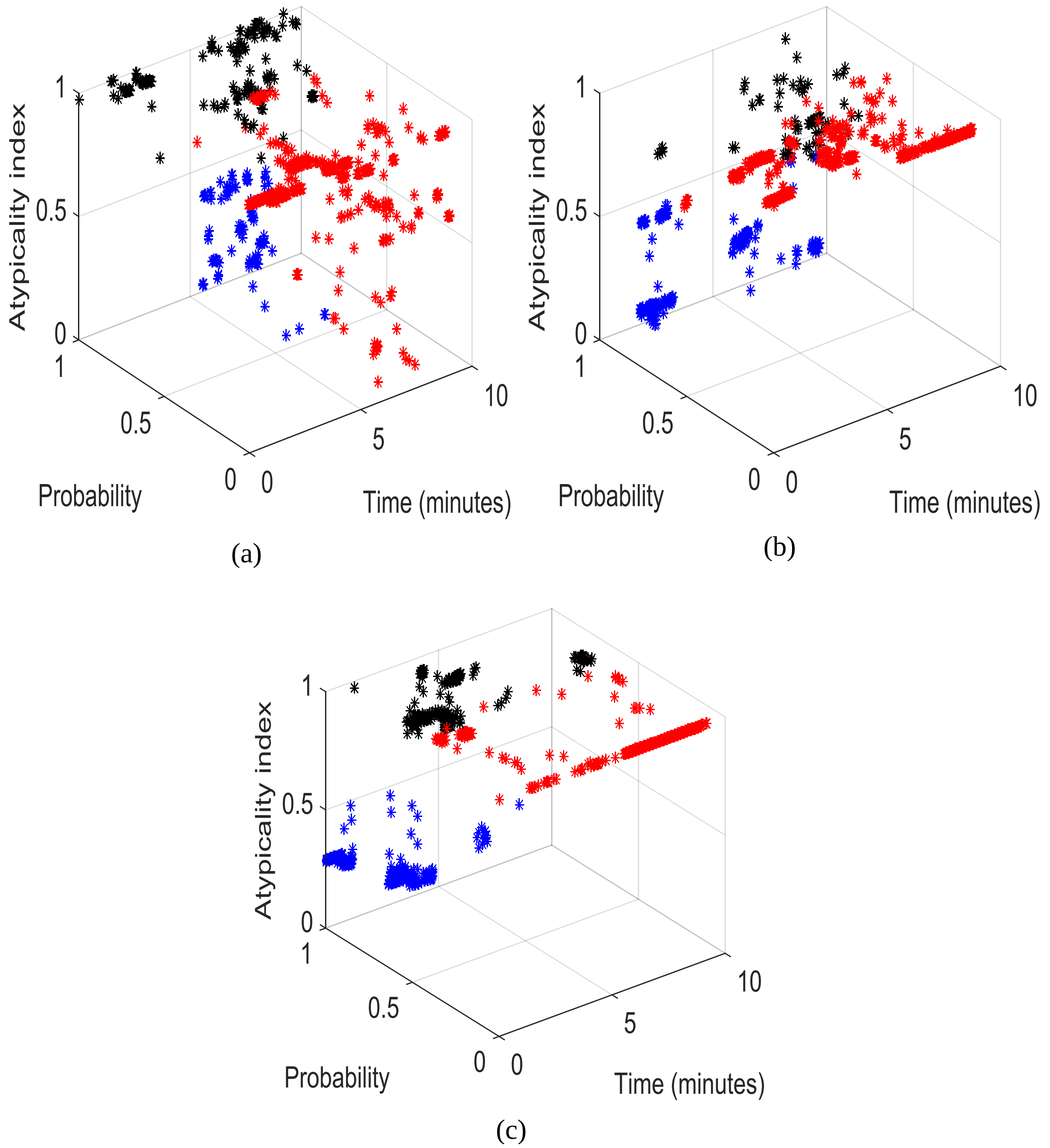


Figure 0.10 Atypicality index plots for the Bayesian classifier for (a) low (BC-1), (b) medium (BC-2) and (c) high QoS (BC-3). Blue coloured points represent packets with high probabilities and low atypicality indices. Red coloured points represent packets with low probabilities and high atypicality indices. Black coloured points represent high probability and high atypicality index.

6.4 PART B: Investigation to Quality of Service Behaviors of VoIP Over IEEE 802.11ac and 802.11n

In this part of the study, the QoS behaviour of IEEE 802.11ac (80 MHz) wireless protocol for VoIP transmission in different traffic load scenarios was studied and it was compared against IEEE 802.11n (20 and 40 MHz) protocols. Two QoS classification methods, one based on probabilistic neural network (PNN) and the other Bayesian probability were utilized and the consistency of their QoS classifications was compared. The study showed that IEEE 802.11 ac (80 MHz) was robust in maintaining quality of service for VoIP as the number of transmission point to point (PPP) links was increased from 1 to 10 while the QoS for the two protocols deteriorated. Jitter was the main factor affecting QoS in IEEE 802.11ac. Comparison QoS classification by the PNN and Bayesian demonstrated their effectiveness and consistency of their performance.

6.4.1 Methodology

The experiment was performed in a computer network laboratory (size 4 m×6 m) with two wireless access points (APs) and 20 PCs. The design supported 10 PPP links involving 20 PCs that communicated via access point 1 (AP-1) and access point 2 (AP-2) as shown in Figure 6.11. The setup gave flexibility in testing for different traffic conditions.

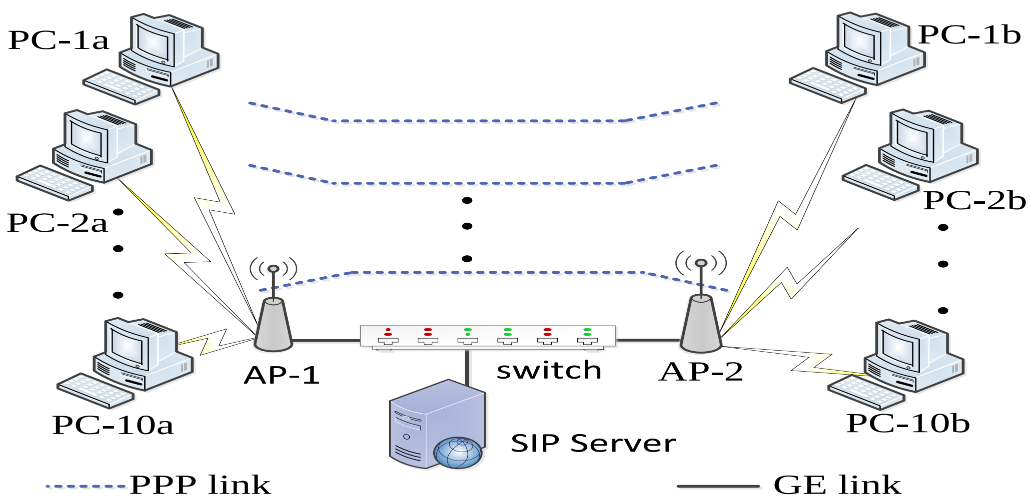


Figure 06.11 Network layout

The APs were of type Cisco© AIR-AP1852E. These supported IEEE 802.11g/n/ac protocols. They have four external antennae. Cisco© 3560-CX catalyst switch was used to connect the APs and SIP server via 1 Gbps links. On the PC side, wireless adaptors of Linksys AC1200

Dual-Band were used in all scenarios. VoIP connectivity was done by the SIP server. SIP Softphones configured over the Windows© PC.

Initially one to one PPP link was established between PC-1a and PC-1b. The traffic included video, VoIP and TCP. Following this test, the number of PPP links was increased to three PCs in each side. PC-1a connected to PC-1b, PC-2a connected to PC-2b and PC-3a connected to PC-3b at the second minute of the transmission. Then the number of PPP links was in turn increased to 5, 7 and 10 PCs in each side at times 4, 6, and 8 minutes from the start of the transmission, the transmission ended at minute 10. The tests investigated the network behaviour and QoS by increasing PPP links between AP-1 and AP-2. Each PC that connected to AP-1 (i.e. PC-1a to PC-10a) in these PPP links transmitted the same traffic that included video, VoIP and TCP to its peer PC connected to AP-2. The traffic was sent simultaneously. The manner of increasing the number of PPP links every two minutes was by manual configuration of the PCs connected to the AP-1 to send traffic to its counter PCs connected to AP-2 as indicated in Table (6.3).

Table 0.3 Communication timing of PPP links

Time (minutes)	Number of PPP links
0 - 2	1
2 - 4	3
4 - 6	5
6 - 8	7
8 - 10	10

Wireshark was installed on PC-1a and PC-1b to capture packets. Wireshark captured RTP packets. The captured packets were processed using Matlab© and a statistical package SPSS© to measure network delay, jitter and %PLR (Sanders, 2017) and use these values to quantify overall QoS for VoIP.

In order to obtain QoS performance for the wireless protocols i.e. IEEE802.11ac (80 MHz) and 802.11n (20 and 40 MHz), one channel was used for IEEE 802.11n (20 MHz bandwidth) in first scenario, then two channels were used for 802.11n (40 MHz). For IEEE 802.11ac, one channel was configured with (80 MHz). Table (6.4) summarizes wireless channels bandwidth, frequencies and maximum physical data rate.

Table 0.4 IEEE 802.11 standards, frequency and channel bandwidth used in the study

Protocol	Frequency (GHz)	Channel width (MHz)	Maximum data rate (Mbps)	Modulation and coding scheme
802.11n	2.4	20	65	7 (1 Spatial stream)
802.11n	2.4	40	135	7 (1 Spatial stream)
802.11ac	5	80	325	7 (1 Spatial stream)

Iperf software was used to measure actual throughput rate using TCP packets. It was used to connect the two computers as server/client, then to send TCP traffic from the server to the client and return to get the actual throughput rate. The Iperf software measured the actual throughput between PC-1a and PC-1b during all established PPP links (i.e. 1, 3, 5, 7 and 10 PPP links). TCP throughput was measured for a given TCP packet size that varied from 250 bytes to 64 Kbytes (de Carvalho et al., 2017).

6.4.2 The operations of approach

i. Wireshark was configured and used to capture VoIP packets between PC-1a and PC-1b during all change of PPP links and their associated traffic from start until minute 10 which was the end of 10 PPP links transmissions.

ii. Delay, jitter and %PLR were computed according to Equations (3.1) - (3.3).

iii. QoS requirements of VoIP traffic applications were applied to train the Bayesian and PNN methods (i.e. the training examples) based on recommendations in Table (6.1).

6.4.3 Results and discussion

i. Throughput and traffic analysis

Figure 6.12 shows the average throughput for 802.11n (20 and 40 MHz) and 802.11ac (80 MHz) for 1, 3, 5, 7 and 10 VoIP PPP links. All PPP links had similar VoIP, video, and TCP traffic. A decline in the throughput was observed with an increase in the number of PPP links for all wireless protocols. IEEE 802.11ac had the highest throughput and for 802.11n (20 MHz) the lowest. The throughput for 802.11n (20 MHz) reduced from 59.07 Mbps (1 link) to 3.484 Mbps for 10 links. This reduction for IEEE802.11n (40 MHz) was from 128.77 Mbps to 13.60 Mbps and for IEEE802.11ac (80 MHz) was from 318.11 Mbps to 170.13 Mbps. For 802.11ac even with 10 PPP links the throughput rate remained high as compared to 802.11n which dropped significantly. Throughput has been measured by Iperf software that was introduced in section 4.9.

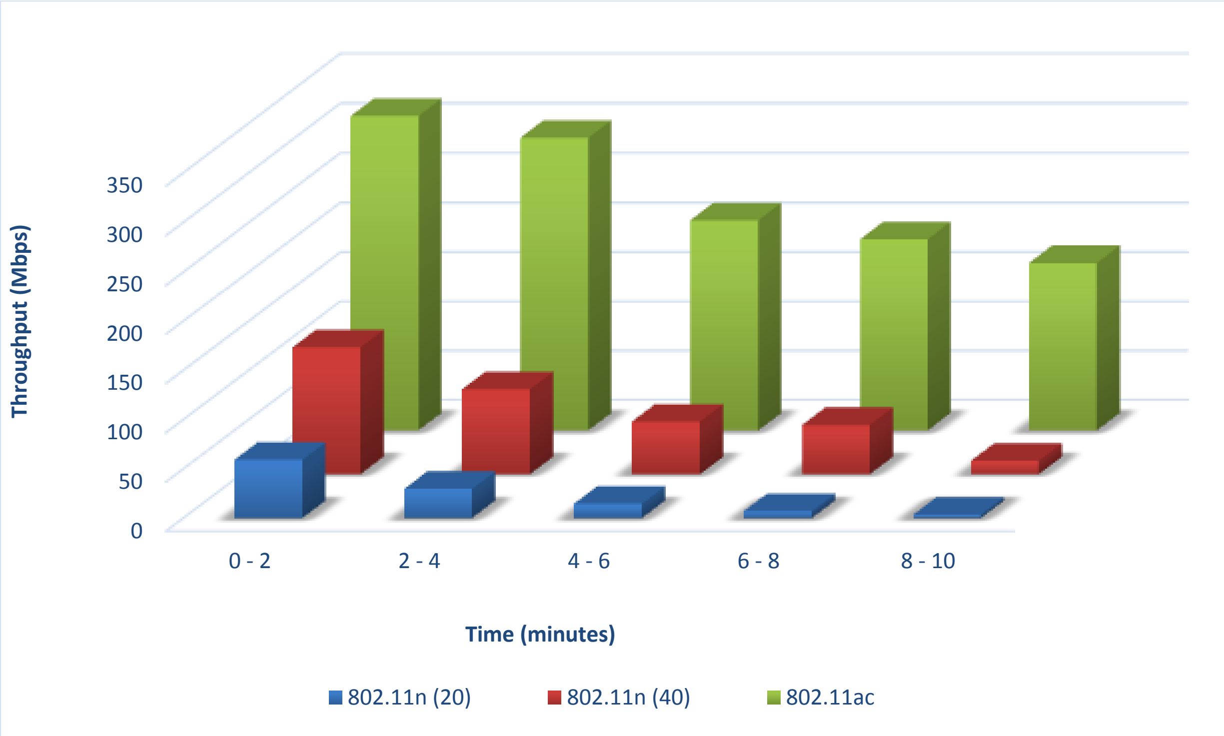
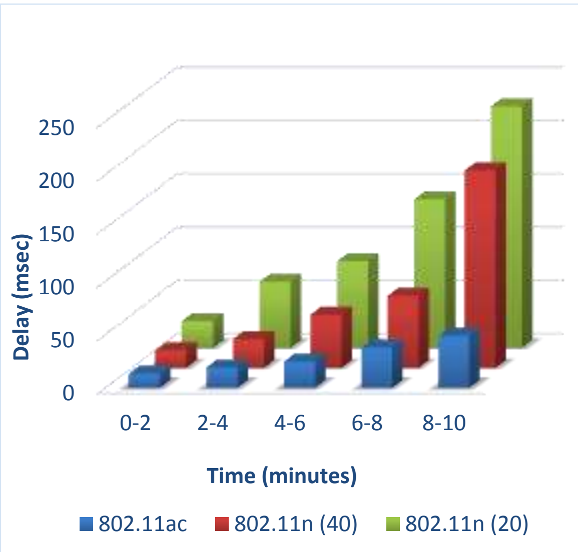
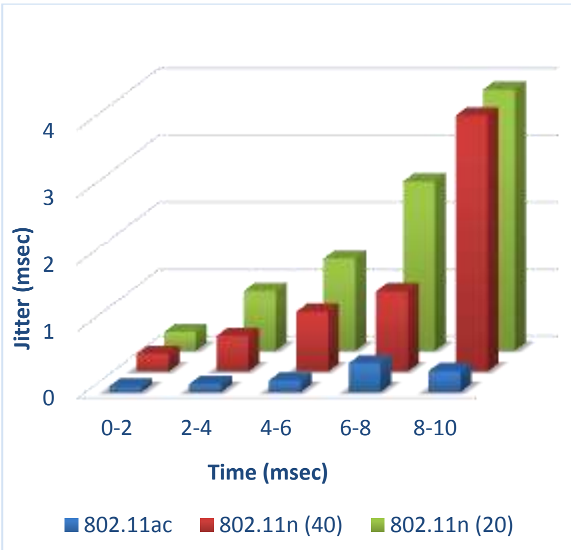


Figure 0.12 Average throughput results

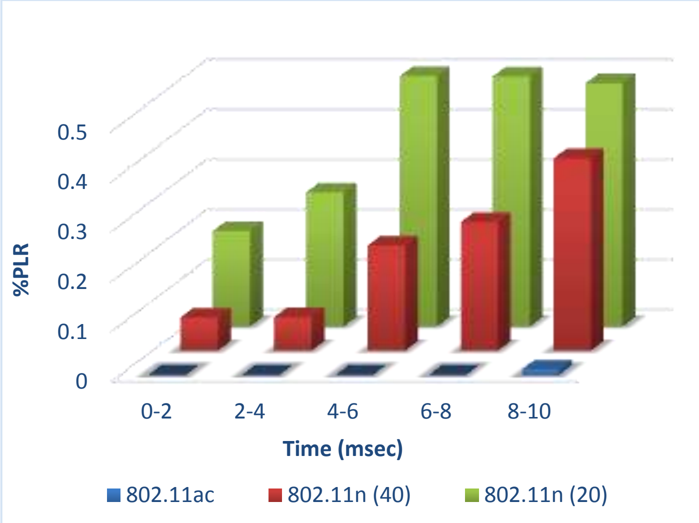
Figures 6.13 (a) - (c) indicate the manner of average delay, jitter and %PLR for VoIP traffic changed as the number of links was increased from 1 (from 0 to 2 minute) to 10 (from 8 to 10 minutes).



(a)



(b)



(c)

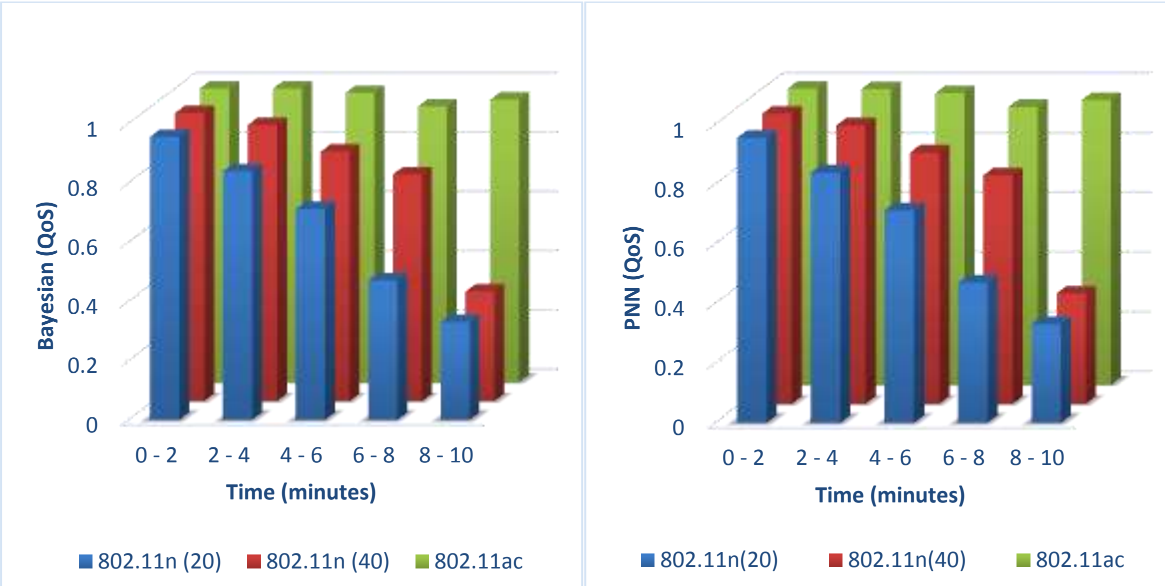
Figure 0.13 (a) Delay (b) Jitter and (c) %PLR

For the IEEE 802.11n (20 MHz, shown in green), the average delay shown in Figure 6.13 (a) was 24 msec at 1 PPP link and increased gradually to 226 msec for 10 links. For IEEE 802.11n (40 MHz, in red) the delay was 16 msec at 1 PPP link and increased gradually to 67 msec at 7 PPP links (from time 6 to 8 minutes) then increased dramatically to 185 msec at 10 PPP links. The Figure shows delay for 802.11ac (80 MHz, in blue) was lowest with 13 msec at 1 PPP link and increased to 48 msec for 10 links. Figure 6.13 (b) shows the average jitter measurements. For IEEE 802.11n (20 MHz, plotted green), jitter was 0.27 msec at the start (1 PPP link) and increased to 3.89 msec at minute 10 (10 links). For IEEE 802.11n (40MHz, plotted red) a lower jitter at the start (1 PPP link) 0.26 msec and increased to 3.81 msec minute 10 (10 PPP links). For IEEE 802.11ac (80 MHz, shown in blue), jitter was 0.08 msec for 1 link and increased to about 0.31 msec for 10 links. Figure 6.13 (c) shows the results for %PLR. The 802.11n (20 MHz, plotted green), 802.11n (40MHz, plotted red) and 802.11ac (80 MHz, shown in blue) show similar trends to delay and jitter as %PLR were higher for 802.11n (20 MHz) as compared with 802.11ac (80 MHz).

ii. QoS Analysis

Figures 6.14 (a) - (b) indicate the average QoS by Bayesian and PNN methods for IEEE 802.11n (20 MHz in blue), 802.11n (40 MHz, in red) and IEEE 802.11ac (80 MHz in green). The average was taken according to PPP links time periods, from 0 to 2 minutes for 1 link, 2 to 4 minutes for 3 links, 4 to 6 minutes for 5 links, 6 to 8 minutes for 7 links and 8 to 10 minutes for 10 links. QoS decreased as number of links increased for all protocols. For

IEEE802.11n (20 MHz), the QoS fell rapidly from about 0.9 for a single link to about 0.3 for 10 links while for IEEE802.11ac decrease was from 0.99 for a single link to about 0.91 for 10 links, highlighting the robustness of IEEE802.11ac for VoIP traffic as traffic load increases. IEEE 802.11n (40 MHz in red colour) showed a good QoS during all PPP links except 10 links which started at minute 8 and the QoS dropped rapidly from 0.88 to 0.45. The Bayesian and PNN QoS classification approaches showed consistent results in QoS classification.



(a) (b)

Figure 0.14 QoS classification by (a) Bayesian (b) PNN methods: blue for IEEE 802.11n (20 MHz), red for 802.11n (40 MHz) and green for IEEE 802.11ac (80 MHz)

Figures 6.15 (a) - (f) provide classification boxplots for both Bayesian and PNN methods. For IEEE 802.11n (20 MHz) in Figures 6.15 (a) - (b), the median values for low, medium and high QoS were at 7.5, 6.5 and 2 minutes. Some outlier packets that belonged to low QoS between 0 and 2 minutes could be observed. Figures 6.15 (c) - (f) show the QoS classifications for IEEE 802.11n (40 MHz) and IEEE 802.11ac (80 MHz) respectively. Comparison of Figures 6.15 (e) - (f) with Figures 6.15 (a) - (b) and Figures 6.15 (c) - (d) indicated that IEEE 802.11ac had sustained a higher QoS for the longer duration during VoIP transmission as the number of links was increased from 1 to 10. The Bayesian and PNN methods showed consistent performance.

