University of Southern Queensland
Faculty of Health, Engineering and Sciences

CROSS-LAYER OPTIMISATION OF QUALITY OF EXPERIENCE FOR VIDEO TRAFFIC

A thesis submitted by

Qahhar Muhammad Qadir

B.Sc. (Eng.) & M.Sc. (Eng.)

in fulfilment of the requirements for the degree of

Doctor of Philosophy

2016

Abstract

Realtime video traffic is currently the dominant network traffic and is set to increase in volume for the foreseeable future. As this traffic is bursty, providing perceptually good video quality is a challenging task. Bursty traffic refers to inconsistency of the video traffic level. It is at high level sometimes while is at low level at some other times. Many video traffic measurement algorithms have been proposed for measurement-based admission control. Despite all of this effort, there is no entirely satisfactory admission algorithm for variable rate flows. Furthermore, video frames are subjected to loss and delay which cause quality degradation when sent without reacting to network congestion. The perceived Quality of Experience (QoE)-*number of sessions* trade-off can be optimised by exploiting the bursty nature of video traffic.

This study introduces a cross-layer QoE-aware optimisation architecture for video traffic. QoE is a measure of the user's perception of the quality of a network service. The architecture addresses the problem of QoE degradation in a bottleneck network. It proposes that video sources at the application layer adapt their rate to the network environment by dynamically controlling their transmitted bit rate. Whereas the edge of the network protects the quality of active video sessions by controlling the acceptance of new sessions through a QoE-aware admission control. In particular, it seeks the most efficient way of accepting new video sessions and adapts sending rates to free up resources for more sessions whilst maintaining the QoE of the current sessions.

As a pathway to the objective, the performance of the video flows that react to the network load by adapting the sending rate was investigated. Although dynamic

rate adaptation enhances the video quality, accepting more sessions than a link can accommodate will degrade the QoE.

The video's instantaneous aggregate rate was compared to the average aggregate rate which is a calculated rate over a measurement time window. It was found that there is no substantial difference between the two rates except for a small number of video flows, long measurement window, or fast moving contents (such as sport), in which the average is smaller than the instantaneous rate. These scenarios do not always represent the reality.

The finding discussed above was the main motivation for proposing a novel video traffic measurement algorithm that is QoE-aware. The algorithm finds the upper limit of the video total rate that can exceed a specific link capacity without the QoE degradation of ongoing video sessions. When implemented in a QoE-aware admission control, the algorithm managed to maintain the QoE for a higher number of video session compared to the calculated rate-based admission controls such as the Internet Engineering Task Force (IETF) standard Pre-Congestion Notification (PCN)-based admission control. Subjective tests were conducted to involve human subjects in rating of the quality of videos delivered with the proposed measurement algorithm.

Mechanisms proposed for optimising the QoE of video traffic were surveyed in detail in this dissertation and the challenges of achieving this objective were discussed. Finally, the current rate adaptation capability of video applications was combined with the proposed QoE-aware admission control in a QoE-aware cross-layer architecture. The performance of the proposed architecture was evaluated against the architecture in which video applications perform rate adaptation without being managed by the admission control component. The results showed that our architecture optimises the mean Mean Opinion Score (MOS) and number of successful decoded video sessions without compromising the delay.

The algorithms proposed in this study were implemented and evaluated using Network Simulator-version 2 (NS-2), MATLAB, Evalvid and Evalvid-RA. These software tools were selected based on their use in similar studies and availability

at the university. Data obtained from the simulations was analysed with analysis of variance (ANOVA) and the Cumulative Distribution Functions (CDF) for the performance metrics were calculated.

The proposed architecture will contribute to the preparation for the massive growth of video traffic. The mathematical models of the proposed algorithms contribute to the research community.

This dissertation is dedicated to

my lovely mother,

my deceased father, who had wished to see this work,

my beloved wife and my children,

my siblings.

Certification of Dissertation

I certify that the ideas, designs and experimental work, results, analyses and conclusions set out in this dissertation are entirely my own effort, except where otherwise indicated and acknowledged.
I further certify that the work is original and has not been previously submitted for assessment in any other course or institution, except where specifically stated.

Qahhar Muhammad Qadir
0061022180

_____ ____ /____ /2016

Signature of Candidate Date

ENDORSEMENT

_____ ____ /____ /2016

Dr. Alexander A. Kist, Principal supervisor Date

_____ ____ /____ /2016

Dr Zhongwei Zhang, Associate supervisor Date

Acknowledgments

First and foremost, I praise almighty Allah for granting me the blessing, health, patience, and knowledge to accomplish this work. My special thanks to my principal supervisor Associate Professor Alexander A. Kist who has been my mentor and support throughout the period of my candidature. His constructive and critical comments made a real difference. I would also like to express my appreciation to my associate supervisor Dr. Zhongwei Zhang for his comments and suggestions. Without Alex and Zhongwei supervision and constant support, this dissertation would have not been possible.

A special thank-you to my family for their prayers and cheerfulness at all the times. They provided me with the hassle free environment necessary for the achievement of my goal. Words cannot express how grateful I am to each of you, I owe you all.

I should have not forget volunteers who participated in the subject tests and spent hours in front of the computer screen. Last but not least, thanks to Prof. Yury Stepanyants, Dr. Saddam Al-Lwayzy, Dr. Iain Brookshaw, Prof. Shahjahan Khan and Ms. Sandra Cochrane who assisted me in one way or another throughout this work.

Qahhar Muhammad Qadir

University of Southern Queensland

December 2016

Publications

The research that is reported in this thesis has led to the following publications:

Peer reviewed journal publications

Qadir M., Q., Kist, A. A. and Zhang Z., "A QoE-Aware Cross-Layer Architecture for Video Streaming Services", under revision.

Qadir M., Q., Kist, A. A. and Zhang Z., "A Novel Traffic Rate Measurement Algorithm for QoE-Aware Video Admission Control", *IEEE Transaction on Multimedia*, Vol. 17, No. 5, pp. 711-722, May 2015.

Qadir M., Q., Kist, A. A. and Zhang Z., "The probability relationship between videos instantaneous and average aggregate rates", *Multimedia Tools and Applications*, Vol. 74, No. 9, pp 1-16, May 2015.

Qadir M., Q., Kist, A. A. and Zhang Z., "Mechanisms for QoE optimisation of Video Traffic: A review paper", *International Journal of Information, Communication Technology and Applications*, Vol. 1, No. 1, pp. 1-18, March 2015.

Peer reviewed conference publications

Qadir M., Q., Kist, A. A. and Zhang Z., "Optimization of Quality of Experience for Video Traffic", *22nd International Conference on Telecommunications*, Sydney, Australia, April 2015

Qadir, S.[1], Kist, A. A. and Zhang Z., "QoE-Aware Cross-Layer Architecture for Video Traffic over Internet", *IEEE TENSYMP*, Kuala Lumpur, Malaysia, April 2014.

Qadir, S.[1] and Kist, A. A., "Video-Aware Measurement-Based Admission control", *IEEE ATNAC Conference*, Christchurch, New Zealand, November 2013.

Qadir, S. [1] and Kist, A. A., "Quality of Experience Enhancement Through Adapting Sender Bit rate", *IEEE TENCON Spring Conference*, Sydney, Australia, April 2013.

[1]The author has changed his name from "Safeen Qadir" to "Qahhar Muhammad Qadir".This and earlier papers were published under his previous name.

Contents

List of Figures

List of Tables

Definitions

adaptive architecture	A network architecture in which video sources implement rate adaptation only
$CalR(k)$	Calculated Rate over k slots
CBAC	*CalR*-Based Admission Control
cross-layer architecture	A network architecture in which video sources implement rate adaptation and the gateway implements the QoE-aware admission control
$IAAR(t)$	Instantaneous Aggregate Arrival Rate of F at t
ISP access links	ISP links which are directly connected to and controlled by the gateway in Figure 1.2
mean MOS	The average of the MOS of admitted video sessions over 30 simulation runs
mean *number of sessions*	The average of the number of admitted video sessions over 30 simulation runs
non-adaptive architecture	A network architecture in which video sources do not implement rate adaptation and the gateway does not control video sessions
number of flows	The number of video flows
number of sessions	The number of successfully admitted video sessions for a specific simulation run
Pro-IAAR(t)	Proposed *IAAR* at t
Pro-IBMAC	Proposed *Pro-IAAR*-Based Measurement Admission Control

Notations

$AR(l)$	PCN admissible rate on link l
c	A counter
C_l	Link capacity
d	Destination image
$\mathrm{E}\langle IAAR(t)\rangle$	Expectation value of $IAAR$ at t
$\mathrm{E}\langle X_{inst}(t)\rangle$	Expectation value of X_{inst} at t
f	A video flow
F	A set of video flows
F-statistics	F values of ANOVA
h	A variable
j	j^{th} time slot
k	Total number of time slots
$k\tau$	Measurement time window
l	A network link
M	A set of network links
n	Number of video sessions
N	A set of network nodes
p/p-value	p value of ANOVA
$p_i(t)$	Probability the session i is active/inactive at t
Pr	Probability
$r(l)$	PCN traffic rate on link l
R_k	Peak rate of a video session over k slots
s	Source image

$SR(l)$	PCN supportable rate on link l
t	Time
$x_i(t)$	Instantaneous arrival rate (throughput) of video session i at t
$x_i^{\min}(t)$	Minimum rate of $x_i(t)$
$x_i^{\max}(t)$	Peak rate of $x_i(t)$
$X_{inst}(t)$	Instantaneous aggregate arrival rate of F at t
x_{new}	Rate of requested video session
$Y(k)$	Sum of $X_{inst}(t)$ over k slots
α	A coefficient of β prediction model
β	Total bitrate of enrolled video traffic that exceed C_l without degradation to QoE
δ	Upper bound of the probability that $\mu_r(t)$ is smaller than $X_{inst}(t)$ by $n\epsilon$ or more
ϵ	A positive number
$\mu_r(t)$	Average aggregate arrival rate of F at t
σ	A coefficient of β prediction model
τ	Width of a time slot

Acronyms

2G	Second Generation
3D	Three Dimensional
3G	Third Generation
3GPP	3rd Generation Partnership Project
4G	Fourth Generation

A

ABR	Adaptive Bit Rate
ACR	Absolute Category Rating
AIHD	Additive-Increase Heuristic-Decrease
ANOVA	Analysis of Variance
ARPANET	Advanced Research Projects Agency Network
AS	Autonomous System
AVC	Advanced Video Coding

B

BPSK	Binary Phase Shift Keying

C

CBR	Constant Bit Rate
CDF	Cumulative Distribution Function
CDN	Content Delivery Networks
CIF	Common Intermediate Format
CINA	Collaboration Interface between Network and Applications

D

DASH	Dynamic Adaptive Streaming over HTTP
DIV	Distortion In Interval
DSCQS	Double-Stimulus Continuous Quality-Scale
DSIS	Double-Stimulus Impairment Scale
DVB-H	Digital Video Broadcast-Handheld
DVQ	Digital Video Quality

E

ECN	Explicit Congestion Notification

F

FEC	Forward Error Correction
FIFO	First In First Out
FR	Full-Reference
FT	Flow Termination
FTP	Tile Transfer Protocol

G

GoP	Group of Picture

H

HAS	HTTP Adaptive Streaming
HSDPA	High Speed Downlink Packet Access
HTTP	Hypertext Transfer Protocol
HVS	Human Visual System
HWN	Heterogeneous Wireless Networks

I

IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IETF	Internet Engineering Task Force

IP	Internet Protocol
IPTV	IP Television
ISO/IEC	International Organization for Standardization/IEC
ISP	Internet Service Provider
ITU-T	International Telecommunication Union-Telecommunication

L

LAN	Local Area Network
LCD	Liquid Crystal Display
LTE	Long Term Evolution

M

MAC	Media Access Control
MAD	Mother And Daughter
MARC	Mobile-Aware Adaptive Rate Control
MBAC	Measurement-Based Admission Control
MCS	Modulation and Coding Scheme
MDP	Media Degradation Path
MIH	Media Independent Handover
MIMO	Multi-Input Multi-Output
MOS	Mean Opinion Score
MPCN	Mobile Packet Core Network
MPD	Media Presentation Description
MPEG	Moving Picture Experts Group
MPQM	Moving Pictures Quality Metric
MS-SSIM	MultiScale Structural Similarity
MSE	Mean Squared Error

N

NBN	National Broadband Network
NGN	Next Generation Network
NR	No-Reference

NS-2	Network Simulator-version 2

O

OFDMA	Orthogonal Frequency Division Multiple Access
OSI	Open Systems Interconnection

P

P2P	Peer-to-Peer
PCN	Pre-Congestion Notification
PQSM	Perceptual Quality Significance Map
PSNR	Peak-Signal-to-Noise Ratio
PSQA	Pseudo Subjective Quality Assessment
PSTN	Public Switched Telephone Network

Q

QCIF	Quarter Common Intermediate Format
QoE	Quality of Experience
QoS	Quality of Service
QP	Quantisation Parameter
QPSK	Quaternary Phase Shift Keying

R

RAN	Radio Access Network
RMSE	Root Mean Squared Error
RNN	Random Neural Network
ROI	Region Of Interest
RR	Reduced-Reference
RS	Reed-Solomon
RTP	Real-time Transport Protocol

S

SBR	Sender Bit Rate

SDSCE	Simultaneous Double Stimulus for Continuous Evaluation
SLA	Service Level Agreement
SNR	Signal-to-Noise Ratio
SS	Single Stimulus
SSCQE	Single Stimulus Continuous Quality Evaluation
SSIM	Structural Similarity
SVBR	Shaped-Variable Bit Rate
SVC	Scalable Video Coding

T

TCP	Transport Control Protocol
TCP/IP	Transport Control Protocol/Internet Protocol
TFRC	TCP Friendly Rate Control

U

UDP	User Datagram Protocol
UMTS	Universal Mobile Telecommunication Systems

V

VBR	Variable Bit Rate
VCEG	Video Coding Experts Group
VoD	Video on Demand
VoIP	Voice over IP
VQM	Video Quality Metric
VSSIM	Video Structural Similarity

W

WF	Water-Filling
WiFi	Wireless Fidelity
WLAN	Wireless Local Area Network

Chapter 1

Introduction

The transmission of video traffic over the Internet has grown exponentially in the past few years and it shows no sign of waning. The majority of the Internet traffic currently is video and this trend is expected to continue for the foreseeable future. The emergence of video based applications such as video calls, sports broadcasts and telemedicine have continually increased the amount of video traffic over the Internet. Cisco predicts that, "the sum of all forms of video (TV, Video on Demand [VoD], Internet, and Peer-to-Peer [P2P]) will be in the range of 80 to 90 percent of global consumer traffic by 2018" and that, "it would take an individual over 5 million years to watch the amount of video that will cross global IP networks each month in 2018. Every second, nearly a million minutes of video content will cross the network by 2018" (Cisco documentation 2014*a*). In 2011, 58.6% of the total Internet traffic in North America was caused by real-time entertainment services such as Hulu and Netlix (Weller & Woodcock 2013). Figure 1.1 shows that video will remain the dominant data for mobile devices as well. These Cisco figures are based on a combination of analysts' projections, in-house estimates and forecasts, and direct data collection.

With the inevitable dominance of video traffic on the Internet and constant increasing of user expectation for higher quality, it is becoming a challenging task to provide perceptually good video quality. This is partly due to the bursty nature of video traffic, changing network conditions and the behaviour of network

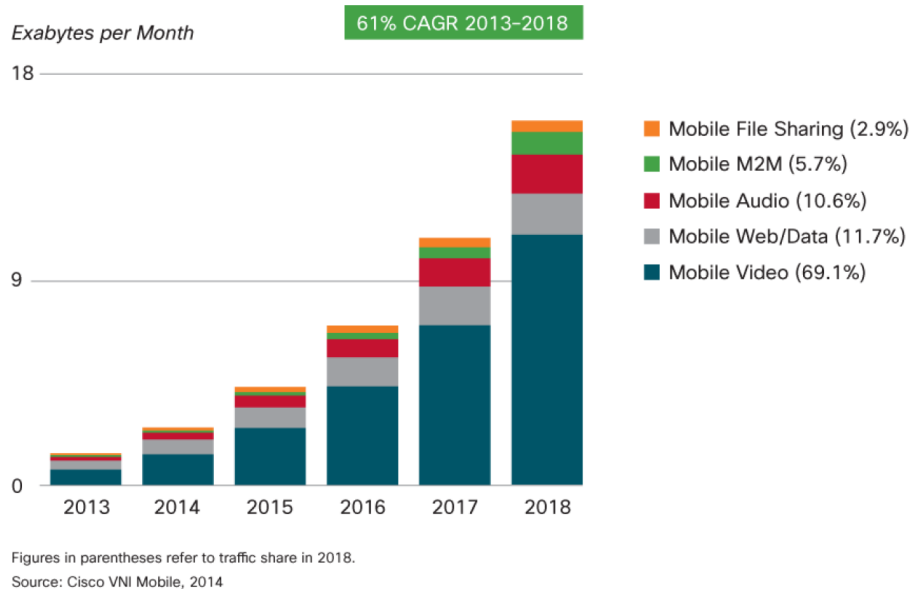


Figure 1.1: Mobile video Multiplies other traffic. Adopted from (Cisco documentation 2014*b*)

transport protocols. Bursty traffic refers to inconsistency of the video traffic level. It is at high level sometimes while is at low level at some other times.

Cisco forecasts that, "the number of devices connected to IP networks will be nearly twice as high as the global population in 2018" (Cisco documentation 2014*a*). Non-PC devices generate the majority of IP traffic (Cisco documentation 2014*b*), and most of these devices have high quality video playback capabilities. This feature is a key driver of the evolution of new mechanisms recommending video rate adaptation towards delivering enhanced Quality of Experience (QoE) for a higher number of accommodated sessions. One approach to maintain good QoE is done through transport protocols such as the Transport Control Protocol (TCP). Rate adaptation may also be implemented by the sender, receiver, or both. The sender can encode the video content at different bit rates and switch these bit rates dynamically. Different techniques such as receiver-driven layered multicast and buffer requirements are used at the receiver (Liu et al. 2011). In this study, the sender style rate adaptation is performed by the video sources.

This massive demand for video anytime and anywhere has led to the development of adaptive streaming solutions that are able to deliver video with predictable QoE. One of these mechanisms which delivers video over the Internet through web

browsers is HTTP Adaptive Streaming (HAS) (Oyman & Singh 2012). A client and the web/media server decide the rate at which they communicate. Many companies have introduced HAS solutions such as Microsoft Smooth Streaming, Apple HTTP Live Streaming and Adobe HTTP Dynamic Streaming. Other solutions have also been proposed to tackle the challenge of video traffic growth such as WiFi offloading (Maallawi et al. 2014).

Since video traffic is very bursty, it is hard to estimate traffic parameters. This is one of the weaknesses of the Measurement-Based Admission Control (MBAC) solutions which rely on more predictable traffic rates. The challenge in delivering video services therefore, is more rigorous when it is associated with the QoE of video sessions.

1.1 Problem Statement

"So is the Internet really broken? Okay, maybe that was an exaggeration. But the 40-year-old router sure needs an overhaul. I should know"
Lawrence Roberts, one of the founders of the Internet, 2009 (Roberts 2009)

Forty-eight years ago, the ancestor of today's Internet, the Advanced Research Projects Agency Network (ARPANET) was built to send data as small independent packets with no attention to their arrival time or order (Roberts 2009). Since then, enhancements have been added to the initial infrastructure of ARPANET to do more than what was originally designed for, through the addition of intelligence to the network hosts and routers. This is due to the critical feature of self-controlling behaviour of the TCP which kept the Internet stable for decades.

Packet management techniques such as redundancy bits, flow control and admission control provided some sort of reliability of packet delivery. Furthermore, techniques have been added to handle critical and time sensitive traffic such as voice. For instance, the differentiation of services can provide priority to these services. Furthermore, Internet Service Providers (ISP) have deployed massive

over-dimensioned optical backbone networks to accommodate the growth in realtime traffic; often running well below the full link capacity.

Although these techniques have enabled the Internet to provide some level of guaranteed Quality of Service (QoS) for realtime traffic, some consider the Internet is broken when facing the challenges of modern Internet traffic (Roberts 2009). Evolution and popularity of video application such as videoconferencing and video streaming services, as well as video devices, have contributed to the explosive growth of the video traffic on the Internet. QoE extends the scope of expectation beyond the network layer to include higher layers. To protect the quality of video, both an admission control at the edge of network and rate adaptation at source of the flows are required. Admission control algorithm however, must not rely on the worst-case bounds or instantaneous video arrival rate as they do not reflect the bursty nature of video traffic. This is due to the fact that the burstiness of video flows can be compensated by the silence of other flows. The perceived *QoE-Session* relationship can be greatly optimised by exploiting the bursty nature of video traffic.

Taking these into accounts, we propose the following hypothesis: *"QoE can be optimised by combining techniques from application and network layers. In addition to implementing rate adaptation by the video applications, a QoE-aware admission control can balance the QoE and number of sessions relationships"*. This dissertation attempts to validate this hypothesis.

The hypothesis is based on the following facts:

- The Internet has been over-provisioned in the way that huge bandwidth is offered to handle multimedia traffic spikes. However, on average it is running below its full capacity (Roberts 2009)
- Although, rate adaptation ameliorates the QoE perceived by end users due to the self-controlling behaviour of TCP, it can not alone provide an acceptable QoE (Chen et al. 2015, Latré & De Turck 2013).

- Video streams share limited bandwidth and compete on access to the network. This causes packet loss and delay which leads to QoE degradation. Admission procedures are necessary to maintain the QoE of active video sessions; however they are not required to be static, they can be problematic. Admitted sessions and QoE became a direct trade-off

- Currently, there is no entirely satisfactory admission algorithm for variable rate flows (Auge et al. 2011).

1.2 Scope of the Thesis

This work assumes a simplified network diagram as shown in Figure 1.2. It shows a typical scenario where video sources are depicted on the left hand side. They share the bandwidth of the *ISP access links* (ISP links which are directly connected to and controlled by the gateway in Figure 1.2), the focus of this thesis. As routing and load balancing are beyond the scope of this study, a single *ISP access link* is considered for structuring and evaluating the mathematical foundations. It is also assumed that there is sufficient bandwidth available in the backbone, i.e. the Internet. The proposed QoE-aware admission control is implemented at the ISP gateway while the sources perform rate adaptation based on the available bandwidth of the *ISP access links*.

Bottlenecks may exist in any network in Figure 1.2 such as the access network (connecting end users to their ISP), ISP network, Internet, or destination network (Chen et al. 2013). The thesis focuses on the optimisation of QoE in relation to the *number of sessions* on the *ISP access links*. The motivation for this is that new access technologies such as Fiber To The Home eliminate the bottlenecks in the access links. Fast bitrate technologies are deployed in the infrastructure of the Internet in addition to high performance devices such as fast forwarding switches/routers and servers. Furthermore, the massive increasing demand for video by video sources challenges the ISP network where the traffic is aggregated to provide acceptable QoE for each video session.

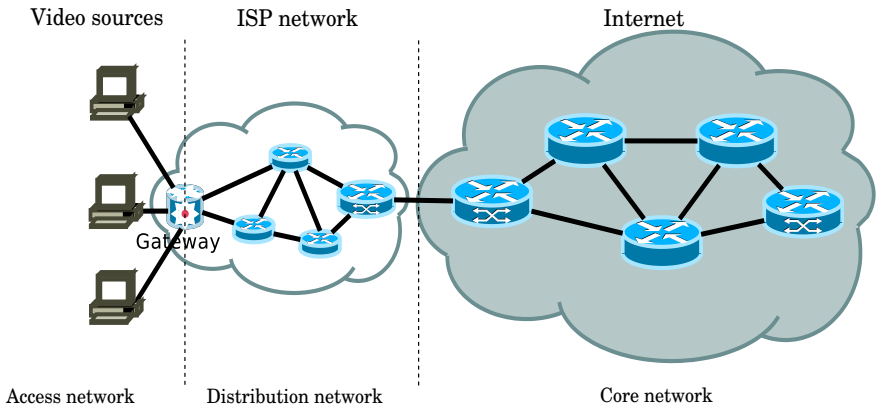


Figure 1.2: Topology scenario considered in the thesis

This study does not consider the bottlenecks caused by a Wireless Local Area Network (WLAN) connecting end users to the wired network. Since, quality degradation is typically noticed most in video streaming service, this work focuses on this type of video services. This is not a principal limitation of the models that have been developed as part of this thesis. They can be adapted to other bottleneck situations easily.

1.3 Research Objectives

The main aim of this thesis is to improve the QoE of video traffic by implementing the adaptability of video streams to share a bottleneck bandwidth. It considers optimisation techniques across different layers and network equipment. The following objectives are addressed:

Objective One

To analyse the impact of Sender Bit Rate (SBR) on the perceived video quality and evaluate the performance of video flows in the *adaptive architecture* and *non-adaptive architecture*. In the *non-adaptive architecture* video sources do not implement rate adaptation. Whereas, video flows in the *adaptive architecture* are generated by sources that have the ability to change the sending rate according to available resources such as bandwidth and buffers. This is done at the application layer in contrast to TCP where rate adaptation is done at the

transport layer. Applications that have the capability to adapt their rate need to be more aware of what is occurring in the network. Variations in the sender rate indicate the level of the quality delivered to end users.

Objective Two

To model and evaluate a suitable rate to be used by admission procedures for video traffic. *Calculated Rate* (*CalR*) over time windows has been proposed to better suit variable rates. This rate will be compared to the instantaneous rate in the context of bursty video traffic.

Objective Three

To determine the number of video sessions that can share the bandwidth of a network link without affecting the QoE of active sessions. Links cause most network bottlenecks (Chen et al. 2013, Camara et al. 2010). The traditional way to handle this and maintain the quality of on-going traffic, is to have some sort of service management techniques such as flow and admission controls. Current amounts of video traffic on the Internet require a less restrictive technique in order to serve maximum number of users with acceptable quality. This is possible because video traffic is bursty in nature and error correction at the decoder level can tolerate some packet loss.

Objective Four

To optimise QoE while utilising link capacity more efficiently through techniques across the Transport Control Protocol/Internet Protocol (TCP/IP) layers. The challenge of the Internet's transport protocols is to maximise the network utilisation in terms of the number of accommodated video sessions while keeping QoE acceptable. This is in addition to scaling down the video quality due to the encoding level of adaptive traffic. These two performance metrics are in a trade-off relationship. It is in both the user's and Internet provider's interests to optimise the QoE-*number of sessions* trade-off.

1.4 Main Contributions

This dissertation provides a cross-layer and cross-device QoE optimisation for video streaming services. It addresses the problem of QoE degradation in a bottleneck network. In particular, it allows video sources at the application layer to adapt to the network environment by controlling the transmitted bit rate dynamically. While, the edge of the network protects the quality of active video sessions by controlling the acceptance of new session through a proposed QoE-aware admission control. The application layer contributes to the optimisation process by dynamically adapting source bit rate based on the conditions of the network and the network layer controls admission of new video sessions based on the rate follows the novel mechanism introduce here. The thesis contributes to the research field of QoE optimisation of video traffic. The main contributions are summarised in the following points:

Contribution One

A comprehensive survey of mechanisms proposed for optimising QoE of video traffic has been undertaken. The focus was the work that had been published in the last 10 years. The mechanisms have been categorised according to their functions and compared in each category. The survey was published in (Qadir et al. 2015*a*).

Contribution Two

A novel model is proposed to quantify the probability relationship between the instantaneous and average aggregate rates. The proposed model has been validated through extensive simulations. The estimated quantified probability has been investigated using different video contents (slow moving content such as news and fast moving content such as sports) and measurement windows. The model was published in (Qadir et al. 2015*c*, Qadir & Kist 2013*b*).

Contribution Three

A novel algorithm for traffic measurement supported by the mathematical model has been proposed. The proposed algorithm measures the *exceedable video aggregate rate* that is able to keep the video quality unimpaired. Statistical analysis

has been used to validate the parameters of the proposed model. The algorithm was published in (Qadir et al. 2015*b*).

Contribution Four

The measurement algorithm proposed in the previous point has been implemented, in a QoE-aware admission control procedure for video admission. Extensive simulations, subjective tests and statistical analysis were performed to confirm the suitability of the proposed algorithm for video streaming services. The QoE-aware admission control was published in (Qadir et al. 2015*b*).

Contribution Five

A cross-layer architecture has been proposed to optimise the QoE of video traffic. The combination of rate adaptation at the application layer and the proposed QoE-aware admission control at the network layer was presented. The proposed architecture through extensive simulations and statistical indices, has shown a considerable improvement of the QoE-*number of sessions* trade-off when compared to an architecture without the proposed QoE-aware admission control algorithm. The performance of the architecture was evaluated and published in (Qadir et al. 2015*d*, Qadir et al. 2014).

1.5 Dissertation Outline

This dissertation is divided into seven chapters. Relevant literature is discussed in the individual chapters. A schematic diagram of the remaining chapters is shown in Figure 1.3. The following points summarise the organisation of the thesis.

Chapter Two explains QoE for video streaming services. A background overview of QoE is provided. The reason behind the transition from QoS to QoE is explained. The trend towards QoE-driven management of the Internet is discussed. QoE models and metrics as well as methods of subjective tests are surveyed.

Chapter Three investigates QoE improvement through adapting SBR. Related studies are reviewed and the foundation for modelling video traffic is established.

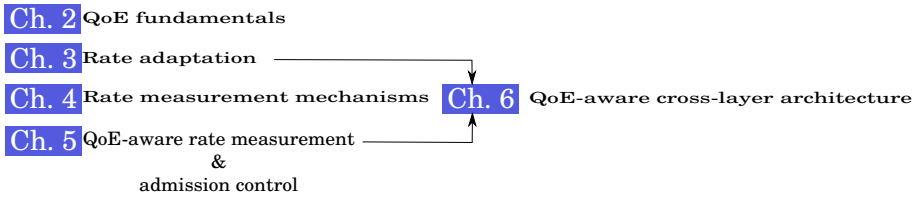


Figure 1.3: Schematic diagram of the chapters of dissertation

The performance of the video flows in the *adaptive architecture* and *non-adaptive architecture* are studied. The investigation was published in (Qadir & Kist 2013*a*).

Chapter Four investigates the suitability of the instantaneous and average aggregate traffic rates for video traffic. An algorithm for quantifying the probability relationship between both rates is modelled. The impact of the number of video flows, video content and measurement window on this probability are investigated.

Chapter Five proposes and models a QoE-aware traffic measurement algorithm for video traffic. A parameter that defines the limit of the exceedable traffic is modelled and the model parameters are found using analysis of variance (ANOVA). The performance of the proposed algorithm is studied and simulation results are compared to the subjective and predicted results from the proposed model.

Chapter Six presents the design of a cross-layer architecture for optimising QoE of video traffic based on the models proposed in Chapters 3, 4 and 5. An overview research conducted in the area of QoE optimisation through different techniques and across layers is provided. The performance of the proposed architecture are compared to other architectures.

Chapter Seven concludes the dissertation with open issues in the area of QoE in the context of video streaming service.

Chapter 2

QoE of Video Streaming Services

Over the last decade, efforts have been made to provide QoS within the core network by considering technical performance parameters at the network layer such as bandwidth, delay, and jitter (variation in delay). *Differentiated Services* (Blake et al. 1998) is an example of these paradigms that can ensure QoS. However, quality from the end user perspective, does not equate to QoS on the network layer. The research community and ISPs have made subjective quality as perceived by the end users known as QoE, a main research target. The International Telecommunication Union-Telecommunication (ITU-T) defines QoE as "The overall acceptability of an application or service, as perceived subjectively by the end-user" (ITU-T Document FG IPTV-IL-0050 2007). The design of the Internet has to consider extending the scope of QoS to consider end-to-end quality, be content-aware and user centric. The European network of excellence (Qualinet) aims at extending the network-centric QoS by introducing the concept of QoE (Qualinet 2013).

QoE is the quality as experienced by end users. The purpose of introducing QoE is to include all aspects of multimedia systems that are related to media quality. Approaching quality from an end user experience or perceived QoE is a relatively new field and requires more research in most areas. Examples of such areas are optimisation and enhancement, measurement and assessment, monitoring and management, requirement and prediction. Various layers from video encoding to

decoding and across the access and core networks are involved in providing an end-to-end QoE to end users.

QoE as a main performance metric target is used in this study. It is discussed in the context of video streaming services.

2.1 Factors Affecting QoE

The perception of quality mainly depends on (but is not limited to) the quality of the source in addition to all other elements of the communication system such as the network, equipment, codecs, techniques, protocols and terminals (Stankiewicz et al. 2011). Various technical and non-technical factors affect the quality measure of QoE. Among these factors are those which are related to service preparation, delivery and presentation. Technically, the perceived video quality is mainly affected by the trade-off relationship between encoding redundancy and network impairment. Brooks & Hestnes (2010) list a number of technical and human variables such as conscious and unconscious psychological factors to be considered in developing the concept of QoE and its measurement. Figure 2.1 lists the attributes of QoE and shows a breakdown of QoE into a set of parameters. In the networking domain, for example, quality is closely linked to network parameters such as bandwidth, delay and packet loss ratio.

Moller & Raake (2014) suggest that QoE in the context of media services is subject to a range of complex and strongly interrelated factors categorised into human, system and context. Physical characteristics (e.g., gender, age, audio and visual acuity), emotions (e.g., mood, motivation and attention), mental constitution, educational background, and socio-cultural/economic background are some of the human-related factors that may play an important role in the context of QoE. System factors include characteristics related to content (e.g., audio, 3D video, music), media (e.g., encoding, resolution, sampling rate, frame rate), network (e.g., delay, loss, jitter) and devices (e.g., speed, display resolution and size). Context factors such as the physical (location and space), temporal (time of the

Attribute	Parameter	Examples
Communication situation	User task	Give instruction, negotiate an outcome
	User group	Business people, elderly people
	User environment	Conference room, in a parked car
Service prescription	Service type	Video call, audio call, video on demand, IPTV
	Terminal type	Laptop computer, mobile handset
Technical parameters	Bit rate	1 Mb/s, 64 kb/s
	Media protocol	H.264, MPEG2, AAC
	Network protocol	TCP-IP, UDP-IP, RTSP
	Delay	50 ms, 500 ms, 1 s
	Audio-video asynchrony	0, 50 ms, –100 ms
	Jitter	50 ms, 100 ms, 1 s
	Packet loss	0.5%, 1%, 5%
	Video frame rate	7 frames/s, 25 frames/s, 30 frames/s
	Video resolution	CIF, 1920 × 1080, XGA
User experience	Task effectiveness	Task accuracy, value of negotiated agreement
	Task efficiency	Task time, number of speech interruptions
	User satisfaction	Acceptability of the service, satisfaction with communication
	User enjoyment	Level of engagement, level of fun

Figure 2.1: QoE technical and non-technical parameters. Adopted from (Brooks & Hestnes 2010)

day), social, economic, task (nature of the experience) and technical/information context can be classified separately, or are included from human and system factors. Volk et al. (2010) group these factors into the transport, application, service and content (inclusive of human perception) factors. Others categorise these factors in a more human-centric manner such as (Laghari & Connelly 2012) putting them into the psychological, physiological and cognitive factors. Some of these factors are those which are related to internal aspects of human beings such as biological, psychological, cognitive factors or external aspects such as social, economic, and technical factors. In addition to system elements identified by Stankiewicz et al. (2011) and explained earlier in this section, environmental, psychological and sociological factors also influence the overall QoE evaluation. Users' expectation, experience with similar services and profile (e.g., occupation, age, education) as well as pricing policy, viewing condition, screen illumination and size are some examples of the non-systematic factors (Stankiewicz et al. 2011).

The discussion here has highlighted some of the factors at the present time. We will discuss our assumption in details in Section 5.6.

2.2 Video Quality Assessment

Video has changed the main role of some Internet enabled devices to a simple TV screen. It has therefore, become crucial for video content providers to increase the user engagement and resource utilisation. The objective of initially developed models was to address compression artifacts. Frame freezing due to unreliable transmissions such as Real-time Transport Protocol (RTP) over User Datagram Protocol (UDP) has promoted more sophisticated models that can conceal some level of packet loss. More recently, progressive download over HTTP led to new models (Moller & Raake 2014). Reliable prediction models to assess video quality have become indispensable and have received a lot of attention by the research community during the last decade. The outcome of these efforts include a number of video quality assessment models with different levels of computational complexity and accuracy. In general, quality is assessed by the following principal methods (Moller & Raake 2014):

1. *Subjective assessment* is conducted in a laboratory where human viewers assess a number of video sequences following the ITU recommendations (ITU-T Recommendation P.910 1999, ITU-R Recommendation BT.500-12 2009, ITU-R Recommendation BT.710-4 1998, ITU-T Recommendation P.910 2008, ITU-T Recommendation P.910 1998, ITU-T Recommendation P.920 2000). Since people have different perceptions of the same video content, groups of people carry out subjective tests by grading the sequences. This is time-consuming and costly; however it is worthwhile as real users are involved in the tests. Subjective experiments are considered the most reliable method of quality assessment (Staelens et al. 2010). Subjective tests conducted as part of this research project are discussed in Section 5.6. These tests are used to validate the simulated QoE results

2. *Objective assessment*, through algorithms and mathematical equations, are normally called "models". They are intended to overcome the drawbacks of subjective tests (Stankiewicz et al. 2011). In contrast to subjective assessment, this type of assessment is less costly and time-consuming; however it lacks the user's judgement. The disadvantage of this method is that the result is not informative enough and not accurate, thus needs to be verified by subjective methods (Stankiewicz et al. 2011). For this reason, the next method of assessment is used

3. Objective assessment with additional consideration of context and user behaviour (Dobrian et al. 2011). This method is a hybrid of the subjective and objective methods in which both the technical parameters and human rating are taken into account (Cherif et al. 2011) (Piamrat, Viho, Bonnin & Ksentini 2009).

The ITU recommends both objective modelling of measurable technical system performance and subjective testing with people (Brooks & Hestnes 2010). The European telecommunications standards institute developed a complementary approach based on combining objective measures of user performance with quantitative subjective measures (ETSI STF 354 n.d.). The ITU classifies objective quality assessment methodologies into five categories (Takahashi et al. 2008). Figure 2.2 summaries these methods.

Media-layer model

As no priori information about the system is required, this model can be applied to unknown system such as codec comparison/optimisation. QoE is predicted from speech/video signals. The ITU-T Recommendation J.144 (2001) for video and ITU-T Recommendation P.862.1 (2003) for speech are two examples. These models are also called signal-based models.

Media-layer models according to the amount of reference information required for prediction, can be further divided into Full-Reference (FR), Reduced-Reference (RR) and No-Reference (NR) (Chikkerur et al. 2011). FR requires full and RR partial information about the reference and distorted signals, while NR relies

	Media-layer model	Parametric packet-layer model	Parametric planning model	Bitstream layer model	Hybrid model
Input information	Media signal	Packet header information	Quality design parameters	Packet header and payload information	Combination of any
Primary application	Quality benchmarking	In-service nonintrusive monitoring (e.g., network probe)	Network planning, terminal/ application designing	In-service nonintrusive monitoring (e.g., terminal-embedded operation)	In-service nonintrusive monitoring
Existing standards and ongoing projects in ITU					
Speech	ITU-T P.862	ITU-T P.564	ITU-T G.107	—	ITU-T P.CQO
Audio	ITU-R BS1387	ITU-T P.NAMS [IPTV]	ITU-T G.1070 [videophone] ITU-T G.OMVS [IPTV]	ITU-T P.NBAMS [IPTV]	—
Video	ITU-T J.144[SD] ITU-T J.vqhdtv[HD] ITU-T J.mm**[PC]				ITU-T J.bitvqm [IPTV]
Multimedia	(ITU-T J.148)				—

Figure 2.2: Taxonomy of objective quality assessment methods. Adopted from (Takahashi et al. 2008)

only on the distorted information for quality evaluation (Deng et al. 2015). FR compares the reference signal with distorted signal and RR uses the partial information from the reference to estimate the QoE metric. Systems that do not have access to the reference implement NR by analysing the output signal only. The full-reference and reduced-reference media-layer objective video quality assessment methods are reviewed, classified and compared in (Chikkerur et al. 2011).

Parametric packet-layer model

Unlike the media-layer model, the parametric packet-layer model does not require access to the media signal. Instead, QoE is solely predicted from the header of the packet. Since, it doesn't inspect the payload of the packet, it makes content-based QoE evaluation difficult. In addition to commercial models, ITU-T Recommendation P.564 (2007) is the standard packet-layer model.

Parametric planning model

QoE is predicted by this model from the quality planning parameters for networks and terminals. The ITU's E-Model (ITU-T Recommendation G.107 2015) is an example of this type of model. It is widely used for network planning in the Public Switched Telephone Network (PSTN) and Voice over IP (VoIP). The ITU's new model (ITU-T Recommendation G.1070 2012) has been recently adopted for videophone services.

Bitstream-layer model

To overcome the content-based QoE evaluation flaw of the parametric packet-layer model and computational complexity of the media-layer model, the bitstream-layer model uses encoded bitstream information and packet-layer information to predict QoE.

Hybrid model

Two or more previously discussed models are combined to predict the QoE in this method.

2.3 Quality Metrics

Objective video quality metrics have been proposed because the QoS parameters such as throughput, delay and jitter do not precisely define the QoE of multimedia services (Latré et al. 2009). The most reliable measure of QoE depends on the Mean Opinion Score (MOS). This metric is defined by the ITU as "The mean of opinion scores, i.e., of the values on a predefined scale that subjects assign to their opinion of the performance of the telephone transmission system used either for conversation or for listening to spoken material" (ITU-T Recommendation P.800.1 2006). MOS was initially recommended for voice telephone services and is today also widely used for video services. MOS is considered as an absolute metric compared to other comparative metrics which compare the quality of two tests. Absolute and comparative metrics are illustrated in Tables 2.1 and 2.2 respectively (Stankiewicz et al. 2011). This study relies on the absolute metric (MOS), however Other objective metrics are also briefly discussed in the following three categories.

1. **Traditional point-based metrics**

   The Mean Squared Error (MSE) and Peak-Signal-to-Noise Ratio (PSNR) are two examples of point-based metrics. PSNR is mostly used for its simplicity and good correlation with subjective video test results. The definition of the PSNR of source image s and destination image d is given by Equation (2.1)

(Riley & Richardson 1997). PSNR tool are available to calculate the PSNR value. A possible mapping of PSNR to MOS is shown in Table 2.3 (Ohm 2004). However, this is a problematic approach as PSNR does not directly correspond to MOS (Gross et al. 2004). This straightforward mapping depends on many parameters such as coding, resolution and reference video. A more linear approach is recommended for assessing the QoE of video which is transferred over the lossy networks (packet/frame loss).

$$\mathrm{PSNR}(s,d) = 20\log\frac{\mathrm{V_{peak}}}{\mathrm{MSE}(s,d)} \tag{2.1}$$

where

$\mathrm{V_{peak}} = 2^h - 1$; h bit colour depth

MSE(s,d)= mean square error of s and d.

2. **Natural visual characteristic metrics**

The Video Quality Metric (VQM) (Pinson & Wolf 2004) and Structural SIMilarity (SSIM) (Wang, Bovik, Sheikh & Simoncelli 2004) are two examples of the natural visual characteristics metric. The non standardised (expanded) version of VQM can be used to measure the perceived video quality for various video applications such as wireless or IP-based video streaming systems (Chikkerur et al. 2011). SSIM estimates the perceived quality frame by frame and is considered to have a higher correlation with subjective quality ratings (Group 2008). The SSIM index assumes that the Human Visual System (HVS) is more oriented towards the identification of structural information in video sequences. It produces a score between 0 and 1 from the original and received signals (Wang, Bovik, Sheikh & Simoncelli 2004). There are derivatives of SSIM such as the Video (VSSIM) (Wang, Lu & Bovik 2004), MultiScale SSIM

Table 2.1: Absolute metrics

MOS	Quality	Impairment
5	Excellent	Imperceptible
4	Good	Perceptible
3	Fair	Slightly annoying
2	Poor	Annoying
1	Bad	Very annoying

Table 2.2: Comparative metrics

Score	Description
3	Much better
2	Better
1	Slightly better
0	About the same
-1	Slightly worse
-2	Worse
-3	Much worse

(MS-SSIM) (Wang et al. 2003) and speed SSIM (Wang & Li 2007) (Chikkerur et al. 2011)

3. **Perceptual HVS metrics**

   This metric is based on HVS characteristics. The subjective quality of moving pictures that contain arbitrary impairments is predicted by this metric (Chikkerur et al. 2011). The Moving Pictures Quality Metric (MPQM) (Lambrecht & Verscheure 1996), Digital Video Quality (DVQ) (Watson et al. 2001), and Perceptual Quality Significance Map (PQSM) (Lu et al. 2003) are a few examples of the perceptual HVS metrics.

The FR and RR approaches can use any of the above metrics. A comparison for each of the natural visual characteristics and perceptual (HVS) metrics is provided in (Chikkerur et al. 2011).

Table 2.3: Possible PSNR to MOS mapping

PSNR	MOS	Quality
> 37	5	Excellent
31 - 37	4	Good
25 - 31	3	Fair
20 - 25	2	Poor
< 20	1	Bad

2.4 QoE Prediction Models

QoS-based approaches attempt to guarantee services by either ensuring the value of a particular service metric under the desired limit (e.g., delay under 30 milliseconds) or differentiating and prioritising traffic into classes such as high, medium or low. On the other hand, QoE models include more subjective aspects related to user perception for measuring network performance (Ernst et al. 2014). The video prediction models discussed in the previous section are limited to short videos of 10 seconds length and laboratory viewing environment which is different from actual viewing conditions.

Addressing quality from end users' perceptual points-of-view is a new strategy. Proper selection of quality related parameters and mapping are an essential part of model construction. However, research in this area is limited. Most of the existing models are either limited to a few parameters as explained in Section 2.1 or restricted to a specific underlying network. Aspects such as audio-visual quality, field testing, and user impact characterization must be considered to obtain a more accurate QoE-centric prediction model (Moller & Raake 2014). The ITU-T Study Group 9 (ITU-T Recommendation J.343 2014) is working on the standardisation of non-intrusive hybrid perceptual/bitstream models for IP television (IPTV) and mobile video streaming applications (Khan et al. 2012). Therefore, objective QoE models which cover most services' end-to-end parameters that directly or indirectly related to quality, become an important research area.

A generic objective QoE model was constructed in (Volk et al. 2010). It is mapped vertically from the transport layer to the application layer, and horizontally with concatenation of a point-to-point QoS to an end-to-end QoE. A QoE model diagram for the communication ecosystem has been built in (Laghari & Connelly 2012) to allow interactive relationships between the human, internal and external factors mentioned in Section 2.1.

A non-intrusive QoE prediction model was established in (Khan et al. 2012) for low bitrate and resolution H.264 encoded videos. It targets the Universal Mobile Telecommunication Systems (UMTS) and is an extension of previous work (Khan, Sun, Ifeachor, Fajardo, Liberal & Koumaras 2010). QoE-content type and sender bitrate from the application layer and block error and mean burst length from the network layer are taken as parameters of the model. Joskowicz et al. (2013) present a general parametric model based on the results of a comparison of several parametric models. The model takes into account bit rate, frame rate, display resolution, video content and the percentage of packet loss.

2.5 Methodology for Subjective Quality Assessment

Subjective tests aim to assess the performance of a system by using measurements that directly reflect the perception of people who are using the system. It complements objective measurements of a system. The ITU provides methodologies for assessing picture quality. These include general methods, grading scales and viewing conditions as well as guidelines for analysing collected data (ITU-R Recommendation BT.500-13 2012, ITU-T Recommendation P.910 1999). The following methods are recommended:

1. Double-Stimulus Impairment Scale (DSIS) [ITU-R Rec. BT.500-13]
   In this method, the reference sequence is presented then the test sequence in an order that is known to the assessor. Both sequences are rated on a discrete five-level scale, ranging from very annoying to imperceptible

2. Double-Stimulus Continuous Quality-Scale (DSCQS) [ITU-R Rec. BT.500-13]
   Reference and test video sequences are presented twice in a cyclic fashion and random order. Both sequences are rated on a continuous quality scale from 1 (bad) to 100 (excellent)

3. Single Stimulus (SS) [ITU-R Rec. P.910]
   This method is also called Absolute Category Rating (ACR). Sequences are presented one at a time and are rated independently on a scale from 1 (bad) to 5 (excellent)

4. Pair-comparison [ITU-R Rec. P.910]
   The same test sequences are presented under varying conditions in pairs and both are evaluated

5. Single Stimulus Continuous Quality Evaluation (SSCQE) [ITU-R Rec. BT.500-13]
   The test video sequence are presented and rated instantaneously on a scale of bad to excellent

6. Simultaneous Double Stimulus for Continuous Evaluation (SDSCE) [ITU-R Rec. BT.500-13]
   The reference and test video sequences are presented at the same time and judged by moving the slider of a handset-voting device.

The SS/ACR method with five grade scale from 1 to 5 was used to conduct the subjective tests in this study (as explained in Section 5.6). Similar studies (Khan et al. 2012) used this method for rating the quality of video over the IP networks.

2.6 Summary

In this chapter, the technical and non-technical factors that affect QoE were analysed. The existing video quality models were classified and motivation for more accurate QoE-centric was justified. Perceptual quality metrics, as well as methods of subjective tests, were presented. The next chapter investigates the effect of adapting SBR on QoE.

Chapter 3

QoE Enhancement through Adapting Sender Bit Rate

With the rapid growth of video traffic over the Internet, providing perceptually good video quality is a challenging task. Improving QoE can be achieved by focusing on all relevant layers and across the networks end-to-end. Video frames are subject to loss and delay which degrades quality when sent without reacting to the congested network. Constant rate encoding does not guarantee smooth video quality and is not feasible for the Internet (Kim & Ammar 2005), while adjusting the encoding rate can minimise network congestion and improve video quality. Adaptive encoding, switching between multiple pre-encoded rates or hierarchical encoding can be implemented to address this issue (Koo & Chung 2010).

Scalable video encoding techniques have been proposed to cope with the problem of Internet resource uncertainty and support device variety. The scalable Video Coding (SVC) extension of the H.264/AVC standard from the joint video team of the ITU-T Video Coding Experts Group (VCEG) and the ISO/IEC Moving Picture Experts Group (MPEG) provides the transmission and decoding support of video partial bit streams to different applications and devices. It enables lower temporal, spatial resolution or reduced quality while retaining a reconstruction quality that is high relative to the rate of the partial bit streams (Schwarz et al. 2007).

Rate-adaptation has been proposed as a mechanism to enhance the QoE of video services. In this chapter, QoE improvement by adapting SBR, is investigated. Related works in the area of rate adaptation to achieve quality improvement are surveyed. The impact of SBR on QoE is analysed to see how the perceived video quality is affected by this parameter. Furthermore, a mathematical relationship between QoE and bit rate is established which can be extended to include other parameters. Then, implementing rate adaptation by video sources for enhancing the video quality is evaluated.

3.1 Related Work

Adaptive video rate is not a new topic. It has been proposed by researchers to enhance video quality. Kim & Ammar (2005) address the problem of quality variations for layered Variable Bit Rate (VBR) video over the Internet while efficiently utilising the available network bandwidth. They propose an optimal adaptation algorithm and a real-time adaptation algorithm based on whether the network conditions are known a priori. The quality adaptation algorithm is composed of quality and rate smoothing algorithms. The quality smoothing algorithm reduces the quality variability for the layered Constant Bit Rate (CBR) video using bidirectional layer selection; and the rate smoothing algorithm ensures that the data rate of the encoded video is sufficiently smooth to exhibit nearly CBR. The experimental results showed that the proposed algorithms maintain consistent video quality over TCP and TCP Friendly Rate Control (TFRC); however the algorithms are limited to layered video delivery such as SVC.

In (Hamdi et al. 1997) a closed-loop rate control algorithm is proposed which adapts the MPEG video coder parameters according to the value of a leaky-bucket counter forcing the output to conform to a sustainable rate. A burst tolerance parameter is used to describe the traffic characteristics of a connection. The encoder Quantisation Parameter (QP) is adjusted on a Group of Picture (GoP) basis by the Shaped-VBR (SVBR) algorithm to ensure that the output satisfies the burstiness constraint, imposed by the leaky-bucket traffic control.

The proposed algorithm is based on the parameters of the leaky-bucket such as rate and virtual buffer size. Despite the reduction of VBR traffic burstiness, the leaky-bucket increases delay due to extra buffering.

A rate control algorithm was proposed by Rodriguez-Escalona (2011) for H.264/SVC VBR applications with buffer constraints. Unnecessary QP fluctuation is managed based on the Gaussian processes regression model. Buffer starvation is prevented by allowing an incremental variation of QP with respect to the previous picture. The experimental results included a consistent quality, secured buffer, and smooth target bit rate. The algorithm proposes a set of buffers (one per temporal resolution sub-stream) which introduce more buffering delay. Moreover, it is assumed that consecutive pictures within the same scene often exhibit similar degrees of complexity which is not a valid assumption for video scenes.

Koo & Chung (2010) propose an adaptive streaming scheme called Mobile-Aware Adaptive Rate Control (MARC) which adjusts the quality of the bit-stream and transmission rate of video streaming in mobile broadband networks based on the status of the wireless channel and network as well as client buffer for SVC. The scheme provides a seamless multimedia playback service in wireless broadband networks and improves the QoS of multimedia streaming services by mitigating the discontinuity of multimedia playback and allocating a suitable buffer to a client. An Additive-Increase Heuristic-Decrease (AIHD) congestion control is proposed to reduce rate oscillation. Simulation results show that the proposed MARC can appropriately control the transmission rate of video streaming based on the mobile station status in the wireless network, though it is limited to the layered video such as SVC.

An online estimation of QoE using a tool called Pseudo Subjective Quality Assessment (PSQA) is introduced in (Piamrat, Ksentini, Bonnin & Viho 2009). Here, the rate is adapted dynamically for multicast in wireless Local Area Networks (LAN). The multicast transmission rate is decreased when the user QoE is lower and increased otherwise. The multicast data rate is adapted by the access point at the Media Access Control (MAC) level assuming that every multicast node runs PSQA. The simulation shows that QoE and wireless channel utilisation are

increased compared to the existing solutions including the Institute of Electrical and Electronics Engineers (IEEE) 802.11 standard. The tool is based on statistic learning using the Random Neural Network (RNN). The RNN is trained using mapping between QoE scores and technical parameters. It has to be re-trained whenever new parameters have to be taken into consideration. The application of this work is limited to wireless LANs managed by one access point.

The authors of (Khan, Sun, Jammeh & Ifeachor 2010) use a QoE prediction model from their previous work (Khan et al. 2009*b*) to adapt SBR for video over wireless that is suitable for some network resources and content types. The model identifies the optimum trade-off between video SBR and frame rate. It optimises QoE and wireless network utilisation through SBR adaptation based on the requested QoE. For a requested QoE level, an appropriate SBR is identified by content providers and optimised resources are provided by network operators. QoE is predicted by relying on a limited number of parameters such as content type, SBR and frame-rate from the application layer and packet error ratio from the network layer.

A user-centric discretized streaming model was specially designed for live rate-adaptive streaming in modern Content Delivery Networks (CDN)s in (Liu et al. 2014). The objectives are to enhance the minimum satisfaction among users and maximise the average satisfaction of users. Algorithms were also proposed for the CDN's content placement, content delivery and user assignment. The system with limited CDN resources in a dynamic environment achieves high user satisfaction shown by a large simulation campaign.

To improve the video quality, rate adaptation has also been proposed within cross-layer design (Khalek et al. 2012). Politis et al. (2012) has proposed an algorithm to control the SVC rate by matching the video data rate to current network conditions. Packets are dropped from one or more of the enhancement layers if the SVC video rate exceeds the available bandwidth. A QoE and proxy based multi-stream scalable (temporal and amplitude) video adaptation for wireless network is presented in (Hu et al. 2012) which, according to the simulation results, outperforms TFRC in terms of agility to track link quality in addition

to support for differentiated services and fairness with conventional TCP flows. The proxy at the edge of a wireless network maximises the weighted sum of video qualities of different streams by iteratively allocating rates for each stream based on their respective rate-quality relations, wireless link throughputs and buffer status (without feedback from receivers). The subjective quality is related to a given rate by choosing the optimal frame rate and quantisation stepsize through an analytical rate-quality trade-off model. The study is limited to the layered video. Furthermore, it did not justify how quality based on which the rate is allocated to individual stream, has been estimated without feedback from the receiver.

3.2 Video Quality Model

In this section, we draw a mathematical relationship between QoE and the arrival rate of a video source. Let $x_i(t)$ be the instantaneous arrival rate (SBR) of video session i at time t. We consider a network of N nodes and $M \subseteq N \times N$ links, where link $l \in M$ and F denotes the set of flows where $f \in F$. The instantaneous aggregate arrival rate $X_{inst}(t)$ of on-going flows F at time t is

$$X_{inst}(t) = \sum_{i=1}^{n} x_i(t) \tag{3.1}$$

for $i > 0$ and $t > 0$. Where n is the *number of sessions*.