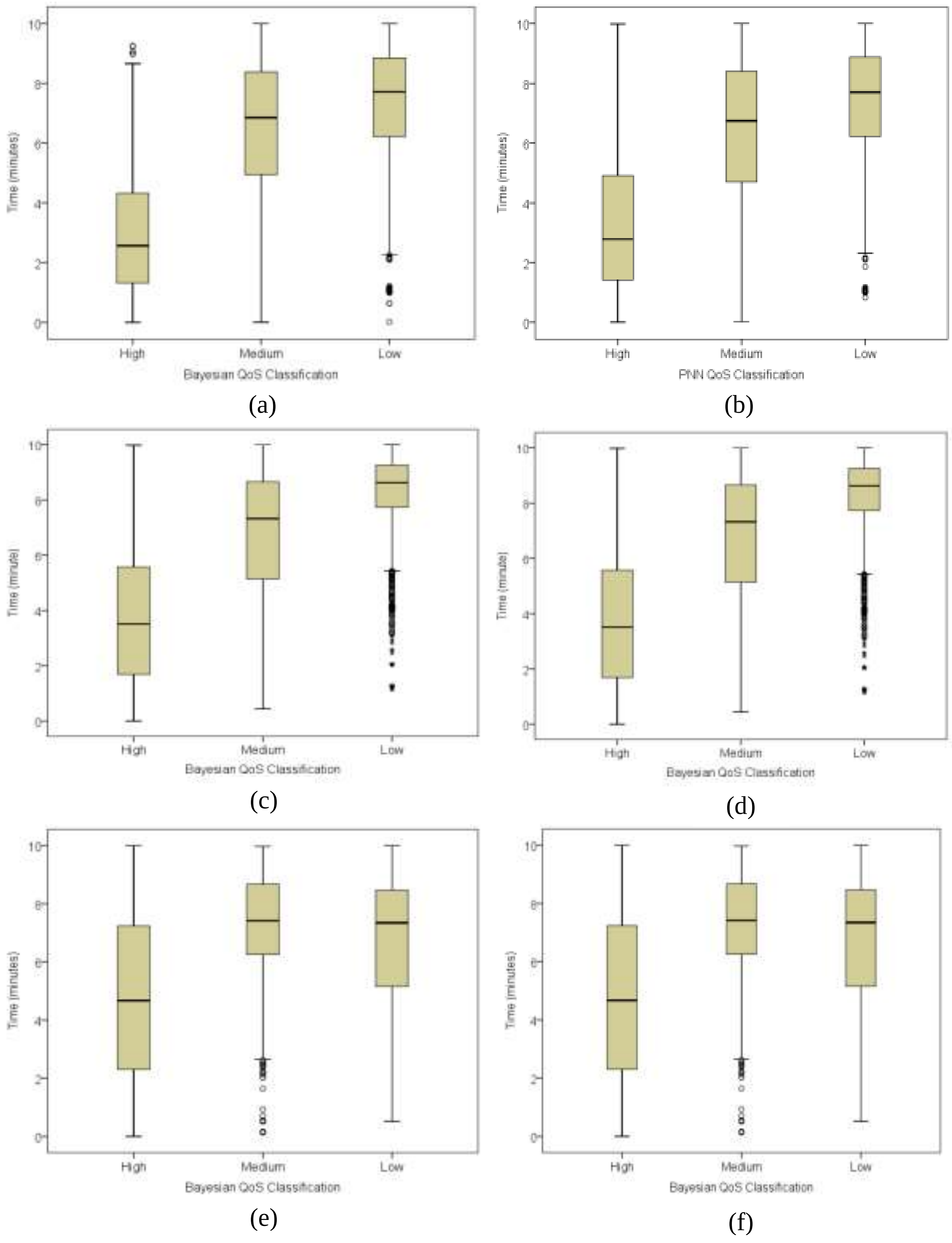
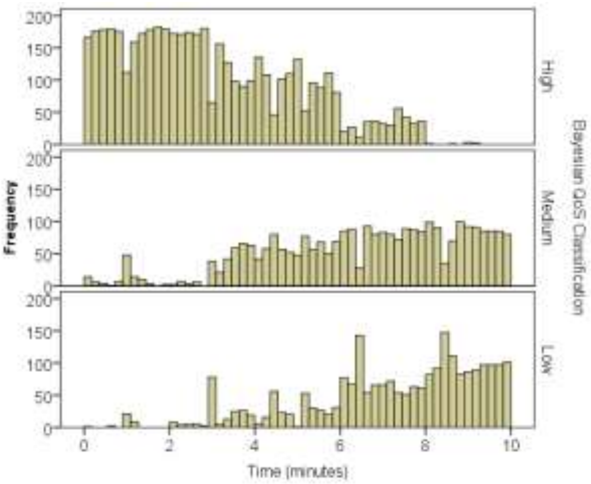


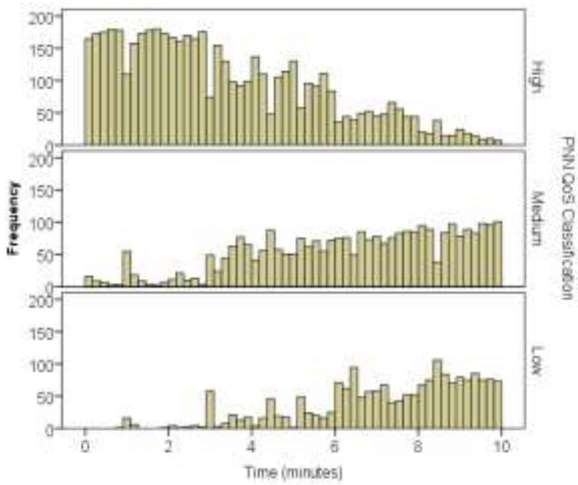
Figure 6.15 Boxplots of the classified packet for the Bayesian and PNN approaches to classify QoS. (a) and (b) are for IEEE 802.11n (20 MHz), (c) and (d) are for 802.11n (40 MHz) and (e) and (f) are for IEEE 802.11ac (80 MHz)

Figures 6.16 (a) - (f) provide histogram analysis for QoS classification by the Bayesian and PNN methods. Figures 6.16 (a) - (b) show classified results for IEEE 802.11n (20 MHz) for

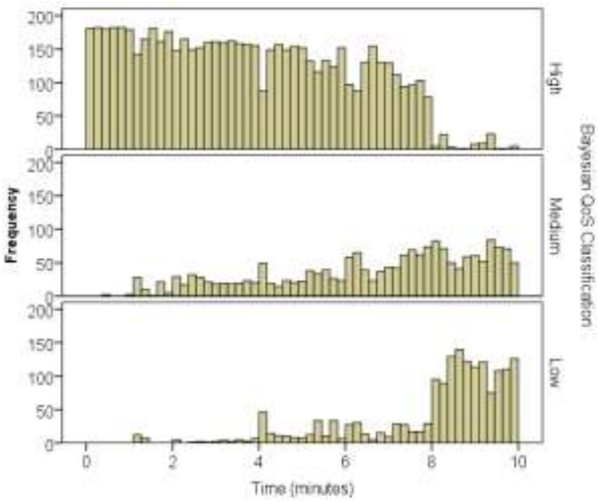
Bayesian and PNN methods respectively. A large proportion of packets had a high QoS up to 4 minutes (corresponding to 3 operational links) and thereafter there was a rapid decrease in QoS packets. Figures 6.16 (c) - (d) show the QoS classification results for IEEE 802.11n (40 MHz) for Bayesian and PNN respectively. Up to minute 8 (corresponding to operational 7 links), the QoS for packets was overwhelmingly high and thereafter there was a sharp decrease for 10 links. Figures 6.16 (e) - (f) show QoS classification results for IEEE 802.11ac for Bayesian and PNN methods respectively. The QoS for the full duration of the transmission was overwhelmingly high. Again, consistent behaviour was observed between PNN and Bayesian QoS classification methods.



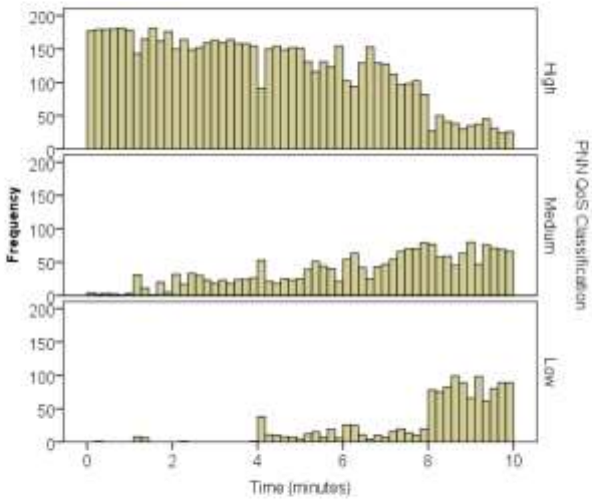
(a)



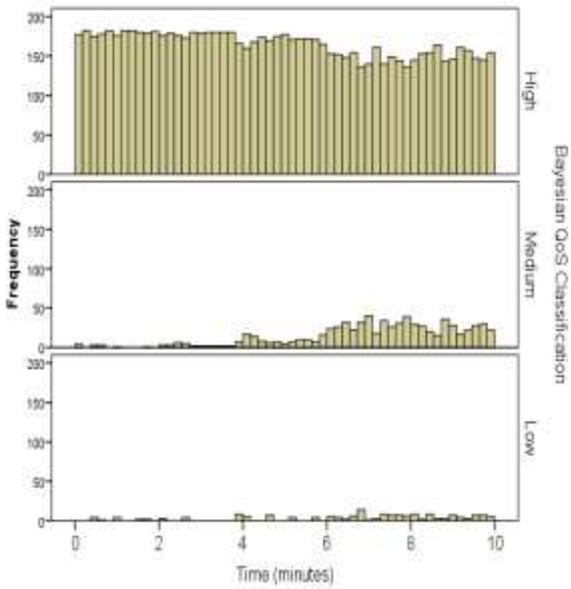
(b)



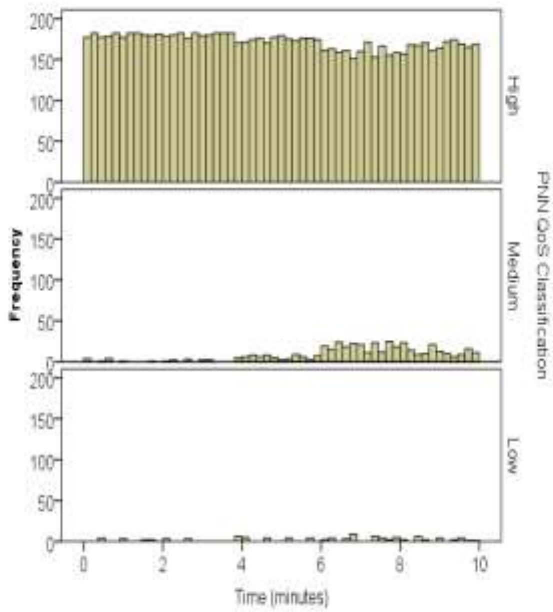
(c)



(d)



(e)

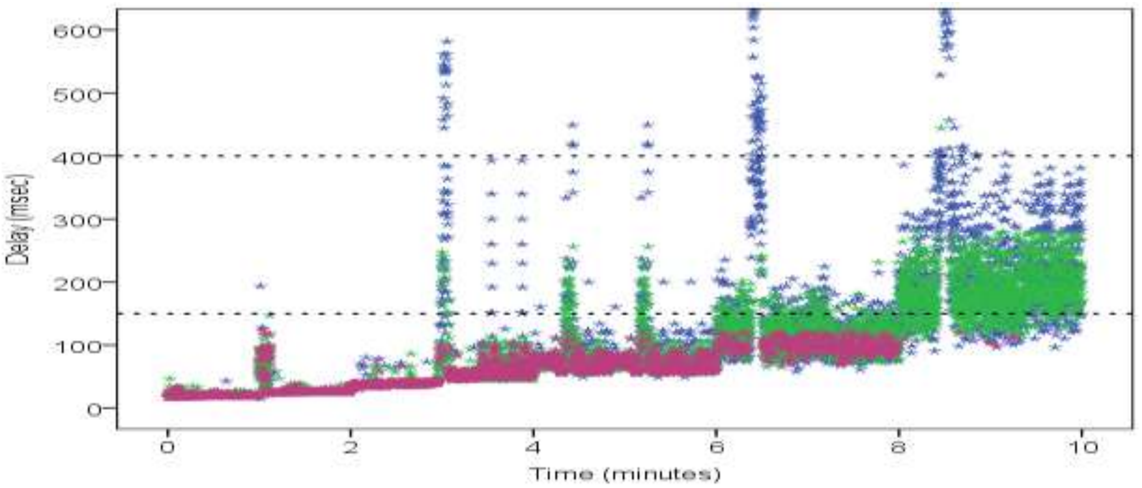


(f)

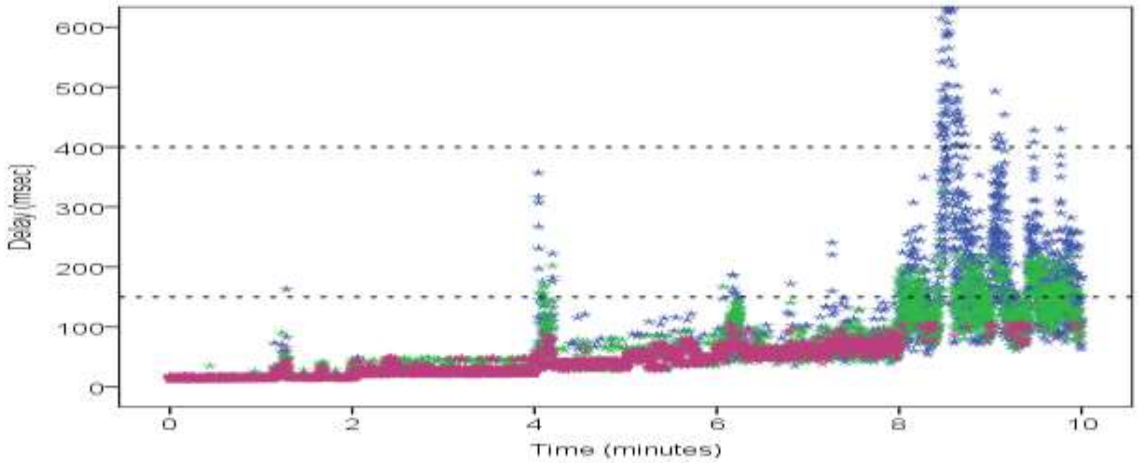
Figure 6.16 Packet classifications for 802.11n (20 MHz), 802.11n (40 MHz) and 802.11ac (80 MHz) using the Bayesian and PNN approaches. (a) and (b) are for IEEE 802.11n (20 MHz), (c) and (d) are for 802.11n (40 MHz) and (e) and (f) are for IEEE 802.11ac (80 MHz)

iii. Interpretation of results for delay and jitter and their Relations to QoS

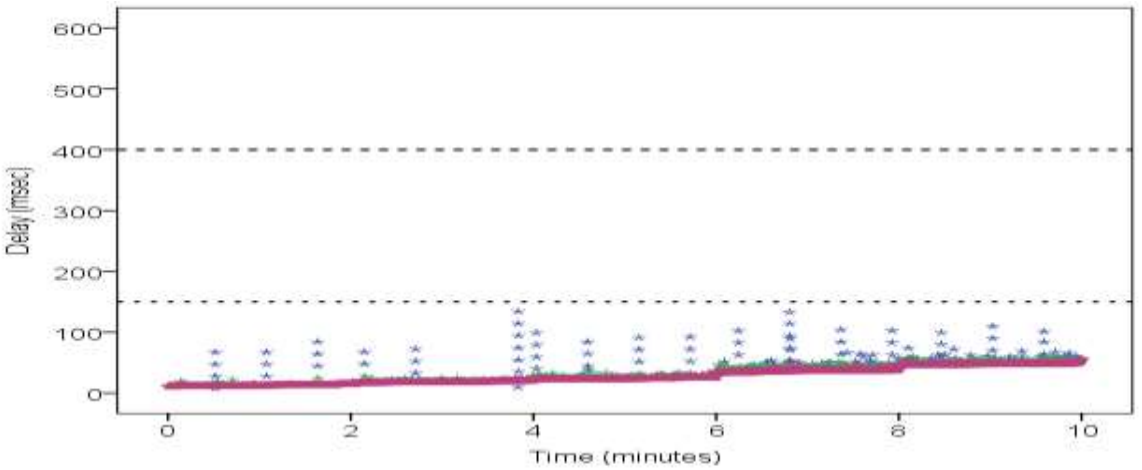
Figures 6.17 (a) - (c) show an interpretation of the causes for packets that classified into high, medium or low QoS by the Bayesian classifier according to the delay parameter using SPSS scatter plots. PNN results were not included due to similarity with Bayesian method. Figure 6.17 (a) shows the results for IEEE 802.11n (20 MHz), Figure 6.17 (b) for 802.11n (40 MHz) and Figure 6.17 (c) for 802.11ac (80 MHz). Red, green and blue colour indicates high, medium low QoS packets respectively. The dotted black line appearing at 150 and 400 msec indicates to the ITU recommended delay value for high QoS for VoIP. For 802.11n (20 MHz), delay for most packets exceed the threshold after 6 minutes (corresponding to more than 5 operational links) resulting QoS to become low. Figure 6.17 (b) indicates that for 802.11n (40 MHz) delay sharply rose at minute 8 where 10 links were operational and otherwise QoS was low. Figure 6.17 (c) shows the results for 802.11ac (80 MHz) and delay had remained below the ITU recommended value proving high QoS for the interval of VoIP transmission.



(a)



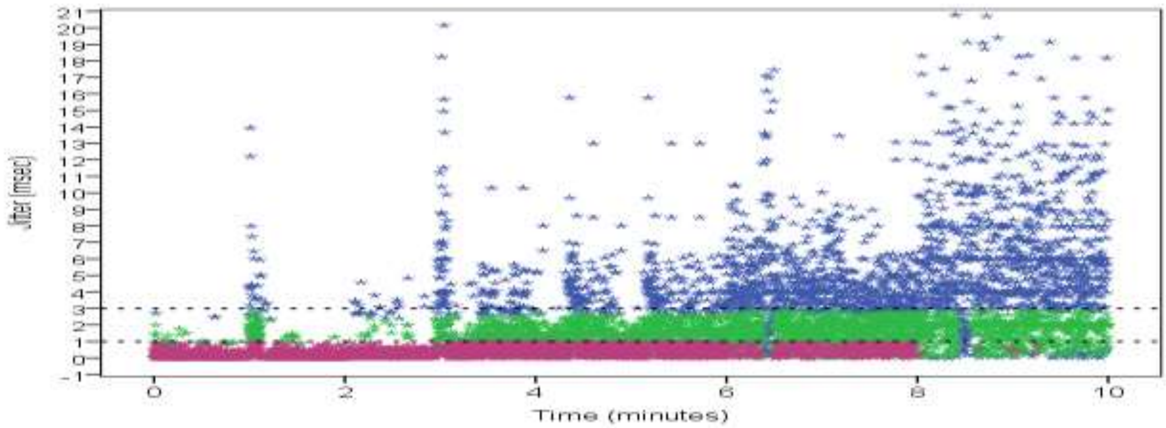
(b)



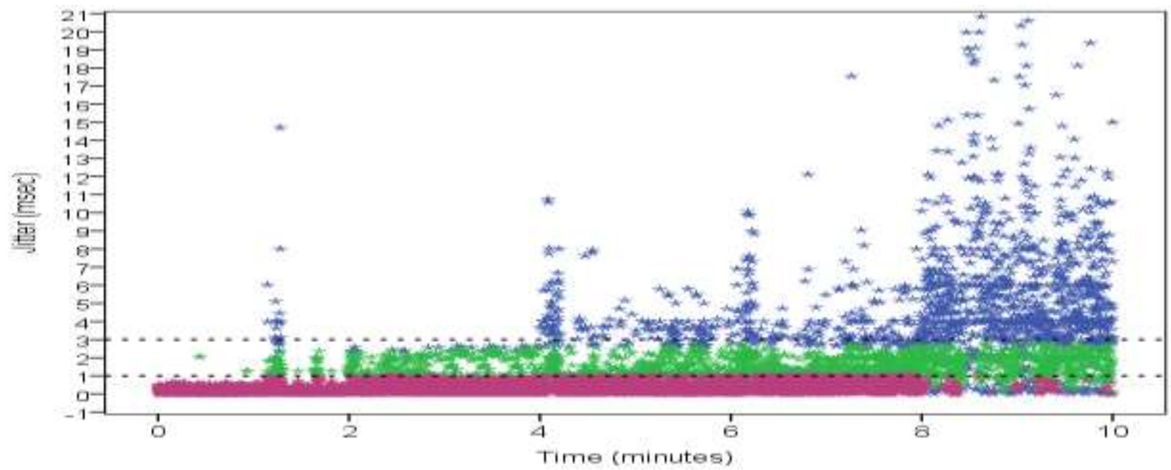
(c)

Figure 0.17 Classified packets and delay relationships by Bayesian model (a) 802.11n (20 MHz), (b) 802.11n (40 MHz), (c) 802.11ac (80 MHz). Colours: red for classified high QoS, green for classified medium QoS and blue for classified low QoS

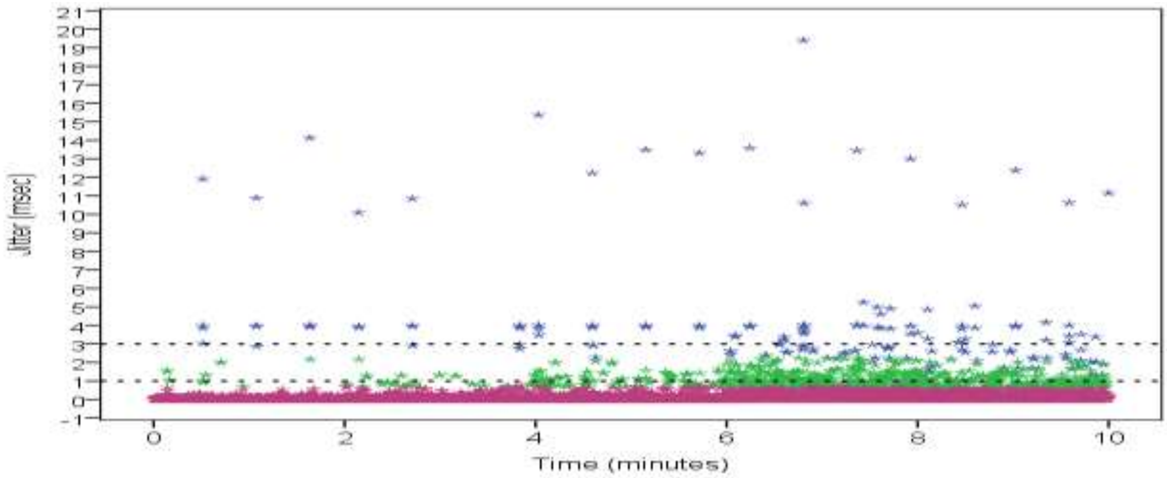
Figures 6.18 (a) - (c) show jitter analysis for the three protocols. The dotted black line on the vertical axis at 1 and 3 msec indicates the ITU recommended jitter value for high QoS. Figure 6.18 (a) shows the results for IEEE 802.11n (20 MHz). The Figure shows that many packets had jitter higher than 1 msec and a large increase at minute 6 reducing the QoS thereafter. Figure 6.18 (b) shows the results for IEEE802.11n (40 MHz). Jitter sharply increases at minute 8 resulting in low QoS thereafter. Figure 6.18 (c) shows the jitter result for IEEE 802.11ac (80 MHz). While the delay was always within acceptable range in 802.11ac, jitter for few packets exceeded the recommended ITU value which resulted in medium and some low QoS packets throughout transmission.



(a)



(b)



(c)

Figure 0.18 Classified packets and jitter relations by Bayesian model (a) 802.11n (20 MHz), (b) 802.11n (40 MHz), (c) 802.11ac (80 MHz). Colours are red for classified high QoS, green for classified medium QoS, and blue for classified low QoS

Some of jitter values were significantly high in 802.11ac as indicated in Figure 6.18 (c), exceeding the recommended ITU value. While all delay values for 802.11ac in Figure 6.17 (c) were within recommended ITU value, jitter exceeded it, causing low and medium QoS of 802.11ac for some packets. The 802.11n (40 MHz) performed well for all PPP links except for 10 links where its delay, and jitter and %PLR ratio increased rapidly affecting QoS. The Bayesian and PNN QoS classification methods showed consistency in their classifications. They both had fast learning and robust performance with minimal parameters to adjust.