$x_i(t)$ is taken into consideration, as an application layer parameter affecting the video quality, based on our experimental results and results of (Ries & Nemethova 2008, Khan et al. 2012, Calyam et al. 2007). From (Thakolsri et al. 2009), a user's QoE (in terms of MOS) for video streaming can be defined by a simplified utility function as a function of transmission rate as is given by Equation (3.2)

$$U = f(x_i(t)), \;\; f : x_i(t) \rightarrow \text{MOS}. \tag{3.2}$$

Figure 3.1: A snapshot of the video sequences used in Chapter 3 and Chapter 6, MAD (left) and Grandma (right)

Equation (3.2) indicates that a higher SBR guarantees a better quality. The relationship between SBR and MOS is plotted and analysed in Section 3.4.

3.3 Evaluation Environment

In this section, an *adaptive architecture* in which video sources adapt their SBR, was compared to a *non-adaptive architecture* in which video sources send without adapting their SBR.

NS-2 (NS-2 n.d.) and Evalvid-RA (Lie & Klaue 2008) were used to simulate the 30 second Mother And Daughter (MAD) and 28 second Grandma video sequences shown in Figure 3.1. The topology shown in Figure 3.2 with a bottleneck link similar to the *ISP access links* of the distribution network in Figure 1.2 was considered for evaluating the performance of both architectures. Twenty four video sources were competing for the bandwidth of the link. There were also (48) File Transfer Protocol (FTP) sources active on the link. The FTP sessions created background traffic and video sessions started randomly during the first 20-50 seconds of the simulation. In total, 500 seconds were simulated. The videos in the *non-adaptive architecture* were encoded with QP of 2 whereas the videos in the *adaptive architecture* were encoded with QP between 2-31 using ffmpeg (*FFMPEG Multimedia System* 2004) encoder (30 video sequences with different

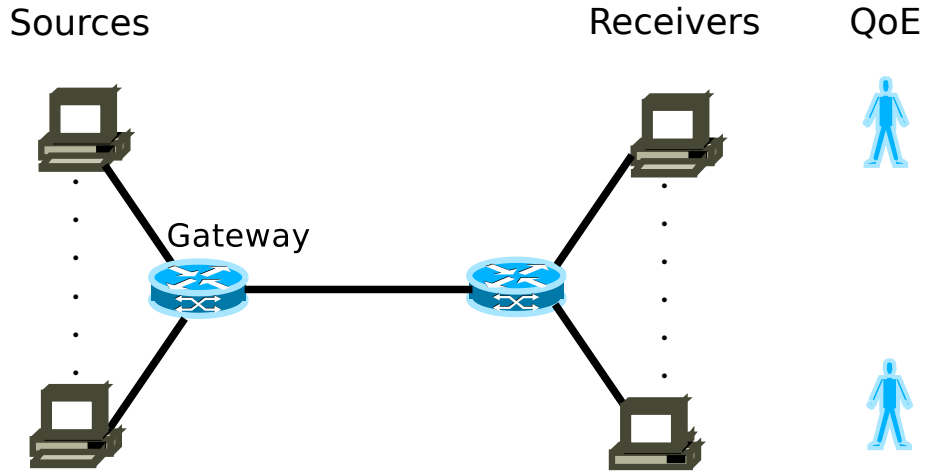


Figure 3.2: Network topology used in the simulations in Chapter 3 and Chapter 6

bit rates). The description of the video contents as well as coding and network parameters are shown in Tables 3.1 and 3.2 respectively.

The MAD and Grandma video sequences were utilised by the NS-2 simulator through a video trace file using EvalVid-RA. The objective of having two different video resolutions, Quarter Common Intermediate Format (QCIF) and Common Intermediate Format (CIF), was to see the impact of video frame size on the performance metrics not to compare these two resolutions. Due to dissimilar characteristics of each resolution, different link capacity and queue size were used in the simulation to subject both videos to the bottleneck condition. Same link capacity and queue size do not guarantee this condition for both videos (One large and another small). Same simulation parameters for both resolutions do not add credibility as we are not comparing them as mentioned earlier in this section. The studied metrics for both resolutions are plotted under each other in this chapter and Chapter 6 for the sake of convenience not comparison. MOS was measured

Table 3.1: Description of video sequences used in Chapter 3 and Chapter 6

Description	**Video sequence 1**	**Video sequence 2**
Name	Mother And Daughter (MAD)	Grandma
Description	A mother and daughter speaking at low motion	A woman speaking at low motion
Frame size	CIF (352x288)	QCIF (176x144)
Duration (second)	30	28
Number of frames	900	870

Table 3.2: Simulation parameters used in Chapter 3 and Chapter 6

	Parameter	**Value**
Encoder	Frame rate (fps)	30
	GoP	30
	Video quantizer scale/QP	2 (Non-adaptive traffic)
		2-31 (Adaptive traffic)
Network	Link capacity (Mbps)	32 (MAD)
		7 (Grandma)
	VBR sources	24
	FTP sources	48
	Packet size (byte)	1052
	UDP header size (byte)	8
	IP header size (byte)	20
	Queue size (packet)	300 (MAD)
		100 (Grandma)
	Link delay (millisecond)	1
	Queue management	Droptail
	Queue discipline	FIFO (First In First Out)
	Simulation time (second)	500

using Evalvid (Gross et al. 2004) which provides a set of tools to analyse and evaluate video quality by means of PSNR and MOS metrics. The Evalvid MOS metric (referred to as simulated MOS in this dissertation) calculates the average MOS value of all frames for the entire video. The MOS metric represents the impression of end users for the entire received video and has been widely used by the research community (Zheng et al. 2015, Li & Pan 2010, Khan, Sun & Ifeachor 2010, Kim & Chung 2012, Khan et al. 2009*b*, Tommasi et al. 2014, Papadimitriou & Tsaoussidis 2007, Khan et al. 2009*a*, Ma et al. 2012, Aguiar 2008, Erdelj 2013, Tan 2013, Escuer 2014). Although the MOS metric does not map very well to the subjective impression for a long video sequence, it is used for short (up to 45 second) video sequences in this dissertation.

In order to see the impact of rate adaptation on the video quality, similar simulation parameters and environments were kept for both cases except that the video sources were adapting their rates in the first case by switching between the available 30 video sequences while they were not in the second. Performance metrics such as MOS, the number of admitted sessions (*number of sessions*), delay and jitter were measured. The Cumulative Distribution Function (CDF) of the mean was calculated for each metric for the 24 video sources over 30 runs.

The CDF function of MATLAB was used in this study. CDF or complementary CDF (CCDF) has been used by researchers for the similar purpose (Menth & Lehrieder 2012, El Essaili et al. 2014, Liu et al. 2014, Zhao et al. 2014, Li et al. 2015, Dobrian et al. 2011).

3.4 Results and Discussions

This section presents and discusses the results obtained from a number of simulations. Figure 3.3 explains the relationship between MOS and SBR. The figure shows how the video quality is influenced by the bit rate. It can be noticed that there is a logarithmic relationship between MOS and SBR. A bitrate of 100Kbps or higher provides the maximum value of MOS (5) and excellent video quality for the specific video content described in Table 3.1. However, since the maximum MOS value for any multimedia applications is 4.5 (Thakolsri et al. 2009), this simulation result can not be generalised. Furthermore, this relationship depends on the video content type (Khan et al. 2012). A lower MOS and less quality are expected for medium and high content movement videos for the same bitrate (Khan et al. 2012).

In a further simulation, rate adaptation is implemented by the video sources and investigated in terms of quality, number of successfully admitted and decoded sessions, delay and jitter. As both architectures simply accept all the VBR and FTP flows without any restrictions, only video sessions that have been successfully decoded and played back by the receiver were considered for the *number of sessions* metric. There would be more sessions, but as they were not decoded and played back successfully by the receiver, they have not been taken into account.

The CDF of the mean MOS of the video flows in the *adaptive architecture* and *non-adaptive architecture* for both video sequences are depicted in Figure 3.4. Although enhancement in the quality of the video flows in the *adaptive architecture* can be clearly seen in the figure, based on (Ohm 1999) it is still considered a poor quality. This modest enhancement is due to the higher awareness of the

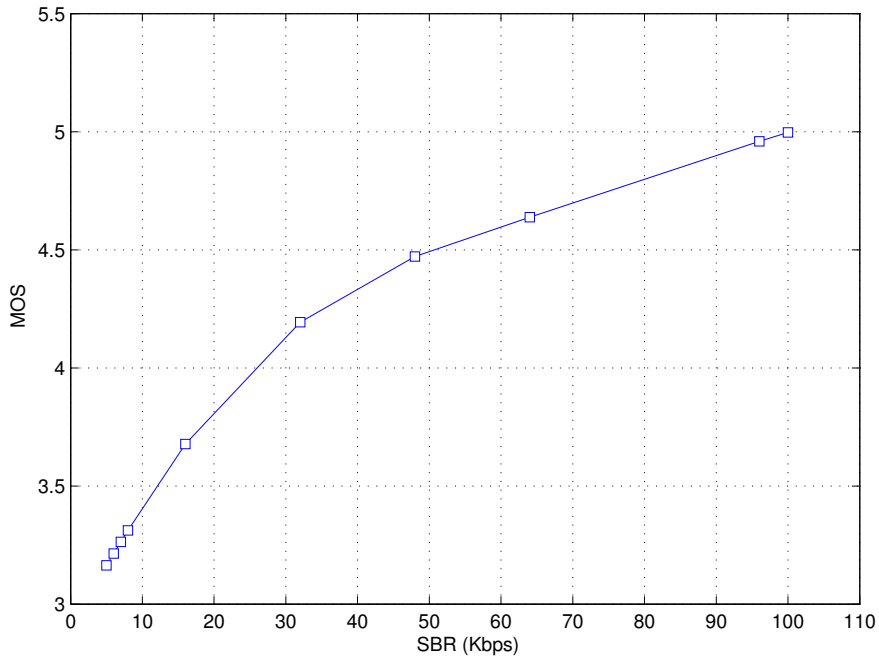
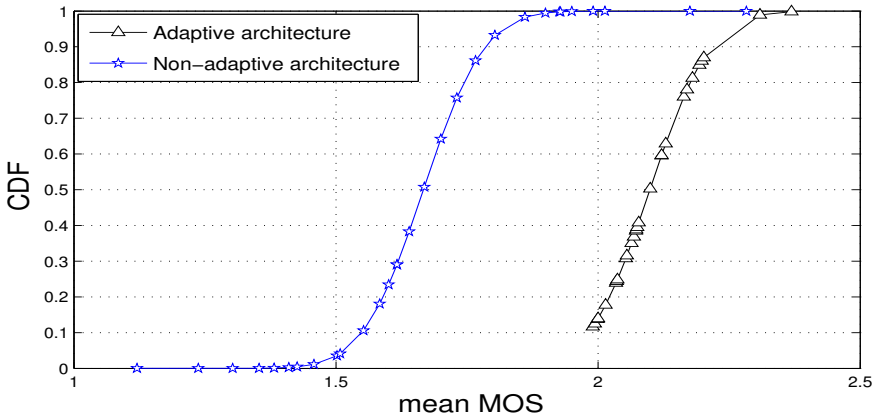


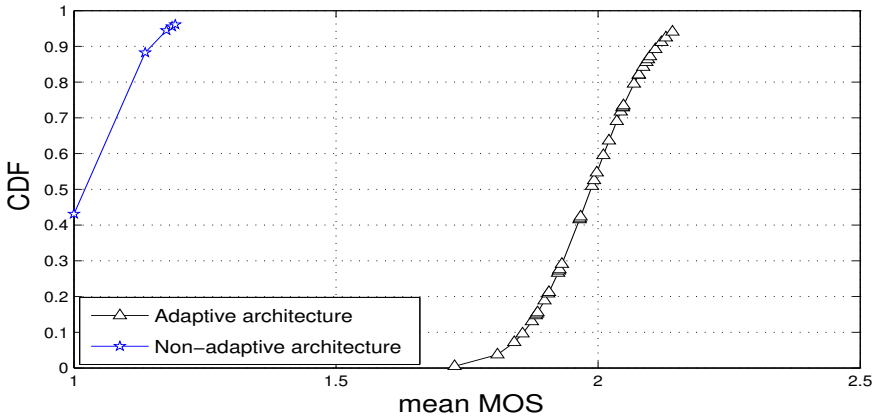
Figure 3.3: Relationship of MOS with the instantaneous arrival rate

video flows about the network condition in the *adaptive architecture* than the video flows in the *non-adaptive architecture*. The video sources in the *adaptive architecture* attempt to scale their sending rate according to the resources available. This is done at the application layer in contrast to the traditional TCP self-controlling done at the transport layer. Variations in the sender rate indicate the level of the quality delivered to end users. FTP traffic is also allowed to share the bandwidth in either scenario, thus not being penalised by the video flows. This is the main reason the video flows do not achieve high values of MOS. As video traffic is the main target of this dissertation, the fairness among flows (FTP and VBR) is not investigated.

A higher number of video sessions can be decoded successfully in the *adaptive architecture* than in the *non-adaptive architecture*. However this depends on the video resolution. The CDF of the mean number of the video sessions in the *adaptive architecture* and *non-adaptive architecture* for both sequences is shown in Figure 3.5. The figure shows that the *adaptive architecture* is more efficient for the QCIF format as 10 more QCIF video sessions while only 2 more CIF video sessions were accommodated. The bar chart in Figure 3.6 illustrates the mean MOS of the video flows and mean number of the video sessions in the *adaptive*



(a) MAD (CIF)

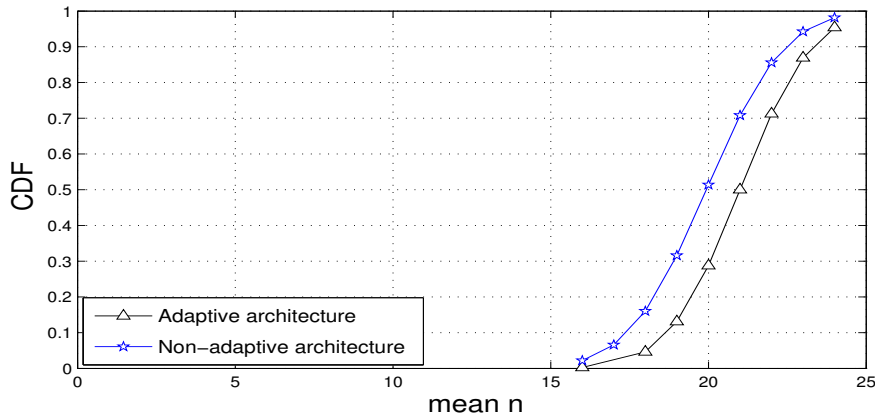


(b) Grandma (QCIF)

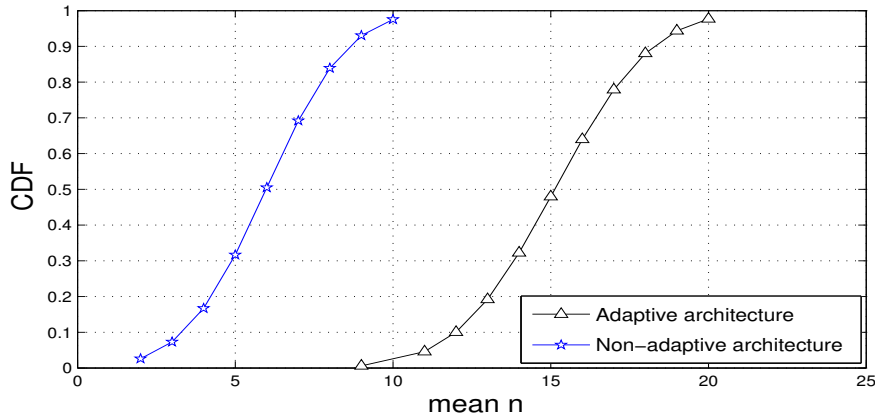
Figure 3.4: CDF of the mean MOS of the video flows in the *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

architecture and *non-adaptive architecture* for both resolutions. Please note that we do not compare the *number of sessions* of both resolutions due to their specific simulation settings.

We can notice from the above figures that the video flows in the *adaptive architecture* are generally optimised in terms of MOS and the number of successfully decoded video sessions. However, this optimisation is resolution dependent. The mean MOS of the video flows and *number of sessions* in the *adaptive architecture* are substantially higher than in the *non-adaptive architecture* for the QCIF sequence. This can be noticed in Figure 3.6. The computed mean MOS of the video flows and number of QCIF sessions in the *adaptive architecture* were 1.98 and 15.12 respectively compared to 1.01 and 5.97 in the *non-adaptive architecture*.



(a) MAD (CIF)

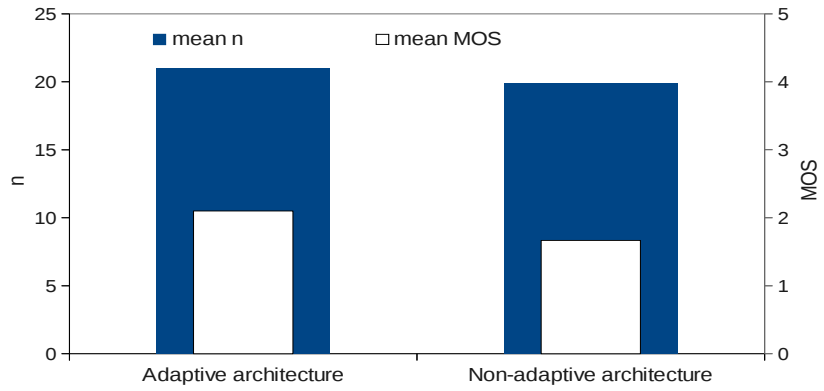


(b) Grandma (QCIF)

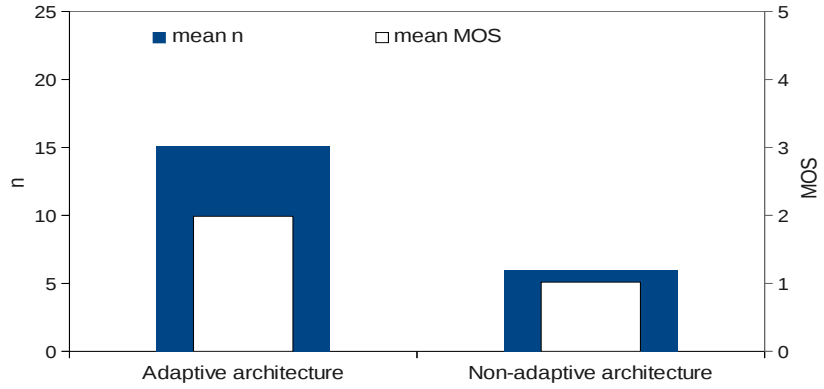
Figure 3.5: CDF of the mean *number of sessions* in the *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

While, there were 2.09 and 21 respectively for the CIF sequence in the *adaptive architecture* compared to 1.66 and 19.93 respectively in the *non-adaptive architecture*.

Nevertheless it can be seen in Figures 3.7 and 3.8 that the delay and jitter of the video flows in the *adaptive architecture* and *non-adaptive architecture* are very close for both resolutions. This indicates that implementing rate adaptation does not come at the cost of delay or jitter; thus it can be recommended for delay-constraint applications such as realtime video.



(a) MAD (CIF)

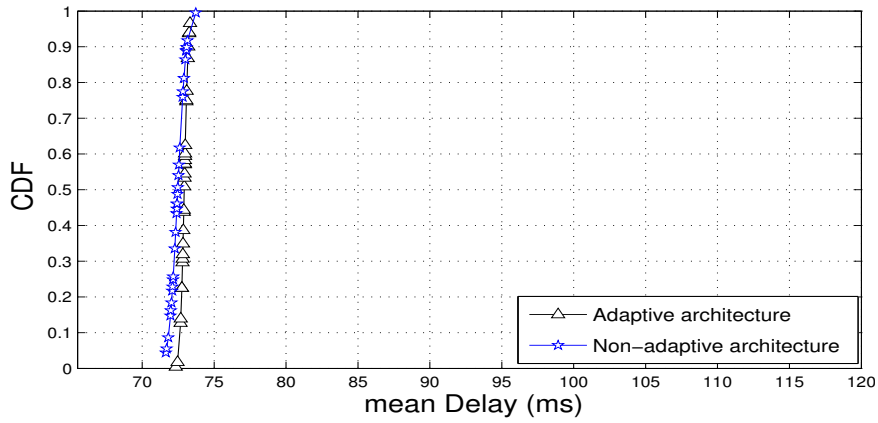


(b) Grandma (QCIF)

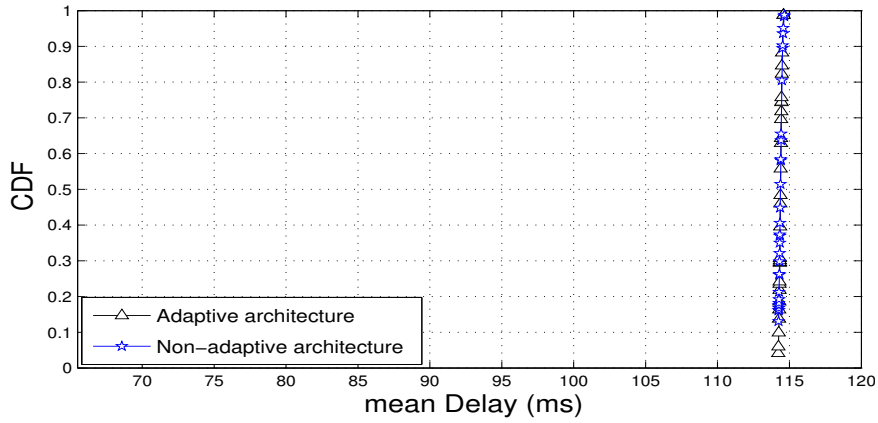
Figure 3.6: Mean MOS of the video flows and mean *number of sessions* in the *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

3.5 Summary

The impact of adapting SBR on QoE has been studied in this chapter. Furthermore, a simple mathematical relationship between QoE and bit rate has been presented. This relationship can be used for estimating and predicting QoE from the bitrate point of view. The video flows in the *adaptive architecture* was compared to the video flows in the *non-adaptive architecture* in terms of mean MOS, mean number of successfully decoded video sessions, delay and jitter for two video resolutions (QCIF and CIF). Simulation results have shown that controlling SBR over a congested network optimises the QoE-*number of sessions* while maintaining delay and jitter. However, the optimisation is more pronounced for QCIF format than CIF. Hence rate adaptation can be implemented by video streaming



(a) MAD (CIF)

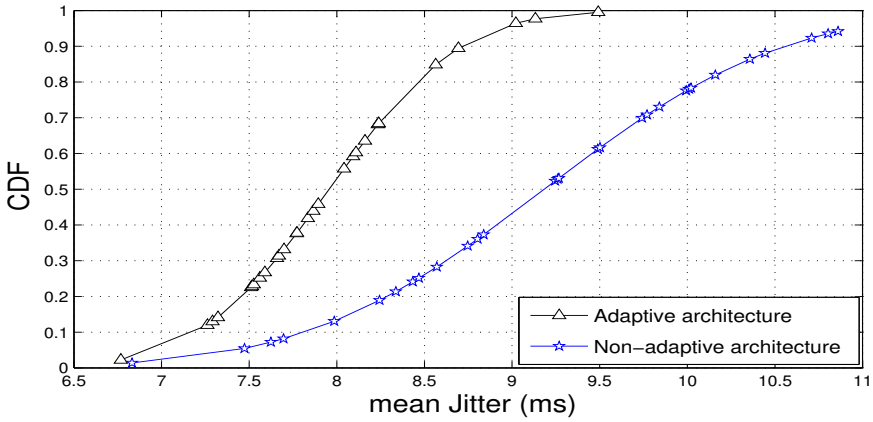


(b) Grandma (QCIF)

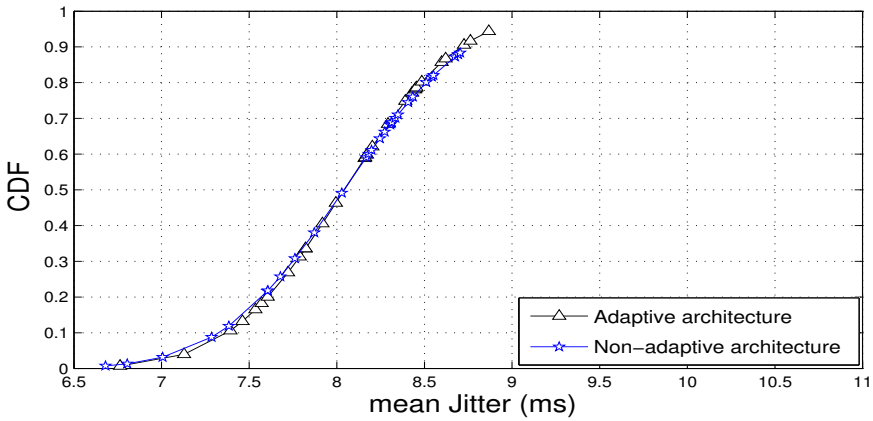
Figure 3.7: CDF of the mean delay of the video flows in the *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

applications to provide an acceptable level of QoE for a higher number of video users.

The next chapter investigates how dependent the video rate is on the content type, number of video flows and time window. *CalR* has been proposed for MBAC instead of the instantaneous rate as a better criteria for video flows. The suitability of each of the instantaneous rate and average aggregate rate (*CalR*) for video flows, as well as the circumstances that best suit each of these two rates, are studied.



(a) MAD (CIF)



(b) Grandma (QCIF)

Figure 3.8: CDF of the mean jitter of the video flows in the *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

Chapter 4

Instantaneous versus Calculated Video Rates

Using the instantaneous aggregate arrival rate as an admission control parameter contributes to either bandwidth under-utilisation or over-utilisation. Being bursty in nature and variable in rate at a particular point in time, the rate of video flows can be any value between a minimum and maximum value. At the time the decision is made, if the measured rate is at the minimum value, bandwidth may be over-utilised due to the acceptance of more sessions than the link can accommodate. In contrast, the bandwidth may be under-utilised if the measured rate is at a maximum value due to rejection of more sessions than the link can accommodate. Since video traffic is sent at a variable rate, the aggregate rate is considerably lower than the sum of the peak rates (Nevin 2010). Therefore admission decisions should not be based on worse-case bounds. Burstiness can be taken into account by considering the past history of the traffic. This will achieve a better trade-off between utilisation and perceived QoE.

Traditional admission algorithms rely on $X_{inst}(t)$ for their operations. The average aggregate rate ($CalR$) has been proposed to better suit variable rates such as video traffic. The Pre-Congestion Notification (PCN) based admission control which has been standardised by the Internet Engineering Task Force (IETF) (Eardley P. 2009) relies on $CalR$ for a measurement period to introduce admissi-

ble and supportable rate thresholds and define three areas of congestion (Menth et al. 2010).

In the previous chapter, it has been shown that SBR has a substantial impact on QoE. As a result, the aggregate rate of video traffic has also impact on QoE. Whereas modelling and measurement of the instantaneous and average aggregate arrival rates have been widely covered by the research community, this chapter investigates the suitability of the average aggregate arrival rate instead of the instantaneous aggregate arrival rate for video traffic. The probability relationship between these two rates is quantified and validated. Furthermore, the impact of the number of video flows, contents (slow moving content such as news and fast moving content such as sports) and measurement window on the quantified probability is demonstrated.

4.1 Proposed Model for Probability Estimation

This section presents mathematical models for the measurement of the instantaneous and average aggregate rates and for the estimation of the probability relationship between both rates.

Since the flow rate is only meaningful if it is associated with a corresponding interval, an associated interval needs to be specified (Qiu & Knightly 2001). Assume that the time t is slotted with width τ which is the minimum interval of the measured rate and larger than the packet transmission time. The average aggregate arrival rate is considered over an interval of length $k\tau$ where the interval $k\tau$=[$t\tau$,(t+k)τ] and k is the total number of time slots. The impact and setting of the interval length (measurement window) is discussed in Section 4.3.3. Let $Y(k)$ denote the sum of the instantaneous aggregate arrival rate over a number of time slots as determined by Equation (4.1)

$$Y(k) = \sum_{j=1}^{k} X_{inst}^{j}(t) \tag{4.1}$$

where j denoted the jth time slot and $X_{inst}^{j}(t)$ is the jth $X_{inst}(t)$. Now we find how $X_{inst}(t)$ is related to its mean. Let $x_i(t)$ be an independent random variable with a minimum rate $x_i^{\min}(t)$, a peak rate $x_i^{\max}(t)$, and $x_i^{\min}(t) \leq x_i(t) \leq x_i^{\max}(t)$.

From the Hoeffding inequality theorem (Hoeffding 1963), the probability that $X_{inst}(t)$ exceeds its mean $\mu_r(t)$ by a positive number $n\epsilon$ for $\epsilon > 0$, is given by Equation (4.2). The theorem defines the upper bounds for the probability that the sum of n random variables will be greater than the average of the sum by a positive number $n\epsilon$ or more for $\epsilon > 0$ (Hoeffding 1963). Equation (4.2) quantifies this probability relationship between $X_{inst}(t)$ and $\mu_r(t)$.

$$Pr\{X_{inst}(t) - \mu_r(t) \geq n\epsilon\} \leq \delta \tag{4.2}$$

where δ is the upper bound of the probability that $\mu_r(t)$ is smaller than $X_{inst}(t)$ by $n\epsilon$ or more as given by Equation (4.3). This study does not explore how smaller $\mu_r(t)$ is than $X_{inst}(t)$ as long as it exceeds $n\epsilon$. Thus, for the sake of simplicity, we denote this relationship as $\mu_r(t)$ is smaller than $X_{inst}(t)$ in the remainder of this chapter.

$$\delta = \exp\left(\frac{-2n^2\epsilon^2}{\sum_{i=1}^{n}[x_i^{\max}(t) - x_i^{\min}(t)]^2}\right). \tag{4.3}$$

In Equation (4.2), the average aggregate arrival rate $\mu_r(t)$ is the expectation value of $X_{inst}(t)$ as expressed by Equation (4.4)

$$\mu_r(t) = \mathrm{E}\langle X_{inst}(t)\rangle. \tag{4.4}$$

The expectation value of $X_{inst}(t)$ can be calculated using Equation (4.5)

$$\mathrm{E}\langle X_{inst}(t)\rangle = \sum_{i=1}^{n} x_i(t)\ p_i(t) \tag{4.5}$$

Figure 4.1: A snapshot of the test video sequences from left to right: Tokyo Olympiad (74-minutes), Silence of the lambs (30-minutes), Star wars IV (30-minutes), Sony demo (10-minutes) and NBC news (30-minutes)

where $p_i(t)$ represents the probability that session i is active at time t. We quantify and validate δ in Equation (4.3) through simulating real video sequences.

4.2 Evaluation Environment

Five different video traces (Tokyo Olympiad, Silence of the lambs, Star wars IV, Sony demo and NBC news) from publicly available libraries (Seeling et al. 2004, Van der Auwera et al. 2008) were used. MATLAB was used to evaluate the proposed model through analysing the video trace files and measuring the rates. The sequences were of 133127, 53953, 53953, 17681 and 49523 frames respectively. All the sequences had a frame size of CIF (352x288) and a rate of 30fps. Spatial and temporal impacts were not considered in this study. The aim was to have a range of video content from slow moving pictures such as news to fast moving pictures such as sport. Typical snapshots of the video sequences used in this chapter are shown in Figure 4.1. The encoding settings are shown in Table 4.1.

We classified the contents into slow and fast moving contents based on the calculated peak-to-mean ratio and coefficient of variance (Frost & Melamed 1994) of each content as shown in Table 4.2. As depicted in the Table, NBC news has a peak-to-mean ratio of 2.25 and coefficient of variance of 0.22, while other contents have peak-to-mean ratios in the range of (4.03-6.09) and coefficient of variance in the range of (0.46-0.60); therefore they are grouped together as fast moving content.

The first frame of the sequences was randomly selected from the streams, and rates were measured for the interval of 150 frames (5 seconds). The instantaneous aggregate rate was measured at the end of each interval and average aggregate rate was measured over the interval. As the instantaneous rate varies, it may have any value within the measurement interval. In order to see how the *number of flows* influences δ, different *number of flows* were simulated. For each *number of flow*, measurements were taken 30 times, 100 random runs of the scheme for each time (3000 measurements in total). δ was calculated for each run.

4.3 Results and Discussion

The data collected from the MATLAB simulations was analysed with one-way ANOVA (Miller & Brown 1997) to confirm the significance of parameters (Source in Table 4.3) on δ. ANOVA can be used to investigate the effect of parameters on δ and find the difference between means given by each parameter. The ANOVA results are shown in Table 4.3 for *F-statistics* and *p-values*; and the CDF of *F-statistics*. A parameter with (p<0.01) is considered to have significant impact on δ. The *p-values* of 6.11^{-18}, 1.65^{-17} and 1.9^{-12} show that δ was affected by each of the content, *number of flows* and measurement window respectively. The values of p also allow for a ranking of the parameters. It can be concluded that δ was affected most by the content, then the *number of flows*, and lastly by the measurement window. Please note that the parameters in Table 4.3 are ranked according to their importance, from most to least.

Table 4.1: Encoder settings

Video parameter	**Value**
Encoder (VBR)	MPEG-4
Frame size	CIF(352x288)
Frame rate	30fps
GoP size	16

Table 4.2: Classification of slow and fast moving contents

Content type	Video sequence	Description	Peak-to-mean ratio	Coefficient of variation
Fast moving	Tokyo Olympiad	Entire sequence is moving	5.27	0.53
	Silence of the lambs		6.09	0.60
	Star wars IV		4.03	0.46
	Sony demo		4.49	0.56
Slow moving	NBC news	Moving of head and shoulder only	2.25	0.22

4.3.1 Impact of *Number of Flows* on δ

The number of video flows potentially shape the trend of the traffic rate at the aggregate level. This is investigated in this section through simulation of the testing sequences. The mean and confidence intervals of δ are plotted against the *number of flows* in Figure 4.2. The flows were sourced from a variety of video contents introduced in Section 4.2. δ for news and sport videos is demonstrated later in this section. The overall trend of the curve is decreasing which means that, the probability that the average aggregate arrival rate is less than the instantaneous aggregate arrival rate decreases with the increase in the *number of flows*. For as few as 15 flows, the average is less than the instantaneous rate, thus considering the average rate is likely that more sessions will be accepted. The average is still estimated to be less than the instantaneous even for a *number of flows* greater than 15, but with less likelihood. This indicates that the average is a better option for any numbers of flows. The exponential shape of δ in Figure 4.2 reflects the exponential expression of Equation (4.3); δ decays sharply with the increase of the number of video flows.

Table 4.3: ANOVA results for δ and each of content, *number of flows* and measurement window

Source	Sum of squares	Degree of freedom	Mean squares	F-statistics	p-values
Content	2926.61	3	975.538	39.84	6.11^{-18}
Number of flows	3429.7	15	228.645	8.55	1.65^{-17}
Measurement window	1783.4	5	356.681	15.19	1.9^{-12}

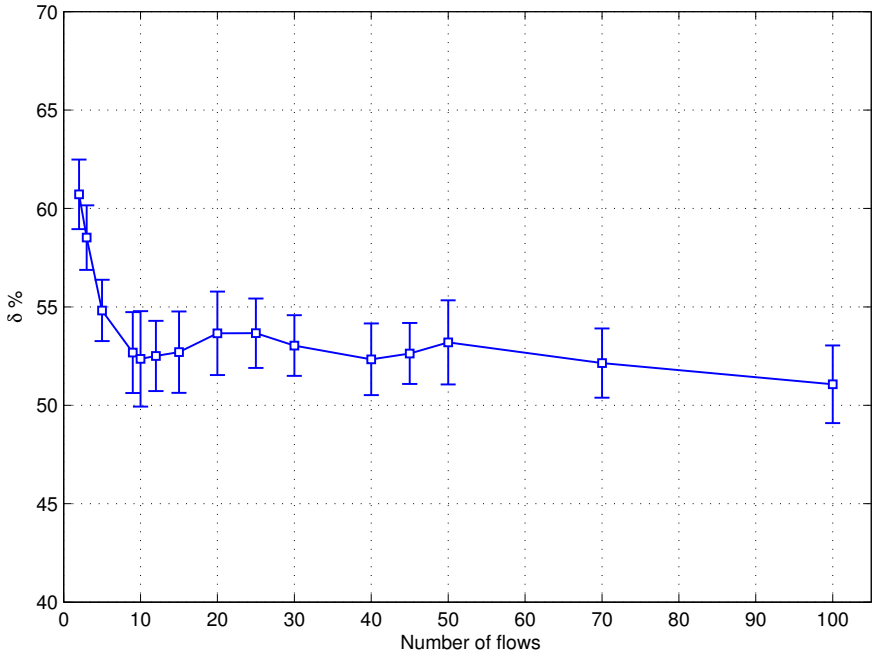


Figure 4.2: Mean and confidence interval of the probability relationship between the instantaneous and average aggregate rates for different *number of flows*

Figure 4.3 shows the CDF of δ for different *number of flows* over 3000 simulation runs. The average rate is seen to be smaller than the instantaneous rate; however it is more predictable with a higher level of certainty for a small number of video flows, as shown in Figure 4.3. The figure confirms the trend shown in Figure 4.2: the probability that the instantaneous rate exceeds 50% is higher for a fewer number of video flows. This phenomenon can be justified as the burstiness or variability of video flows is more evident for a fewer number of video flows than a larger *number of flows*. As the *number of flows* increases, both rates approach each other indicating that there is no significant difference in considering either rate. δ fluctuates around (or a bit higher than) 50% for more than 15 flows which produces uncertainty in the instantaneous rate. However, considering the average rate for any *number of flows* will still contribute to reducing the burstiness of a set of instantaneous rates within the measurement period which potentially lead to more consistent admission decisions.

Figures 4.4 and 4.5 show the mean and confidence intervals of the instantaneous and average aggregate rates over the simulation time for 5 and 100 flows respectively. The simulation was run 1000 times, then the mean and confidence interval

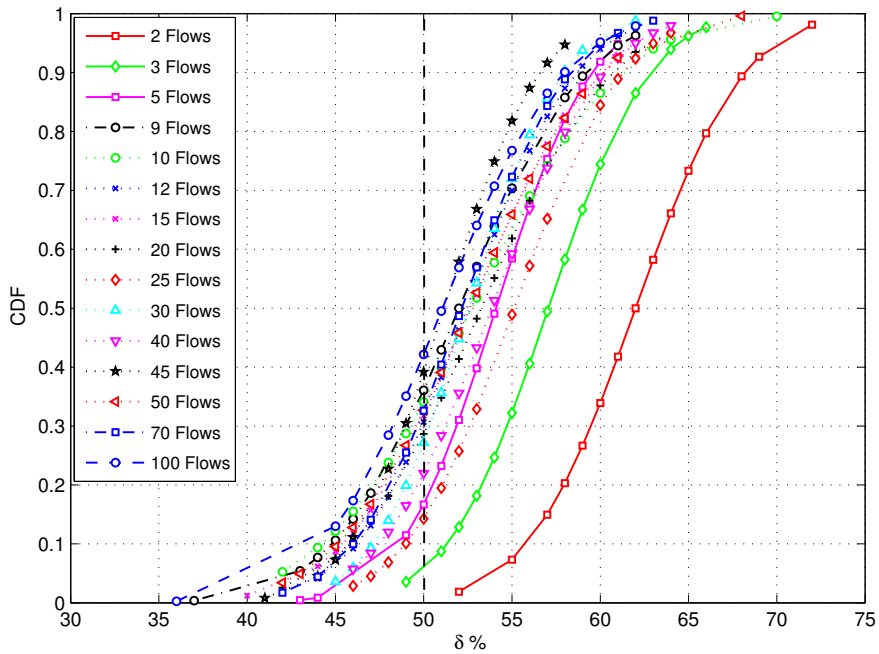


Figure 4.3: CDF of the probability relationship between the instantaneous and average aggregate rates for different *number of flows*

of each rate were calculated. The burstiness is more observable in the case of 5 flows because the overall rate gets smoother (less bursty) in the case of 100 flows. The rising trend of the gap between the rates in Figure 4.4 is due to a longer measurement window as will be explained by Figures 4.8 and 4.9 in Section 4.3.3. There is a substantial difference between both rates (the average rate is seen to be less than the instantaneous) in Figure 4.4 for a small *number of flows* (5 flows for instance) and this difference increases with the increase of the measurement window.

Figure 4.4 can be verified by Figure 4.2 in which δ is 55% with a 95% confidence interval for 5 flows. As mentioned earlier, the mean of both rates is calculated from 1000 runs out of which the average was smaller than the instantaneous by 55% for 5 flows. The CDF of δ for 5 flows in Figure 4.3 confirms this justification. On the other hand, there is a trivial difference between the rates for as large as 100 flows, and it is more observable for long measurement windows as can be seen in Figure 4.5. The rates in Figure 4.5 are seen twisted together with no rate favouring the other, confirming the probability uncertainty of Figure 4.2 at high *number of flows*.

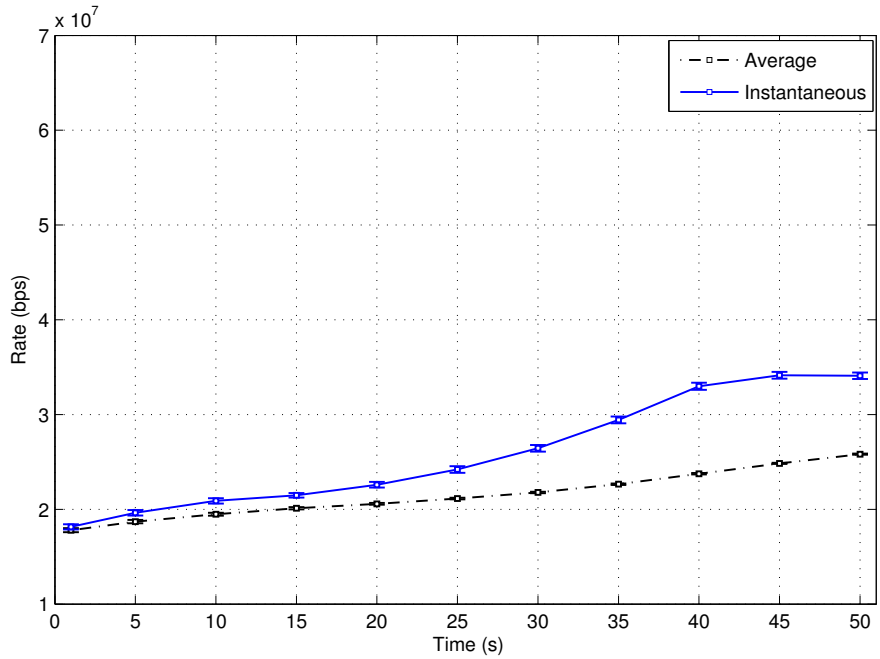


Figure 4.4: Mean and confidence interval of the instantaneous and average aggregate rates for 5 flows over time periods

Table 4.4 compares the burstiness of both rates for each of 5 and 100 flows using peak-to-mean ratio and coefficient of variance methods (Frost & Melamed 1994). As shown in Table 4.4, the burstiness of the average is less than of instantaneous, and decreases with the increase in the *number of flows*. In contrast to burstiness difference of the instantaneous rates of 5 and 100 flows, there is a marginal difference between the burstiness of the average rate of 5 and 100 flows. This is due to a higher smoothness of the average rate compared to the instantaneous. It can also be noticed that the burstiness of both rates comes closer for as large as 100 flows in this study. The peak-to-mean ratio method calculated the burstiness of 1.12 (both rates) for 100 flows compared to 1.3223 (instantaneous) and 1.2 (average) respectively for 5 flows. While it was found to be 0.114 (both rates) for 100 flows compared to 0.23 (instantaneous) and 0.118 (average) respectively for 5 flows by the coefficient of variation.

Table 4.4: Burstiness of the instantaneous and average aggregate rates

	Peak-to-mean ratio		**Coefficient of variation**	
Rate	**5 flows**	**100 flows**	**5 flows**	**100 flows**
Average	1.2	1.127	0.1184	0.1141
Instantaneous	1.3223	1.1254	0.2309	0.114

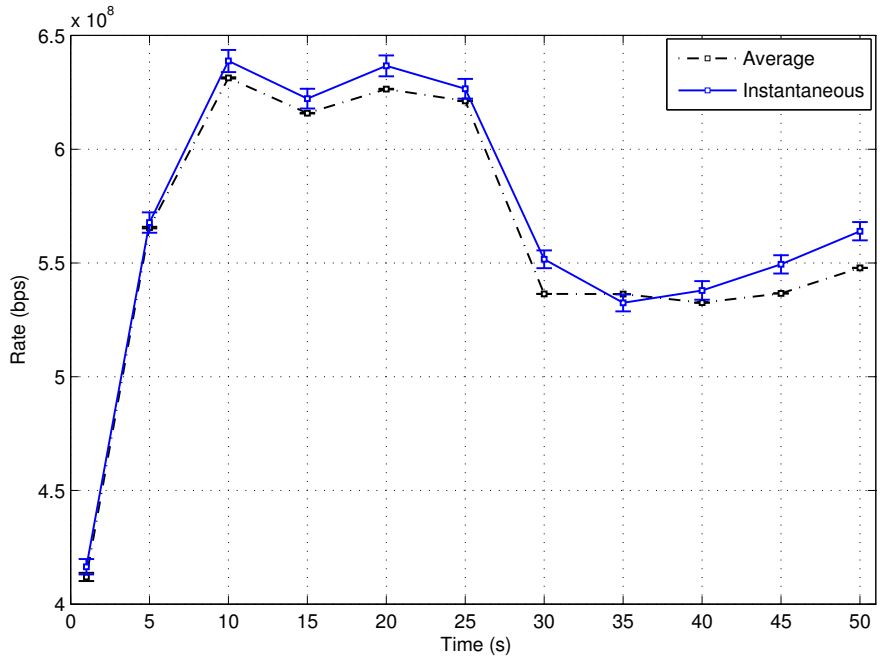


Figure 4.5: Mean and confidence interval of the instantaneous and average aggregate rates for 100 flows over time periods

4.3.2 Impact of Video Content on δ

Video content also has impact on δ. Figure 4.6 shows the relationship between δ and the *number of flows* for news and sports. There is a considerable difference between news (46%) and sports (59%) for 5 flows, while a small change from 49% (news) to 51% (sport) for 40 flows. This indicates that the average rate in terms of the *number of sessions* is more suitable for a small number of fast moving video scenes than slow moving video scenes. This can also be observed from the CDF of the quantified δ for news and sport contents which is plotted in Figure 4.7. Figure 4.7 confirms the δ shown in Figure 4.6 that is δ over 50% is estimated higher for a smaller number of fast moving flows (5 sport flows in the figure) than the same number of slow moving flows (5 news flows in the figure). It shows a significant difference in δ between 5 news and 5 sport flows and a trivial difference between 40 news and 40 sport flows.

The uncertainty in the instantaneous arrival rate which is essentially caused by the burstiness of video traffic and/or rate adaptation strategy, will contribute negatively to decisions made by admission control procedures for a small *number*

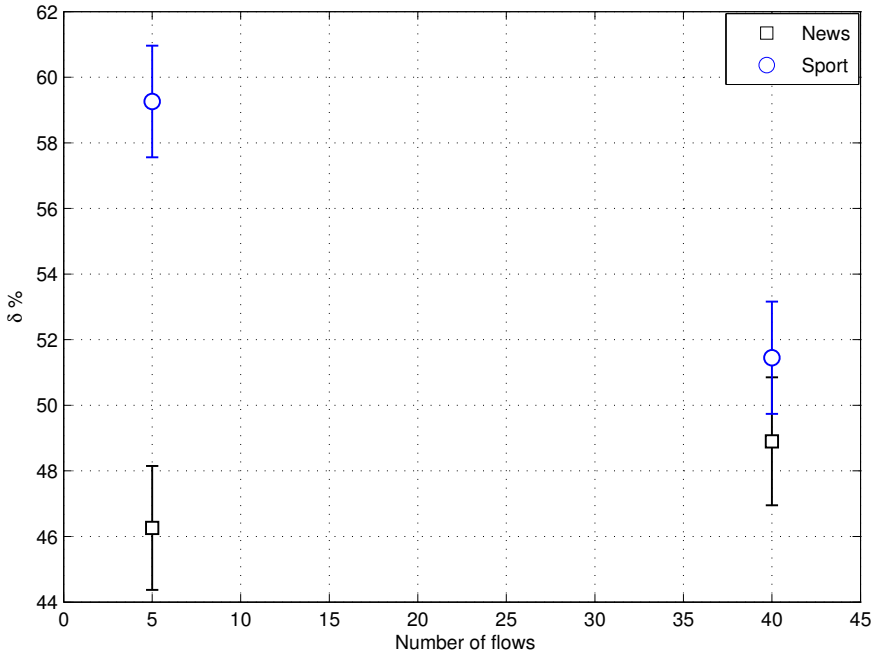


Figure 4.6: Mean and confidence interval of the probability relationship between the instantaneous and average aggregate rates for news and sport

of flows. At the time of admission decision, if the measured rate is at the minimum value, the bandwidth might be over-utilised due to acceptance of more sessions than the link can accommodate. In contrast, it might be under-utilised if the measured rate is at the maximum value due to rejection of sessions that could have been accommodated. To avoid this scenario, and utilise bandwidth more efficiently, the average aggregate arrival rate over a period of time is a more efficient decision factor to be taken by admission control procedures for a few *number of flows*. Thus, more flows are likely to be admitted and bandwidth is utilised more efficiently.

4.3.3 Impact and Setting of Measurement Time Window ($k\tau$) on δ

This section analyses the impact and setting of the measurement time window $k\tau$. An improper setting of $k\tau$ will contribute to bandwidth over-utilisation as explained below. As bandwidth availability is the main factor in making the admission decision for a new flow in an interval, $k\tau$ defines the degree of risk as-

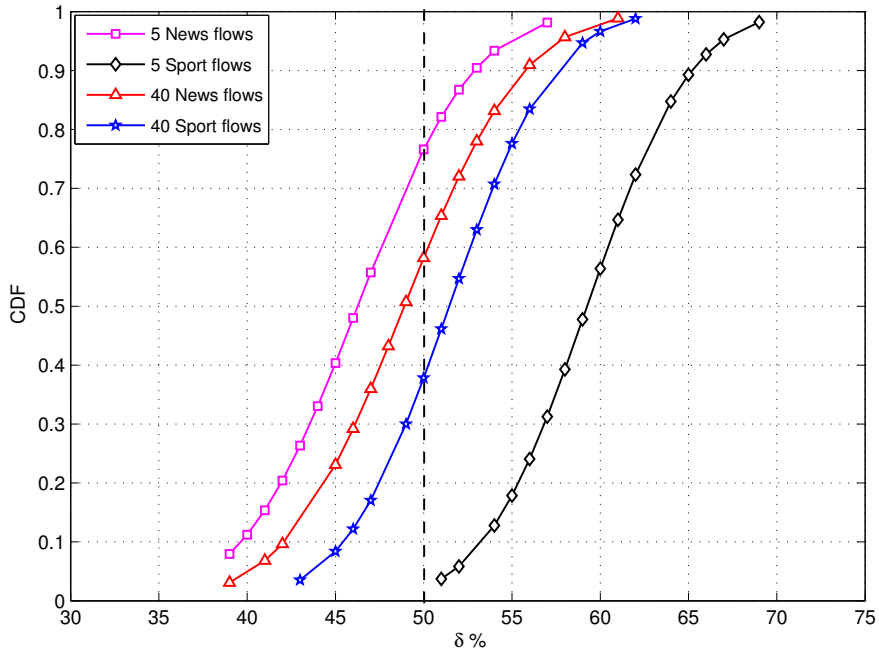


Figure 4.7: CDF of the probability relationship between the instantaneous and average aggregate rates for news and sport

sociated with this decision. If $\mu_r(t)$ is taken over short $k\tau$, the admission algorithm operates similar to admission procedures based on the instantaneous rate. This is due to that fact that $\mu_r(t)$ is close to $X_{inst}(t)$ for short intervals. In contrast, if $\mu_r(t)$ is taken over long $k\tau$, then the admission algorithm acts differently as $\mu_r(t)$ is likely to be less than $X_{inst}(t)$ for long intervals. This may cause bandwidth over-utilisation where more sessions are admitted by the admission algorithm risking the quality of existing video sessions. Figure 4.8 confirms the above interpretation: $\mu_r(t)$ has a higher likelihood estimation to be less than $X_{inst}(t)$ for a long measurement window. Figure 4.8 that the estimated δ increases for longer measurement windows.

Another concern for setting $k\tau$ is the operational environment such as the ISP domain where there is a continuous change in the number of video sessions. This is due to persistent admittance or release of sessions. $k\tau$ must allow measurement algorithms to estimate the average aggregate rate of existing sessions as a basis for its admission decision. Failure to do this, it allows new sessions to be admitted or rejected based on an outdated measured rate which may cause resource (bandwidth) over-utilisation or under-utilisation respectively. To workaround this

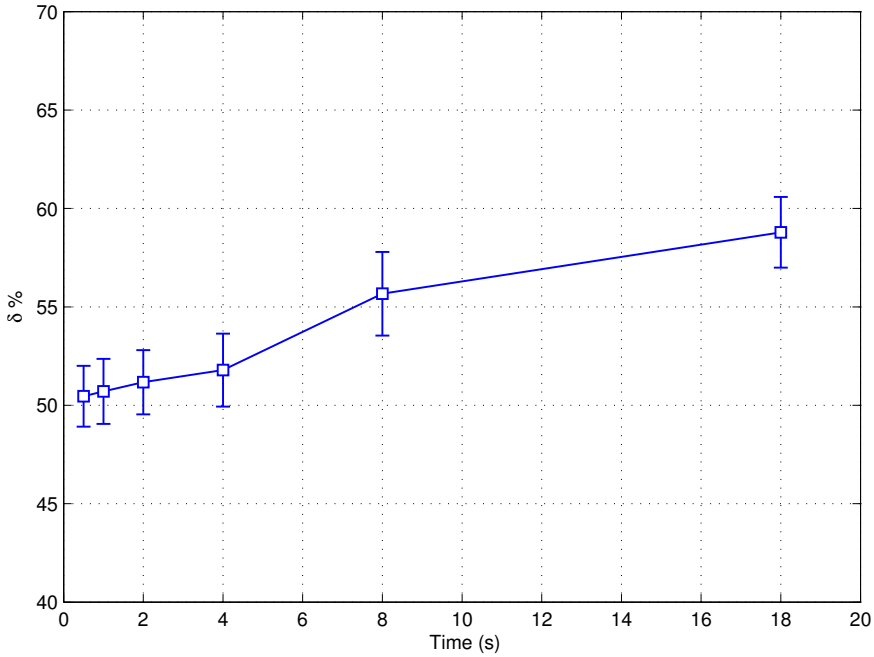


Figure 4.8: Mean and confidence interval of the probability relationship between the instantaneous and average aggregate rates of 40 flows for different measurement windows

issue, the average aggregate rate needs to be updated whenever a new flow is admitted/terminated, as well as at the end of each $k\tau$.

Further simulations were performed to investigate the impact of the measurement period on δ. Figure 4.8 shows the mean and confidence interval of δ for different measurement time periods for 40 flows. It can be seen that δ is higher for the longer periods than for the shorter. On the one hand, considering a longer measurement period provides higher probability that the average is less than the instantaneous rate which is likely to result in more sessions being accepted. On the other hand, it makes admission control less reactive to the changes in traffic rate as discussed above. To further confirm this interpretation, the CDF of δ for different measurement windows over 3000 simulation runs is plotted in Figure 4.9. This figure shows that the probability that the average is smaller than instantaneous exceeds 50% for larger measurement windows, for example 18 seconds in Figure 4.9.

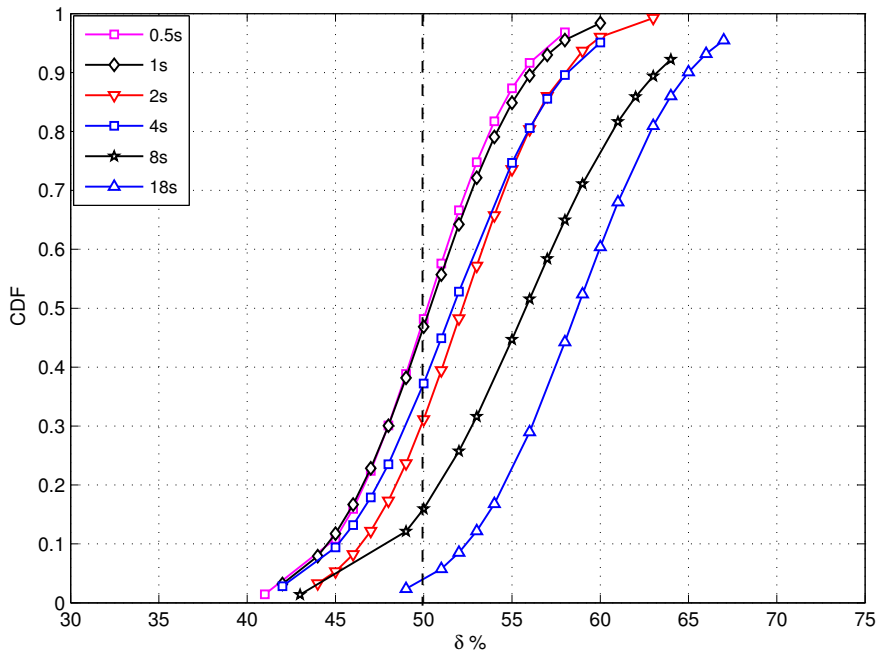


Figure 4.9: CDF of the probability relationship between the instantaneous and average aggregate rates for different measurement windows - 40 flows

4.4 Summary

In this chapter, we presented a mathematical model to quantify the probability relationship between the instantaneous and average rates in the context of video admission control. The average rate was found to be less than the instantaneous rate and potentially more efficient decision factor for admitting a small *number of flows*. This behaviour was more pronounced for fast moving video contents, such as sports, than for slow moving contents such as news. Whereas difference in rates is less significant for a higher *number of flows*, the average rate still does smooth the burstiness of the instantaneous aggregate rate and stabilise admission decisions.