6.5 Summary

This chapter explained two novel QoS evaluation methods. The first method was Bayesian based to analyse and classify the QoS for VoIP packets, whereas the second method was based on probabilistic neural network (PNN). Both methods were developed and applied over actual testbed laboratory network with variations of traffic parameters delay, jitter and %PLR that reflected the practical network conditions. Both methods showed consistency in their classifications. Both models successfully classified the QoS parameters of the received VoIP packets into their corresponding low, medium, and high QoS types. The measures indicate that the Bayesian method had a better precision for classification than to PNN. This is because the three paths associated with the Bayesian method assisted in sorted the packets in their groupings. PNN only has a single training parameter. The smoothing parameter σ should be selected properly. If σ is too small, the estimated PDF will be so non-linear that the

PDF at a testing point will be almost zero if this point is not close enough to any one of the training points, thus reducing the network's capacity to generalize. If, on the other hand, σ is too large, then over a wide range of input values the estimated PDF will be almost constant, and in that case the actual values of the training and test patterns does not seem to play any role in the determination of which class the test input pattern belongs to.

Advantages of both approaches were that they had fast learning and robust performance with minimal parameters to adjust. The capability, simplicity and robustness of the developed methods made them effective mechanisms for QoS analysis. SPSS© was used to examine the traffic parameters and QoS relations which provided valuable information as to the causes of low QoS. In addition, Atypicality index for the Bayesian classifier examined accuracy. Atypicallity index confirmed that most packets had been classified by the Bayesian approach correctly. Furthermore, the developed methods were used to classify VoIP traffic over different Wi-Fi 802.11n/ac using multiple protocols in practical laboratory environments. IEEE 802.11ac showed consistent behaviour for delay, jitter and %PLR as the number of VoIP transmission links increased. Tests showed that jitter was the main traffic parameter that caused low and medium QoS for packets in IEEE 802.11ac. The Advantages of proposed probabilistic methods include faster training and accuracy.

Chapter 7 Video Transmission Quality of Service and User-Experience Evaluation in Hybrid Computer Networks

In this chapter, objective evaluation techniques were developed for performance assessment of a video transmission over a hybrid computer network. The traffic measures, packet delay, jitter and %PLR were processed to determine network quality of service (QoS) for the video while video visual parameters: PSNR and SSIM with image difference ID or entropy difference ED (PSNR, SSIM and ID/ or ED) were used to determine quality of experience (QoE) for the video. Fuzzy inference system (FIS) was used for these processing. In order to obtain an overall measure of video quality, QoS and QoE measures were combined using FIS. This measure was correlated with both traffic parameters and visual parameters to demonstrate the effectiveness of evaluations. With regard to decreasing the number of images processed and thus reduce the computational need, the traffic was sampled using systematic sampling. As part of the evaluation, image labelling and sampling were adapted to increase accuracy of the measurements due to transmission impairment and frame loss. A novel approach whereby the images were partitioned to better localise possible distortions was devised. In this study, the developed fuzzy logic-based approaches were able to correctly measure the quality of transmitted video over a hybrid computer network and the devised method of image partitioning enhanced measurement of QoE (Salama and Saatchi, 2019_a). In addition, SPSS was used to examine the relationship between the overall measure of video quality with traffic parameters and video visual parameters. Moreover, subjective tests in the Mean Opinion Score (MOS) form with 25 participants were performed to validate the developed overall video assessment method. According to ITU-T (2008), at least 24 subjects must be used for experiments conducted in a controlled environment. This means that after subject screening, every stimulus must be rated by at least 24 subjects. The QoE results were consistent with the developed FIS system.

7.1 Introduction

Prior to reviewing the methodology, a brief explanation of the some QoS and QoE procedures is provided. QoS measures relevant to this study were delay, jitter and %PLR. The QoE measures relevant to this study were PSNR, SSIM, ID and ED. Peak signal to Noise

Ratio PSNR in dB is determined by Equation (7.1) (Maimour, 2018) and (Brito and Figueiredo. 2017)

$$PSNR(X,Y) = 10\log_{10}\left(\frac{MPP^2}{MSE(X,Y)}\right) \qquad (7.1)$$

Where MPP is the Maximum Possible Pixel value of the image and it is equal to 2^n -1, the number of bits *n* used to represent each sample (e.g. when *n* is 8 bits per sample, MPP=255). Larger measures of PSNR indicate a reduced distortion and thus a higher quality. The MSE is the mean square error between two images *X* and *Y* and is measured by Equation (7.2)

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[X(i,j) - Y(i,j)]^2 \qquad (7.2)$$

Where *m* and *n* represent the image dimension and *i, j* signify a pixel's location for an image.

Structural Similarity Index (SSIM*)* for computing image quality for image windows (*x* and *y)* of the same dimension for an image (Maimour, 2018) and (De Grazia et al., 2018) is determined by Equation (7.3)

$$SSIM(x,y) = \frac{(2\mu_x\mu_{y+c_1})(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_{y+}^2c_1)(\sigma_x^2+\sigma_{y+}^2c_2)} \qquad (7.3)$$

Where μ_x and μ_y are the averages of the pixels within the windows *x* and *y* respectively, σ_x^2 and σ_y^2 are the variances of pixels, σ_{xy} is the covariance of the pixels within *x* and *y*. The included variables c_1 and c_2 to stabilise the division with weak denominator. They can be defined as $c_1 = (k_1L)^2$ and $c_2 = (k_2L)^2$ where the dynamic range $L = 2^n - 1$, where *n* is the number of bits per pixel. While the elements k_1 and k_2 are set by default 0.01 and 0.03. The computed value of SSIM is between 0 to 1, with values closer to 1 indicating a higher similarity and vice versa.

Image Difference (ID) is an indicator of complete pixel to pixel variations (differences) between two images of the same dimension. It was determined by obtaining the histogram of pixel measures of the images to be compared. In this study, the operation was on grey images the pixel value range was from 0 to 255. Euclidian distance in Equation (7.4) was used to measure the variance between the two histograms.

$$ID(X,Y) = \sum_{i=0}^{i=255}(FX_i - FY_i\,)^2 \qquad (7.4)$$

Where FX_i and FY_i are the occurrence frequencies pixel with value i related with images X and Y respectively. The ID value of zero specifies identical images and larger ID value represent greater image differences.

7.2 Related studies

Establishing perceived video deterioration due to network perturbation is essential in assessing video transmission. Furthermore, the network perturbations effect on video can variety from noise, distortion and errors. According to (ITU-T, 2008) not all network losses result in a noticeable degradation. (Lal et al., 2018) reported that the current approaches for providing QoS do not show that all issues related to video quality, such as varying connection status, mobility and changeable congestion. In addition, computing the effect of network perturbation on the video transmission is a challenging task (Pokhrel et al., 2016) and (Pokhrel, 2014). Objective video assessment approaches can decrease the cost and operation time (Paudel et al., 2014).

There were several studies related to objective video QoE for video (Barman and Martini, 2019), (Duanmu et al., 2018), (Maimour, 2018), (Su et al., 2016), (Zheng, et al., 2015) and (Zanforlin et al., 2014). However there were very limited work were reported on video quality that integrate the traffic parameters and visual information (Nasralla et al., 2018).

PSNR is the most objective method in assessing image and video performance but it has limited features and usually with biased results (Preethi and Loganathan, 2018), (Pinki, 2016) and (Alvarez et al., 2011). Studies have reported that PSNR is more sensitive to additive Gaussian noise than the SSIM, while the opposite is observed for jpeg compression (Navarro and Molimard, 2019), (Ece and Mullana, 2011) and (Hore and Ziou, 2010). Furthermore, most objective QoE evaluation methods compare received image to the original transmitted image to determine QoE. This operation requires availability of image sequence to be able to compare the corresponding transmitted and received images (Maimour, 2018). Transmission impairments, aggravates frame loss which leads to unpaired frame comparisons between the original and distorted images, and therefore results in inaccuracies in QoE scores (Sankisa et al., 2016), (Akramullah, 2014), (Soares, 2013), (Alvarez et al., 2011) and (Canadell Pulido, 2008).

There were several studies relating to QoS and QoE (Barman and Martini, 2019), (Nasralla et al., 2018) and (Chen et al., 2014). The study in (Nourikhah and Akbari, 2016) used Bayesian data analysis to estimate the overall users' satisfactions in opinions form for a known range of QoS measures. The study in (Kim and Choi, 2014) found the relationship between QoS parameters like delay, jitter, %PLR, burst loss and group of picture length to QoE. Another study used formulae to relate QoE from QoS (Kim et al., 2012). In a study by Stanojević et al. (2018) a technique that used delay, jitter, %PLR and bandwidth to measure four types of video degradations were reported (Stanojević et al., 2018). However, these studies did not consider user perception and validation results.

Some studies investigated the impact of network parameters such as encoding process, average number of bits for one coding unit and packet loss rate on QoE (Cheng et al., 2017) and (Qian et al., 2016). A proposed technique based on Random Neural Network (RNN) was developed to assess the MAC parameters effecting video transmission in 802.11n standards (Paudel et al., 2014). In their study subjective testings were carried out to correlate MAC-level factors like aggregation, load, queue size and bit error rate with the QoE.

A limitation of current objective techniques is that they mostly rely on PSNR, VQM or SSIM which do not provide consistent assessment (Stanojević et al., 2018), (Usman et al., 2018), (Orosz et al., 2014) and (Kim and Choi, 2014). Therefore, in this study, two more video parameterscalled image difference ID and entropy difference ED were included for video QoE assessment. In addition, a novel approach whereby the images were partitioned to better localise possible distortions was devised.

According to Vega et al. (2014) when connecting with wireless, where interference and contextual factors could influence network services, quality assessment is insufficient and mostly inadequate. Thus, the evaluation of a lossy wireless network requires consideration of not just the physical network transmission characteristics (QoS) but also how these impacts the end-user service (QoE). Thus, integrated QoS/QoE is important.

In this study, we propose objective QoE assessment that integrate multiple media parameters (PSNR, SSIM, ID/ or ED) system based on fuzzy logic (Salama and Saatchi, 2019_a). The difference of these QoE parameters affects the performance of the video transmission and, accordingly, the user satisfaction feedback. In this study we proposed integrated QoS/QoE assessment model based on fuzzy inference system as the relation between QoS and QoE can be nonlinear (Pokhrel, 2014). For QoS, three network parameters were used to assess network QoS using three network parameters (delay, jitter and %PLR). Moreover, subjective tests in the Mean Opinion Score (MOS) form with 25 participants were performed to validate the developed overall video assessment method. In addition, the video transmission assessment established in this study was compared against a technique that used spatial efficient entropic differencing (Bampis et al., 2017) and consistent results were observed. The features of the work outlined in this chapter are (specifics of each part are described in the following sections):

- Frame labelling dealt with the problem of frame loss by sampling and thus improved QoE measurement accuracy. This required each image to have serial number in the form of a label.
- Reduction in processing need through systematic sampling of the received images. This was implemented by processing a subset of the received images according to labels.
- Improved image distortion assessment through a procedure referred to as image partitioning. This enabled localised image distortions to be represented more adequately.
- Integration of traffic parameters (delay, jitter and %PLR) to determine QoS using FIS and integration of image distortion computes (PSNR, SSIM and ID/ or ED) to determine QoE using a second FIS.
- Integrating QoS and QoE to obtain a single value that indicated the overall quality of transmitted video using a third FIS. .
- An analysis by SPSS to examine the relation between overall quality with video traffic parameters (delay, jitter and %PLR) and video visual parameters (PSNR, SSIM and ID) was carried out. Subjective tests in the Mean Opinion Score (MOS) form with 25 participants were performed to validate the developed overall video assessment method.

7.3 Methodology

7.3.1 Wireless network set up

The hybrid network designed to transmit the video is shown in Figure 7.1.

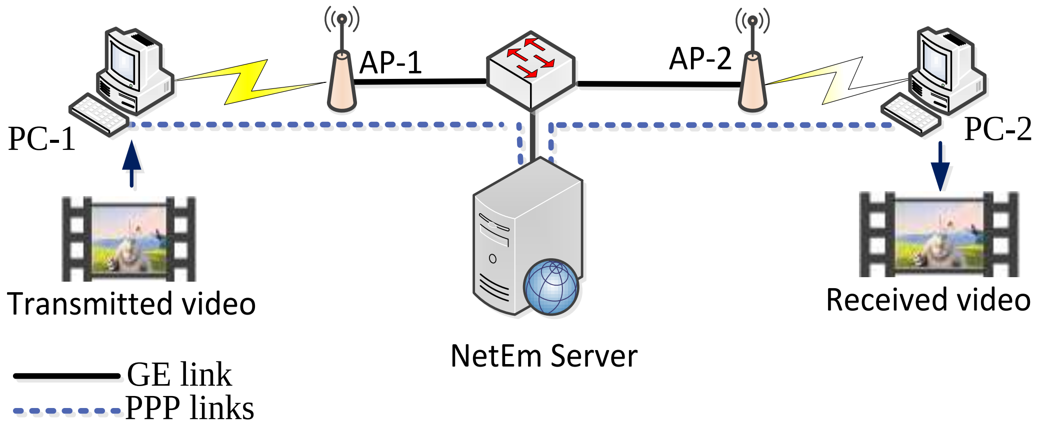


Figure 0.1 Network setup used in the study

The details of the test setup have been introduced in chapter 4. It combined two Cisco© Access Points (APs) AIR-AP1852. Catalyst 3560 switch linked via 1 GE the Aps. NetEm ran over the Windows© PC. The arrangement established PPP connections between the PC-1 and PC-2. The NetEm was positioned in between the PPP links to control the traffic parameters, i.e. delay, jitter and %PLR to be changed to produce different transmission quality (i.e. high, medium and low video quality transmissions). The video was sent over the PPP link from PC-1 to PC-2 over NetEm server. The Big Buck Bunny (Kovacs et al., 2015) clip was selected as video testing. Streaming duration was 90 seconds and includes of 1350 frames. The frame pixel resolution was 1280×720 pixels. The video encoded using H.264 and format was MPEG-2.

The packets associated with the video were transmitted from PC-1 to PC-2 using Video LAN Client (VLC) media player and RTP protocol. The sequence number and time-stamp advantages in RTP allowed measurements of delay, delay variation (jitter) and %PLR. Through NetEm, traffic delay, jitter and %PLR were increased in three stages during the streaming. During first stage, traffic parameters had lower values measures, whereas increasing values in the final stage. Throughout all stages, the QoS, QoE and overall integrated QoS/QoE were measured.

7.4 Mechanism for video quality evaluation

The stages in determining the transmitted video quality is shown in Figure 7.2.

Three similarly structured FIS were implemented to achieve the required operations. Though the whole video assessment could be achieved by a single FIS, three FIS models were used to allow a modular system, thus making it easier to understand, design, implement and troubleshoot.

The numerical FIS inputs were fuzzified by membership functions that represented the QoS and QoE levels (a quantity between 0 and 1). Each FIS knowledgebase included the data for processing the relations between the inputs (delay, jitter, %PLR, PSNR, SSIM and ID) and produced an output indicating video quality. The inference engine performed reasoning by comparing the input measures with the knowledge domain. The coding was IF-THEN rules.

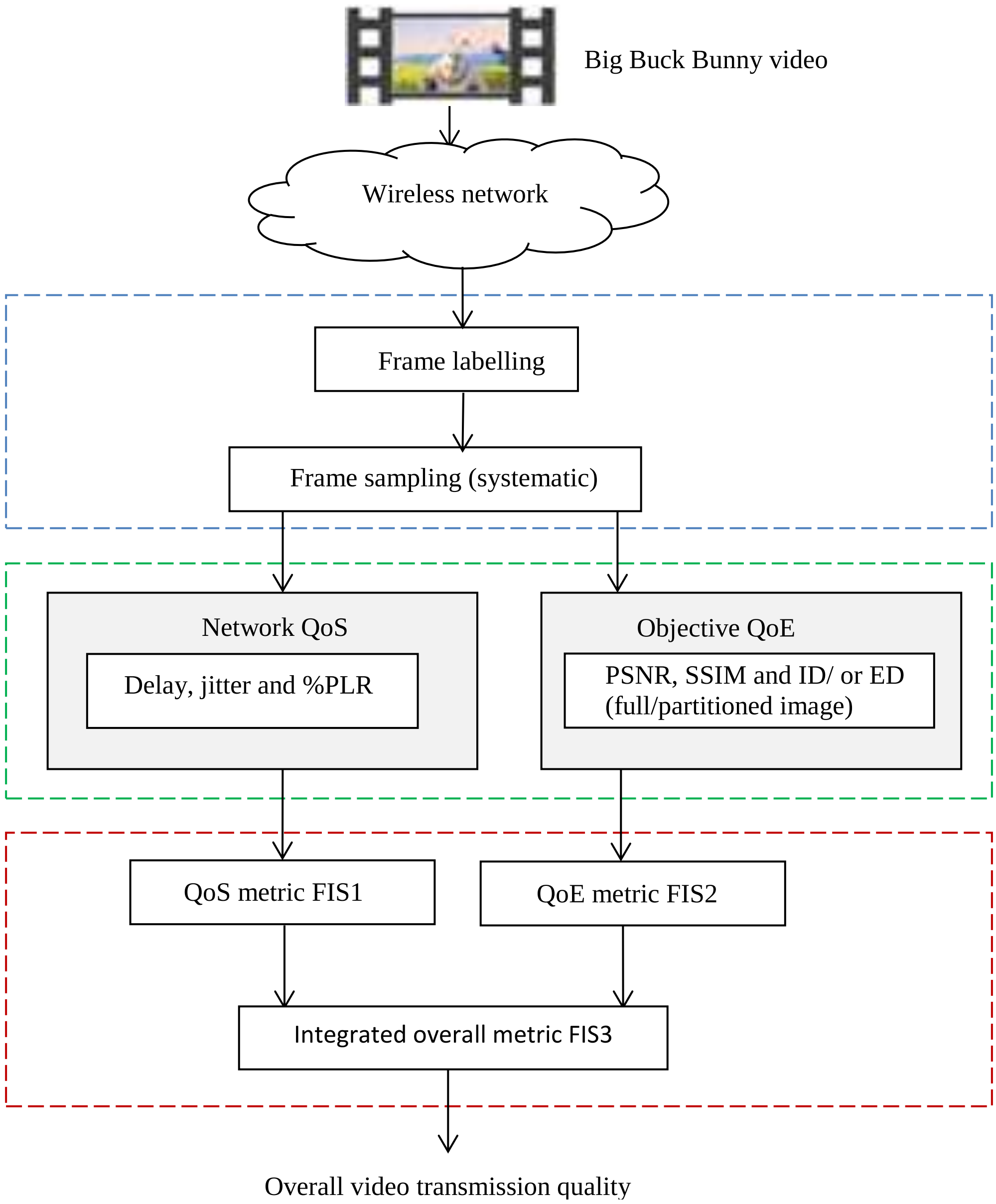


Figure 0.2 Stages in determine video transmission quality

De-fuzzification was a procedure for the outcomes of the combined rules to provide an aggregated membership function from the measurements.

The first FIS (FIS1) handled the input measurements (delay, jitter and %PLR) to provide QoS. While, the second FIS (FIS2) handled PSNR, SSIM and ID/ or ED to provide QoE. Then, the third FIS (FIS3) integrated the outputs of FIS1 and FIS2 to produce the overall video transmission quality. The specifics of the tasks to advance these FIS systems are clarified next:

- Each image before transmission was labelled with a serial number, starting with 1 and sequentially increasing till transmission of the last image. Two equal labels were used.

These were placed on the top right and left corners of all image. Its replication on two sides was to assure an alternative label in case of one label became unreadable due to distortion. The labelling was needed to allow the received images to be compared with the corresponding transmitted (original) images to increase comparison accuracy. Systematic sampling (a sample is selected from the whole set at a fined period) was applied to the received images to decrease the required image number for processing. The time period chosen for systematic sampling was 1 second. This resulted in a reduction of images from 1350 to 90 (i.e. 1 image from every 15 images was chosen). The selected received images were compared with their corresponding sent images by using the image labels.

- Traffic parameters; delay, jitter and %PLR were obtained for the received images packets and were computed by FIS1 to obtain the QoS. Whereas, PSNR, SSIM and ID/or ED were measured for the chosen received images and their corresponding original images (transmitted) that processed by FIS2. This process was repeated for both full and petitioned images approaches.
- The QoS and QoE determined in above steps were integrated using FIS3 to determine the overall quality of transmitted video.

7.4.1 Implementation of the FIS1

QoS was measured by FIS1 that process delay, jitter and %PLR. Nine rules were combined into the FIS1 knowledge base as described in Table (7.1). Three fuzzy membership functions have been used to signify each of the three inputs and three membership functions signified FIS1 output (QoS).

The most common membership functions are Gaussian which has been most commonly used in literature due its smooth representation of input, and the error is minimized. It allows the desired values to be interpreted appropriately. The amount of overlap and the range of each variable were determined by experimenting with a number of suitable values and selecting the ones based on ITU recommendations for video transmission parameters as shown in Figure 7.3 (Salama et al., 2017_d), (Dogman et al., 2014, and 2012_b) and (Al-Sabou et al., 2007).

The method to define a fuzzy rule base for fuzzy logic controllers was based on experience knowledge. The rules are expressed in linguistically forms and the size of the rule base is small enough to allow modelling of the systems to be easily interpreted and analysed. In this part nine rules have been chosen based on experience and best outcome results.

Table 0.1 The rules for FIS1 knowledge base (Salama et al., 2017_d) and (Dogman et al., 2014, and 2012_b)

Rule	Delay	Operator	Jitter	Operator	%PLR	FIS (output)
1	Low	AND	Low	AND	Low	High
2	Low	AND	Low	AND	Medium	High
3	Low	AND	Medium	AND	Low	High
4	Medium	AND	Low	AND	Low	High
5	Medium	AND	Medium	AND	Low	Medium
6	Medium	AND	Low	AND	Medium	Medium
7	Low	AND	Medium	AND	Medium	Medium
8	Medium	AND	Medium	AND	Medium	Medium
9	High	OR	High	OR	High	Low

The membership functions shown as blue, red and green colours signify classes of high, medium and low values respectively. Every fuzzy rule was related to membership functions and the rules' consequences were mapped to the related output membership functions. The output membership functions were combined, and the centroid technique was adapted to execute the de-fuzzification that in turn delivered the FIS1 output.

In order to develop FIS1, its knowledgebase that measured QoS, traffic QoS bound required to be predefined. For a video transmitting, Good QoS (i.e. QoS > 67%) corresponded to delay less than 150 ms, jitter less than10 ms, and %PLR less than 1%. Medium QoS (i.e. 33% < QoS ≤ 67%) corresponded to medium QoS parameters (i.e. 150 < delay <400 ms, 10 < jitter <20 ms, and 1% < %PLR < 2%). And Low QoS (i.e. QoS ≤ 33%) corresponded to delay > 400 ms, jitter > 20 ms, and %PLR > 2% (Salama et al., 2017d), (Dogman et al., 2014, and 2012b) and (Al-Sabou et al., 2007).