In the next chapter, the average rate is implemented in the admission control of video sessions and compared to a proposed rate in terms of QoE and *number of sessions*.

Chapter 5

Protecting QoE through a QoE-Aware Measurement Algorithm

Admission control is a well known technique to keep traffic loads at acceptable levels and guarantee quality for admitted sessions via resource reservation. This idea has been adopted in the past in QoS architecture such as *Diffserv*. The aims of having admission control mechanisms are to guarantee the contracted QoS for real-time flows and achieve a higher network utilisation. Although, the core link capacity of networks has increased tremendously due to high-speed optical transmission links and high performance routers, high utilisation and performance guarantee remain challenging issues. This is mainly because admission controls lead to a trade-off between QoS and network utilisation. Explicit admission control can provide QoE where the network has the right to deny sessions to ensure that the QoE of current sessions is not affected by new accepted sessions. On the other hand, ISPs are concerned with maximising revenue by accepting as many sessions as possible.

To avoid congestion for non-adaptive traffic, binary-based admission control is the dominant technique (Latré 2011). Based on the resources available, it either allows or blocks new traffic. Inelastic traffic specify the maximum and minimum

bitrates during the admission process. The network nodes police the maximum rate to ensue that it is not exceeded, and attempt to guarantee the transmission of the minimum bit rate. These kinds of admission controls (which reserve a fixed amount of resources for each session) are suitable for services with constant bit rates such as voice telephony. However, such schemes are ineffective for video traffic with bursty bit rates. Furthermore, rate adaptation which potentially increases burstiness and rate variation, has been proposed as a tool to optimise video quality and QoE (Khalek et al. 2012, Politis et al. 2012, Rengaraju et al. 2012, Qadir & Kist 2013*a*).

MBAC has been proposed as a solution. In contrast to the parameter-based admission control, it is better suited to video traffic. The primary aim of MBAC is to eliminate or reduce the need for flow state information and control overheads. MBAC also maximises utilisation at an eventual cost of QoS degradation (Lima et al. 2007) with an emphasis on the computational complexity and characterisation of statistical multiplexing gains (Qiu & Knightly 2001). MBAC relies on the measurement of video characteristics such as current load and peak rate. Specifically, its functionality relies on the interval during which the traffic is measured. A long period makes MBAC less reactive to changes in the network load; whereas a shorter period leads to function similar to the traditional instantaneous rate-based admission control mechanisms.

Despite all the efforts, there is no entirely satisfactory admission algorithm for variable rate flows (Auge et al. 2011). Admission control algorithms must not rely on worst-case bounds or instantaneous video arrival rate, as they do not reflect the bursty characteristic of video traffic. This is due to the fact that the burstiness of video flows can be compensated by the silence of other flows. The IETF has standardised the PCN-based admission control (Eardley P. 2009) for the Internet (Menth & Lehrieder 2012) which merely relies on *CalR* for a measurement period. The perceived QoE-*number of sessions* relationship can be greatly optimised by exploiting the bursty nature of video traffic.

Chapter 4 concluded that there is no considerable advantage of the average over instantaneous aggregate rate for video flows. In that vein, a novel rate for video

admission that is QoE-aware is proposed. Relevant works are reviewed and the traffic rate measuring algorithm for video admission control mechanisms is presented. The proposed algorithm contributes to the measurement mechanisms for a QoE-aware admission control. Whereas traffic measurement algorithms and MBAC have been widely covered by the research community, the proposed algorithm includes QoE in the optimisation of QoE-*number of sessions* trade-off.

5.1 Related Work

MBAC has been studied for over a decade. It includes two main components: measurements of network load and admission policies. Since, the application of the measurement algorithms is primarily in admission control systems, they are reviewed also in this section. We refer interested readers of admission control procedures and classifications to (Menth et al. 2010, Lima et al. 2007, Wright 2007). MBAC algorithms are proposed for integrated service packet networks, e.g. (Jamin, Danzig, Shenker & Zhang 1997, Casetti et al. 1997). Four MBAC algorithms are presented in (Gibbens & Kelly 1997) based on Chernoff bounds. Several MBAC algorithms are presented to estimate the network load in (Breslau et al. 2000). Work presented in (Menth et al. 2010) provides a survey of PCN-based admission control and introduces PCN to the research community. Lima et al. (2007) compare the architecture of centralised, distributed, hybrid, class-based and active/passive MBAC and their limitations on the quality control of network services.

The changing nature of network traffic over an interval has been studied as an essential part of the MBAC functionality. Floyd (1996) has proposed an admission control scheme for controlled-load services that estimates the equivalent capacity of a class of aggregated traffic based on Hoeffding bounds. The work concludes that the equivalent capacity based admission is efficient for classes with as few as 50 connections. However it is similar to peak-rate admission control procedures for classes with only 10 connections. The work also presents a formulation of equivalent capacity that is suitable for classes with either a moderate number

of admitted connections or a wide range in peak rates of admitted connections. The suitability of the average instead of the instantaneous arrival rate for video streaming admission decision has been investigated in (Qadir & Kist 2013*b*).

Work presented in (Auge et al. 2011) proposes a MBAC scheme based on measured mean and variance of load offered to a cross-protect priority queue. As traffic flow rate is only meaningful when it is associated with a corresponding interval length. A measurement algorithm and an admission control algorithm for the MBAC have been introduced by Qiu & Knightly (2001). The algorithms employ adaptive and measured peak rate envelopes of aggregate traffic flows to allocate resources for multiclass networks with link sharing. The flows' behavior as a function of interval length is described by a proposed rate envelope. The envelope characterises extreme values (maximal rates) of the aggregate flow to avoid packet loss. A new flow is admitted by the proposed admission algorithm if predicted performance parameters, such as packet loss and delay, satisfy the QoS requirements of both the new and existing flows.

Ammar et al. (2012) introduced a knowledge-base admission control scheme which determines whether to accept a flow based on QoS performance parameters such as maximum tolerable delay or packet loss rate. The proposed scheme achieves a good trade-off between flow performance and resource utilisation when compared to (Jamin, Shenker & Danzig 1997) and (Qiu & Knightly 2001). Nam et al. (2008) proposed a delay-aware scalable admission control scheme which guarantees the delay bound for delay sensitive applications. The scheme relies on a threshold called admissible bandwidth. The calculation of the admissible bandwidth is a crucial part of the proposed admission control to optimise the delay-utilisation trade-off. An accurate estimation of the admissible bandwidth guarantees the delay bound of admission-controlled traffic for moderate delay bounds while maintaining high utilisation.

The efficiency of the MBAC algorithms depends on interactions on several timescales, ranging from very short time scales to the entire session. Nevin (2010) has studied how uncertainty in the measurement of MBAC varies with the length of the observation window and has described a methodology for analysing measure-

ment errors and performance. The concept of similar flows and adding slack in bandwidth were introduced to minimise the probability of false acceptance.

Admission control has also been proposed to better support applications with QoS requirements in wireless networks. Appropriate thresholds for admission decision have been studied by Xu et al. (2013). A flow-level mechanism for a multiple antennas equipped node to maximise flow acceptance and improve network throughput, has been introduced by Hamdaoui & Ramanathan (2007). A QoE-based admission control for wireless networks has been proposed by Piamrat et al. (2008). Access points control video sessions based on the MOS scores computed by a pseudo-subjective quality assessment tool run on the access point. Most recently, Chendeb Taher et al. (2014) proposed a model-based admission control algorithm to predict QoS metrics. An appropriate decision for new flows is taken based on the algorithm and QoS constraints of the flows. The average number of satisfied users has been maximised in (Lee et al. 2014) through a QoE-aware scheduling framework by sending a single bit feedback to indicate the satisfaction level.

Other studies have compared the performance of MBAC algorithms. The simple sum; a parameter-based admission control algorithm has been compared to three measurement-based algorithms; the measured sum, acceptance region and equivalent bandwidth in (Jamin, Shenker & Danzig 1997). The comparison was based on the link utilisation and adherence to service commitment through the simulation of single and multiple-hop scenarios. The robustness of (Floyd 1996), (Jamin, Shenker & Danzig 1997) and (Qiu & Knightly 2001) in meeting the QoS target have been compared in (Nevin et al. 2008). They have been further evaluated without assuming any explicit knowledge on incoming flows or on-going traffic by Ammar et al. (2011) based on maximum tolerable packet loss rate and maximum packet queuing delay. All of the three studied algorithms were found to meet the first target of maximum tolerable packet loss rate while only (Qiu & Knightly 2001) was able to always meet the second target of maximum packet queuing delay.

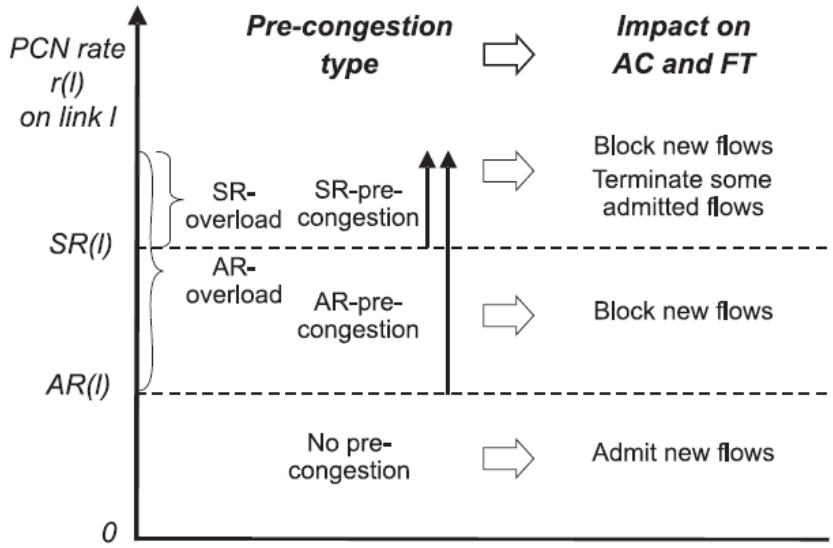


Figure 5.1: The admissible and supportable rate *AR(l)*, *SR(l)* defines three types of pre-congestion. Adopted from (Menth et al. 2010)

Yerima (2013) has concluded that the combination of MBAC and parameter-based admission control can improve the admission control and network utilisation efficiency. Moore (2002) has conducted an implementation-based comparison of MBAC algorithms using a purpose built test environment. The study found that there is no a single ideal MBAC algorithm due to computation overheads, multiple timescales present in both traffic and management, and error resulting from random properties of measurements which dramatically impact the MBAC algorithm's performance.

As a cutting edge proposed admission control mechanism for multimedia network, PCN-based admission control (Eardley P. 2009) has attracted the attention of researchers. PCN defines admissible rate *AR(l)* and supportable rate *SR(l)* thresholds for each link l. Figure 5.1 illustrates these thresholds.

There is no pre-congestion and further flows may be admitted if the PCN traffic rate *r(l)* is below *AR(l)*. The link is considered AR-pre-congested and no further flows are admitted if the PCN traffic rate *r(l)* is above *AR(l)* (AR-overload). If the PCN traffic rate *r(l)* is above *SR(l)* (SR-overload), the link is SR-pre-congested. In this case, no further flows are admitted and some already admitted flows will be terminated.

Several modifications to the PCN algorithm have been proposed in (Latré, Klaas, Wauters & DeTurck 2011). An extension to the PCN-based admission control system was proposed in (Latré, Vleeschauwer, Meerssche, Schepper, Hublet, Leekwijck & Turck 2011). A novel metering algorithm based on a sliding-window, to cope with the bursty nature of video sessions and another adaptive algorithm to facilitate the configuration of the PCN have been proposed.

The performance of PCN-based admission control is investigated in (Menth & Lehrieder 2012) under different challenging conditions such as insufficient flow aggregation, long-trip times, delayed media, on/off traffic, inappropriate marker configuration, smooth feedback and multipath routing. Overadmission is caused due to late blocking for PCN-based on threshold marking while it is caused by weak precongestion signals for PCN-based on excess traffic marking.

Most of the MBAC algorithms that have been discussed in the literature are per-aggregate algorithms. Jiang et al. (2005) proposed a per-flow MBAC algorithm for flow-aware networks in which dynamic priority scheduling is adopted to aggregate flows. A newly admitted flow is given a lower priority by the proposed algorithm, however its priority is improved when an existing flow leaves. An enhancement to MBAC has been proposed to mitigate the impact of fair rate degradation and ensure better quality in flow-aware networks by Wojcik et al. (2013).

Zhang, Xu, Hu, Liu, Guo & Wang (2013) have proposed a video quality model for Skype video calls based on measurements which can be used for user QoE-aware network provisioning. The model can find the minimum bandwidth needed to accommodate a number of concurrent Skype video calls with satisfactory MOS. Xu et al. (2014) have conducted a study to investigate the system architecture, video generation and adaptation, packet loss recovery, and QoE of video-conferencing solutions. iChat, Google+, and Skype were all covered in the work. The delivered quality was measured in terms of the end-to-end delay in a wide range of real and emulated network scenarios. The study found that the layered video coding and server architecture (used by Google+ and Skype) can significantly improve user conferencing experiences. As a supporting mechanism in flow and admission control, techniques have been developed for estimating available band-

width (Nam et al. 2012, Guerrero & Labrador 2010, Nam et al. 2013, Lubben et al. 2014, Cavusoglu & Oral 2014).

In this study, we include QoE in the area of the QoE-*number of sessions* optimisation. The proposed measurement algorithm implemented in a QoE-aware admission control, maintains QoE of video sessions at required level. Details are discussed in Section 5.3.

5.2 Assumptions

The work in this chapter is based on the following assumptions:

- Video traffic is the dominant Internet traffic (Cisco documentation 2014*a*). It is the only traffic subject to admission control. Other traffic volumes are small in comparison and therefore only video traffic will be considered
- Video traffic is bursty in nature as video applications generate traffic at a very variable rate (Nevin 2010)
- Explicit admission control is required to provide an acceptable level of QoE on bottleneck links (Nevin 2010)
- "Flash crowds" are not considered, i.e. many admission requests that arrive within the reaction time of admission mechanism are admitted and network overloaded (Eardley P. 2009)
- MOS Fairness among sessions is not an objective of this study, i.e. the goal for video quality is to ensure the minimum required level of MOS for each session, but not necessary all sessions are scored with the highest MOS level
- This study assumes that the access network (links between the video sources and the ISP gateway in Figure 1.2) is not the bottleneck.

5.3 Proposed Models

In this section, a novel algorithm for traffic measurement supported by a mathematical model is proposed. The algorithm measures the exceedable video aggregate rate that is able to keep the video quality unimpaired. The exceedable rate is the total bitrate of enrolled video traffic that can exceed the available link capacity without degradation to the user's perception of quality. The proposed measurement algorithm is then investigated in a QoE-aware admission control procedure for video admission.

The relationship between the *Instantaneous Aggregate Arrival Rate* (*IAAR*) and the proposed rate is established mathematically. We call the proposed measured rate "*Proposed Instantaneous Aggregate Arrival Rate*" (*Pro-IAAR*) and the proposed admission control procedure based on *Pro-IAAR* "*Pro-IAAR-Based Measurement Admission Control*" (*Pro-IBMAC*). We also call the admission control procedures which are based on *CalR* such as PCN, "*CalR-Based Admission Control*" (*CBAC*).

5.3.1 Proposed Model for Measurement Algorithm

In this section, we describe a new approach to measure traffic rate that suits video traffic. For the benefit of comparison, we introduce the traditional approach of traffic measurement *IAAR* then present our proposed measurement algorithm *Pro-IAAR*. Since, the measurement mechanism is proposed for video admission procedures, it is modelled as a part of the proposed admission control scheme *Pro-IBMAC*. *IAAR* at any time $t>0$ and $i>0$ can be expressed by Equation (5.1)

$$IAAR(t) = X_{inst}(t). \tag{5.1}$$

Assuming that $x_i(t)$ is a discrete random variable that takes any set of values from a finite data set $x_1(t)$, $x_2(t)$, ... $x_n(t)$ each of probability $p_1(t)$, $p_2(t)$, ... $p_n(t)$ respectively.

A new session will be accepted by *CBAC*, only if the sum of *CalR(k)* for the time window $k\tau$ plus the peak rate of the new session R_k is less or equal to the link capacity C_l as given by Equation (5.2)

$$CalR(k) + R_k \leq C_l. \tag{5.2}$$

In our proposed scheme we consider *Pro-IAAR(t)* as an admission parameter instead of *CalR(k)*. Now we find how *Pro-IAAR(t)* is related to *IAAR(t)*. We utilise the Hoeffding inequality theorem (Hoeffding 1963) to develop a model for the proposed *Pro-IAAR(t)*. The reason behind this approach is that the Hoeffding theorem relates *IAAR(t)* and the average of *IAAR(t)*; $\mu_r(t)$ through Equation (4.2). Then we develop a relationship between the *Pro-IAAR(t)* and *IAAR(t)*. Hoeffding bound was first used for admission control algorithms by Floyd (1996).

From Equations (4.4) and (5.1), $\mu_r(t)$ can be formulated by Equation (5.3)

$$\mu_r(t) = \mathrm{E}\langle IAAR(t)\rangle = \sum_{i=1}^{n} x_i(t)\ p_i(t). \tag{5.3}$$

The term $\mu_r(t)+n\epsilon$ in Equation (4.2) represents the proposed *Pro-IAAR(t)* which is given by Equation (5.4) and ϵ is given by Equation (5.5). The proof of Equation (5.5) is provided in Appendix A.

$$Pro\text{-}IAAR(t) = \mu_r(t) + n\epsilon. \tag{5.4}$$

$$\epsilon = \beta\mu_r(t)\frac{n-1}{n} \qquad 0 < \beta \leq 1. \tag{5.5}$$

Parameter β reflects how much the total bitrate of enrolled video traffic can exceed the available link capacity without degrading the quality perceived by end users. It governs the degree of efficiency of the proposed *Pro-IBMAC*. Therefore, choosing the proper value for β controls the degree of risk of the admission decision as it balances the QoE-*number of sessions* trade-off relationship. The value of β that optimises this relationship is referred to as "proposed value" in this dissertation. The condition $\epsilon>0$ of Equation (4.2) is satisfied by setting $\beta>0$ in Equation (5.5) (assuming that n>1). Although Equation (5.5) is also valid for $\beta>1$, the scope of the proposed scheme is only for $0<\beta\leq 1$. High values of β within this range lets *Pro-IBMAC* function similar to traditional admission control mechanisms, while a smaller value leads to accepting more sessions and compromising QoE. We propose a model for β in Section 5.3.2.

A new requested session will be accepted by *Pro-IBMAC* if the condition in Equation (5.6) meets

$$Pro\text{-}IAAR(t) + R_k \leq C_l. \tag{5.6}$$

Substituting Equations (5.3) and (5.5) into Equation (5.4), then Equation (5.4) into Equation (5.6), we get

$$\sum_{i=1}^{n} x_i(t)\ p_i(t)\{1+\beta(n-1)\} + R_k \leq C_l. \tag{5.7}$$

In Equation (5.7), R_k is the peak rate for a new session and C_l is the link capacity. Studies recommend that peak rate be measured for R_k using techniques such as token buckets (Floyd 1996) and traffic envelopes (Qiu & Knightly 2001). Others compute the peak rate of a new incoming flow by tracking the first A (where A is a positive integer) packets of the flow and using a sliding window (Ammar et al. 2012). R_k over interval $k\tau$ can be given by Equation (5.8) (Qiu & Knightly 2001)

$$R_k = \frac{1}{k\tau}\ \max\ Y(k). \tag{5.8}$$

Table 5.1: Description of video sequences used in Chapter 5

Description	**Video sequence 1**	**Video sequence 2**
Name	Mother And Daughter (MAD)	Paris
Description	A mother and daughter speaking at low motion	A woman playing with a ball and a man spinning a pen continuously at high motion
Frame size	CIF (352x288)	CIF (352x288)
Duration (second)	30	35
Number of frames	900	1065

In summary, the proposed *Pro-IBMAC* in Equation (5.7) employs *Pro-IAAR(t)* in Equation (5.4) which is based on the Hoeffding inequality theorem. The value of δ in Equation (4.3) specifies the level of optimisation (in terms of *number of sessions* that can be fitted on a particular link) achieved by considering *Pro-IAAR(t)* compared to *CalR(k)* in Equation (5.2).

5.3.2 Proposed Model for β

The tunable parameter β affects the operation of the proposed algorithm. The value can be set to optimise the trade-off relationship between *QoE* of enrolled sessions and *number of sessions*. In this section, we develop a model for β. We estimate the value of β using two publicly available video sequences; a 30 second clip called Mother And Daughter (MAD) and a 35 second clip called Paris. A snapshot of the video sequences are shown in Figure 5.2. These two video sequences are used to validate the proposed β model for various video contents. Similar short sequences have also been used for video streaming service and subjective tests (Khan et al. 2012).

While choosing the videos, the following points were taken into consideration:

1. Long video is not practical for subjective tests in which subjects evaluate a numbers of videos.

Figure 5.2: Snapshots of the video sequences used in Chapter 5, MAD (left) and Paris (right)

2. Since the aim was to evaluate the admission control-specifically the acceptance or rejection of sessions-and evaluate the admission rate, the duration of video is not expected to have effect on the evaluation of the proposed algorithm.

The MAD sequence was taken as slow moving content due to the low motion of its video scenes, and Paris as fast moving content due to fast motion of its video scenes. This classification is based on common convention and the size of their encoded frames, as faster content produces larger frame sizes. Other studies have classified video contents in a similar way, e.g. (Khan et al. 2012). Details about the video sequences are shown in Table 5.1. Other simulation settings including the coding and network parameters are explained in Section 5.4.

We ran extensive simulations to find parameters that potentially affect β. C_l, n and QoE were found to have impact on β. QoE was estimated by the *simulated MOS* which will be explained in Section 5.4. To understand the impact of any of these parameters on β; the values of the other two parameters (controlling parameter) were kept fixed. Figures 5.3, 5.4 and 5.5 show the relationship between β and each of C_l, n and QoE. The values of the controlling parameters for both sequences are also shown in these figures.

Empirical Equation (5.9) shows the mathematical relationship between these four parameters. However, in this study we focus on a value of β that produces excellent quality (MOS=5) only. Thus QoE was not considered as a variable in the proposed model of β. The exponential relationship between β and QoE

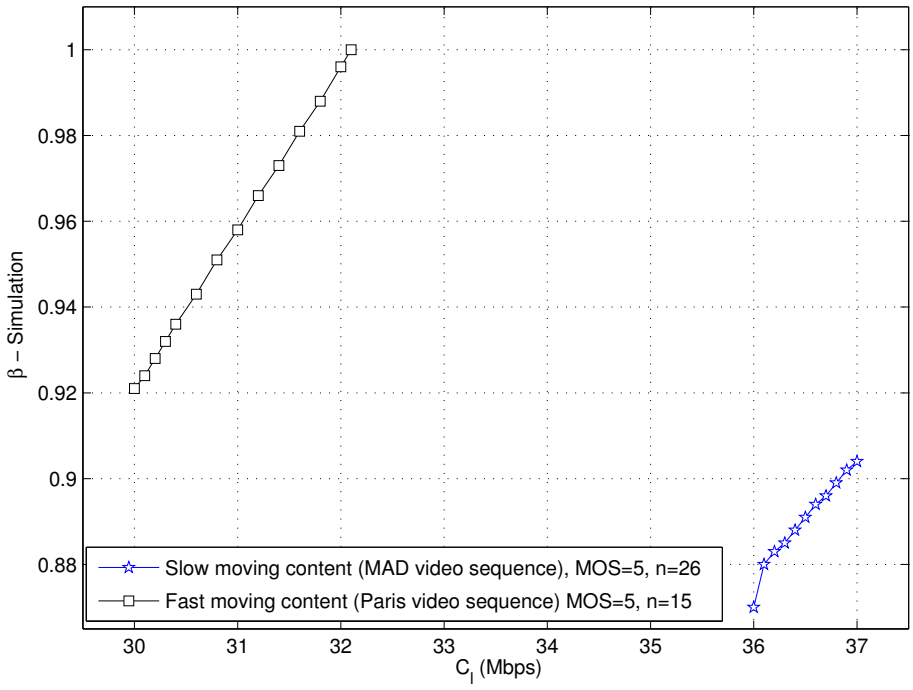


Figure 5.3: β - Link capacity relationship

shown in Figure 5.5 will be included to the model of β in future studies to obtain multi-class MOS.

$$\beta \propto \frac{\text{QoE}, C_l}{n}. \tag{5.9}$$

The simulation data was analysed with 2-way repeated ANOVA (Miller & Brown 1997) to confirm the significance of C_l and n in modelling of β. The method also finds the difference between means given by the remaining two parameters C_l and n. ANOVA lets us understand the effect of parameters and their interaction on β which will later be used in regression modelling. The ANOVA results are shown in Table 5.2 for *F-statistics* and *p-values*. Parameters with (p<0.01) are considered to have significant impact on β. The analysis indicates that β is affected by each of C_l and n as *p-values* are 0 and 0.0023 respectively. The result also shows that there is no interaction effect of both parameters on β because *p-value* is 0.6249. This can be justified by the fact that n is determined by C_l, the higher capacity of the link, the higher the *number of sessions*. Based on the values of p in Table 5.2, we can conclude that β is affected more by C_l than by n.

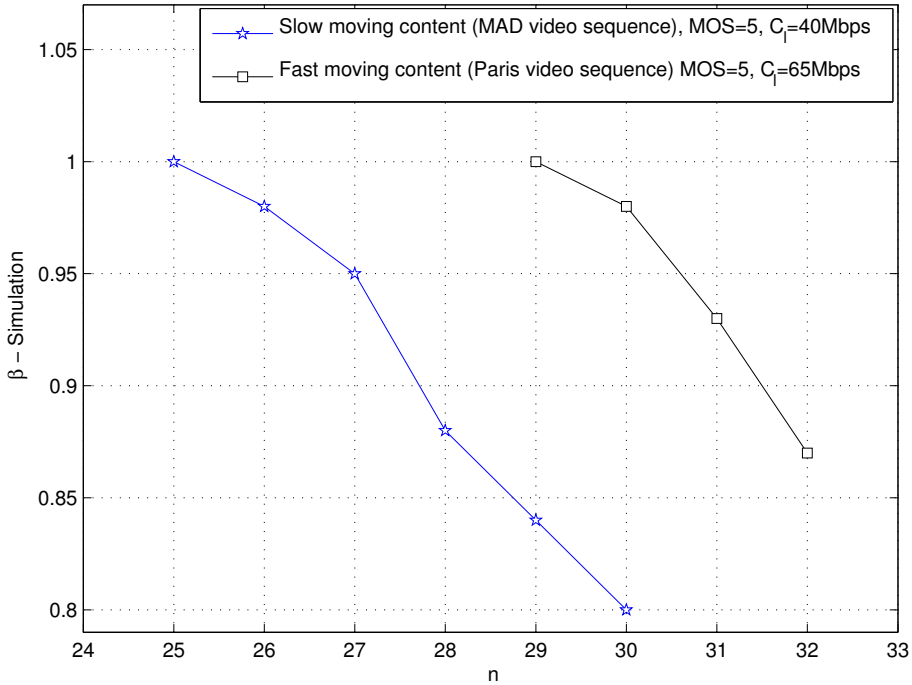


Figure 5.4: β - *Number of sessions* relationship

The relationship between β, n and C_l can be established from the ANOVA analysis and Figures 5.3, 5.4 and 5.5. We found that there is a linear relationship between β and C_l and a polynomial relationship between β and n. Finally, the rational model shown in Equation (5.10) was formulated to estimate the value of β from nonlinear regression analysis of the simulation data using MATLAB

$$\beta = \alpha + (\frac{C_l}{\sigma * n}). \tag{5.10}$$

The values of the coefficients of Equation (5.10) are listed in Tables 5.3 and 5.4. As n is determined by the size of video frames (content dependent), different values for the model coefficients were found for slow (MAD sequence) and fast (Paris sequence) moving contents. Tables 5.3 and 5.4 also shows the correlation coefficient (R^2) and Root Mean Squared Error (RMSE) of the proposed model for both contents.