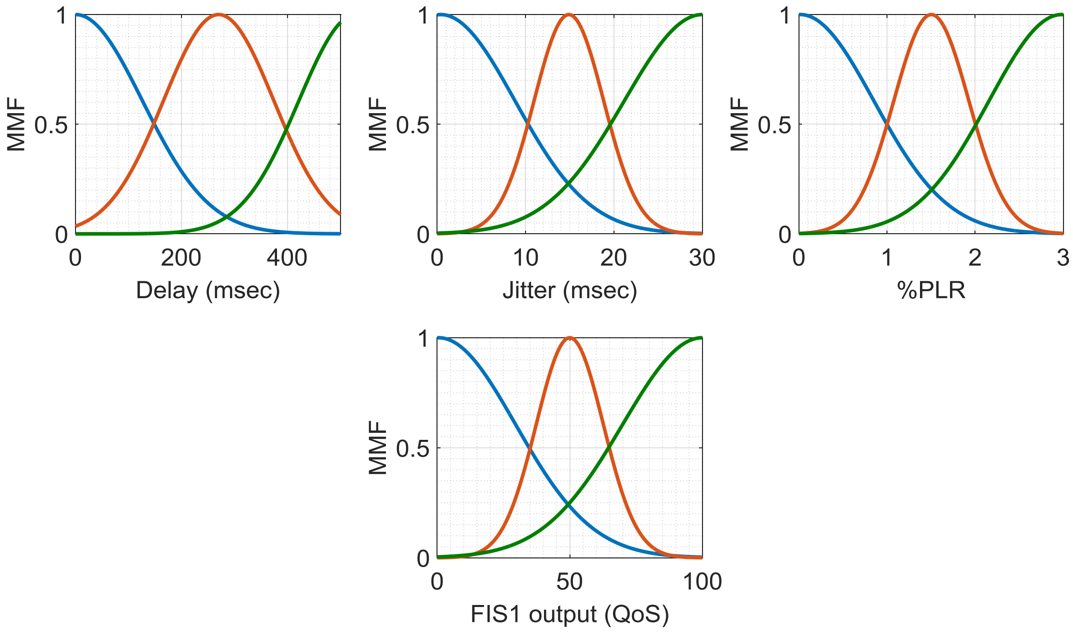


Figure 7.3 Membership functions for FIS1: inputs (top three Figures), output (bottom Figure)

7.4.2 Implementation of FIS2

FIS2 used input measures of PSNR, SSIM and ID/ or ED and processed them to obtain QoE. The QoE computations were achieved by two manners. In the first method, PSNR, SSIM and ID were measured for the complete (full) images. Whereas, the second method, each image was partitioned into four identical sections (top-right, top-left, bottom-right and bottom-left) and the measures for PSNR, SSIM and ID/ or ED for each section were individually measured. The suitability of these two methods in providing QoE was obtained and compared. The reason for partitioning images was to examine whether localised distortions could be recognised and signified more accurately.

The FIS2 inputs were PSNR, SSIM and ID. They were fuzzified by three Gaussian membership functions labelled as high, medium and low quality which shown in Figure 7.4 as green, red and blue. The output was defuzzied by three membership functions that signified high, medium and low QoE. The knowledgebase for the FIS2 was set up to measured QoE. The QoE bound required to be predefined for video streaming. These were set to: Low QoE (i.e. QoE ≤ 33%) was associated to PSNR ≤ 25, SSIM ≤ 0.88, and ID/ or ED ≥ 0.66, Medium QoE (i.e. 33% < QoE ≤ 67%) was associated to medium QoE (i.e. 25 < PSNR ≤35, 0.88 < SSIM ≤ 0.95, and 0.33 ≤ ID/ or ED < 0.66). Good QoE (i.e. QoE > 67%) was associated to PSNR more than 35, SSIM more than 0.95, and ID less than 0.33. The

PSNR and SSIM limitation bounds values have been chosen according to previous studies (Al-Jawad et al., 2018), (Brito and Figueiredo, 2017), (De Grazia et al., 2017) and (Testolin et al., 2014). The ID results were normalized between 0 and 1. The normalization required knowing the highest and lowest values for each parameter. These were obtained by running the code that indicated the QoE parameters.

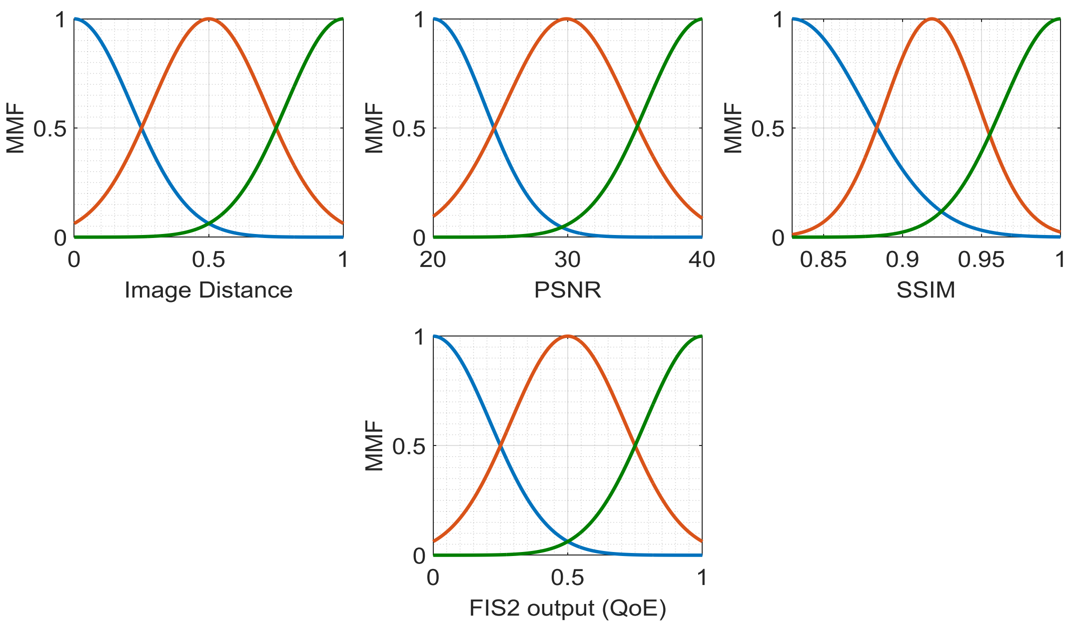


Figure 7.4 FIS2 membership functions, inputs (top Figures), output (bottom Figure)

The knowledge base for FIS2 with rules as listed in Table (7.2). The rules mapped the inputs to FIS2 to its output and provide QoE as high, medium and low values.

Table 7.2 The rules for FIS2 knowledgebase

Rule	PSNR	Operator	SSIM	Operator	ID	FIS output
1	High	AND	High	AND	Low	High
2	High	AND	High	AND	Medium	High
3	High	AND	Medium	AND	Low	High
4	Medium	AND	High	AND	Low	High
5	Medium	AND	Medium	AND	Low	Medium
6	Medium	AND	High	AND	Medium	Medium
7	High	AND	Medium	AND	Medium	Medium
8	Medium	AND	Medium	AND	Medium	Medium
9	Low	AND	Low	AND	Medium	Low
10	Medium	AND	Low	AND	High	Low
11	Low	AND	Medium	AND	High	Low

7.4.3 Implementation of FIS3

FIS3 integrated the QoS and QoE measures that were obtained by FIS1 and FIS2 to provide the overall transmission performance. The output was in the range of 0 (minimum performance) to 5 (maximum performance). Three Gaussian membership functions stated to as high, medium and low were used to fuzzy the QoS and QoE measures. They are indicated in green, red and blue plots in Figure 7.5.

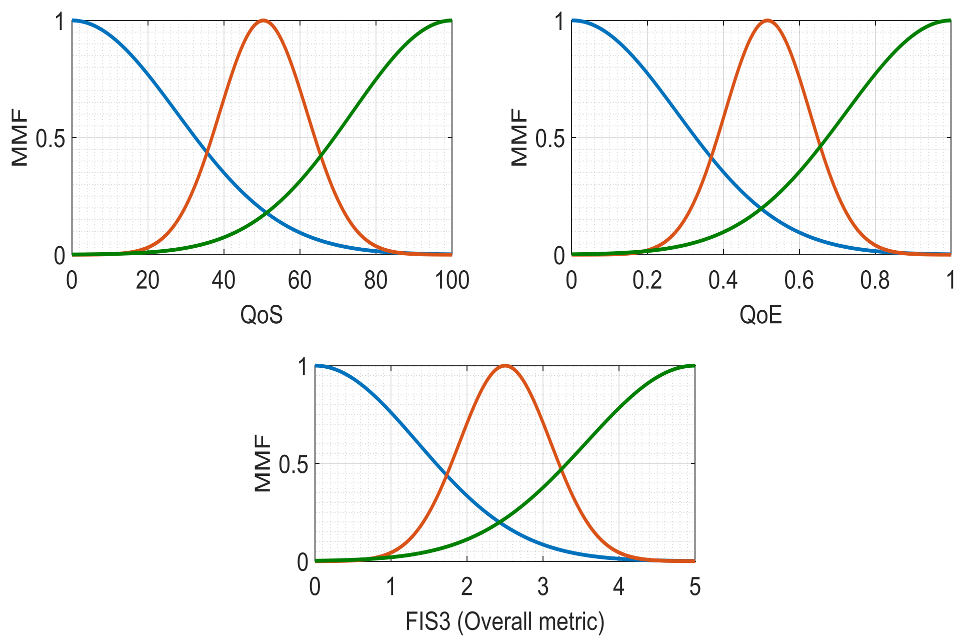


Figure 0.5 FIS3 membership functions (a) inputs (b) output

Five rules were incorporated as part of FIS3 knowledge base which are indicated in Table (7.3). The rules mapped the two inputs (QoS and QoE) to the overall transmission performance of the video as low, medium and high values.

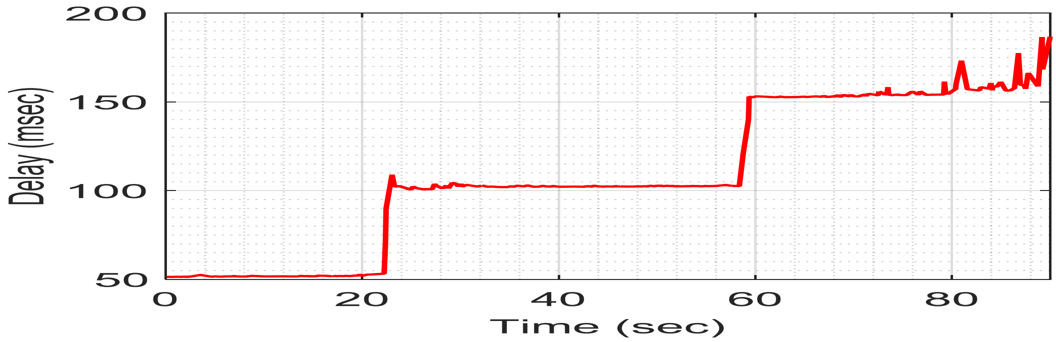
Table 0.3 The rules for FIS3 knowledge base

Rule	QoS	Operator	QoE	Operator	FIS output (overall quality metric)
1	High	AND	High	AND	High
2	High	AND	Medium	AND	High
3	Medium	AND	High	AND	High
4	Medium	AND	Medium	AND	Medium
5	Low	OR	Low	OR	Low

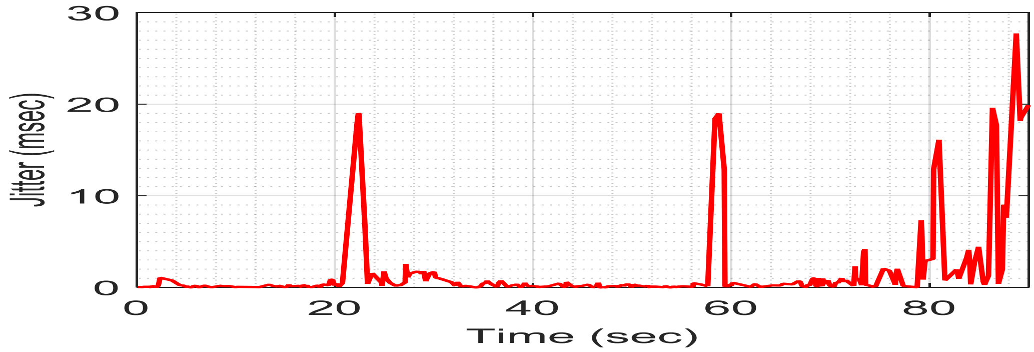
7.5 Results and Discussions

7.5.1 Network QoS by FIS1

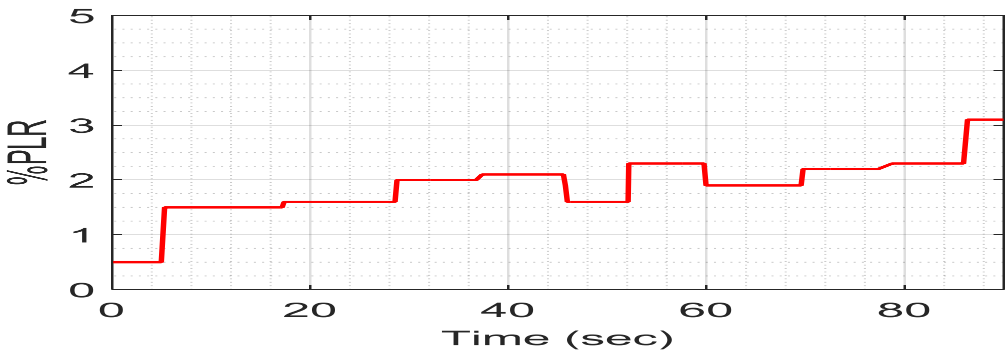
Figures 7.6 (a) - (c) indicate the traffic computation for delay, jitter and %PLR respectively. Figure 7.6 (d) provides the QoS measured by FIS1 for the video traffic based on the membership functions in Figure 7.3 with fuzzy rules in Table (7.1). The increase in delay, jitter and %PLR was controlled by NetEm that caused reduction of the QoS. At the start of the streaming, at time 5 seconds, QoS was high at 75% with (delay= 51 msec, jitter=0.51 msec, %PLR=0.5). At time 43 seconds QoS was 47% (delay=102 msec, jitter=0.039 msec, %PLR= 2.1), At time 65 seconds QoS was 54% (delay=152 msec, jitter=0.406 msec, %PLR=1.9), At time 90 seconds QoS was 19.2% (delay=186 msec, jitter=18.18 msec, %PLR= 3.1). It can be seen that QoS declined by time as traffic parameters of delay, jitter and %PLR increases. Curve fitting function (the polynomial of 4^{th} degree) was performed to illustrate the measurements trends for the plots. QoS varied according to the delay, jitter and %PLR variations. The values associated to 0- 34 as low QoS, 35-65 as medium QoS and 66 to 100 as high QoS.



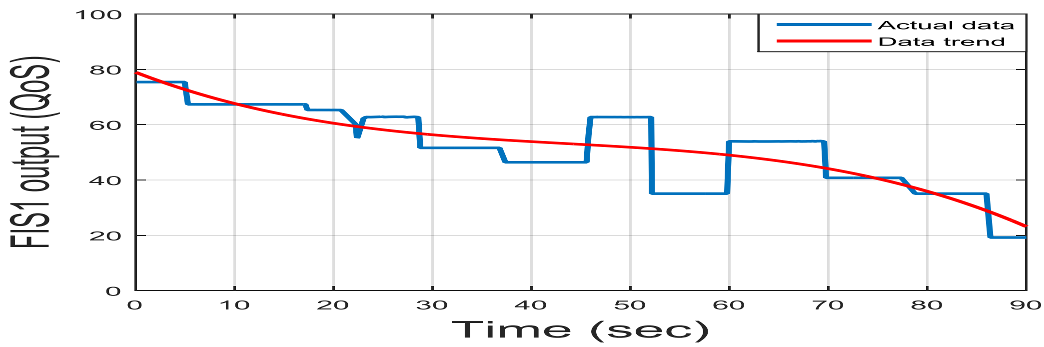
(a)



(b)



(c)



(d)

Figure 0.6 (a) Traffic delay (b) jitter (c) %PLR (d) QoS obtained from FIS1

7.5.2 Objective QoE by FIS2

Figure 7.7 provides a normal streamed image with serial numbers presented as labels on its top right and left corners. The labels are applied to ensure the received images were compared correctly to the corresponding transmitted image, even in situations the images did not arrive in order (e.g. due to packet loss)

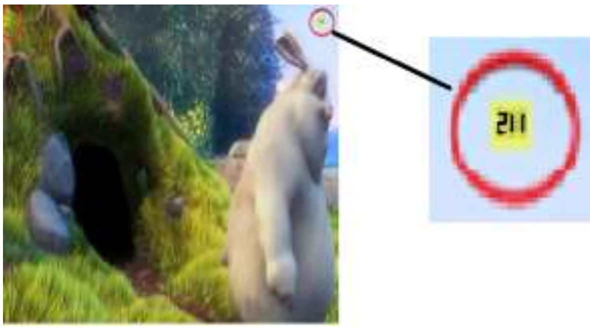


Figure 0.7 A typical transmitted image with its serial numbers as labels indicated on its top corners

The PSNR, SSIM and ID were computed by comparing sent and received video images following systematic sampling. The distortion was localised through image partitioning. Figures 7.8 (a) - (b) indicate the transmitted and received images at time 65 seconds. A distortion is visible at the bottom of the received image. The measured PSNR and SSIM were 36.08 and 0.999 respectively and ID was 0.48.

(a) (b)

Figure 7.8 (a) The transmitted (original) image (b) received (distorted) image with label=1170 at time 65 second

The four partitions approach is shown in Figure 7.9 for same image in Figure 7.8 (b).

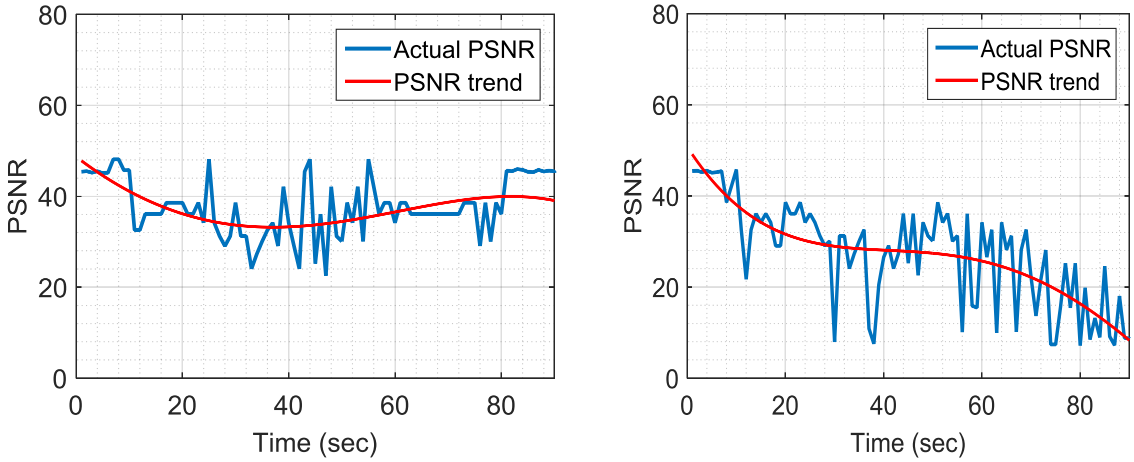
Figure 0.9 Partitioned received image at time 65 sec

The PSNR, SSIM and ID measures for each section were measured and the minimum measures for PSNR and SSIM and the maximum ID among the four sections were chosen. The minimum value was used to consider the worst-case scenario. The measures of PSNR, SSIM and ID for a full image approach and partitioned image approach are shown in Table (7.4). Sections 1 to 4 signify top left, top right, bottom left and bottom right of the image respectively. In Figure (7.8), the selected visual video parameters PSNR, SSIM and ID were 28.13, 0.997 and 0.60 respectively. Table (7.4) provides the visual video parameters or the chosen image and its four partitions.

Table 0.4 PSNR, SSIM and ID for a full and partitioned image (these were obtained from the image shown in Figure 7.8 (b) and its partitions in Figure 7.9)

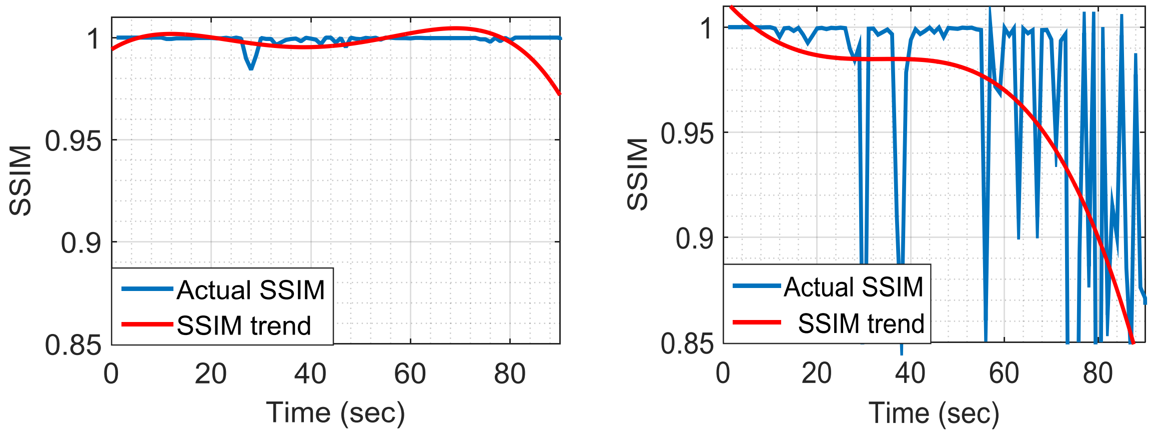
Parameter	Full image	Partitions				Selected value
		1	2	3	4	
PSNR	36.08	33.22	33.56	29.32	28.13	28.13
SSIM	0.999	0.998	0.999	0.998	0.997	0.997
ID	0.48	0.41	0.42	0.47	0.60	0.60

Figures 7.10, 7.11, 7.12 and 7.13 show PSNR, SSIM, normalised ID and ED for the video images (following systematic sampling) at the receiver and their comparisons with their counterparts for the sent images. For each plot, (a) is for the full image and (b) for the partitioned image.



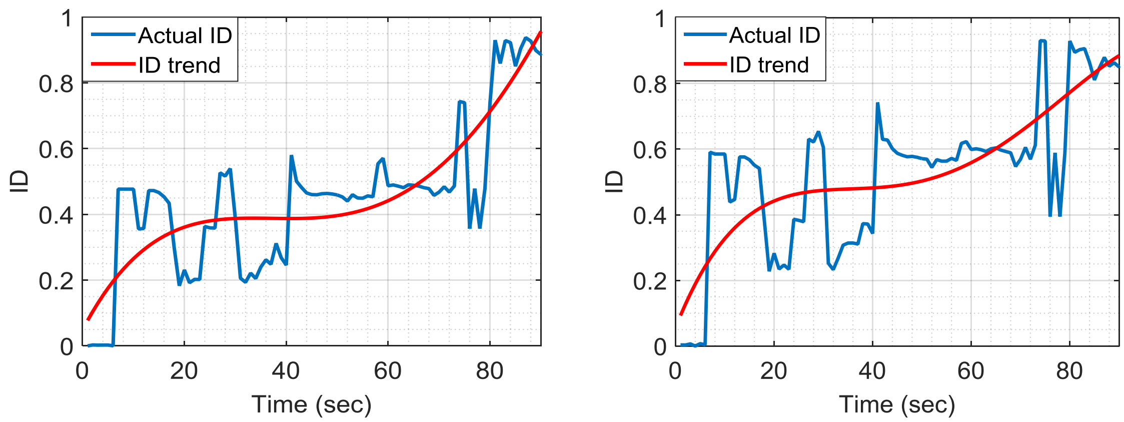
(a) (b)

Figure 0.10 PSNR (a) full image, (b) partitioned imagepartitioned



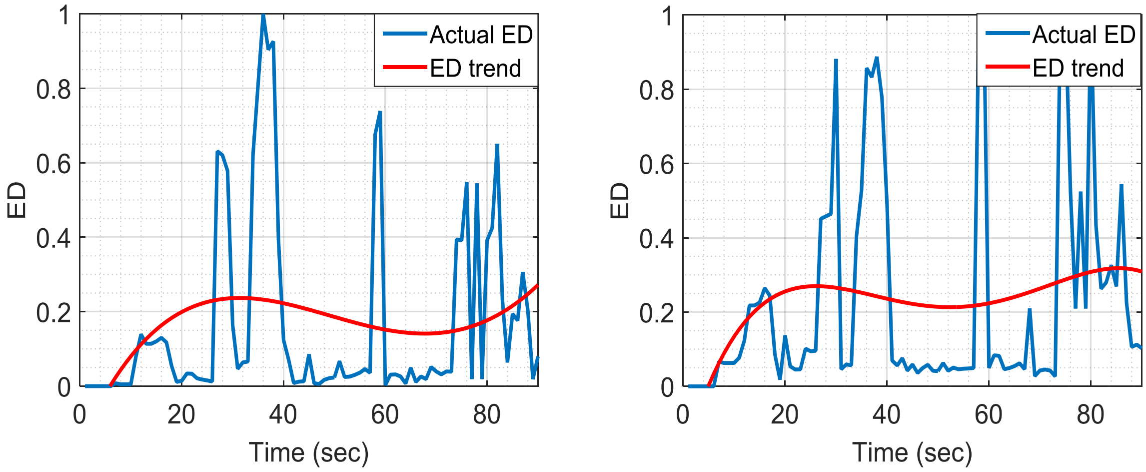
(a) (b)

Figure 0.11 SSIM (a) full image, (b) partitioned image



(a) (b)

Figure 7.12 ID (a) full image, (b) partitioned image

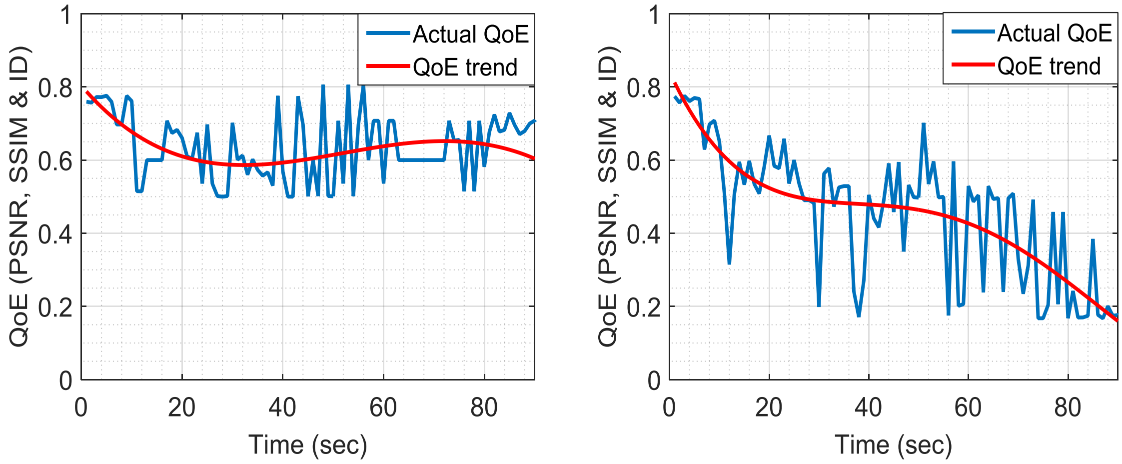


(a) (b)

Figure7.13 ED (a) full image, (b) partioned image

PSNR, and SSIM measures were at their maximum values at the initial of the streaming and they decreased as the traffic parameters were increased according to the NetEm. While, ID was zero at start but by increasing network parameters, the ID increased accordingly. For the full image processing approach, the results for SSIM and PSNR were moderately similar to QoS. However, at time 80 seconds SSIM and PSNR were high but QoS at the time was low. Furthermore, for the partitioned images, SSIM and PSNR measures were very similar in behaviour to network QoS. Even at the end of streaming between 80-90 seconds. The partitioned images SSIM and PSNR measures had similar trends to QoS measures. ID in both cases (i.e. the full and partitioned image methods) was very close. Furthermore, the trend of ID was also very close to QoS. While, the ED was zero at start of the streaming as received images were similar to those sent but by increasing traffic parameters, the ED increased accordingly. According to the results, the partitioned image technique was more accurate in measuring the quality of video transmission than the full image method.

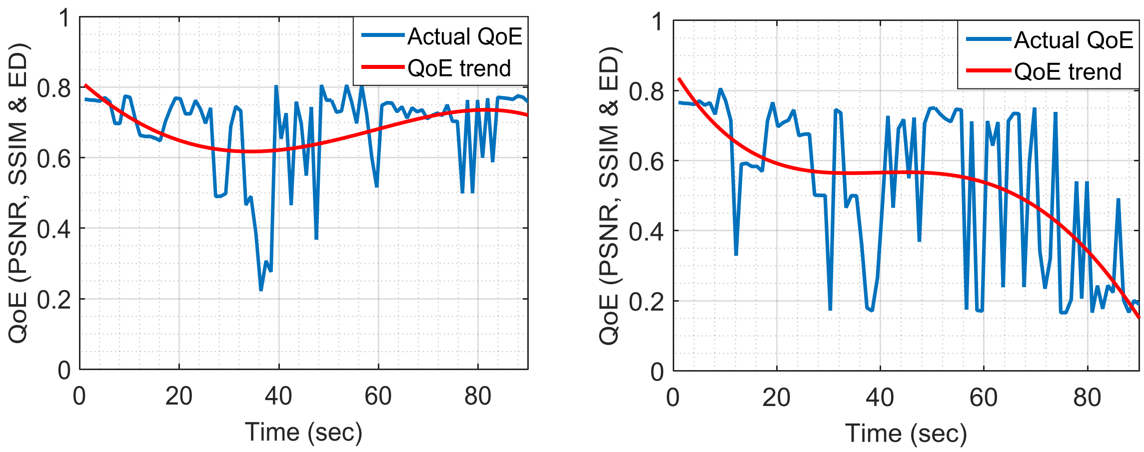
Figures 7.14 (a) - (b) show the QoE metric based on (PSNR, SSIM and ID) the full and partitioned images respectively that have been determined by FIS2 using provided membership functions in Figure 7.4 and fuzzy rules listed in Table (7.2). The partitioned image technique had represented the video quality more accurately. The data trend of QoE according to partitioned image approach in Figure 7.14 (b) is very similar to data trend of QoS results in Figure 7.6 (d).



(a) (b)

Figure 0.14 Video quality determined by FIS2 (a) full image (b) partitioned image

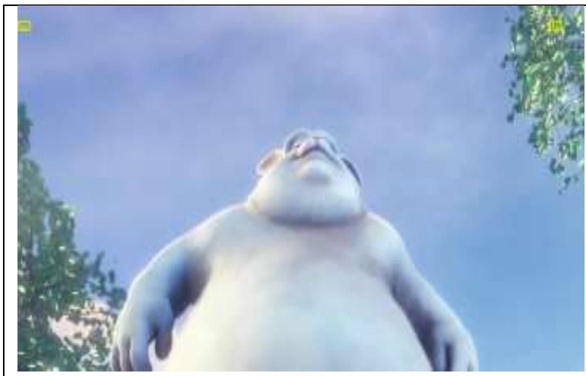
Figures 7.15 (a) - (b) show the objective QoE metric based on (PSNR, SSIM and ED) the full and partitioned images respectively that have been determined by FIS2 using provided membership functions in Figure 7.4 and fuzzy rules listed in Table (7.2). The partitioned image technique characterised the video quality more accurately. The QoE (PSNR, SSIM and ED) trend of partitioned approach was very similar to QoE (PSNR, SSIM and ID).



(a) (b)

Figure 7.15 Video quality determined by FIS2 (a) full image (b) partitioned image

To illustrate how QoS and QoE measures related to individual images with several levels of distortion, some images and their computed values are shown in Figure 7.16 at times of 5, 43, 65 and 90 seconds. The values are provided for whole image processing and partitioned approach. QoS is between 0 to maximum 1 and QoE is from 0 to maximum 1. The partitioning of images into four parts improved quantifying image distortion and thus better determining QoE. To illustrate the point, Figure 7.16 (a) has a small amount distoration. The QoE obtained from the full image and partitioned image approches are 0.78 and 0.77 in partitioned approach. In Figure 7.16 (d), the image is highly distorted. The QoE measured by the full image approach is 0.70 while the QoE measured using partitioning approach is 0.17.



QoS=75.50, delay=51.51 ms, jitter=0.07 ms, %PLR=0.5.

Image partitioning approach:
- **Full image:** QoE =0.78, PSNR=45.09 dB, SSIM=1, ID =0.004.
- **Partitoned**: QoE =0.77, PSNR=45.09 dB, SSIM=1, ID = 0.01.

(a)

QoS=48.01, delay=104.10 ms, jitter=0.56 ms, %PLR=2.1.

Image partitioning approach:
- **Full image:** QoE=0.76, PSNR=45.39 dB, SSIM=0.999, ID =0.48.
- **Partitioned**: QoE=0.49, PSNR=27.30 dB, SSIM= 0.998, ID = 0.62.

(b)

QoS=52.02, delay=157.5 ms, jitter=1.43 ms, %PLR=1.9.

Image partitioning approach:
- **Full image:** QoE=0.59, PSNR=30.06 dB, SSIM=0.99, ID =0.48.
- **Partitioned:** QoE=0.49, PSNR=28.13 dB, SSIM= 0.997, ID =0.61.

(c)

QoS=19, delay=178.5 ms, jitter=19.8 ms, %PLR=3.1.

Image partitioning approach:
- **Full image:** QoE=0.70, PSNR=45.52 dB, SSIM=0.999, ID =0.88.
- **Partitioned**: QoE=0.17, PSNR=8.66 dB, SSIM= 0.87, ID =0.85.

(d)

Figure 0.16 Sample of images illustrating the values for QoS, QoE and the effect of image partitioning of determine QoE. (a) time 5 sec (b) time 43 sec (c) time 65 sec (d) 90 sec. (PSNR in (db), delay and jitter in (msec). %PLR (is %ratio)

7.5.3 Integrated QoS/QoE by FIS3

Figure 7.17 provides a plot for the overall video quality that measured by FIS3 according to the membership functions provided in Figure 7.5 and fuzzy rules listed in Table (7.3). Score 1 is the lowest quality while 5 is the maximum quality for the received video. The inputs were the QoS shown in Figure 7.6 (d) and QoE by partitioned approach (PSNR, SSIM and ID) shown in Figure 7.14 (b).

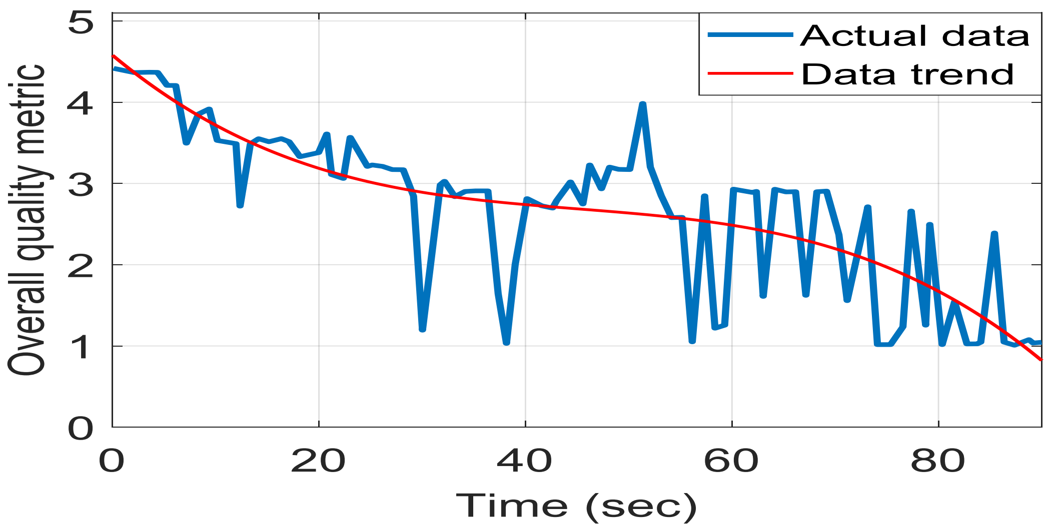


Figure 0.17 Evaluation of video quality transmission by FIS3

The video quality video transmission was very high throughout the first 5 seconds and decreased to its minimum during the end of streaming. The trend correlated well with QoS, QoE and their related parameters thus demonstrating the technique had properly performed the assessment.

To validate the over-all performance results based on developed system, a subjective test was performed. For this purpose, a test sequences were created of sampled received images to be evaluated by 25 human participants. The average provided a MOS (Pokhrel, 2014) score according to the ITU-T recommendation (ITU-T, 1996). The streaming of the video lasted for 90 seconds and contained to 90 sampled images. The distorted (received) video was played to each participant at the start. Because scoring of the specific images while the video was being played was not realistic, windows photo viewers' tool was used to show the video images individually, and once the scoring of an image was attained, the next image was showed. This opinion scale allocated qualitative measures from bad to excellent by mapping the numerical MOS as; excellent (5), good (4), fair (3), poor (2) and bad (1).In this work, a the laboratory environment was used to accomplish the subjective test. The subjective test scores are shown in Figure 7.18. The results showed that the trend of subjective test in Figure 7.18 was close to the trend of the developed objective method in Figure 7.17. There were few variances, for example from 80 to 90 second the subjective test showed quality with 1.4 to 2.2 that was higher than the objective test that showed quality close to 1 for same period.

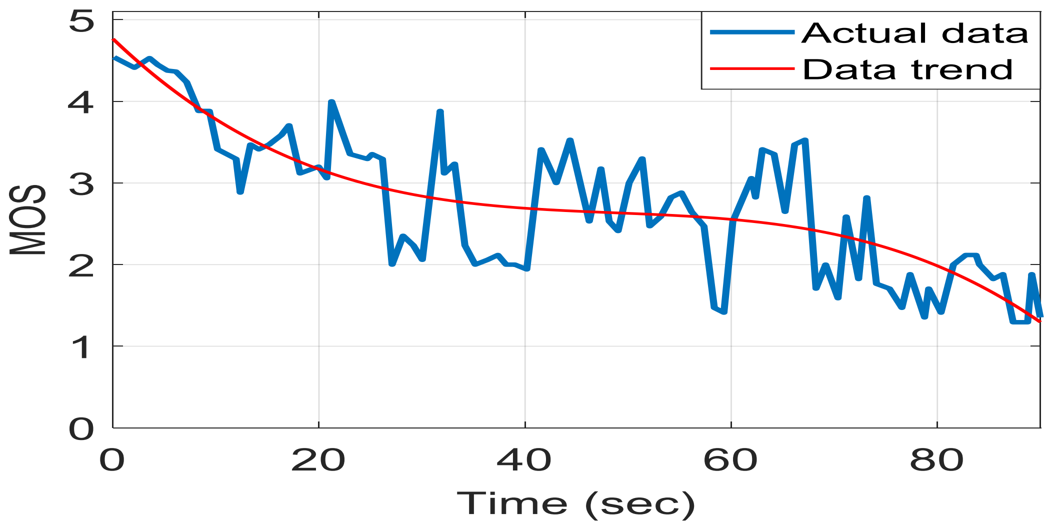


Figure 0.18 Average evaluation of video quality transmission by 25 participants

For an independent comparison of the assessment results from proposed approaches, a recently known image and video quality evaluation proposed in (Bampis et al., 2017) was selected. The authors in that study used assessment of video quality that was termed as Spatial Efficient Entropic Differencing Quality Assessment (SpEED-QA). This proposed approach is an effective natural scene statistics-based method that computes local entropic variations between the tests (received) and reference (original) data in the spatial domain (Bampis et al., 2017). They stated that SpEED-QA had a very competitive performance compared to other objective image and video quality assessment approaches. SpEED-QA was measured by first computing the conditional block entropies of the distorted and reference images. The variations between the entropies of the associating blocks were then attained and an averaged for all blocks (Bampis et al., 2017). Single scale (SPDss) and multiscale methods of SpEED were proposed in (Bampis et al., 2017). Figure 7.19 shows the plot SPDss values for the video used in our study. The multiscale plot was very similar to the single scale and therefore is not shown.

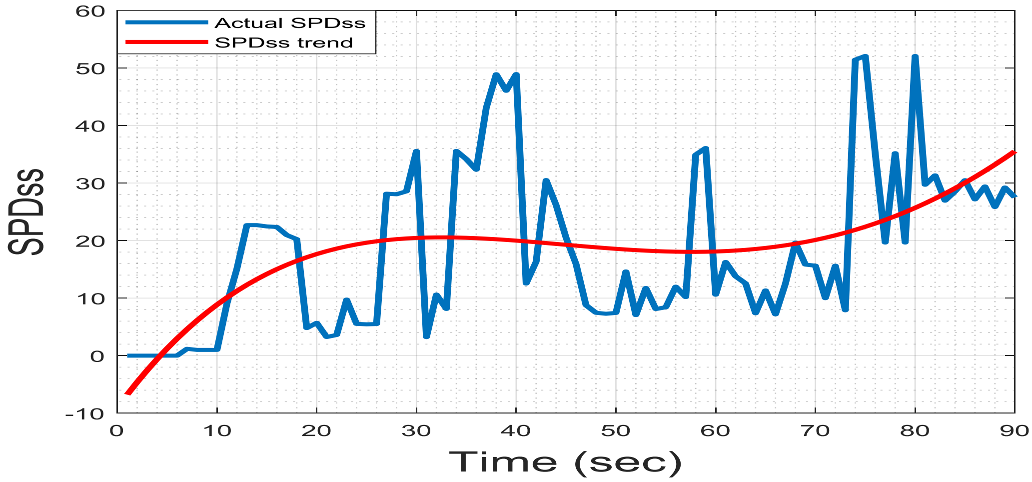


Figure 0.19 Plot of SPDss for the video used in the study

The red line over the plot provides its trend attained by a 4th order polynomial. A relationship can be observed when comparing the plots in Figure 7.19 and those in Figure 7.14 (b) (i.e. FIS2 results which produced from PSNR, SSIM and ID) with the overall video quality achieved by FIS3 (which integrated delay, jitter and %PLR with PSNR, SSIM and ID) provided in Figure 7.17. In Figures 7.14 (b) and 7.17, larger measures illustrate a better quality but in Figure 7.19 lowest measures illustrate a better quality, thus, the trends are inverted. In Figures 7.14 (b) and 7.17, the images associate to times at 30 and 59 seconds have a very low quality as provided by a drop in the plot. The associating images in Figure 7.19 have also a low quality as provided by a large increase in the plot.

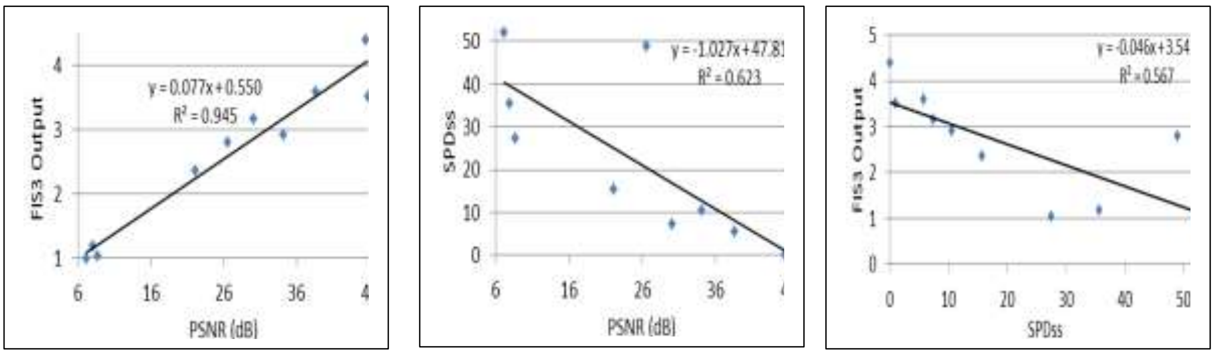
The images associate to the time period between 85 and 90 seconds have lowest quality in Figure 7.17. These images showed minimum QoS as provided in Figure 7.6 (d). However, the associating images when evaluated by SPSS do not show lowest quality. This demonstrates an advantage of the FIS approach proposed in this study that integrates QoS and QoE to deliver an overall quality assessment.

In order to further compare SPDss and the FIS method, the values of PSNR, SSIM, ID, SPDss, FIS2 output and FIS3 output are tabulated in Table (7.5) for images corresponding to 1 second and then every 10 seconds.

Table 7.5 Values for PSNR, SSIM, ID, SPDss, FIS2 output and FIS3 output for images at 1 second and then every 10 seconds

Time (seconds)	PSNR (dB)	SSIM	ID	SPDss	QoE FIS2 Output	QoE FIS3 Output
1	45.49	1.000	0.00	0.00	0.76	4.41
10	45.74	1.000	0.62	0.99	0.58	3.52
20	38.58	0.999	0.30	5.70	0.67	3.60
30	7.95	0.777	0.64	35.58	0.19	1.19
40	26.54	0.994	0.36	48.93	0.49	2.81
50	30.06	0.999	0.61	7.42	0.49	3.17
60	34.15	0.999	0.64	10.58	0.51	2.92
70	22.11	0.994	0.61	15.63	0.32	2.36
80	7.14	0.647	0.99	52.08	0.16	1.01
90	8.66	0.871	0.91	27.49	0.16	1.04

Figures 7.20 (a) - (b) show plots of FIS3 output and SPDss against PSNR respectively. PSNR was used as it was a more sensitive measure for qualifying video quality as compared with SSIM and ID. FIS3 shows a closer correlation to PSNR than SPDss. The correlation is indicated in the Figures by coefficient of determination (R^2) obtained from the best fit through the data points. The values of R^2 are 0.945 and 0.623 for Figures 7.20 (a) - (b) respectively. R^2 indicates the proportionate amount of variation in FIS3 output and SPDss in response to PSNR. Larger values of indicate greater variability in the linear regression model. Figure 7.20 (c) shows a plot of FIS3 output against SPDss. The two are closely related at high quality images. For low quality images, FIST3 grades them as 1 but SPDss has different measures for them therefore the relationship between the two is not as obvious.