The model for β has been proposed based on two video sequences (MAD and Paris), however the methodology applies to faster moving content as well. However, specific parameters of the model are limited to the video format and coding

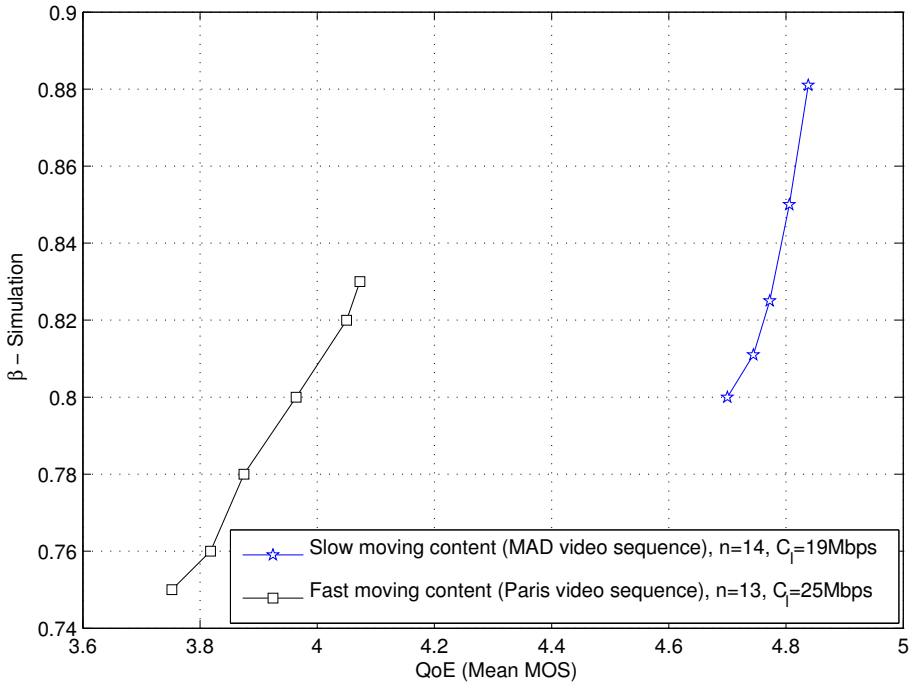


Figure 5.5: β - QoE relationship

parameters used in this simulation. The model can be applied to other formats and coding parameters with different coefficients. Other formats and/or coding parameters generate different frame sizes and bit rates which control the *number of sessions* (parameter n in the model) for a specific link capacity (parameter C_l in the model). They only have impact on the value of the coefficients of the model. The model will be validated by CIF and QCIF video formats in Section 5.7.

Table 5.2: ANOVA results for main and interaction effects

Source	**Sum of squares**	**Degree of freedom**	**Mean squares**	**F-statistics**	**p-values**
C_l	0.33001	1	0.33001	720.02	0
n	0.01807	2	0.00903	19.71	0.0023
C_l *n	0.00047	2	0.00023	0.51	0.6249

Table 5.3: Coefficients of β prediction model and model validation correlation coefficients-slow moving content (MAD video sequence)

α	σ
-0.5429	0.9689

Adjusted R^2 (Validation)	RMSE (Validation)
%88.44	0.0149

5.4 Evaluation Environment

Since the number of admitted sessions for a specific link capacity is the target of this study, only the acceptance/rejection admission control policy was investigated. The queue size and simulation time were chosen so as not to cause packet drops due to insufficient queue length or time. The video format such as CIF or QCIF impacts the number of admitted sessions due to the difference in the size of encoded frames. In this chapter, CIF (352x288) is assumed for input video as an acceptable video format for most video capable devices such as handsets and mobiles (Khan et al. 2012). It is also suitable for videoconferencing systems delivered on telephone lines. While modern devices support much higher resolution, CIF makes packet level simulation practical. A bottleneck link of the dumbbell topology similar to Figure 3.2 was used for evaluating the proposed *Pro-IBMAC* scheme. In addition to β, link capacity was the main variable in the simulation. Other parameters such as link delay, queue length and packet size were kept fixed. Lost packets were replaced with 0 by the etmp4 (Gross et al. 2004) decoder as a way of coping with losses. The values of the simulation parameters and settings are shown in Table 5.5.

Table 5.4: Coefficients of β prediction model and model validation correlation coefficients-fast moving content (Paris video sequence)

α	σ
-0.1227	1.952

Adjusted R^2 (Validation)	RMSE (Validation)
%90.54	0.0124

Table 5.5: Encoder and network settings

	Parameter	Value
Encoder	Frame size	CIF (352x288)
	Frame rate	30fps
	GoP	30
Network	C_l (Mbps)	22, 24, 30, 36, 39, 40
	Topology	Dumbbell
	Packet size (byte)	1024
	UDP header size (byte)	8
	IP header size (byte)	20
	Queue size (packet)	5300
	Queue management algorithm	Droptail
	Queue discipline	FIFO (First In First Out)
	Simulation time (second)	500

New sessions were requested randomly and continuously every second. They were accepted as long as enough bandwidth was available on the bottleneck link, i.e: Equation (5.7) was satisfied. NS-2 (n.d.) was used to measure *CalR(k)* and *Pro-IAAR(t)* and implement *CBAC* and *Pro-IBMAC*. The implementation of the proposed *Pro-IBMAC* is summarised in Algorithm 1.

The time window $k\tau$ impacts the operation of the admission control. The smaller the value of $k\tau$, the more conservative the admission control and more sensitive to the traffic bursts. The larger the value of $k\tau$, the smoother the measured rate and less reactive to the changes in the network load. In practice, $k\tau$ will be a few seconds (Latré 2011). In this dissertation, *IAAR(t)* was averaged over one second.

Algorithm 1 Proposed *Pro-IBMAC*

```
    Given C_l, R_k, n, α, and σ
 1: for Every video session request do
 2:     Compute μ_r(t) from Equation (5.3)
 3:     Compute β from Equation (5.10)
 4:     Compute ε from Equation (5.5)
 5:     Compute Pro-IAAR(t) from Equation (5.4)
 6:     if Equation (5.7) = True then
 7:         Request accepted
 8:     else
 9:         Request rejected
10:     end if
11: end for
```

The MAD video sequence described in Table 5.1, was fed to the NS-2 simulator using EvalVid (Gross et al. 2004). In addition to the MOS metric, we calculated the Distortion In Interval (DIV) metric (Gross et al. 2004) to restrict the MOS metric within a fixed interval (30 frames in this study). This stringent metric calculates the maximum percentage of received frames with a MOS smaller than that of the sent frame within a given interval.

The efficiency of the proposed *Pro-IBMAC* and *CBAC* was evaluated based on *QoE*, n, packet drop ratio, and mean delay. These performance metrics were chosen due to their impact on multimedia traffic such as video. The performance of *Pro-IBMAC* was tested on finding the maximum number of video sessions on a bottleneck link while keeping the *QoE* of each session at acceptable or required level. This was compared to other procedures such as *CBAC*. The objective was to see how *Pro-IBMAC* utilises the available bandwidth compared to *CBAC*. Further simulations were used to investigate the effect of parameter β on the performance metrics.

5.5 Results and Discussions

This section presents the simulation results and discussions. The proposed *Pro-IBMAC* is compared to *CBAC* in terms of MOS and *number of sessions*, packet drop ratio, and delay in Section 5.5.1. The impact of β on the functionality of *Pro-IBMAC* is discussed in Section 5.5.2.

5.5.1 *Pro-IBMAC* vs *CBAC*

We found that there is a considerable difference between the two schemes in terms of the *number of sessions*. The *number of sessions* for *Pro-IBMAC* and *CBAC* is plotted in Figure 5.6. It is always higher for *Pro-IBMAC*. The difference between the *number of sessions* increases with a rise in the link capacity. For example, the *number of sessions* to 22Mbps link is 15 against 14 for *Pro-IBMAC* and *CBAC*

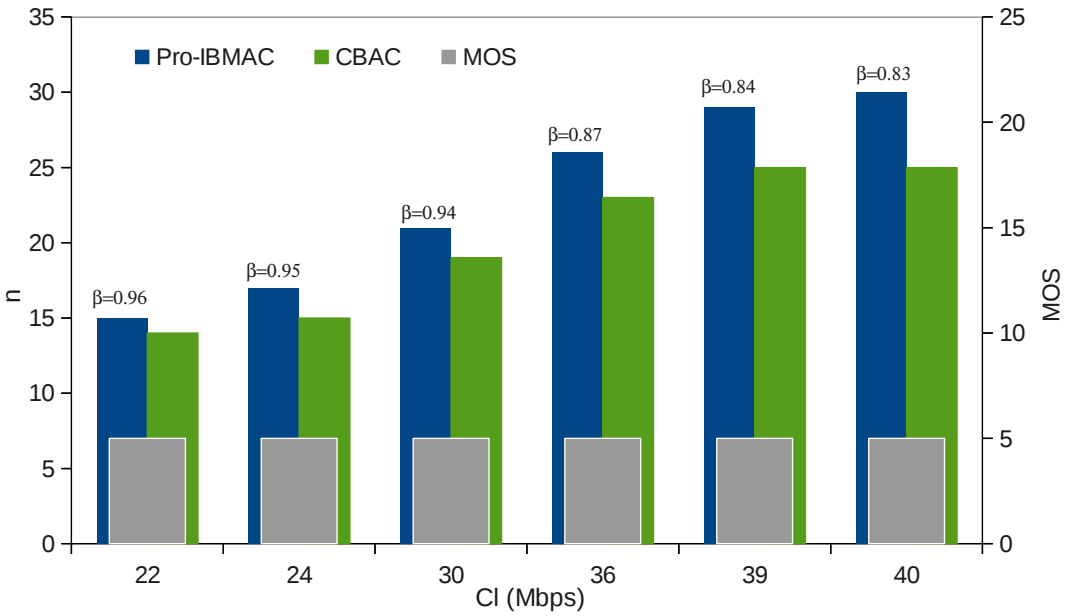


Figure 5.6: MOS of the *CBAC* and *Pro-IBMAC* admitted sessions

respectively, whereas it is 30 against 25 in the case of 40Mbps link. The main role of any admission control is to ensure that the acceptance of a new session does not violate the *QoE* of on-going sessions. We have computed the MOS of every single accepted session for both schemes. We have found that the increase in the *number of sessions* does not come at the cost of QoE as all accepted sessions by *Pro-IBMAC* and *CBAC* scored a MOS of 5. Note that the MOS of video sessions is labelled on the secondary y-axis of Figure 5.6. The value of β that produces this increase in the *number of sessions* and guarantees video quality is also shown in Figure 5.6. This will be further described in Section 5.5.2.

This simulation outcome can not be generalised. *Pro-IBMAC* may not guarantee the same level of *QoE* as *CBAC* in real implementations. This is because our

Table 5.6: Packet drop ratio and admitted sessions of *Pro-IBMAC* and *CBAC*

				Pro-IBMAC		***CBAC***
C_l **(Mbps)**	**Packet drop ratio %**	**MOS**	***DIV* %**	β	n	n
22	0	5	0	0.96	15	14
24	0	5	0	0.95	17	15
30	0	5	0	0.94	21	19
36	0	5	0	0.87	26	23
39	0	5	0	0.84	29	25
40	0	5	0	0.83	30	25

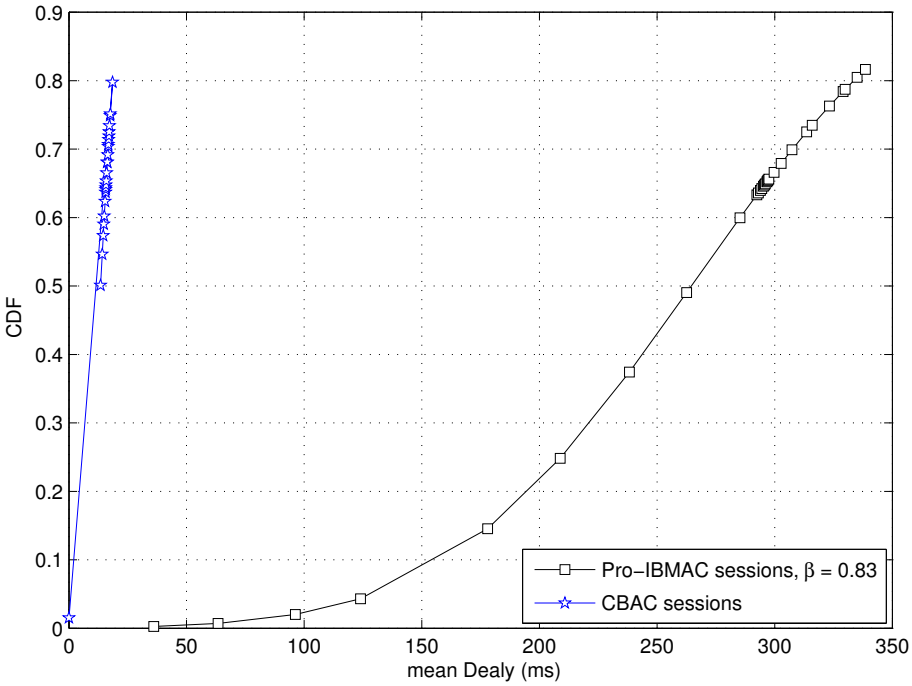


Figure 5.7: CDF of the mean delay of the *CBAC* and *Pro-IBMAC* sessions

proposed scheme is based on a probabilistic approach. Therefore, there is a possibility of the upper bound being lower than the bursty instantaneous rate, especially for small $k\tau$. In this case, the upper bound will be extremely low.

Table 5.6 shows mean MOS and *DIV*. A *DIV* value of zero percent indicates that all received frames have the same MOS as that of the original frames. It also lists the packet drop ratio of the accepted sessions for *Pro-IBMAC* and *CBAC* for each link. Since we aim for a β value that doesn't degrade the MOS of received videos as mentioned in Section 5.3.2, no packet drops were expected.

As for the delay, we measured the mean delay using the NS-2 trace files for both schemes. Figure 5.7 illustrates the CDF of the mean delay for *Pro-IBMAC* and *CBAC* sessions for 40Mbps link. As shown in Table 5.6, 30 sessions are accepted by *Pro-IBMAC* for β=0.83 and 25 by *CBAC*. More sessions on the same link caused a linearly higher delay due to more buffering for *Pro-IBMAC*. The *Pro-IBMAC* sessions therefore, experienced higher delays compared to the *CBAC* sessions. Nevertheless, increases in delay that come at the cost of the QoE-*number of sessions* optimisation can not be tolerated by real-time video traffic. For *Pro-IBMAC* to be applicable to realtime traffic, a proper value of β must

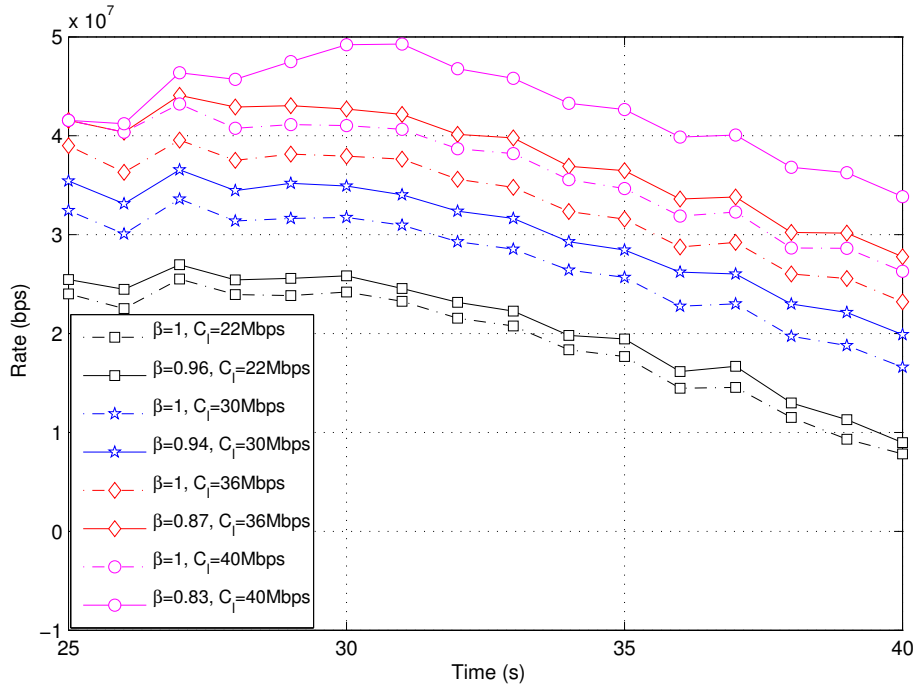


Figure 5.8: *IAAR* and upper limit of the exceedable rate for different link capacities over time period

be selected. Video streaming services can tolerate a delay of up to 5 seconds (Li 2014, Szigeti & Hattingh 2004), thus the model can be used within this limit. In future work, we will further investigate the impact of delay and develop the model of β to include delay as another variable.

5.5.2 Impact of β on *Pro-IBMAC*

As mentioned in Section 5.3.1, parameter β controls the level of risk between the admission decision and QoE of existing sessions. Figure 5.8 shows *IAAR(t)* (dash-dot line) and the upper limit of the exceedable aggregate rate (solid line) versus the simulation time for a number of different C_l. The proposed value of β for four scenarios (22, 30, 36, and 40Mbps) is shown in Figure 5.8. It can be seen that the lower the value of β, the wider the gap between the two rates.

Decreasing β causes an increase in the limit of the exceedable rate. This makes *Pro-IBMAC* flexible and accepts more sessions. This can be better observed in Figure 5.9. It depicts admitted sessions for different link scenarios. The solid line

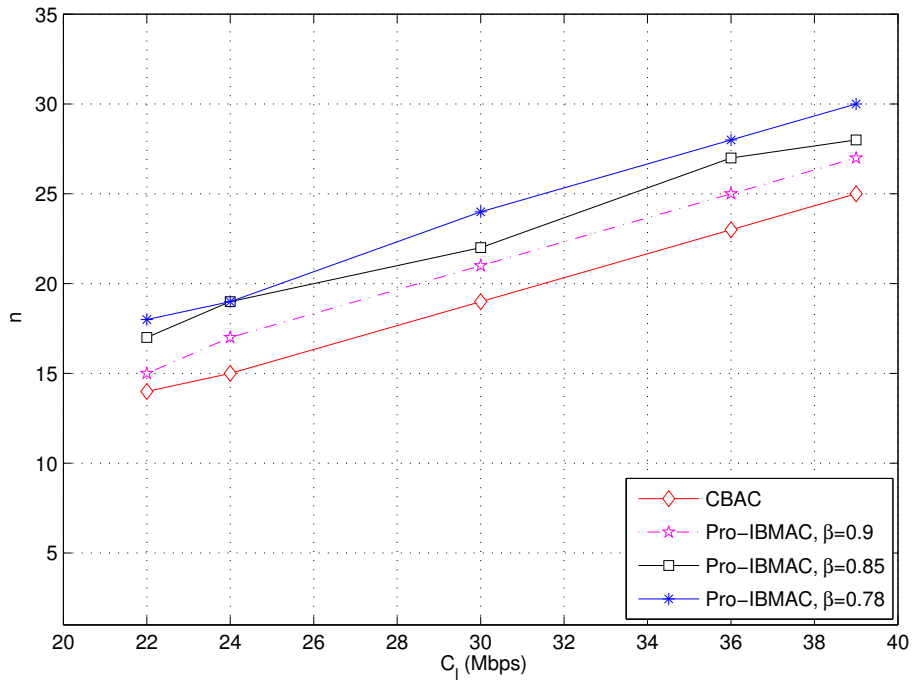


Figure 5.9: Admitted sessions of *CBAC* and *Pro-IBMAC* for different link capacities

shows the *number of sessions* admitted by *CBAC*, while the other three lines show sessions admitted by *Pro-IBMAC* for three different values of β (0.9, 0.85 and 0.78). For the same link, the linear relationship between the *number of sessions* and link capacity allows more sessions to be accepted by lowering the value of β. For instance, for a 39Mbps link, *Pro-IBMAC* accommodates 27, 28 and 30 sessions for β=0.9, 0.85 and 0.78 respectively compared to 25 sessions of *CBAC*. Note that $\beta \geq 0.84$ guarantees accepted sessions with MOS of 5 as shown in Table 5.6.

However, continuously decreasing β degrades the QoE of admitted sessions as more sessions are accepted. Therefore, care is required to fine tune the value of β that optimises the operation of *Pro-IBMAC*. The aim is to accept as many sessions as possible, while keeping the QoE of the sessions at required levels. As per the proposed model, the value of β depends on C_l, n and required *QoE*. We investigated this further for 22Mbps and 24Mbps links. Figure 5.10 shows the *number of sessions* with MOS of 2, 3, 4 and 5 separately, as well as the total *number of sessions* for 22Mbps link. If we consider that the required class of QoE is MOS 5, then the proposed value of β is 0.96, i.e. for β less than 0.96,

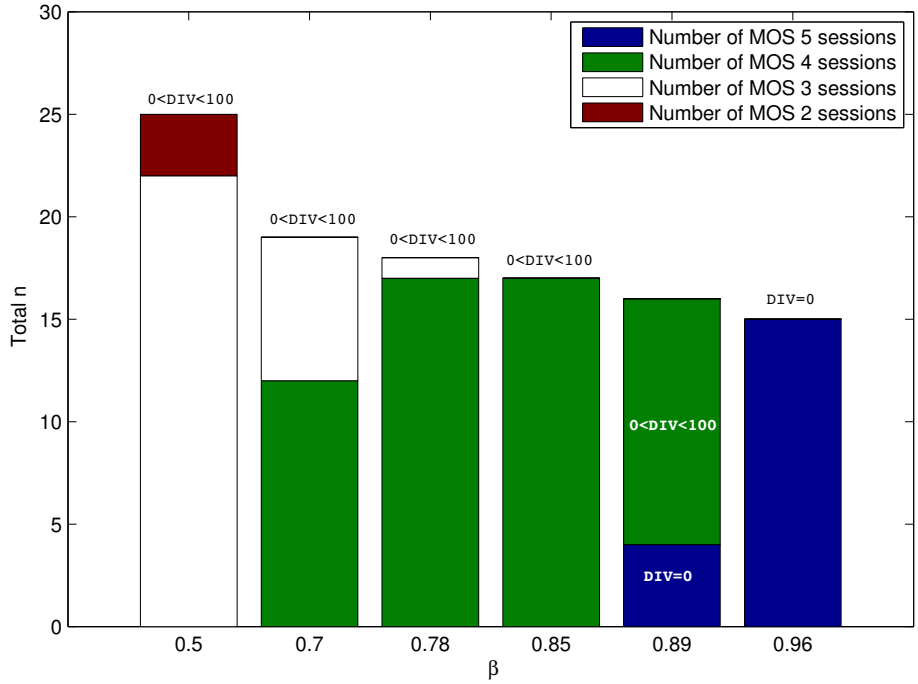


Figure 5.10: Impact of β on MOS and n, C_l=22Mbps

sessions with multi-MOS levels exist, while for $\beta \geq 0.96$ all sessions score a MOS of 5. Figure 5.10 also shows that decreasing β from 0.96 to 0.5 increases the total *number of sessions* and number of MOS 3 and MOS 2 sessions while decreasing the number of MOS 5 and MOS 4 sessions.

In another scenario, we found that the proposed value of β is 0.95 for 24Mbps link as shown in Figure 5.11. β of 0.95 or greater, maintains the MOS of accepted sessions at 5, whereas β less than 0.95 produces sessions with multiple MOS scales. For instance, β of 0.8 creates 18 sessions with MOS of 4 and 1 session with MOS of 3. Whilst, a β of 0.6 leads to 5 sessions with MOS of 4 and 19 sessions with MOS of 3. Note that there are 19 sessions in total for β=0.8 and 24 sessions for β=0.6.

Figures 5.10 and 5.11 also show the DIV values of accepted sessions at different β values. As DIV was 0% for sessions with MOS of 5 and between 0% and 100% for sessions with MOS<5, in the figures we simply labelled DIV=0 to denote all the accepted sessions are MOS of 5 and 0<DIV<100 denote that the MOS of sessions are less than 5.

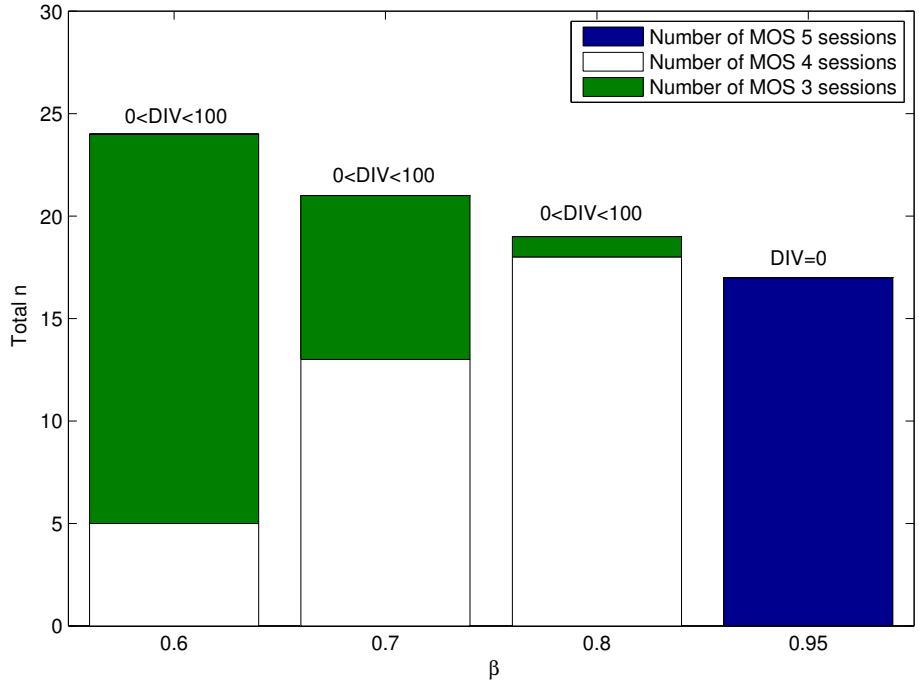


Figure 5.11: Impact of β on MOS and n, C_l=24Mbps

Although most real-time applications can tolerate some packet loss, more than an acceptable level may degrade the quality of received videos. As expected, fewer sessions of *CBAC* will guarantee no packet loss, in contrast extra added sessions of *Pro-IBMAC* cause packet drop when β is set lower than the proposed value. The packet drop increases slightly with an increase in the *number of sessions*. Table 5.7 presents the percentage of the packet drop ratios of the *Pro-IBMAC* admitted sessions for different values of β for 22Mbps links. The ratio increases with the decrease of β due to fitting a higher *number of sessions* on the same link. The table shows 0.45%, 4.06% and 6.70% packet drops for β= 0.89, 0.85 and 0.78 respectively. The proposed value of β (0.96) ensures that no packets are dropped as shown in the table.

Table 5.7: Packet drop ratio and admitted session of *Pro-IBMAC* for different β, C_l=22Mbps

β	**Packet drop ratio %**	n
0.96	0	15
0.89	0.45	16
0.85	4.06	17
0.78	6.70	18

Improper values of β not only cause packet drops, but also degrade the MOS levels and increase the delay. Figure 5.7 demonstrates how a high *number of sessions* caused by a low value of β can contribute to the increase in the delay which can be substantial for a large *number of sessions*.

The disadvantage of lowering the value of β is not only that it causes degradation to the MOS level of video sessions, or increase in the delay and packet loss. We observed that the decoder takes longer time to decode and play back the received video for low values of β. The ISP can tune the value of β to control the trade-off between providing the required level of QoE and increasing their revenue by accommodating more user sessions.

5.6 Subjective Tests

We performed subjective tests to involve human subjects in rating the quality of the videos that were decoded from the simulation outputs. The tests followed the ITU-R Recommendation BT.500-13 (ITU-R Recommendation BT.500-13 2012). The five-grade scale from 1 to 5 of the Single Stimulus (SS) Absolute Category Rating (ACR) method was used in which 1 represents "bad" and 5 represents "excellent" quality. Each video was presented in a random order and rated individually by 17 subjects one at a time. The number of participants exceeded the minimum recommended number (15 subjects).

As the MAD sequence was chosen, 48 videos delivered through different link capacities and different values of β shown in Table 5.6, Figures 5.10 and 5.11 were used in the tests. They were decoded from the simulations and selected from Figures 5.6 (MOS of 5), 5.10 (MOS of 2, 3, 4 and 5) and 5.11 (MOS of 3, 4 and 5). The description of the testing video sequence, coding and network parameters were the same as described in Tables 5.1 and 5.5. Each video was identified by the MOS value calculated with Evalvid, regardless of the capacity of the link and/or value of β. The aim was to have a variety of videos with different MOS values through changing the capacity of the link and value of β.