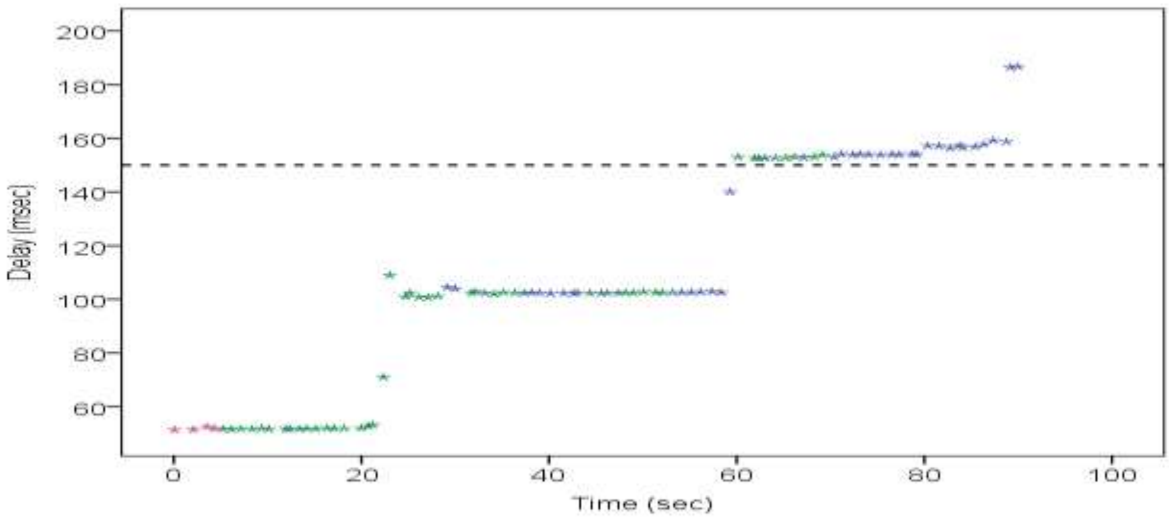


(a) (b) (c)

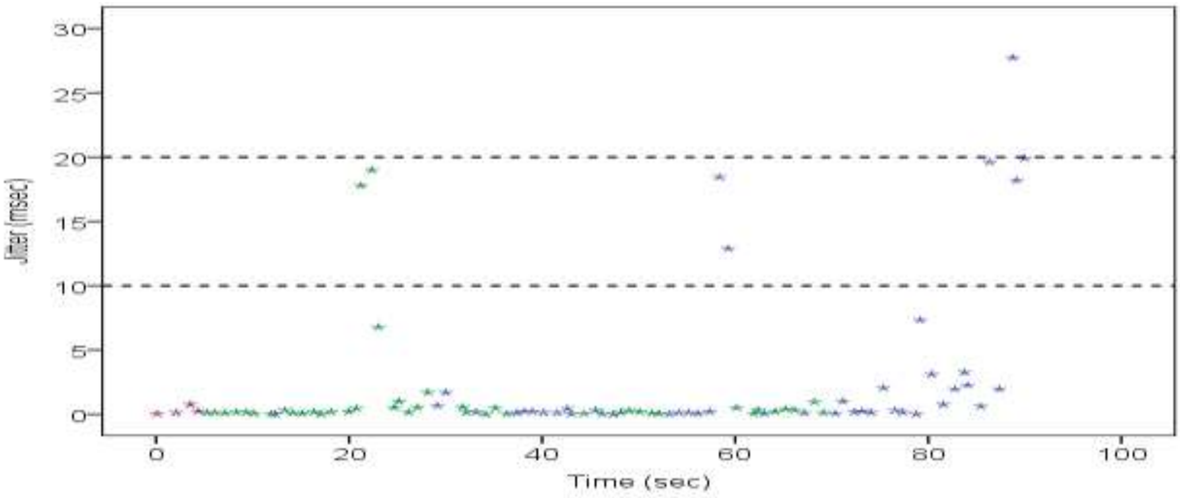
Figure 0.20 Plots for (a) FIS3 output against PSNR, (b) SPDss against PSNR and (c) FIS3 output against SPDss

7.6 Interpretation of results

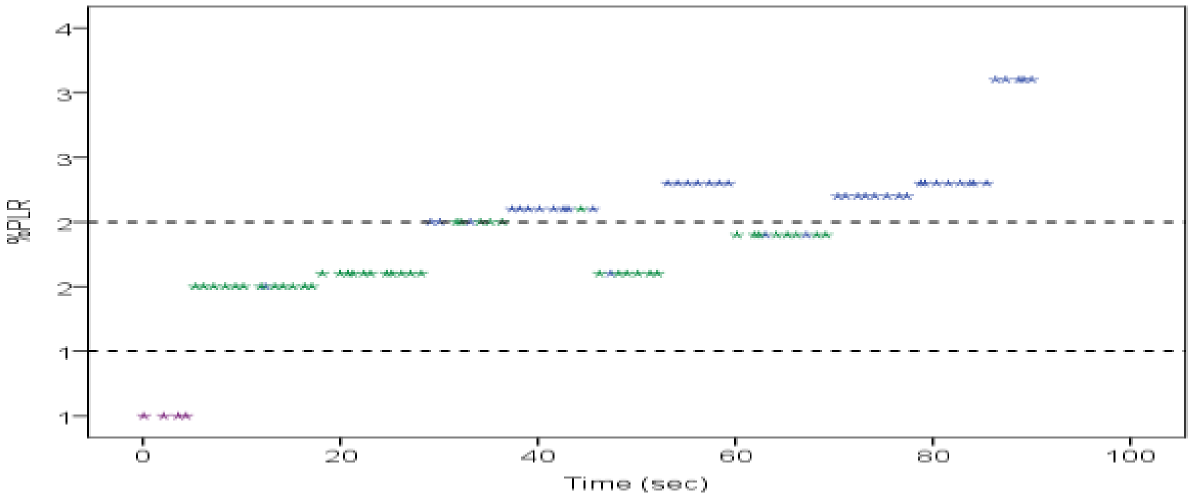
SPSS© was used to analysis the overall quality produced by FIS3 for the video traffic parameters and video visual parameters. The scatter plots in Figures 7.21 (a) - (c) show an overview analysis of the proposed quality assessment. The explanations for packets being classified as low, medium or high overall quality by the proposed FIS3 relates to delay, jitter and %PLR values. Blue colour in the Figures indicates low overall quality (values between 1-2), green indicates medium overall quality (values between 2-4) and red illustrates high overall quality (values between 4-5). The dotted blue lines are positioned as described in section 7.4.1. There were several packets that were allocated into medium class (green) overall quality that have delay values lower than 150 msec, while their jitter or %PLR values were high. Several packets that were classified into medium (green) quality had a small delay, but their jitter or %PLR values were high. It can be seen from Figures 7.21 (a) - (c) that %PLR was the most useful parameter reflecting overall quality. The overall quality classified as poor (blue) when %PLR exceeded the limit recommended values (2%). For delay, many packets were within the recommended delay values but had poor quality (blue). It was the same for jitter as there were many packets classified as poor (blue) but they were within recommended jitter values.



(a)



(b)



(c)

Figure 7.21 An overview analysis of the classifications, the reasons for packets being classified as high, medium or low overall quality metric by the FIS3 model according to (a) delay, (b) jitter and (c) %PLR values

The scatter results in Figures 7.22 (a) - (c) show an overview analysis of the classifications results, the explanations for packets being assigned as low, medium or high overall quality metric by the FIS3 model according to PSNR, SSIM and ID parameter values. Blue colour in the Figures indicates low overall quality metric; green indicates medium overall quality metric and red illustrates high overall quality metric. The dotted lines are placed according to recommended values of PSNR, SSIM and ID described in section 7.4.2. It can be observed from Figures 7.22 (a) - (c) that video visual parameters show different reflection to overall quality. For example, there are many poor (blue) classified packets but they are within recommended PSNR values. There are poor (blue) classified packets but they are within recommended SSIM values. This illustrates the need to combine QoS/QoE parameters

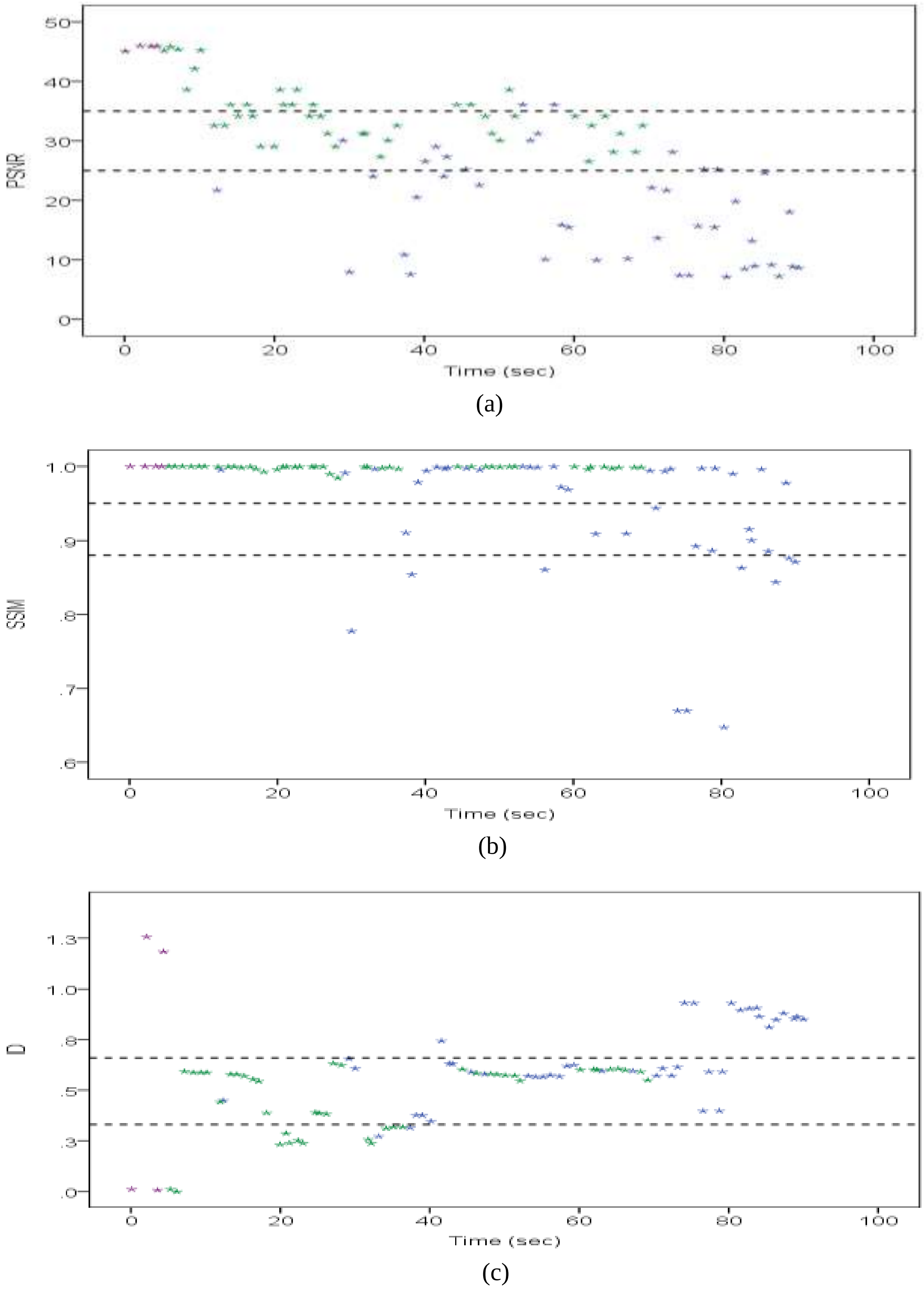


Figure 0.22 An overview analysis of the classifications, the reasons for packets being classified as high, medium or low overall quality metric by the FIS3 model according to (a) PSNR, (b) SSIM and (c) ID values

7.7 Summary

An integrated modular approach to objectively assess quality of video transmission over hybrid networks was developed and its performance was estimated. The approach accommodated traffic factors (delay, jitter and %PLR) in quality of service (QoS) measure and image distortion parameters PSNR, SSIM and ID into quality of experience (QoE) measure. It was demonstrated that image partitioning can be valuable in making qualification of image distortion, more precise and thus improved determination of QoE. A subjective test was performed with 25 participants to validate the results. The subjective test trend showed similar results to the overall integrated QoS/QoE system. An independent comparison to the developed approach in this study was performed against a technique that used spatial efficient entropic variation and comparison results to the FIS based system were obtained.

Chapter 8 Multimedia VoIP and Video Transmission Quality of Service Assessment over an Institutional Network

8.1 Introduction

The main objective in this chapter was to apply all developed methods and techniques of adaptive sampling, Bayesian and PNN QoS evaluation, QoE and integrated QoS/QoE assessment to a large institutional network in practical manner. As explained in literature review, network simulations and emulation testbeds have several limitations related to their reliability, validation and scalability limits (Roshan, 2018), (Rampfl, 2013) and (Petrioli et al., 2015). The evaluations were carried out on the institution's network at its peak usage time to allow heavy traffic load to be accommodated. The VoIP and video transmission time were 90 seconds. The testing took place at peak traffic time 11:00am. The name of the institution for network security purposes is not indicated in this thesis.

8.2 Methodology

The relevant part of the institution's network diagram is shown in Figure 4.4. The testing used two PCs, one in Campus A (PC-1) and the other PC in Campus B (PC-2) for multimedia transmission that included VoIP and Big Bunk Bunny video. The testing was performed in parallel (i.e. VoIP and video separately). Both VoIP and video were transmitted using RTP for its ability to access sequence number and timestamp as explained in Section 3.5. The test process was shown in Figure 8.1 where the left-hand side of the blue line illustrates the VoIP test (PART A) while the right-hand side of the blue line illustrates the video transmission approach (PART B). The multimedia traffic consisting of audio and video transmitted from PC-1 to PC-2. The PC-1 connected by wireless Cisco© AIR-AP1852E on Campus A, the traffic passed through Cisco switch 3850UA, to distribution layer through Cisco 6880X VSS, then to the core routers Cisco 6880X, and reversed to Campus B computer passing through the same network devices. On PC-1 the video streaming was performed by VideoLAN Client (VLC) media player and the compression set to MPEG-4 using UDP/RTP protocol. VoIP was handling between the two PCs using softphone called X-Lite using SIP protocol. Wireshark software was installed on both PCs for capturing generated traffic to measure traffic parameters. The time duration of transmission was 90 seconds.

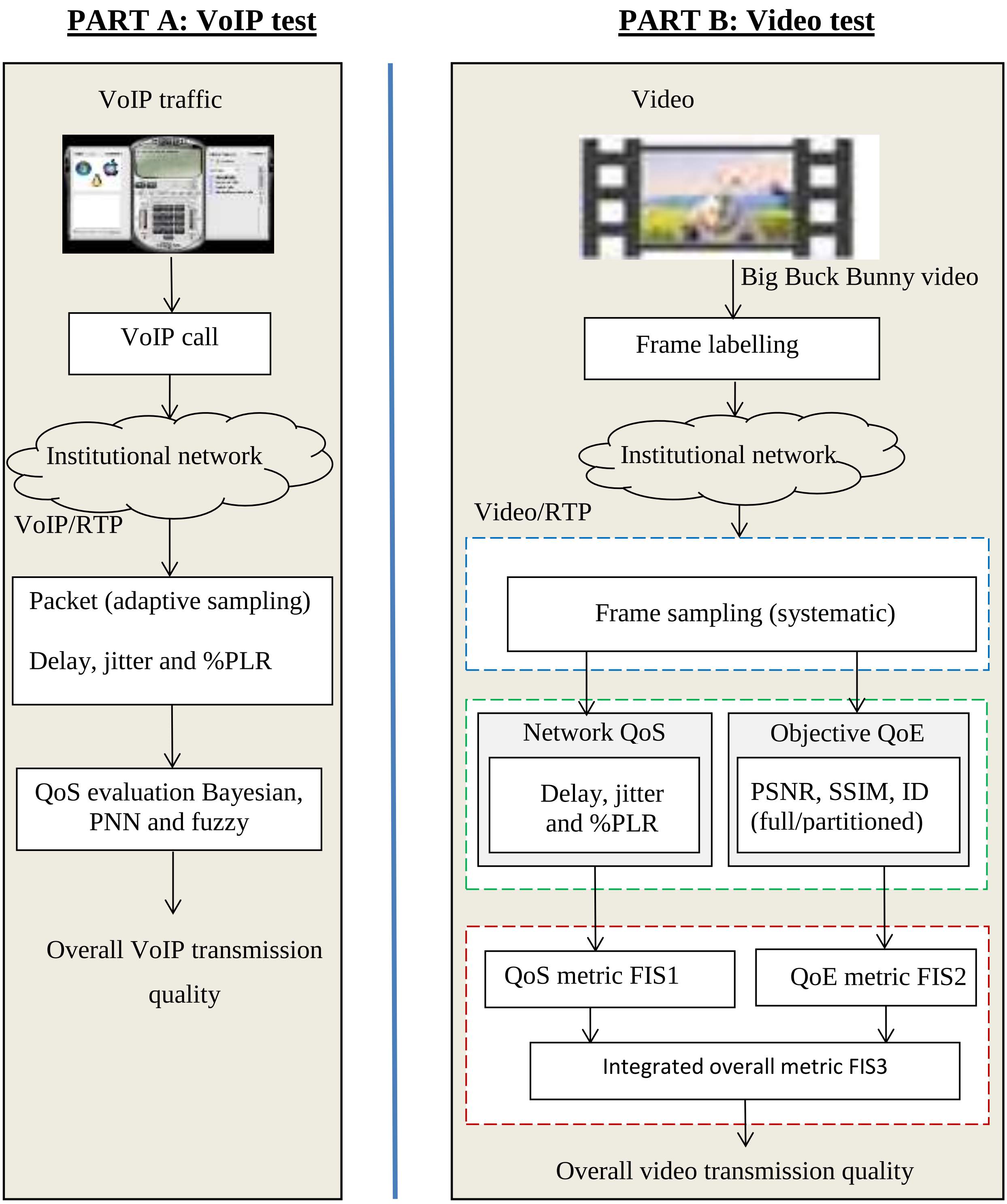


Figure 0.1 Network testing approach

In VoIP (PART A): where the call was established, the RTP packets that travelled from PC-1 to PC-2 were captured by Wireshark and analysed. An adaptive sampling technique, according to the algorithm described in section 5.3, was used due to large number of RTP packets generated, through the established VoIP call. To effectively assess the VoIP call, Bayesian and PNN QoS evaluation methods described in section 6.3 were used. For the video transmission (PART B): QoS, QoE and integrated QoS/QoE were determined based on developed approaches described in section 7.4. Summary for the methods as below:

8.2.1 PART A: VoIP evaluation

- Apply the multi-input adaptive sampling method described in section 5.3.
- Apply Bayesian, and PNN QoS evaluation methods described in section 6.3.

8.2.2 PART B: Video streaming evaluation

The steps to evaluate the quality of received video by apply the approach that defined in section 7.4 with below summary:

- Insert labels to images. This was a number that appeared in the top corners of the images to allow their correct matching with those transmitted.
- Applying systematic sampling to select sample frames.
- Measure QoS of video RTP packets by FIS1.
- Determine an objective measure of QoE using PSNR, SSIM, and ID/ or ED by FIS2.
- Quantify overall video streaming performance by FIS3.
- Use SPSS© to evaluate the relation between overall performance measurements of the video and network traffic parameters (delay, jitter and %PLR) and media parameters (i.e. PSNR, SSIM, and ID/ or ED).

8.3 Results

8.3.1 PART A: VoIP evaluation

1.1.1.1 The adaptive sampling results and discussion

Figure 8.2 (a) shows the adaptive updating of inter-sampling interval (isi) according to the differences in packet delay, jitter and %PLR. Figure 8.2 (b) indicates the manner the traffic difference for delay (TD_D). Figure 8.2 (c) provides the original delay and its data trend while Figure 8.2 (d) provides the sampled delay form and its data trend. It can be observed that the trends for the original delay and its sampled form were very similar. The updated isi varied significantly. In each iteration, isi changed the packet count that represented the number of packets that isi increased or decreased for the next iteration. The number of VoIP RTP packets was 4607 and number of sampled packets was 1584 (i.e. fraction rate was 43%).

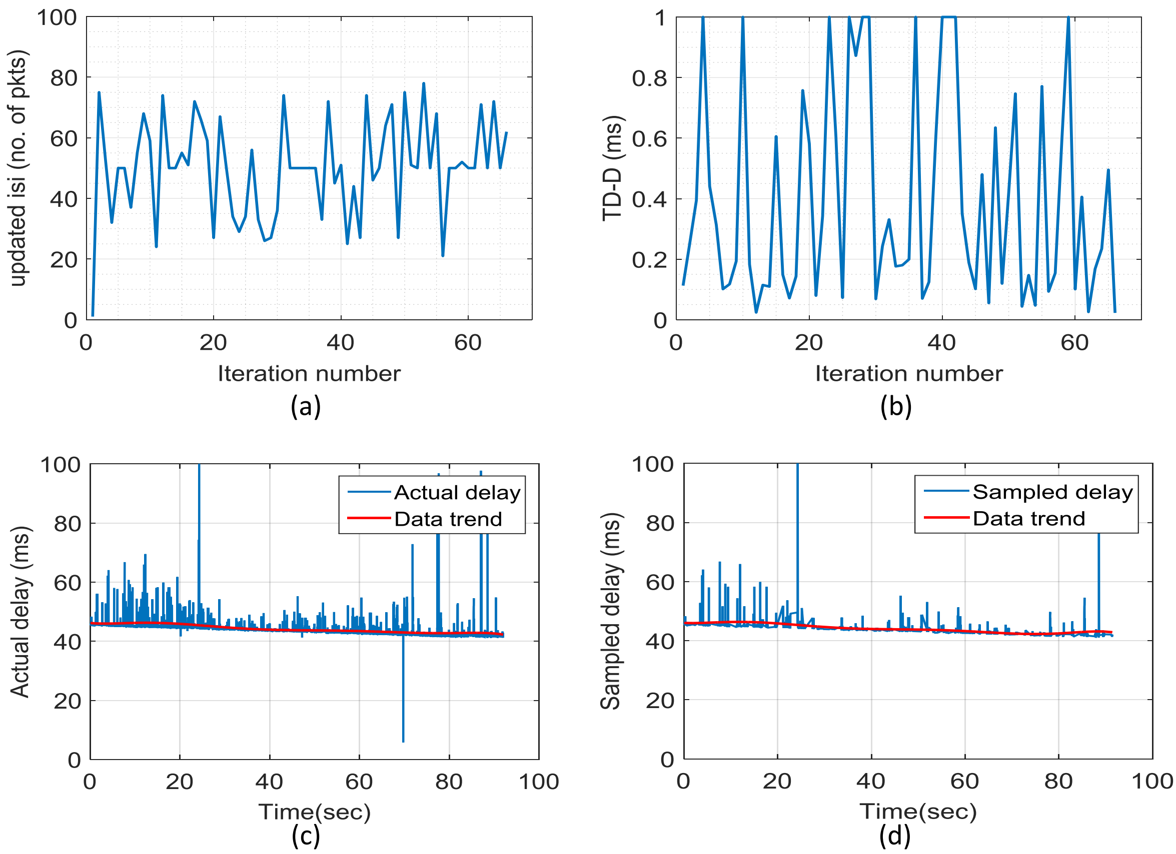


Figure 8.2 Typical results obtained from the developed modular adaptive technique (a) FIS output for the inter-sampling interval (isi) (b) traffic difference for delay TD_D (c) original traffic delay (d) sampled traffic delay

In Figures 8.3 (a) - (c), the manner the proposed adaptive sampling model tracked the jitter is shown. Figure 8.3 (a) shows the traffic difference of jitter TD_J. In Figures 8.3 (b) - (c) the actual (original) jitter and its sampled form are shown. For jitter, the trend for the original jitter is very close to its sampled version. Figures 8.3 (d) - (e) provides the manner developed adaptive sampling model tracked the %PLR. For traffic %PLR, there was no packet loss. Therefore, just two inputs have been used to sample traffic (delay and jitter), this illustrates the importance of the modular sampling design in computer networks that flexible on number of inputs parameters.

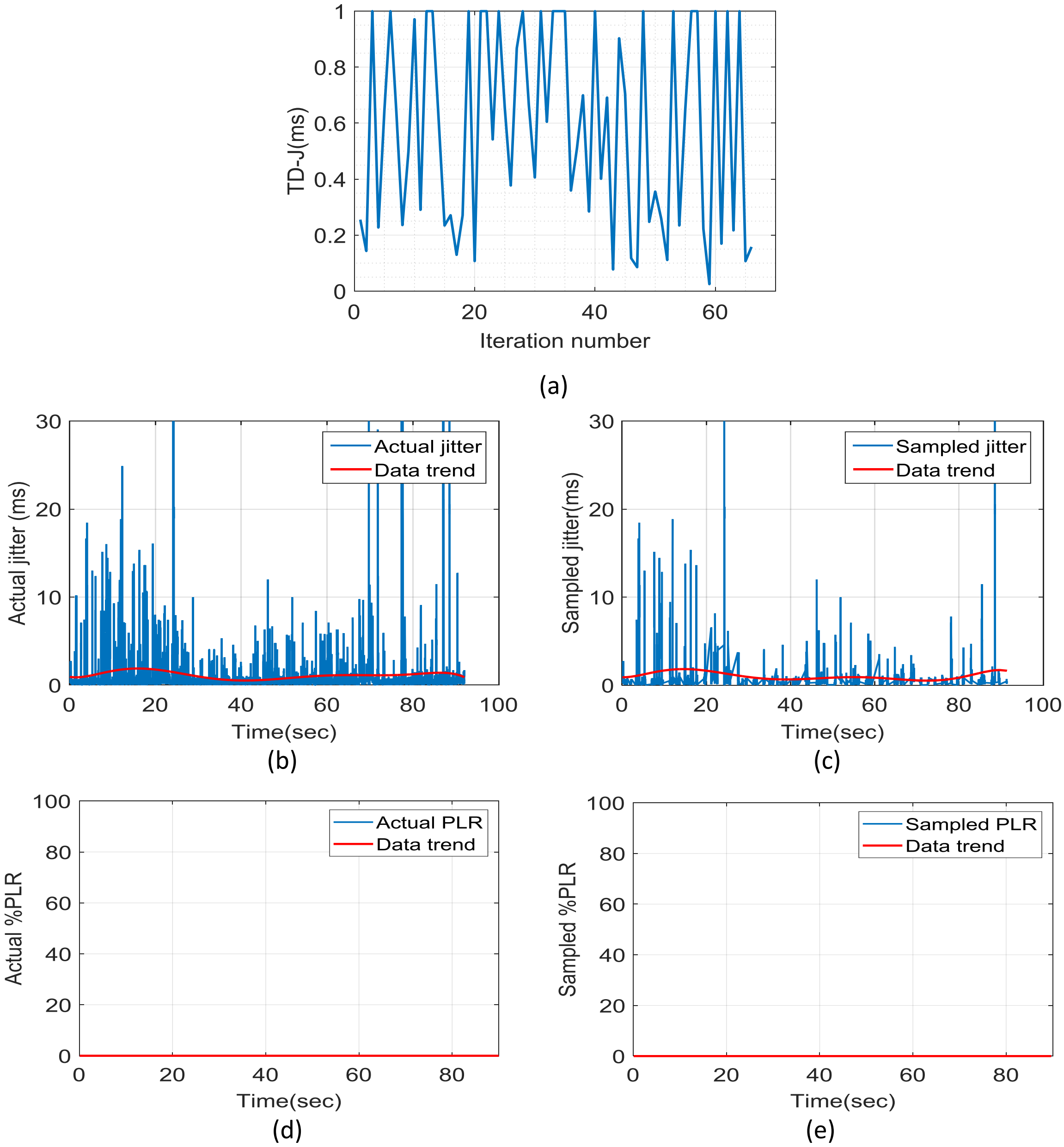
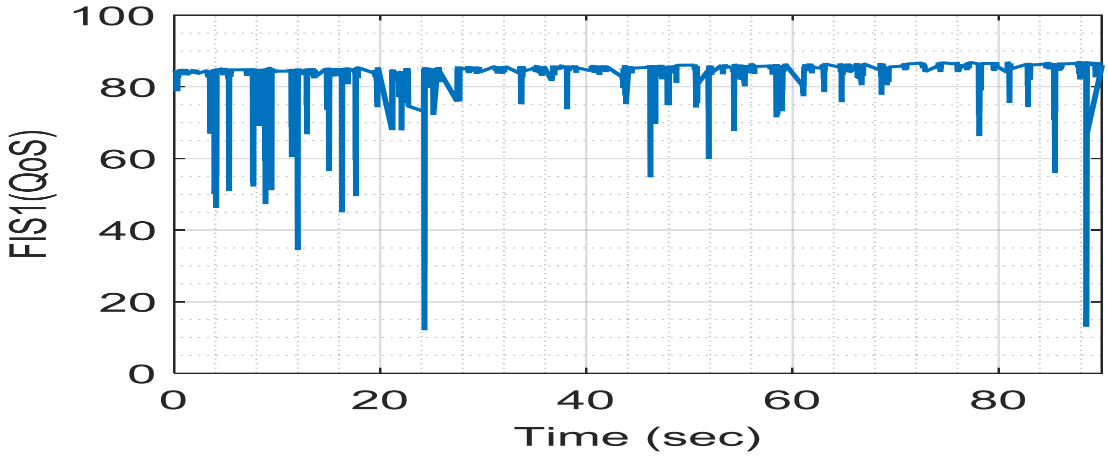


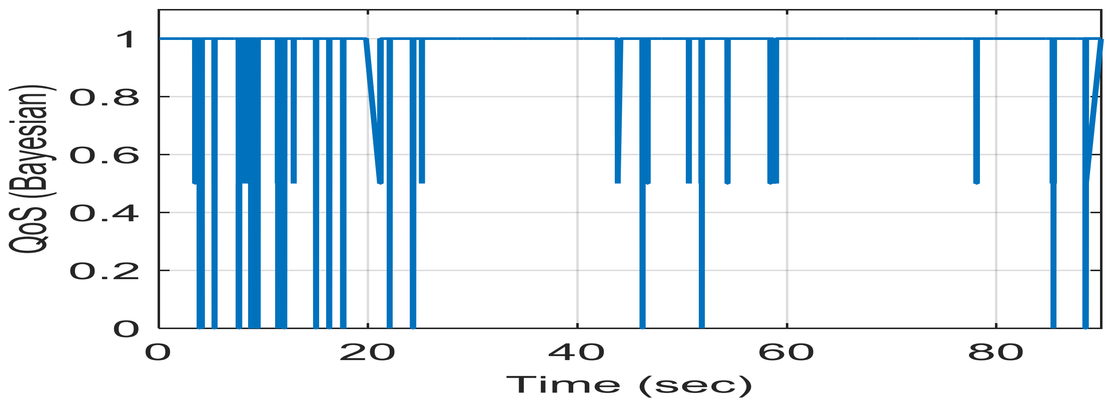
Figure 0.3 Typical results obtained from the developed adaptive technique (a) traffic difference for jitter (b) original traffic jitter (c) sampled traffic jitter (d) original traffic %PLR (e) sampled traffic %PLR

1.1.1.2 VoIP traffic QoS

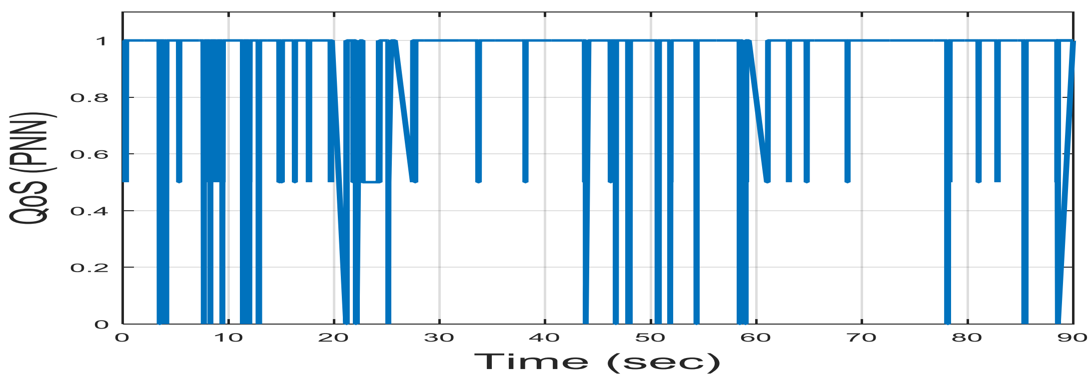
The sampled data for sampled delay, jitter and %PLR in Figures 8.2 (d), 8.3 (c) and 8.3 (e) were used to classify QoS (to reduce processing and computational time). Figures 8.4 (a) - (c) provide the QoS results according to FIS, Bayesian and PNN methods respectively. The VoIP QoS was very high most of the time as delay and jitter were small whereas %PLR was zero for the full period. There are few occasions that QoS was low due to an increase in jitter. The Bayesian approach classified 91.7% of sampled packets as High, 5.6% as Medium and 2.7% of sampled packets as Low quality.



(a)



(b)



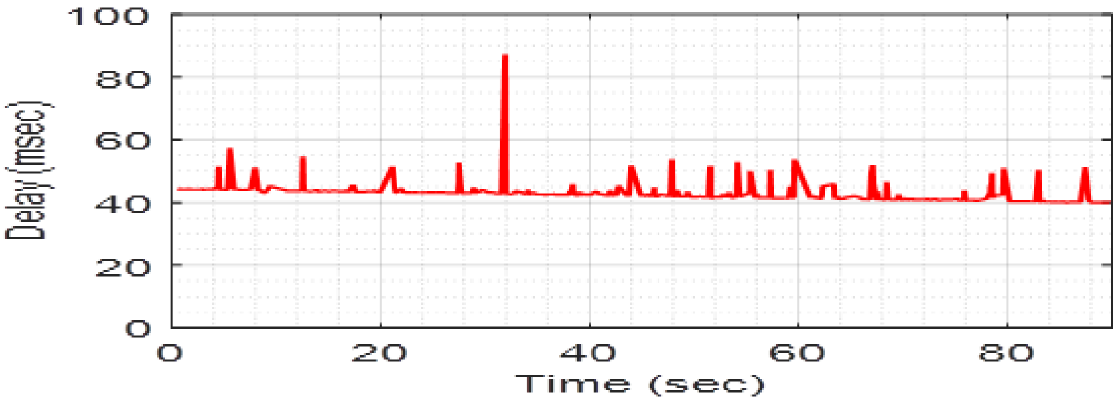
(c)

Figure 0.4 (a) QoS classification by FIS1, (b) QoS classification by Bayesian, (c) QoS classification by PNN

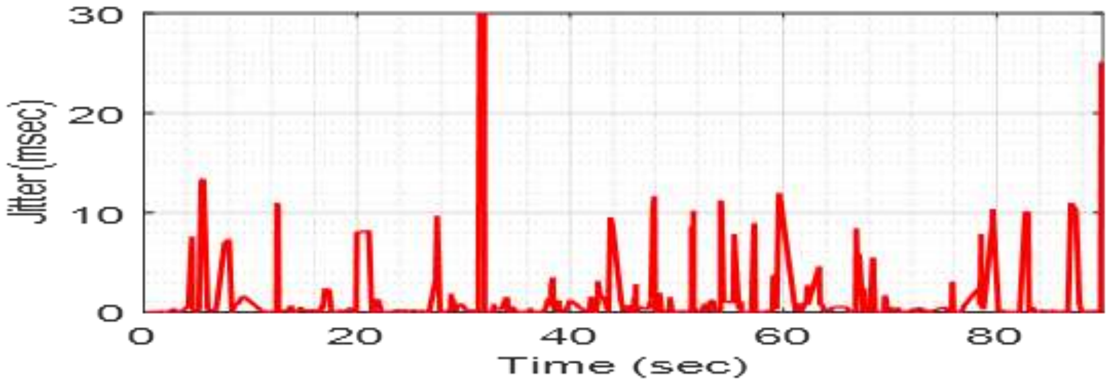
8.3.2 Video streaming results and discussions

1.1.1.3 *Video* QoS by FIS1

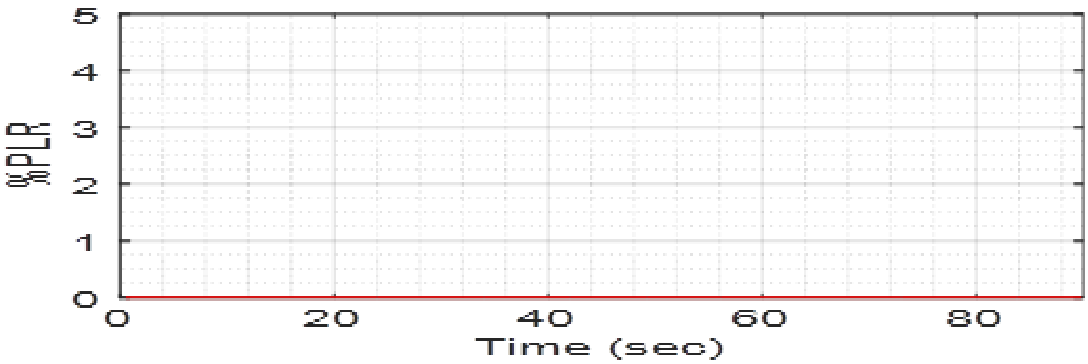
Figures 8.5 (a) - (c) show the traffic measurement plots for the video traffic parameters respectively. Figure 8.5 (d) shows the video QoS measured by FIS1 for the video packets. For the video indicated QoS was high most of the time during the 90 seconds of video transmission corresponding to the 84%. Video QoS varied based on the changes in the delay, jitter and %PLR by the membership functions in Figure 8.5 (d). The measures correspond to 66% to 100% as high QoS, 35%-65% as medium QoS and 0- 34% as low QoS,



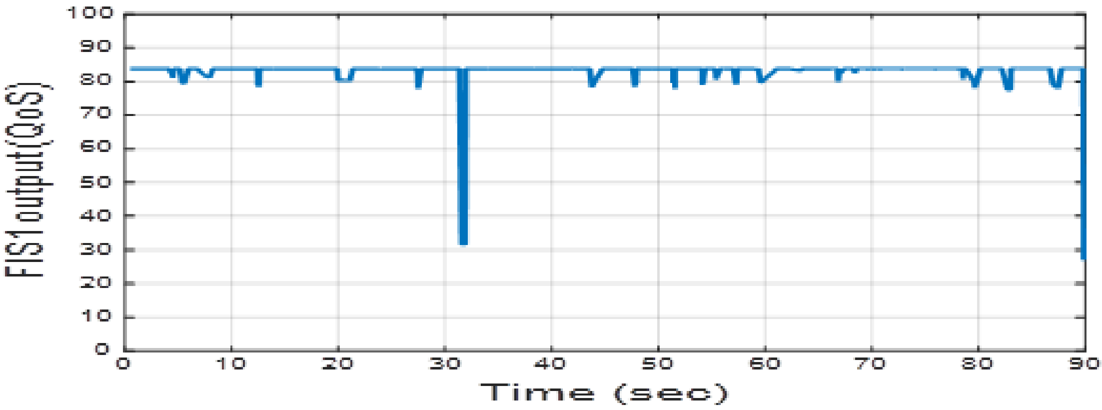
(a)



(b)



(c)



(d)

Figure 0.5 (a) Traffic delay, (b) jitter (c) %PLR, (d) QoS obtained from FIS1

1.1.1.4 Objective QoE by FIS2

Figures 8.6 (a) - (b) show the transmitted and received (distorted) images at time 65 seconds.

(a) (b)

Figure 8.6 (a) The transmitted (original) image (b) received (distorted) image with label=1170 at time 65 second

Figure 8.7 provides the four sections (partitions) from the image in Figure 8.6 (b) as part of indicating the effect of image partitioning on determining video quality.

Figure 0.7 The image received at 65 sec following its partitioning

The measures of PSNR, SSIM and ID for both full-image and partitioned image are provided in Table (8.1). The partitions 1 to 4 signify top left, top right, bottom left and bottom right sections of the image respectively. In Figure 8.7, the selected (worst case scenario) PSNR, SSIM and ID were 31.22, 0.998 and 0.09 respectively. Comparing this received image by the institutional network to same received image in chapter 7 in Figure 7.8 (b) using NetEm emulation network, the distortion was less due to good network conditions. The network traffic parameters conditions delay jitter and %PLR were low as compared to the network conditions in chapter 7 where delay, jitter and %PLR were increased by NetEm.

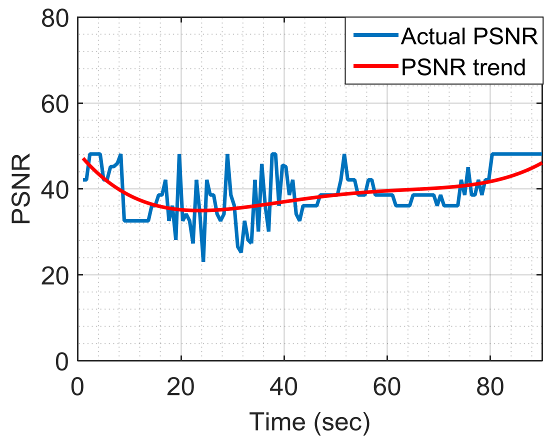
Table 0.1 PSNR, SSIM and ID for a full and partitioned image (these were obtained from the image its partitions in Figure 8.5)

Parameter	**Full image**	**Partitions**				**Selected value**
		1	2	3	4	
PSNR	36.08	38.58	38.58	34.15	31.22	31.22
SSIM	0.999	0.999	0.999	0.999	0.998	0.998
ID	0.1	0.1	0.1	0.1	0.09	0.09

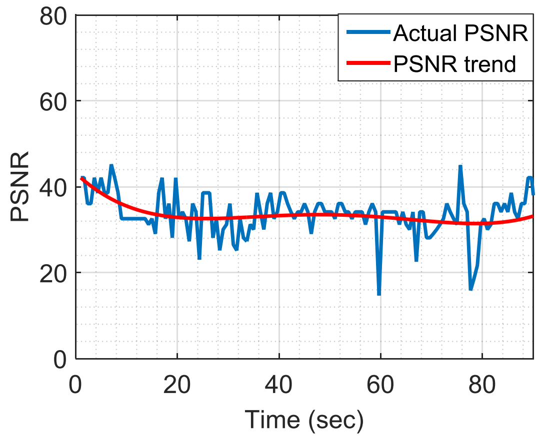
Figures 8.8, 8.9, 8.10 and 8.11 show PSNR, SSIM, normalised ID and ED for the video images (following systematic sampling) at the receiver and their comparisons with their

counterparts for the sent images. For each plot, (a) is for the full image approach and (b) for the partitioned image approach.

The PSNR and SSIM were high for most of video transmission duration. The ID was relatively low (i.e. 0.2) during the transmission and reached its peak at 0.17. For the transmission period, the results for PSNR, SSIM and ID correlated to QoE measure for the video. The ID in both cases (full and portioned image) was very similar. In addition, the trend of ID was also very similar to QoE.

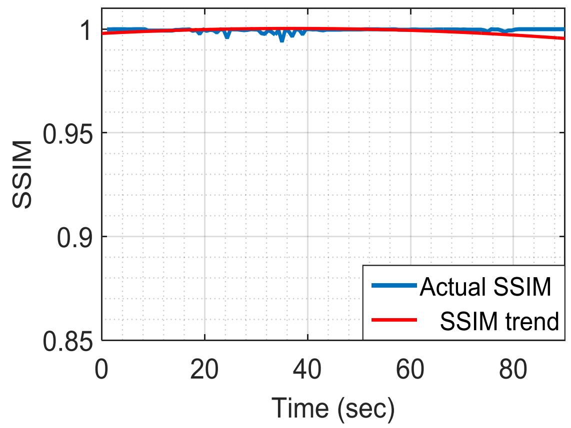


(a)

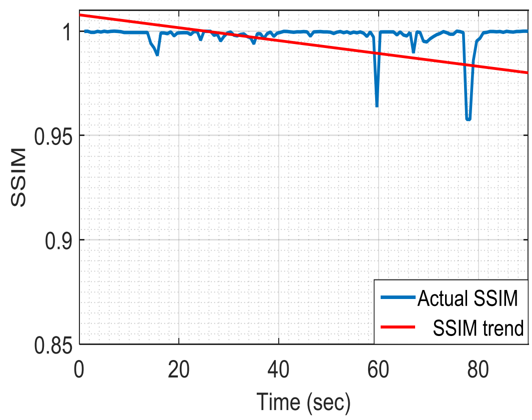


(b)

Figure 8.8 PSNR (a) full image, (b) partitioned image



(a)



(b)

Figure 0.9 SSIM (a) full image, (b) partitioned image

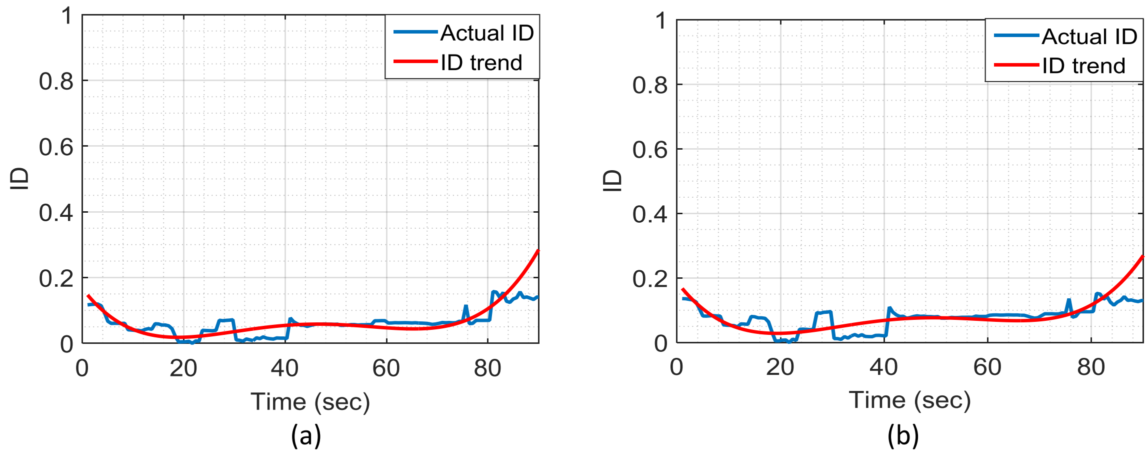


Figure 0.10 ID (a) full image, (b) partitioned image

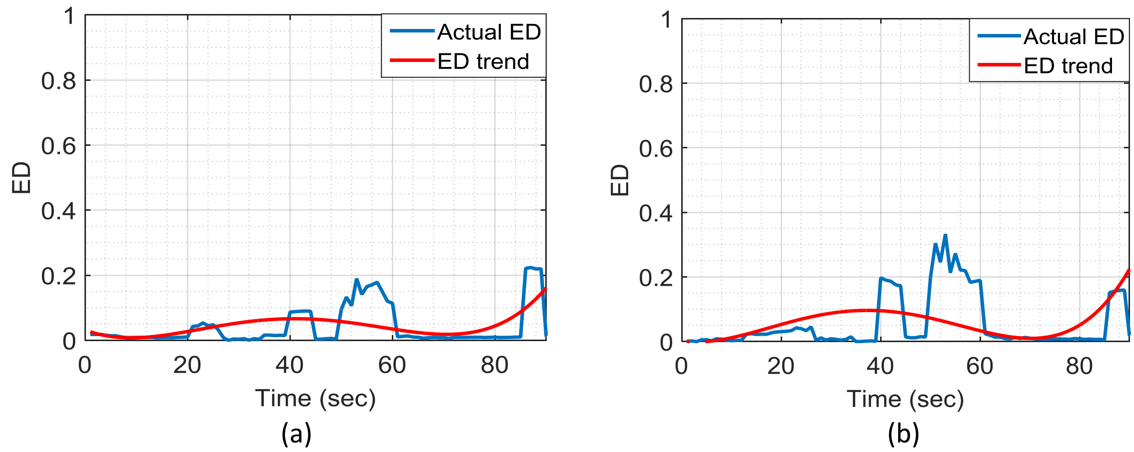


Figure 8.11 ED (a) full image, (b) partitioned image

Figures 8.12 (a) - (b) show the objective QoE metric based on the full and partitioned images respectively using PSNR, SSIM and ID, and on the membership functions and fuzzy rules described in section 7.4.2.

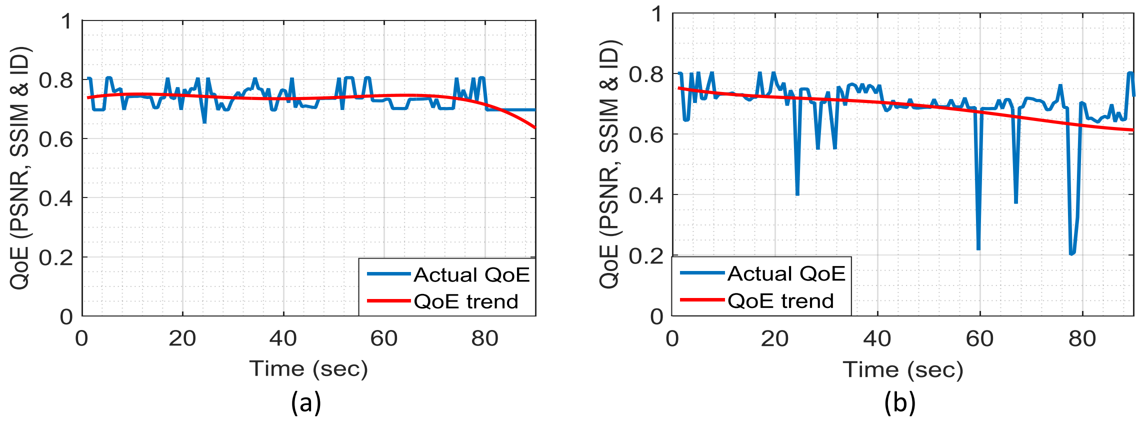


Figure 8.12 Video quality determined by FIS2 (a) full image (b) partitioned image

Figures 8.13 (a) - (b) show the objective QoE metric based on the full and partitioned images respectively based on PSNR, SSIM and ED based on membership functions and fuzzy rules described in section 7.4.2.