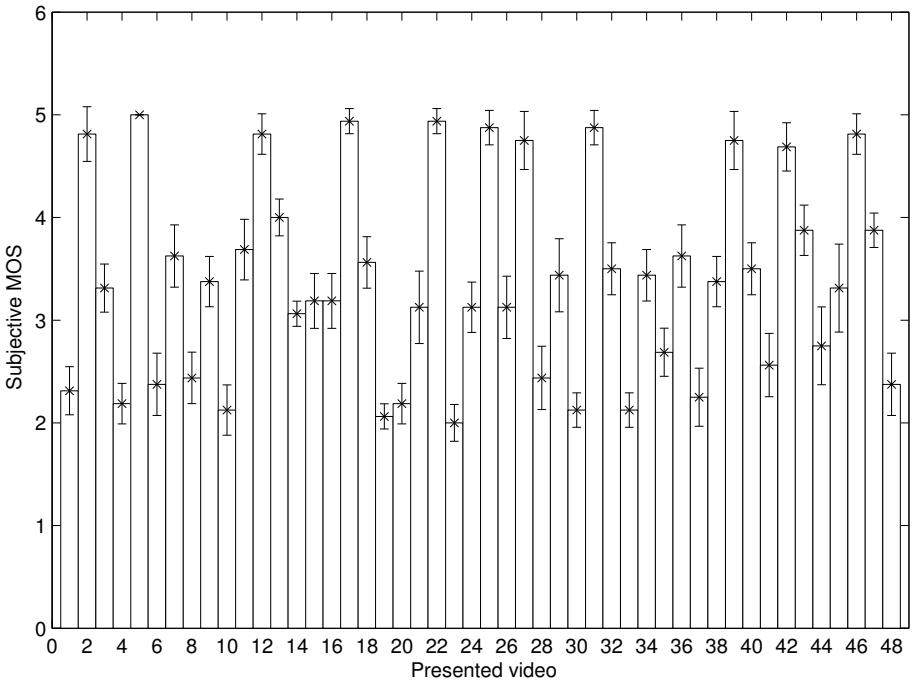


Figure 5.12: Bar chart of subjective MOS with confidence interval for individual video

The *simulated* β and predicted β of the testing videos will be plotted in Section 5.7.

The videos were presented in their original size (352x288), embedded in a separate web page with grey background and rated on the same page. There were two sessions, each lasting up to 30 minutes with 10 minutes break in between. To stabilise the subjects' opinion, five dummy videos were displayed at the beginning of the session without considering their scores. Prior to the actual rating, the subjects were carefully introduced to the assessment method, likely quality artifacts that might be observed, rating scale and timing. They were given unrestricted time and the viewing distance was comfortable.

The tests were conducted in a white background laboratory on 29 inch LCD monitor (Dell P2213) with 1680x1050 resolution and 32 bit true colour. Five female and 12 male non-expert observers participated in the tests. All participants were university students, 1 in the range of 18-25, 7 in the range of 26-30 and 9 over 30. At the end of the tests, subjects who were surveyed on the duration and comfortability of the tests did not express any concern. The subjects were screened for

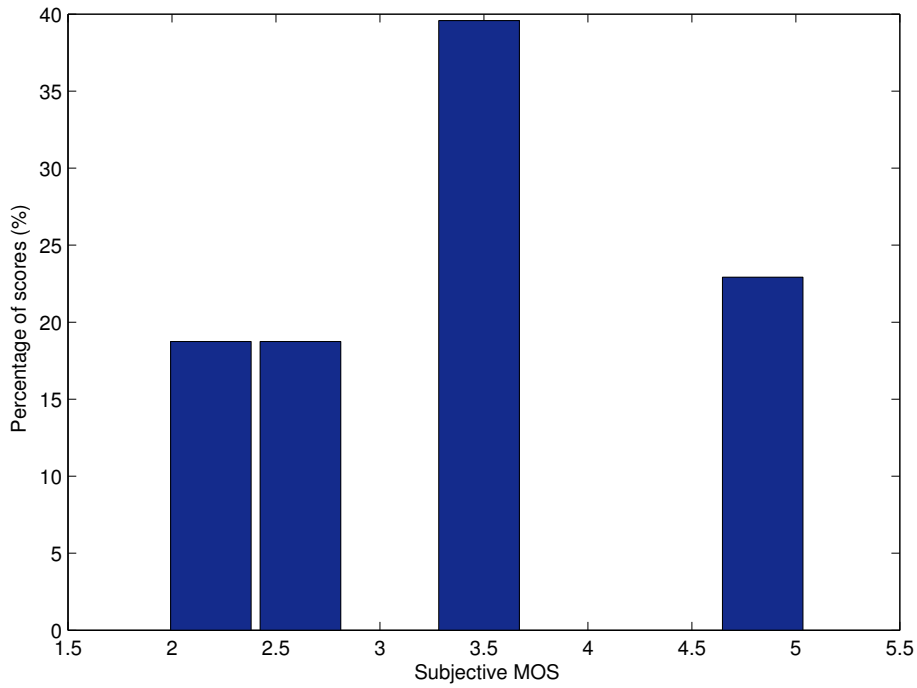


Figure 5.13: Bar chart of the percentage of scores of subjective MOS

any possible outliers, following the screening procedure of the SS method (ITU-R Recommendation BT.500-13 2012). Two subjects have been eliminated and their data were not considered in the analysis. The MOS was calculated by taking the mean score for each of the videos following the procedure described in (ITU-R Recommendation BT.500-13 2012).

The bar chart in Figure 5.12 illustrates the subjective mean MOS of every presented video with the confidence interval. It shows the mean and range (the upper and lower limits) of MOS given to each video by the subjects. The analysis shows that around 40% of the scores went for a MOS of 3.5. The distribution of the scores is plotted in Figure 5.13.

5.7 Validation of the Proposed Models

In this section, the validation of the proposed model of β with simulation results is explained. It also demonstrates the validation of the *simulated MOS* with subjective MOS.

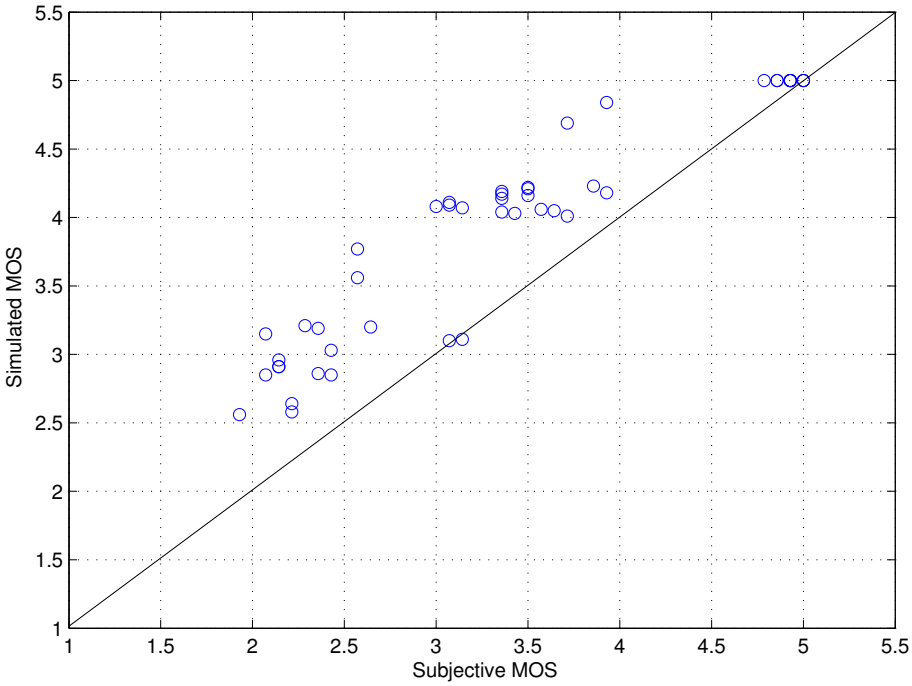


Figure 5.14: Validation of the *simulated MOS* with subjective MOS

The scatter plot in Figure 5.14 shows the *simulated MOS* against subjective MOS. Overall, the subjects were irritated by video impairments, their scores therefore underestimate the simulation scores. Thus, the majority of *simulated MOS* scores are seen higher than subjective MOS. However, both scores are getting closer for less impaired videos (subjective MOS between 4.78-5). These videos were delivered with the proposed values of β for each link capacity as shown in Figure 5.6. Note that as there are about 11 overlapping scores within this range, all can not be seen in the figure. Overlapping of the scores can be further noticed in Figure 5.12, in which there are 11 scores in the range of 4.78-5. The relationship is nearly linear correlated for videos delivered with the proposed value of β that have MOS close to 5. This indicates that the model can provide a better quality for end users with the proposed value of β.

β predicted by Equation (5.10) has been validated by the one found by simulations. Figure 5.15 shows the resulting β's scatter point plot of the predicted β against *simulated* β for slow and fast moving contents separately. As shown in Tables 5.3 and 5.4, the proposed model for β suits fast moving content with a correlation coefficient of 90.54% compared to 88.44% for slow moving content. This can also be observed in Figure 5.15. Thus, the model best suits dynamic

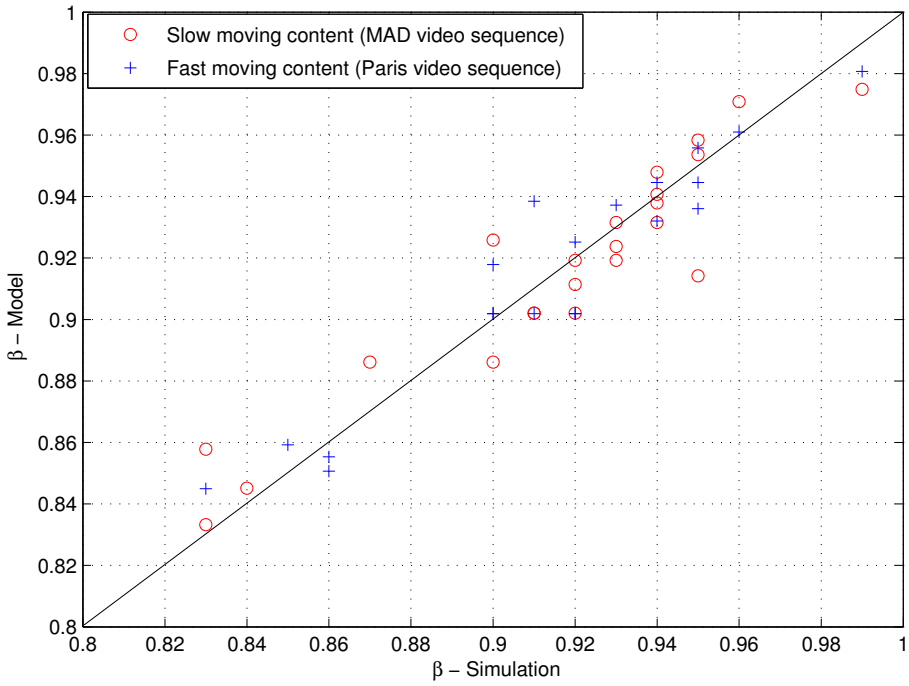


Figure 5.15: Validation of the proposed model of β with simulation results

content with high variation in bitrates. Note that there were few videos for each value of β plotted in Figure 5.15, therefore the number of plotted points is less than the number of testing videos (48).

As mentioned in Section 5.3.2, the model of β can be applied to other video formats with different values of coefficients α and σ. It has been validated by the QCIF video format using the 45 seconds Deadline video sequence of 1374 frames. The model achieved an adjusted R^2 of 83.59% and RMSE of 0.0194. The values of α and σ were -0.1323 and 0.4991 respectively.

5.8 Summary

In this chapter we proposed a novel algorithm to find the upper limit of the video total rate that can exceed a specific link capacity without QoE degradation of ongoing video sessions. A mathematical model for the measurement algorithm was developed and implemented in an admission control system to validate its performance by simulating publicly available video sequences. The exceedable

limit is defined by parameter β in the algorithm. This parameter can be used by ISPs to balance the trade-off between QoE and the *number of sessions*. The simulation results have shown that the proposed admission control compared to the calculated rate-based admission control optimises the trade-off relationship between QoE-*number of sessions* through fine tuning the value of β. The proposed algorithm can be applied within the scope of the video format and coding parameters specified in this chapter.

In the next chapter, the implementation of the proposed rate measurement algorithm along with rate adaptation of video sources in a cross-layer architecture for optimising the QoE of video sessions is investigated.

Chapter 6

QoE-Aware Cross-Layer Architecture for Video Traffic

More promising architectures are required to meet the satisfaction of users and preserve the interest of service providers. This common goal has been targeted by various designs. Different approaches focusing on optimisation metrics, scope and adaptation methods are available. They can be deployed individually or jointly, which is called cross-layer design in the later case, to achieve the goal (Fu et al. 2013).

Optimisation has to resolve the conflict between the interests of end users and network providers. From end users' perspective, maximum quality is expected; whereas low-cost and number of served users are important from network providers' perspective. These two can be jointly optimised through an intelligent design.

This motivation has promoted the development of cross-layer designs for video transmission that are QoE-aware. The main objective is to utilise network resources efficiently and optimise video quality, throughput or QoE through a joint cooperation between layers and optimisation of their parameters. This enables communication and interaction between layers by allowing one layer to access the data of another layer. For example, having knowledge about the available bandwidth (network layer) helps senders to adapt their sending rates (application

layer). As a result of this cooperation, better quality for as many users as possible can be expected.

Although dynamic rate adaptation enhances video quality, accepting more sessions than a link can accommodate will degrade the quality. We have investigated how rate adaptation of video sources can maintain better QoE in Chapter 3. However, the friendly behaviour of the Internet's transport protocol accommodates every video session and makes room for everyone. This causes a degradation of QoE of all video sessions in a bottleneck link because, for a large number of video sessions, the adaptive sources attempt to reduce the transmission rate of all video sources in order to share the available link capacity. This does not consider how much the QoE at the receiving end will be affected by the adaptation process. Furthermore, we have seen in Chapter 3 that the *adaptive architecture* is more efficient for low video resolutions such as QCIF which is no longer a common resolution.

In addition to an adaptable video source is a need for a mechanism to control the number of video sessions. This chapter presents two contributions; a comprehensive survey of mechanisms available for the QoE optimisation and a QoE-aware cross-layer architecture for optimising video traffic. In the next section, the motivation for QoE optimisation and related challenges are discussed first.

6.1 QoE Optimisation Challenges and Motivation

Different media types possess different metrics, and are thus hard to compare. QoE is more complex to satisfy under a highly dynamic environment. This is due to the multidimensional requirements of current services (Fu et al. 2013). It is a subjective metric and hard to be quantified.

The evolution of video capable devices such as smartphones which can connect to the Internet anywhere anytime, has changed users' behaviour from traditional

text-based surfing to real-time video streaming. Media and network operators are challenged by the huge volume of video traffic and high user expectation of quality. They face the crucial task of maintaining a satisfactory QoE of streaming services (Yuedong et al. 2014). The non-optimised designs of mobile applications running these devices have wasted expensive radio resources and limited licensed spectrum at the access level.

To meet users rising demand for bandwidth, operators need to increase the capacity of their network by deploying more spectrum which is expensive and not always available. For example, in 2011, the French regulator ARCEP attributed 4G/800MHz band in France, where 2.639 billion Euros was estimated for a 30MHz duplex and 0.94 billion of Euros for a 70MHz duplex belonging to the 4G 2.6GHz band. This high demand has initiated the need for upgrading network components which is again associated with significant additional costs.

At the source, operators work around the problem by putting less expensive solutions such as content caching over the top services (e.g. Youtube) inside their Autonomous System (AS) which avoids costly inter AS traffic. Other than the technical challenges, service providers are also facing business challenges. Giant companies such as Google and Apple, for example, have started to offer services traditionally provided by service providers (Maallawi et al. 2014).

In the last few years, mobile network operators have been losing revenue from fixed and mobile services (Maallawi et al. 2014). Traditional time-based billing is now obsolete and has been replaced with a monthly-based fix rate regardless of consumed data. In addition to this, users keep switching to cheaper providers. This increase in data traffic and decrease in average revenue per user have demanded new mechanisms to reduce the operational costs and optimise video transmission (Fu et al. 2013). Simply upgrading bandwidth is not a solution (Roberts 2009).

The above challenges have motivated researchers and service providers to find better and cost-effective solutions. Service providers want to be able to opti-

mise the utilisation of resources with the aim of maximising user satisfaction on delivered services.

6.2 A Survey on QoE Optimisation for Video Traffic

The volume of the video traffic over the Internet makes studying QoE very important. Extensive research has been undertaken in the area of QoE optimisation for video traffic. Most recently, a comprehensive survey was presented by Maallawi et al. (2014) on the offload approaches at different parts of the global network (access, core, gateway). Offloading is possibly a way to optimise QoE and manage resources efficiently. The primary objective is to maintain the perceived QoE by redirecting traffic to alternative cost effective paths or by enabling direct communication between nearby devices. This frees up costly congested paths for the 3rd Generation Partnership Project (3GPP) Radio Access Network (RAN) (4G/3G/2G) and Mobile Packet Core Network (MPCN) and avoids transporting low priority traffic on these paths. The survey discusses the alternative ways of offloading and their management in access and core networks. It also compares the offload approaches and raises open issues to be tackled in managing offload such as architecture, decision making process and required information.

Another similar survey was conducted by Ernst et al. (2014). Recent mechanisms within the Heterogeneous Wireless Networks (HWN) are categorised according to their functions (handover, MAC and scheduling, topology and power control). A comparison between approaches is made for each category. The limitation of each approach is also explained and potential trends in the area are identified.

However Maallawi et al. (2014) merely reviews offloading techniques and Ernst et al. (2014) HWN mechanisms. There are a number of studies that consider cross-layer optimisation for the sake of video quality enhancement, such as (Duong et al. 2010, Gurses et al. 2005, Gross et al. 2004); or throughput improvement

such as (Shabdanov et al. 2012). We include only those which are aimed at QoE improvement. We also survey recent studies that have proposed mechanisms for QoE optimisation over a single network layer.

6.2.1 QoE Optimisation through Cross-Layer Designs

QoE-based cross-layer optimisation is a topic being widely investigated. The Application/MAC/Physical (APP/MAC/PHY) cross-layer architecture introduced in (Khalek et al. 2012) enables optimising perceptual quality for delay-constrained scalable video transmissions. Using the acknowledgement history and perceptual metrics, an online mapping of QoS to QoE has been proposed to quantify the packet loss visibility from each video layer. A link adaptation technique that uses QoS to QoE mapping has been developed at the PHY layer to provide perceptually-optimised unequal error protection for each video layer according to packet loss visibility. While at the APP layer, a buffer-aware source adaptation is proposed. The senders rates are adapted by selecting a set of temporal and quality layers without incurring playback buffer starvation based on the aggregate channel statistics. To avoid frame re-buffering and freezing, a video layer-dependent per packet retransmission technique at the MAC layer limits the maximum number of packet retransmission based on the packet layer identifier. The next retransmission of packet is given a lower order of Modulation and Coding Scheme (MCS). The study concludes that the architecture prevents playback buffer starvation, handles short-term channel fluctuations, regulates the buffer size, and achieves a 30% increase in video capacity compared to throughput-optimal link adaptation. In addition to its limitation to SVC, the study did not target any specific underlying wireless technology.

The QoE-driven seamless handoff scheme presented in (Politis et al. 2012) incorporates a rate adaptation scheme and the IEEE 802.21 Media Independent Handover (MIH) framework. The rate is controlled by adapting QP for the single layer coding (H.264/AVC) and dropping the enhancement layers for the scalable coding (H.264/SVC). The work concluded that the proposed QoE-driven

handover implemented in a real test-bed outperforms the typical Signal-to-Noise Ratio (SNR)-based handover and improves the perceived video quality significantly for both coding. However it can be better maintained with H.264/SVC. The study is merely a comparison between the two coding techniques for maintaining the QoE of wireless nodes during the handover process.

An online test-optimisation method is proposed in (Zhou et al. 2013) for resource allocation and optimisation of the total MOS of all users without complete information of the QoE model (also called utility function of each user) or playout time (blind dynamic resource allocation scheme). Instead, MOS is observed over time dynamically. Each user subjectively rates the multimedia service given the allocated resource in the form of the MOS value and reports it back to the base station. The dynamic resource allocation strategy learns a specific user's underlying QoE model by testing different allocated resources (testing) and seeks the optimal resource allocation solution (optimisation). The author adopted the QoE prediction model in (Khan, Sun, Jammeh & Ifeachor 2010) for implementing the dynamic resource allocation scheme. The QoE model is estimated based on the observed MOS for the blind dynamic resource allocation scheme.

The application-driven objective function developed in (Khan et al. 2006) optimises the quality of video streaming over the wireless protocol stack. It uses the application layer, data-link layer and physical layer. The proposed cross-layer optimiser periodically receives information in both directions, top-down and bottom-up from the video server and selects the optimal parameter settings of different layers. The optimisation is based on the outcome of maximisation of an object function which depends on the reconstruction quality at the application layer. The parameters that can be optimised are source rates at the application layer and modulation schemes at the radio link layer (physical layer+ data link layer). i.e. Binary Phase Shift Keying (BPSK) (total rate of 300kb/s) or Quaternary PSK (QPSK) (a total rate of 600 kb/s). The quality-based optimiser was applied to wireless users who simultaneously run voice communication, video streaming and file download applications in (Khan et al. 2007). QoE was measured in terms of PSNR and MOS mapped from an assumed linear PSNR to

MOS mapping. It was assumed that a PSNR of 40 dB represents the maximum user satisfaction and 20 dB the minimum user satisfaction. It was compared to the conventional throughput optimiser and showed a significant improvement in terms of user perceived quality and wireless resource utilisation.

The application-driven cross-layer framework in (Khan et al. 2006) has been extended to a QoE-base for High Speed Downlink Packet Access (HSDPA) (Thakolsri et al. 2009). It combines both capabilities of the HSDPA link adaptation and multimedia applications rate adaptation to maximise user satisfaction. Relevant parameters from the radio link and application layers are communicated to a cross-layer optimiser. The optimiser acts as a downlink resource allocator and periodically reviews the total system resources and makes an estimate of the time-share needed for each user for each possible application-layer rate. It re-adapts the application rate if necessary. The QoE-based cross layer optimised scheme was simulated using OPNET against the throughput optimised and non-optimised HSDPA systems. It was concluded that perceived user quality significantly improved compared to the other two systems. The study made use of the adaptability feature of HAS and aggressive TCP to control the application rate. Furthermore, MOS was defined as a function of the transmission rate only.

Several techniques are proposed in (Latré 2011) to optimise QoE in terms of the number of admitted sessions and video quality in multimedia networks. Traffic adaptation, admission control and rate adaptation are combined within an automatic management layer using both simulation and emulation on a large-scale testbed. The study focused on multimedia services such as IPTV and network-based personal video recording. Traffic flow adaptation modifies the network delivery of a traffic flow by determining required redundancy needed to cope with packet loss. An extension to the PCN-based admission control system which is a distributed measurement based admission control mechanism has been recently standardised by the IETF. A novel metering algorithm based on a sliding-window to cope with the bursty nature of video sessions and another adaptive algorithm to facilitate the configuration of PCN have been proposed. The study has also proposed static and dynamic video rate adaptation algorithms that augment the

PCNs binary-based (accept or reject) with the option of scaling video up or down. The viability of an implementation was investigated using neural networks and compared with an analytical model. The study shows that the QoE optimising techniques can successfully optimise the QoE of multimedia services. Two different rate adaptation algorithms have been proposed in (Latré & De Turck 2013); an optimal one to adapt the video rate based on the maximisation of service provider's revenue or QoE and a heuristic based on the utility of each connection. Relying on a subjective test, Chen et al. (2015) proposes a rate adaptation algorithm and devises a threshold-based admission control strategy to maximise the percentage of video users whose QoE constraints can be satisfied. Per user's QoE constraint was defined by the empirical CDF of the predicted video quality.

A generic and autonomic architecture has been presented in (Latré et al. 2009) to optimise the QoE of multimedia services. The proposed architecture is shown in Figure 6.1. It comprises of Monitor, Action and Knowledge planes. The Monitor plane provides an automatic loop with a complete and detailed view of the network. Parameters such as packet loss, video frame rate and router queue size are monitored through monitor probes at demarcation points (e.g. access nodes, video servers). The Action plane optimises QoE based on a complete configuration of the actions received from the Knowledge plane. An example of these actions is adding the Forward Error Correction (FEC) packets to an existing stream after it has been determined by the Knowledge plane. The Knowledge plane based on the information from the Monitor plane and other relevant data such as historical information, detects network problems and bit errors on a link. It instructs the Action plane to take an appropriate QoE optimising action, e.g. switching to a lower bit rate video or adding an appropriate number of FEC packets. The Knowledge base component of the Knowledge plane stores relevant information about the network during each phase of the automation process (monitoring, reasoning and executing actions). The learning controller provides the knowledge plane with learning capabilities.

The learning process has two stages. First, detecting new video services that the knowledge plane is not trained for and finding the proper actions. Second,

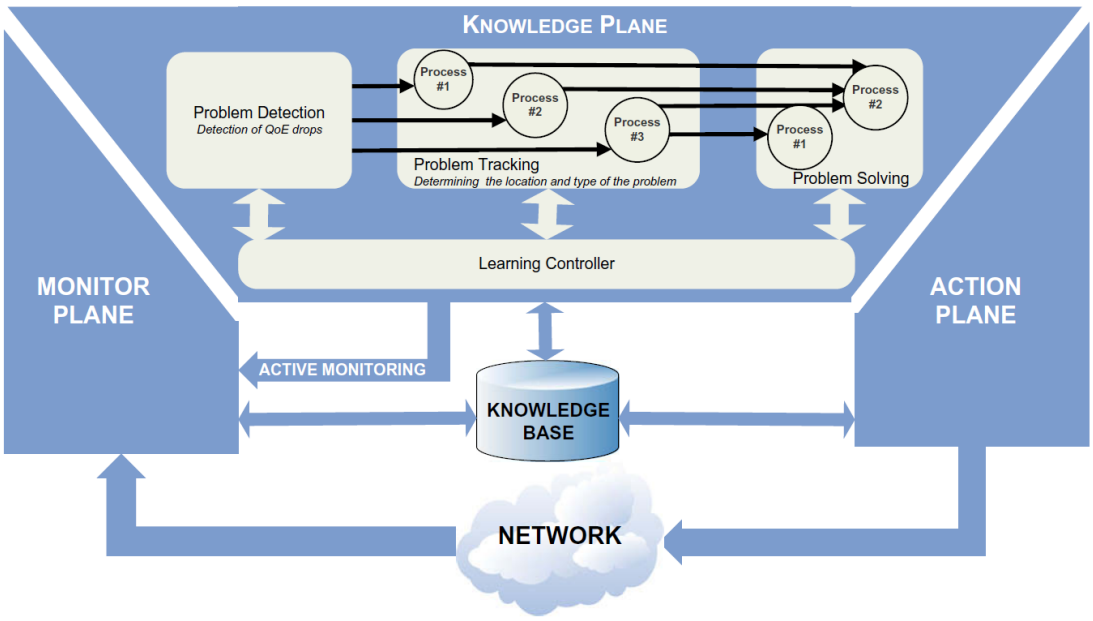


Figure 6.1: An automatic architecture to enable the QoE maximisation of multimedia services (Latré et al. 2009)

detecting wrong decisions and altering them accordingly. The architecture was tested for optimisation of the QoE of video services in multimedia access networks using a neural network based reason. The reasoner applies FEC to reduce packet loss caused by errors on a link and switches to a different video bit rate to avoid congestion or obtain a better video quality. The authors concluded that their architecture was capable of increasing video quality and lowering packet loss ratio when packets are lost due to bit errors or when congestion occurs.