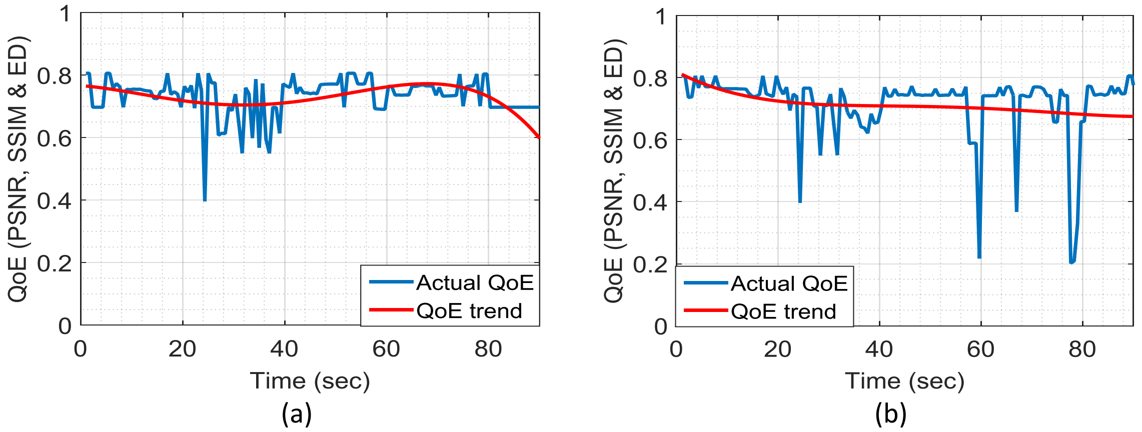
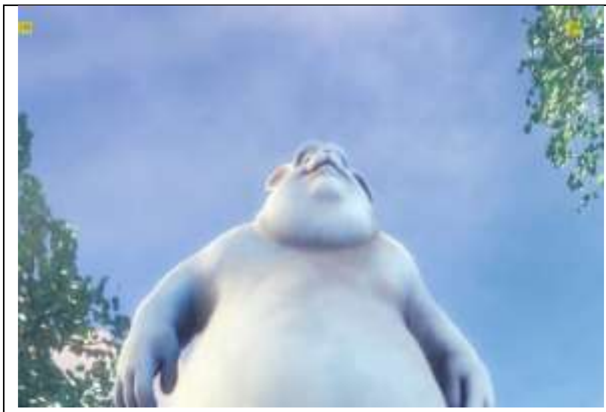


Figure 8.13 Video quality determined by FIS2 (a) full image (b) partitioned image

Both full and partitioned image methods showed high QoE most of the time during video transmission where QoE reached 0.8 (80%) at the beginning and at the end of the transmission. The QoE obtained by FIS2 was consistent when PSNR, SSIM and ID were used and then compared with FIS2 use PSNR, SSIM and ED.

In order to illustrate how QoS and QoE measures related to the individual images with varying levels of distortion, a number of images and their measurement values are shown in Figure 8.14. The values are provided for whole image processing and partitioned approach. QoS is between 0 to maximum 1 and QoE is from 0 to maximum 1. All images were extracted and studied in chapter 7. The received images in the institutional network were less distorted as compared to same images in chapter 7.



QoS=75.50, delay=44.51, jitter=0.31, %PLR=0

Image partitioning approach:

- **Full image:** QoE =0.68, PSNR=48.13, SSIM=0.999, ID =0.11.
- **Partitoned image:** QoE =0.69, PSNR=36.09, SSIM=0.999, ID = 0.13.

(a)

QoS=83.16, delay=42.9, jitter=0.007, %PLR=0.

Image partitioning approach:

- **Full image:** QoE=0.70, PSNR=34.15, SSIM=0.999, ID =0.06.
- **Partitioned image:** QoE=0.55, PSNR=25.20, SSIM= 0.995, ID = 0.09.

(b)

QoS=83.1, delay=42.5, jitter=0.36, %PLR=0.

Image partitioning approach:

- **Full image:** QoE=0.73, PSNR=32.56, SSIM=0.999, ID =0.05.
- **Partitioned image:** QoE=0.72, PSNR=32.56, SSIM= 0.998, ID = 0.08.

(c)

QoS=83.2, delay=40.12, jitter=0.044, %PLR=0.

Image partitioning approach:

- **Full image:** QoE=0.70, PSNR=48.13, SSIM=0.999, ID =0.13.
- **Partitioned image:** QoE=0.80, PSNR=42.11, SSIM= 0.999, ID =0.12.

(d)

Figure 8.14 Sample of images illustrating the values for QoS, QoE and the effect of image partitioning of determine QoE (a) time 5 sec (b) time 43 sec (c) time 65 sec (d) 90 sec (PSNR in (db), delay and jitter in (msec). %PLR (is %ratio)

1.1.1.5 Integrated QoS/QoE FIS3

Figure 8.15 provides a plot for the overall quality metric generated by FIS3. The quality of transmitted video was at its maximum throughout for the first 5 seconds and decreased to its minimum during the end of transmission. This trend correlated with QoS, QoE and their related measurement parameters, thus demonstrating the proposed approach has accurately determined the video quality.

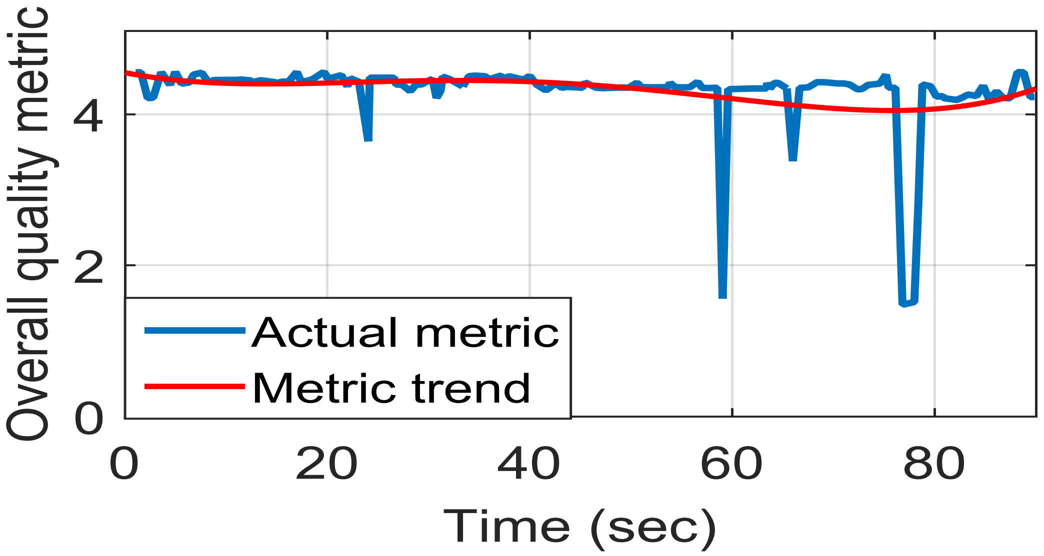
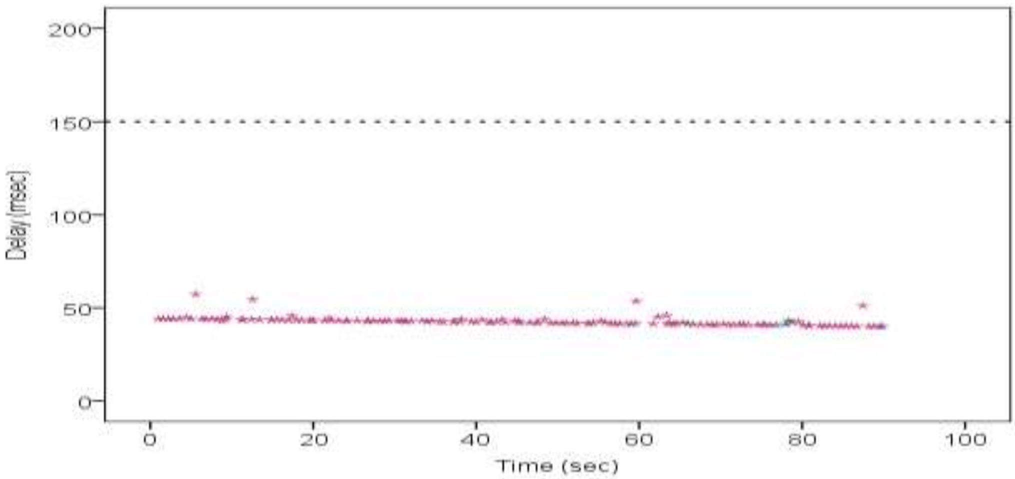


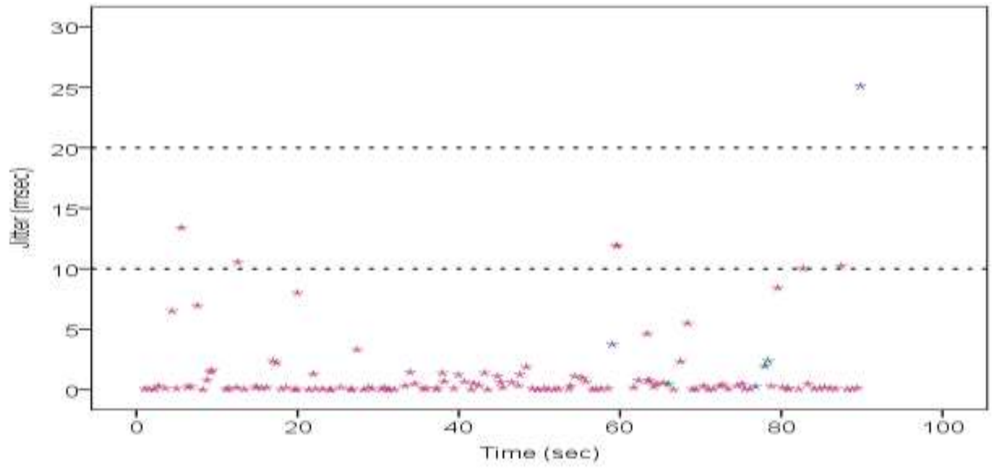
Figure 8.15 Evaluation of video quality transmission by FIS3

1.1.1.6 Interpretation of results

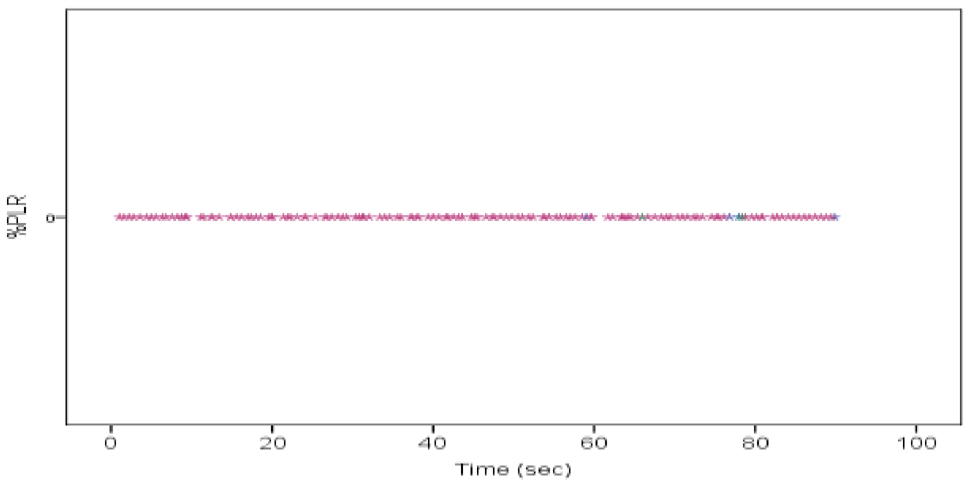
Figures 8.16 (a) - (c) provides an interpretation of the classifications, the explanations for packets being categorised as high quality (values between 4-5), medium (values 2-4) or low (values between 1-2) by the FIS3 according to delay, jitter and %PLR parameter values. Blue, green and red colours in the Figures indicate low, medium and high overall quality. It can be seen from Figure 8.16 that overall video quality was high all the time because delay, jitter and %PLR were within the recommended values.



(a)



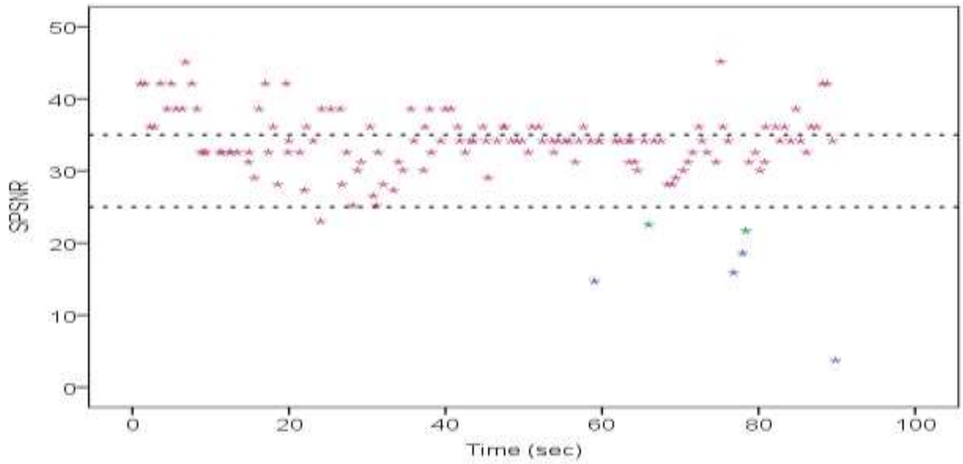
(b)



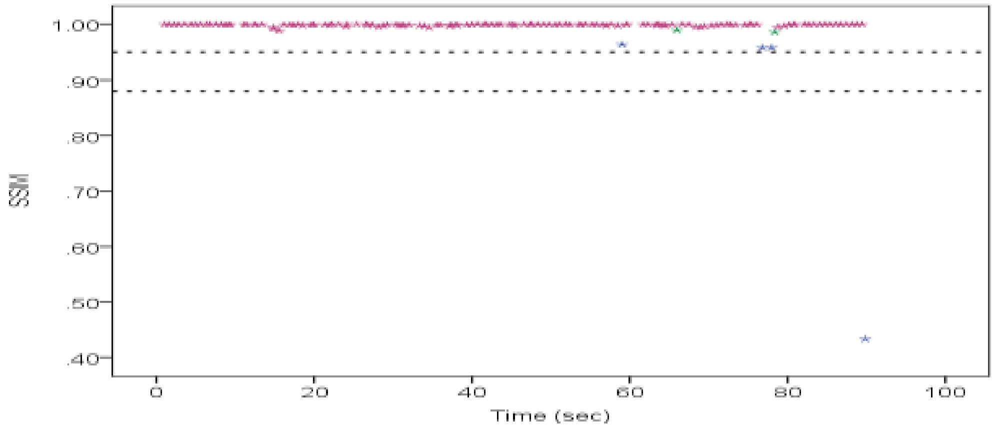
(c)

Figure 0.16 (a-c) Deliver detailed analysis of the classifications, the reasons for packets being classified as high, medium or low overall quality by FIS3 according to delay, jitter and %PLR values. Blue, Green and Red colours in the figures indicates low, medium and high QoS

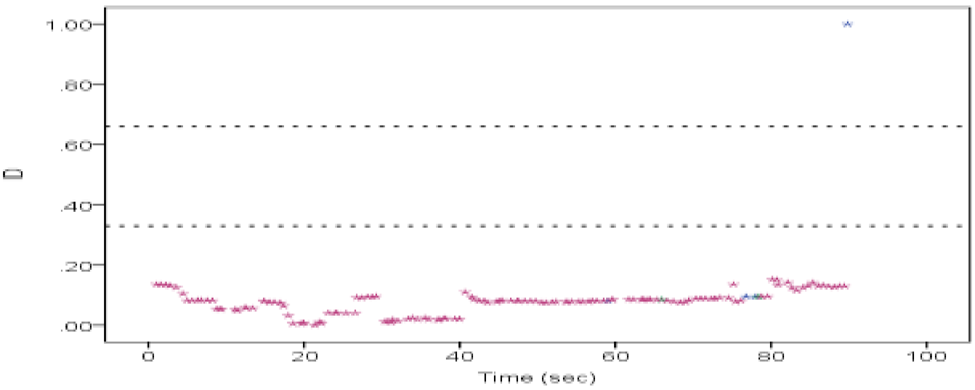
Figures 8.17 (a) - (c) show an overview analysis of the classifications, the explanations for packets being categorised as high, medium or low quality by the FIS3 according to PSNR, SSIM and ID. Blue, green and red colours in the Figures indicate low medium and high quality.



(a)



(b)



(c)

Figure 0.17 (a) - (c) Deliver detailed analysis of the classifications, the reasons for packets being classified as high, medium or low overall quality by FIS3 according to PSNR, SSIM and ID values. Blue, Green and Red colours in the figures indicates low, medium and high QoS

8.4 Summary

This study focused in devising and evaluating techniques to assess multimedia transmission in real network over large instituitional network. Two tests were carried out to transmit VoIP and video between two buildings in different campuses. The developed methods successfully sampled network traffic, classified QoS and QoE for the VoIP and video.

In the VoIP part, an adaptive sampling model to modify the sampling-interval of the traffic was used to sample VoIP traffic according to traffic variations over time. Sampled packets were used to evaluate the VoIP traffic QoS. Bayesian and PNN approaches analysed and classified the QoS for VoIP traffic sent over the network. Both approaches successfully classified the packets to their corresponding high, medium, and low QoS.

In the video part, an integrated modular approach to objectively assess quality of video transmission over the networks was devised. The approach accommodated traffic parameters (delay, jitter and %PLR) in QoS measure and image distortion parameters (PSNR, SSIM and IS/ or ED) into QoE measure. The overall video transmission was determined by combining QoS and QoE measures. Fuzzy Inference System (FIS) was used to perform the evaluations. Both QoS and QoE measures showed that the institutional network performance was within ITU recommended values for multimedia applications.

Chapter 9 Conclusions and Future Work

9.1 Conclusions

In this thesis, our work was mostly dedicated to analysing QoS and QoE for multimedia applications transmitted over hybrid (combination of wired and wireless structures) computer networks. The study carried out with developed multi-input modular adaptive sampling method technique to reduce the necessity of processing all traffic packets or video frames for network performance estimation. Two novel probabilistic QoS evaluation based methods were developed for multimedia traffic. We also proposed a QoE estimation system based on full image and partitioned image approaches that use fuzzy system to estimate the QoE using three media parameters. After that, intensive subjective tests were performed to validate objective QoE approaches. An integrated QoS/QoE assessments method was proposed for better network performance measurements. The aims and objectives of this study have been achieved.

A multi-input modular adaptive sampling method was developed and tested in order reduce the amount of packets processed and stored when analysing computer network traffic. The method was evaluated in simulated and real testbed networks. Its performance was compared with those of conventional non-adaptive sampling approaches of systematic, random, and stratified. The devised sampling approach adaptively adjusted its sampling-interval according to traffic variations over time thus causing in an increase in the number of packets selected when the traffic variations were higher and vice versa. In addition, multiple comparisons were carried out, data trends (curve fitting), mean, standard deviation, biasness measurements and relative standard error (RSE) were obtained to assess the method. The results indicated that the delay, jitter and %PLR measures of sampled traffic from the devised sampling method represented the actual parameters more precisely (i.e. least difference between the original traffic and sampled traffic). The biasness and RSE measurements of delay, jitter and percentage packet loss ratio (%PLR) showed similar findings. The developed adaptive sampling technique features were low computational load and its ease of implementation and most importantly its ability to sample multiple traffic parameters concurrently.

Simulations to explore network performance have limitations and therefore it is helpful alternatives when determining quality of transmitted applications Network emulation was used in this study as part of dealing with this limitation. The network emulator (NetEm) testbed used in the study has Linux Foundation. It allowed network parameters delay, jitter and %PLR to be altered thus facilitating traffic scenarios for the tests.

Two novel probabilistic QoS evaluation-based methods were proposed for multimedia traffic. The first method used Bayesian approach and analysed and classified the QoS for VoIP traffic transmitted over emulated testbed network, whereas the second used probabilistic neural networks (PNN) to assess the QoS for VoIP and video services. The capability, simplicity and robustness of the developed methods made them effective mechanisms for QoS analysis. Both methods successfully classified the measures of QoS parameters of streamed VoIP to their corresponding high, medium, and low QoS types.

Investigations were carried out into the manner VoIP QoS was affected by the IEEE 802.11ac (80 MHz) and IEEE 802.11n (20 and 40 MHz) wireless protocols. These involved the Bayesian and PNN QoS evaluation methods. IEEE 802.11ac provided a good QoS as traffic was increased from 1 point-to-point (PPP) link to 10 links. For IEEE 802.11n (20 MHz) and IEEE 802.11n (40 MHz) QoS deteriorated once more than 7 links became operational respectively. SPSS© statistical package was used to analyse the traffic parameters and QoS relations which provided valuable information as to the causes of low QoS. The study showed the main traffic parameter affecting IEEE802.11ac QoS for VoIP transmission was jitter while the protocol was less susceptible to delay and %PLR. Both PNN and Bayesian QoS classification approaches showed robust performance and consistency in classification results. The Advantages of proposed probabilistic methods are low computational load and a good accuracy.

QoE was determined by fuzzy logic based on full image and partitioned image approaches. Three video visual parameters were used (PSNR, SSIM and ID/ or ED). A novel image partitioning approach was devised to improve QoE evaluation of images. For the whole image processing, the results for SSIM and PSNR were partially associated to QoS. However, for the partitioned images, SSIM and PSNR values were very similar in behaviour to network QoS. The image difference (ID) measure in both approaches (full and portioned image) was close to network QoS trend. It was demonstrated that image partitioning is valuable in making qualification of image distortion, more precise and thus improved determination of QoE. A modular fuzzy logic-based approach to objectively assess quality of video transmission over hybrid networks was implemented and its performance was evaluated. The approach accommodated traffic parameters in QoS measure and image distortion parameters

(PSNR, SSSIM and ID) to determine the quality of transmitted video transmission. The subjective tests involving 25 adult volunteers evaluating the received video quality indicated consistent results with fuzzy logic-based evaluation of the same video.

The study also included the video and audio quality evaluating techniques on an instituitional network. Two tests were carried out to transmit VoIP and video between two buildings in different campuses. Despite the institutional network's large size, and the tests being performed in peak usage time, the developed methods were successfully applied and the sampled network traffic was correctly classified into appropriate low, medium and high quality.

For most part of this research is multimedia transmission quality service over hybrid networks, end-to-end multimedia quality evaluation and objective and subjective quality measurement. The outcomes of this research can be used as building blocks for future work in this area in emulation testbeds and in practical networks. In addition, the findings out of the experimentation in this research could have valuable commercial advantages equally for the service providers and service consumers to improve customer satisfaction. The developed QoS/QoE approaches can be used in sensitive applications such as the e-healthcare. However, performance need to be further confirmed with physical networks before a realistic implementation can be made. In addition to a use in commercial environment, the developed testbed methods out of this research could be also useful in academic research to study a range of other communication transmission standards and network scenarios.

9.2 Future Work

There are remains a number of further possibilities to continue the study. These include:

- **Adaptive sampling approach:** The adaptive sampling method devised could be evaluated in a number of computer network traffic analysis operation including network security where reducing the number of packets processed can result in a faster response to threats. In this study the devised adaptive sampling method was compared against non-adaptive sampling methods (random, systematic and stratified). However its evaluation against adaptive sampling methods reported in other studies will be valuable.
- **Implementation of the proposed methods in other type of networks:** The validation and execution of the devised methods were carried out on Wi-Fi networks.

The implementations of these approaches in other communication networks such as 3G/4G, MANET and long-term evolution LTE can further demonstrate their effectiveness.

- **Implementation of the proposed approaches in other applications:** The validation techniques were carried out using multimedia (VoIP and video) applications. The implementations of these approaches in other applications such as medical images, video games and IPTV can further determine their effectiveness.
- **Implementation of the proposed approaches in other video formats and codecs:** The validation approaches were carried out using MPEG and G711a. The implementations of these approaches in other video formats like WMV WEBM, FLV and AVI can be useful. In addition, other codec can further determine their effectiveness.
- **Incorporating QoS into QoE relations:** The interrelationships between QoS and QoE could be explored further. In this study, delay, jitter and %PLR were used to determine QoS and SSIM, PSNR and ID were used to determine QoE. Other measures could be explored in determining QoS and QoE.
- **Implementation of adaptive sampling approach into Hardware:** Examining how the adaptive sampling could be employed into hardware as a System-on-Chip (SoC) is additional area of more improvement. The proposed sampling could be used for multipurpose network service such as monitoring, traffic engineering or security. Hardware implementation can make it easier to be integrated into network devices.
- **Implementation of QoS/QoE approach into hardware:** Investigating how the QoS/QoE methods devised in this study could be implemented in hardware will be valuable as this case ease their incorporation into network devices.

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