The cross-layer adaptation architecture shown in Figure 6.2 is presented in (Oyman & Singh 2012) for HAS-specific QoE optimisation. The layers of the architecture and corresponding layers of the OSI are depicted in the figure. It relies on tight integration of the HAS/HTTP-specific media delivery with network-level and radio-level adaptation as well as QoS mechanisms to provide the highest possible end user QoE. The following parameters are jointly involved between appropriate network layers:

1. Video level: bit rate, frame rate, resolution codecs

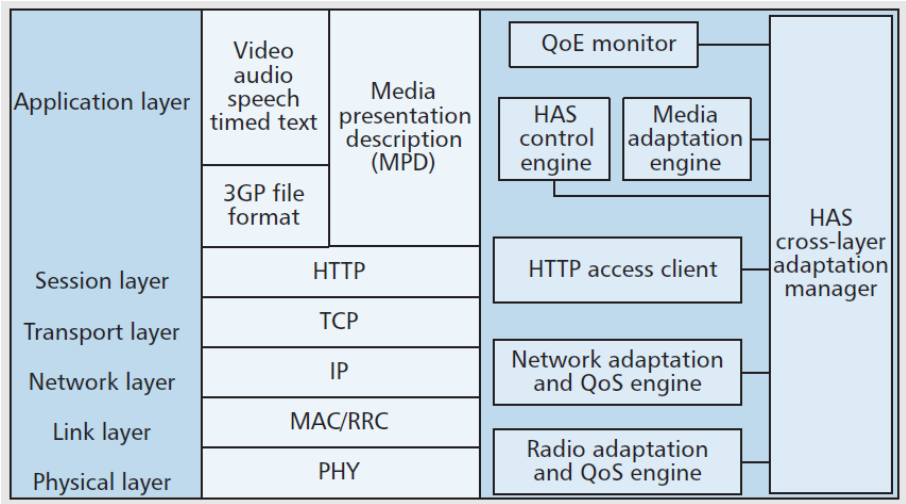


Figure 6.2: A cross-layer adaptation architecture for HAS-specific QoE optimisation (Oyman & Singh 2012)

2. Transport level: Sequence and timing of HTTP requests, number of parallel TCP connections, HAS segment durations, frequency of Media Presentation Description (MPD) updates.

3. Radio and network level: Bandwidth allocation and multiuser scheduling, target QoS parameters for the core network and radio access network, MCS, Orthogonal Frequency Division Multiple Access (OFDMA) time/frequency resource/burst allocations.

The end-to-end QoE optimisation system shown in Figure 6.3 is proposed in (Zhang & Ansari 2011) for Next Generation Networks (NGN). The major elements of the QoE assurance framework as well as their functions at Terminal Equipments (TE), network nodes, and sources are also depicted in the figure. The QoE/QoS reporting component at terminal equipment reports the user QoE/QoS parameters to the QoE management component. The transport functions and relevant parameters are analysed and adjusted accordingly. The updated QoS/QoE of end users is sent to the network and sources.

A joint framework for video transport optimisation in the next generation cellular network is designed in (Fu et al. 2013). The rationale behind the design is to combine several optimisation approaches for more gain. As shown in Figure 6.4, path selection, traffic management and frame filtering modules are proposed for

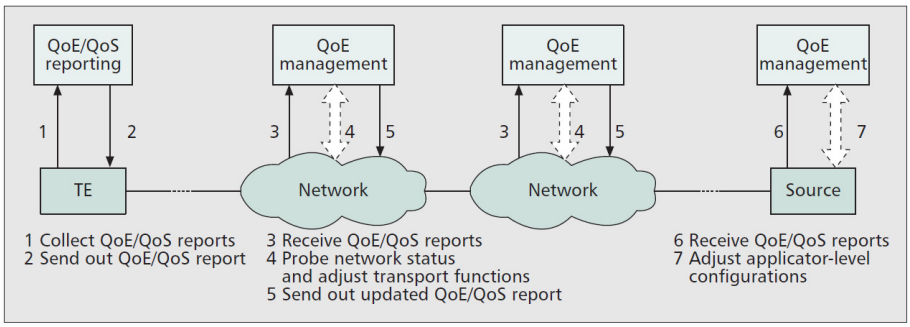


Figure 6.3: A possible end to end QoE assurance system (Zhang & Ansari 2011)

SVC video streaming over UDP/RTP. The path selection module provides the best available end-to-end video path by redirecting the video traffic from a video source to another based on a set of network metrics. The traffic management module at the transport layer allocates transmission data rates for multiple video streams travelling through the core network nodes. The base station implements dynamic frame filtering to cope with the wireless channel variation. Issues such as wide area network congestion, core network node congestion, cache failure and user mobility can be overcome by the presented design.

Dynamic Adaptive Streaming over HTTP (DASH) has recently attracted the attention of the research community. A mobile DASH client decides on the streaming rate and the base station allocates resources accordingly. In contrast to the UDP push-based streaming, DASH is a pull-based client-driven streaming protocol (El Essaili et al. 2014). The QoE-aware cross-layer DASH friendly scheduler introduced in (Zhao et al. 2014) allocates the wireless resources for each DASH user. The video quality is optimised based on the collected DASH information. Furthermore, an improved SVC to DASH layer mapping is proposed to merge small sized layers and decrease overhead. For smooth playback, along with the existing client-based quality selection policies, there is a DASH proxy-based which transparently stabilises bitrates. The authors concluded that their proposed scheme outperforms other schemes.

A proactive approach for optimising multi-user adaptive HTTP video QoE in mobile networks is proposed in (El Essaili et al. 2014). In contrast to the reactive approach in which resources are allocated by the mobile operator without clients'

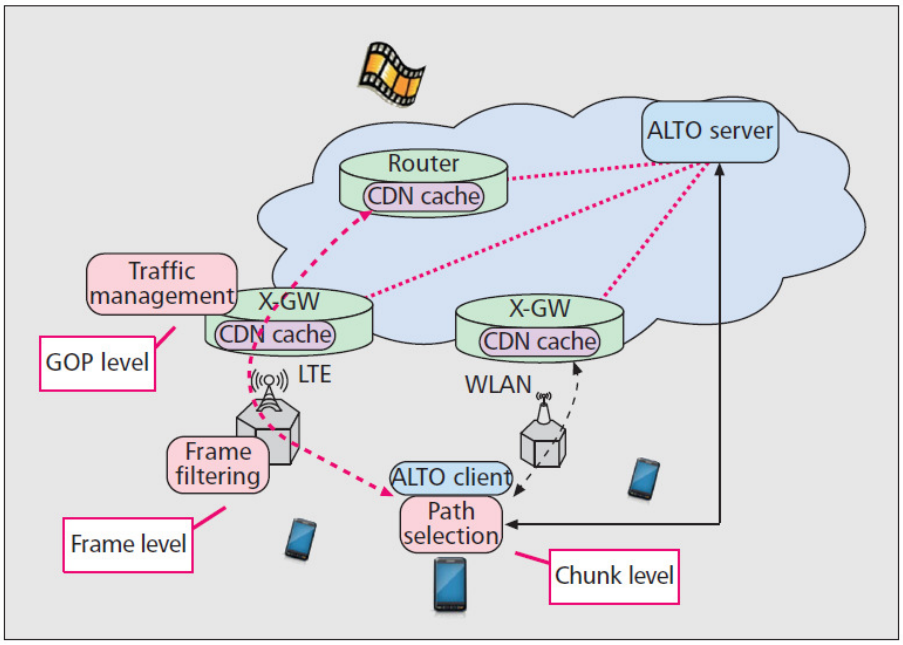


Figure 6.4: Joint framework for multilayer video optimisation (Fu et al. 2013)

knowledge, in the proactive approach a proxy overwrites the client HTTP request based on the feedback from a QoE optimiser. The QoE optimiser on the base station collects information about each client and determines the transmission rate and signals it back to the proxy and resource shaper for adapting the transmission rate of the DASH client. The proxy ensures that the streaming rate is supported by lower layers and QoE optimisation. Subjective tests are conducted for end user perception on QoE.

Two QoE-aware joint subcarrier and power radio resource allocation algorithms are presented in (Rugelj et al. 2014) for the downlink of a heterogeneous OFDMA system. They allocate resources based on the QoE of each heterogeneous service flow. A utility function maximising the minimum MOS experienced by users considered by the first algorithm and the second algorithm balances between the level of QoE and system spectral efficiency. Each user of the OFDMA system can achieve an appropriate level of QoE through an adaptable resource allocation and data rate. Numerical simulation results showed a significant increase of QoE achieved through the algorithms compared to the data rate maximisation-based algorithms.

A joint near optimal cross-layer power allocation and QoE maximisation scheme for transmitting SVC video over the Multi-Input Multi-Output (MIMO) systems proposed in (Chen et al. 2014). The effects of power allocation to bit error rate in the physical layer and video source coding structures in the application layer are considered. The scheme is further extended with Reed-Solomon (RS) code and different MCS. The calculated PSNR and SSIM from simulation demonstrated the efficiency of the scheme over the water-filling (WF) and modified-WF schemes.

An application-level signalling and end-to-end negotiation called Media Degradation Path (MDP) is deployed in (Ivesic et al. 2014) for resource management of the adaptive multimedia services in Long-Term Evolution (LTE). Admission control and resource reallocation in case of limited resource availability as two components of the cross-layer design increase the session admission rate while maintaining an acceptable level of end user QoE. Alternative configuration of MDP is applied to a new session if the available resources are not sufficient for optimal configuration. Since, both configurations are set with users' preference and acceptable quality level, user satisfaction is kept at an acceptable level. The authors considered the impact on end user QoE from the perspective of performing utility-driven adaptation decisions, improving session establishment success, and meeting QoS requirements (i.e. loss thresholds). Neither subjective nor objective MOS is taken into account in the study.

Work in (Debono et al. 2012) addresses the issue of high delay computational power caused by video error concealment techniques at receivers. The QoE of the region of a mobile physicians interest is optimised by adopting a cross-layer design approach in mobile worldwide interoperability for microwave access wireless communication environment while ensuring real-time delivery. Advanced concealment techniques are applied if the Region Of Interest (ROI) is affected, and a standard spatial or temporal concealment otherwise. Cross-layer parameters are determined to reduce the packet error rates by utilising the QoE of the ROI. The strategy does not demand a higher bandwidth as the quality is optimised through better error concealment not encoding with a higher QP. A PSNR of 36 dB was obtained within a reasonable decoding time.

Work presented in (Singhal et al. 2014) combines various techniques across different layers for optimisation of both users' QoE levels and energy efficiency of wireless multimedia broadcast receivers with varying display and energy constraints. The SVC optimisation, optimum time slicing for layer coded transmission, and a cross-layer adaptive MCS are combined to present a cross-layer framework. Users are grouped based on their device capability and channel condition and they are offered options to trade between quality and energy consumption. The scheme compared to energy saving based optimisation, achieved a 43% higher video quality trading off 8% in energy saving and a marginal 0.62% in user serving capacity, whereas compared to quality based optimisation, the scheme results in 17% extra energy saving, 3.5% higher quality, and 10.8% higher capacity.

Work in (Mathieu et al. 2011) argues that the end-to-end QoE can be improved by advocating close cooperation between ISPs and applications via a comprehensive, media-aware and open Collaboration Interface between Network and Applications (CINA). Mutual information is exchanged between the network layer and applications through CINA which bridges the two entities. CINA and other components to support this cooperation are shown in Figure 6.5. The system is expected to support service providers to efficiently distribute high demand content streams and enable dynamic adaptation to satisfy the requirement of users within the underlying network capability. The internal functionality of each block and evaluation through both simulation and testbed are identified as future work.

In (Goudarzi 2012) particle swarm optimisation is utilised to find an optimal rate by which the total weighted QoE of some competing video sources is optimised. It is also used for differentiated QoE enforcement between multiple competing scalable video sources. Scalable video encoders such as H.264/MPEG4 AVC can use the resulting rate for online rate adaptation. The work presented in (Goudarzi & Hosseinpour 2010) adopts a model from the literature to capture the exact effect of network packet loss and finds the optimal rate toward minimising the loss-induced distortion associated with video sources and maximising QoE. The resulting optimal rate is sent back to video encoders for online rate adaptation.

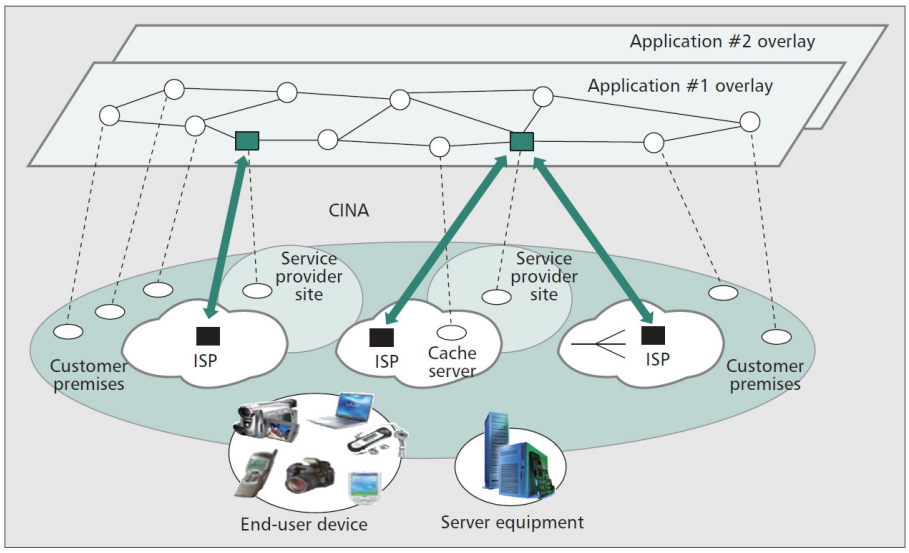


Figure 6.5: Overview of system components and their relationships (Mathieu et al. 2011)

A cross-layer scheme for optimising resource allocation and users' perceived quality of video applications based on a QoE prediction model that maps between object parameters and subject perceived quality is presented in (Ju et al. 2012). Work presented in (Fiedler et al. 2009) promotes an automatic feedback of end-to-end QoE to the service level management for better service quality and resource utilisation. A QoE-based cross-layer design of mobile video systems is presented for this purpose. Challenges of incorporating the QoE concepts among different layers and suggested approaches span across layers such as efficient video processing and advanced realtime scheduling are also discussed.

Subjective user experience (in terms of MOS) of the Web browsing service as a function of response time is measured from experiments in (Ameigeiras et al. 2010). A mapping function from the service response time and user data rate of the wireless link to MOS was derived and incorporated in the design of radio resource allocation algorithms for OFDMA.

The discussion above are summarised and the studies are compared in Table 6.1. Among the discussed literature, Latré (2011), Latré & De Turck (2013) and Chen et al. (2015) have proposed a combined rate adaptation and admission control in a cross-layer design for QoE optimisation. In (Latré 2011) the rate of

layered video flows is re-scaled and protected through a number of changes to the original PCN. In contrast, our architecture accounts for the QoE of video sessions for the optimisation. Latré & De Turck (2013) integrates an existing standardised MBAC system with a novel video rate adaptation, while our work integrates the existing rate adaptation capability of multimedia applications with a QoE-aware admission control. Furthermore, our architecture optimises the link considering the QoE of video sessions whereas Latré & De Turck (2013) accounts for QoE as an output of the system. Finally, Chen et al. (2015) incorporates QoE constraints in the rate adaptation algorithm, but our proposal incorporates QoE in the rate measurement algorithm and admission control.

6.2.2 QoE Optimisation through Scheduling

In contrast to scheduling strategies based on QoS metrics such as delay, jitter or packet loss, QoE-aware schedulers have been proposed. Individual users' QoE is included in a QoE-aware scheduler through one-bit feedback from user to indicate their satisfaction (Lee et al. 2014). The derived user-centric QoE function modelled by the Sigmoid function can significantly improve the average QoE and fairness for wireless users. The packet scheduler presented in (Navarro-Ortiz et al. 2013) improves the QoE of HTTP video users that prioritises flows based on the estimation of the amount of data stored in the players' buffer. Simulation results showed a reduction in the number of pauses at receivers' video playback for OFDMA based systems such as 3G LTE and IEEE 802.16e. Work in (Taboada et al. 2013) focuses on the delay as a main distortion factor over others such as packet loss ratio. A delay-driven QoE-aware scheduling scheme is proposed based on the Markov decision process. Gittins index rule was developed for the scheme which gives the priority to flows that are statistically closer to finish and those whose QoE has not been degraded too much. The rule is a combination of the attained service-dependent completion probability and delay-dependent MOS function. Compared to Round Robin, FIFO and Random, the scheduler outperforms in terms of delay and MOS.

Table 6.1: Comparison of QoE optimisation mechanisms through cross-layer designs

Reference	Approach	Traffic	Date	Network	QoE metric	Limitation
(Latré 2011)	PCN-based admission control, rate adaptation, redundancy	Video	2011	Multimedia access network	PSNR, SSIM	Missing subjective MOS
(Khalek et al. 2012)	Link adaptation, buffer-aware rate adaptation, layer-dependent retransmission	Video	2012	Wireless	MS-SSIM	Limited to SVC
(Chen et al. 2014)	Transmission error & video source coding characteristic	SVC Video	2014	MIMO system	PSNR & SSIM	Missing subjective MOS
(Ivesic et al. 2014)	Admission control & resource reallocation	Adaptive multimedia service	2014	3GPP & LTE	Session establishment success, meeting QoS requirement	QoE not measured objectively or subjectively
(Debono et al. 2012)	Coding, FEC, ARQ, modulation coding	Ultrasound video	2012	Mobile WiMAX	PSNR	Missing subjective MOS
(Singhal et al. 2014)	SVC optimisation, cross-later MCS, optimum time	QCIF, CIF, D1	2014	Wireless	Utility function dependent on QP & frame rate	Missing subjective MOS
(Khan et al. 2007)	Cross-layer optimiser	QCIF	2007	Wireless	PSNR & MOS	MOS mapped from PSNR
(Khan et al. 2006)	Source rate adaptation, estimate wireless capability & quickly adapting to its variation	QCIF	2006	Wireless	PSNR	MOS mapped from PSNR
(Mathieu et al. 2011)	Overview block design	Not specified	2011	Not specified	None	Missing evaluation
(Zhang & Ansari 2011)	QoE assurance framework	Video	2011	NGN	None	Missing evaluation
(Politis et al. 2012)	MIH, QoE-driven rate adaptation	Video	2012	WiFi, 3G/UMTS	PSNR & Subjective MOS	None
(Zhou et al. 2013)	Dynamic resource allocation	QCIF, audio	2013	Wireless	Subjective MOS	Non-dynamic QoE model
(Fu et al. 2013)	Joint framework	Video	2013	Cellular network	Utility function dependent on delay	QoE estimated from delay only
(Zhao et al. 2014)	SVC-DASH mapping, DASH friendly scheduler, resource allocation, DASH-based proxy rate stabiliser	Streaming video over HTTP	2014	Wireless broadband	Average PSNR	QoE mapped from PSNR
(El Essaili et al. 2014)	QoE-based traffic & resource management	Video	2014	LTE	Subjective MOS	Buffer level-based QoE optimisation considered instead of stream-based optimisation

Reference	Approach	Traffic	Date	Network	QoE metric	Limitation
(Rugelj et al. 2014)	Radio resource allocation	Video, audio, best-effort	2014	OFDMA	Utility function (Eq. 8 in the literature)	QoE not measured objectively or subjectively
(Latré et al. 2009)	Adding redundancy, video adaptation	Video	2009	Multimedia access network	SSIM, PSNR	Missing subjective MOS
(Oyman & Singh 2012)	Network and radio levels adaptation, QoS mechanisms	Video streaming	2012	3GPP LTE	None	Missing evaluation
(Thakolsri et al. 2009)	HSDPA link adaptation, multimedia application rate adaptation	Video	2009	HSDPA	MOS adopted utility function dependent on transmission rate & packet loss rate, SSIM	Missing subjective MOS
(Goudarzi 2012)	Optimum rate found by swarm algorithm	Video	2012	Wireless	Adopted utility function (Eq. 7 in the literature)	QoE not measured objectively or subjectively
(Goudarzi & Hosseinpour 2010)	Optimum rate found by an adopted model(Eq. 9 in the literature)	Mobile video	2010	MANET	PSNR-MOS mapping of (Khan et al. 2006)	QoE mapped from PSNR
(Chen et al. 2015)	Admission control & rate adaptation	Streaming video over HTTP	2015	Wireless	Subjective MOS	None
(Latré & De Turck 2013)	MBAC & rate adaptation	VoD	2013	Multimedia access network	SSIM	Missing subjective MOS

A comparison of mechanisms relying on scheduling for QoE optimisation is summarised in Table 6.2. The studies discussed in this subsection utilise QoE-aware scheduling whereas our architecture employs a QoE-aware admission control as a main component for optimising QoE of video traffic.

Table 6.2: Comparison of QoE optimisation mechanisms through scheduling

Reference	Approach	Traffic	Date	Network	QoE metric	Limitation
(Lee et al. 2014)	QoE-aware scheduling	Mobile video	2014	Wireless	Utility function (Eq. 10 in the literature)	Missing evaluation
(Navarro-Ortiz et al. 2013)	Packet scheduling	Mobile video streaming	2013	Wireless	Number of playback interruption	QoE estimated based-on the reduction of playback interruption
(Taboada et al. 2013)	delay-driven QoE-aware scheduling	video	2013	Wireless	Utility function dependent on delay	QoE model based-on delay only

6.2.3 QoE Optimisation through Content and Resource Management

Managing resources is another way to efficiently utilise resources and achieve optimised QoE. Buffer starvation is analysed through two proposed approaches in (Yuedong et al. 2014) to obtain exact distribution of the number of starvations. They are applied to QoE optimisation of media streaming. The first approach is based on Ballot theorem and the second uses recursive equations. The fluid analysis-based starvation behaviour controls the probability of starvation at the file level. Subjective human "unhappiness" is modelled using an objective QoE cost which is a weighted sum function of the start-up/rebuffering delay and starvation behaviour. They are taken as quality metrics as the QoE of streaming service is affected by them. The weight reflects an individual users relative impatience on the delay rather than starvation. A content cache management for HTTP Adaptive Bit Rate (ABR) streaming over wireless networks and a logarithmic QoE model from experimental results are formulated in (Zhang, Wen, Chen & Khisti 2013). Alternative search algorithms to find and compare the optimal number of cached files are also provided. The numerical results estimated high QoE with low complexity under the optimal cache schemes.

Work in (Latré, Klaas, Wauters & DeTurck 2011) presents an extended architecture of the PCN-based admission control to protect video services. Three modifications (highlighted block) are proposed to the original PCN systems as shown in Figure 6.6. First, the sliding-window-based bandwidth metering algorithm instead of the traditional token bucket finds the highest rate value that avoids any congested related losses. Second, to reduce the required headroom, packets are buffered just before the PCN metering function. Third, a video rate adaptation algorithm decides on each video quality level based on the current network load. The performance of the modified PCN architecture was evaluated and resulted in an increase of 17% in the network utilisation for the same video quality.

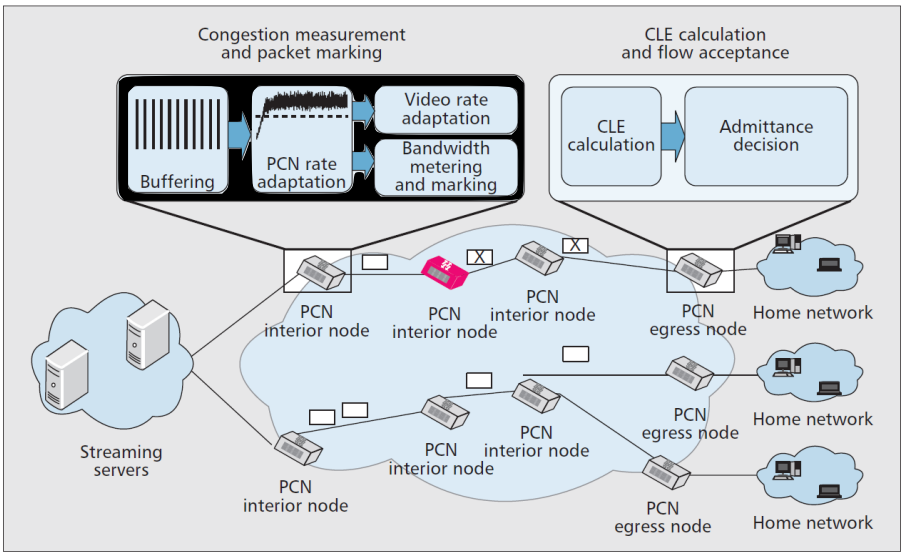


Figure 6.6: Modification of the PCN-based admission control system toward the optimisation of video services in access network (Latré, Klaas, Wauters & DeTurck 2011)

Content encoding for video streaming is addressed with the aim of reducing bitrates and optimising QoE in (Adzic et al. 2012). A process for content-based segmentation from the encoding stage to segmentation stage is proposed for the adaptive streaming over HTTP. It can tailor video streams with better QoE while saving 10% of the bandwidth on average for the same quality level. Changing between mobile-television programs is called zapping which is not immediate but there is a finite delay called zapping delay. A known bound of zapping-delay in Digital Video Broadcast-Handheld (DVB)-H is found in (Vadakital & Gabbouj 2011) as a way to maximise the QoE of mobile video services. Video prediction structures and their reception in time-sliced bursts are analysed using graph theoretic principles. The authors concluded that their system guarantees a zapping delay below some maximum threshold and gradually enhances the quality of video after zapping.

A comparison of mechanisms relying on managing contents and resources for QoE optimisation is summarised in Table 6.3. The literature discussed in this subsection focus on resource management techniques while our proposed architecture exploits the rate adaptation capability of video applications in addition to an efficient utilisation of the network links for optimising the QoE of videos.

Table 6.3: Comparison of QoE optimisation mechanisms through content and resource management

Reference	Approach	Traffic	Date	Network	QoE metric	Limitation
(Yuedong et al. 2014)	Buffer Starvation Analysis	VoD	2014	Not specified	Objective QoE cost	Missing evaluation
(Latré, Klaas, Wauters & DeTurck 2011)	Bandwidth metering, buffering, video rate adaptation at routers	Streaming video	2011	Multimedia access network	SSIM, session, utilisation	Missing subjective MOS
(Zhang, Wen, Chen & Khisti 2013)	Content cache management	HTTP ABR streaming	2013	Wireless	Utility function dependent on required & actual playback rate-based	Non-uniform distribution request & multiple distinctive content on cache not considered
(Adzic et al. 2012)	Content-based segmentation, optimised content preparation algorithm, encoding	Adaptive streaming video	2012	Not specified	PSNR	QoE estimated from PSNR
(Vadakital & Gabbouj 2011)	Bounding Zapping-delay	video	2011	DVB-H	Zapping delay-dependent	Zapping-event between two bursts not considered

6.3 QoE-Aware Cross-Layer Architecture

Much of the research reported in the literature has proposed rate adaptation for layered video such as SVC. The video content (base and enhancements layers) generated by a layered encoder is injected into the network, then the network decides whether they are forwarded or dropped. In contrast, this study proposes online rate adaptation for single layer video. Instead of sending the whole video content to the network, video sources based on the condition of the network, decide at what rate they transmit the content. By using this strategy, the rate is adjusted on the fly and additional redundant data is not sent to the network during times of congestion. This is in contrast to offline coding which completely relies on coarse network state assumptions (Lie & Klaue 2008).

Rate adaptation attempts to change the sending rate of all video sources to share the available link capacity without considering how much the received QoE will be affected by the change. This was investigated in Chapter 3. Therefore, there is a need for a mechanism to control the number of video sessions which can be accommodated while QoE remains at an acceptable level. Unlike current MBACs,

the proposed QoE-aware admission control considers the bursty characteristic of video flows. This was illustrated in Chapter 5 where the model and implementation of the proposed QoE-aware measurement algorithm were introduced.

Figure 6.7 shows the proposed cross-layer architecture. The proposed blocks are highlighted. Rate adaptation is performed by the video sources at the application layer and QoE-aware admission control is implemented by the gateway of the ISP at the network layer. It employs parameters from both layers. The key parameters to be considered for the cross-layer optimisation from the application layer are the instantaneous arrival rate of each video sessions $x_i(t)$ and rate of requested video session x_{new}. At the network layer, link capacity C_l, *number of sessions* n, parameter β (Equation 5.10), and the proposed measured rate *Pro-IAAR(t)* (Equation 5.4) are taken into account. The architecture assumes that there are efficient and reliable routing protocols to route the video traffic through the ISP intra-domain links once they have been placed on the *ISP access link* by the gateway. It also assumes that there is sufficient bandwidth on the access and core networks.

Following Equations (3.2), (5.3) and (5.4), QoE (in terms of MOS) can be simplified as a function of the proposed QoE-aware measured rate by the utility function given by Equation (6.1)

$$U = f(Pro\text{-}IAAR(t)),\ f : Pro\text{-}IAAR(t) \rightarrow \text{MOS}. \tag{6.1}$$

Encoders that allows for variable quality such as MPEG-4, can produce video at different quality level from a video source material. The rate controller adapts the transmission rate based on *Pro-IAAR(t)*. The network load is monitored by the network monitor and estimated by *Pro-IAAR(t)*. Then the information is sent back to the rate controller via the acknowledgement packet of TFRC (as an extension of TCP). TFRC can be utilised for this purpose. TFRC is a congestion control mechanism for unicast transmission over the Internet. In addition to fairness when competing with other flows, it has a much lower variation of throughput over time compared with TCP. This makes TFRC more suitable for

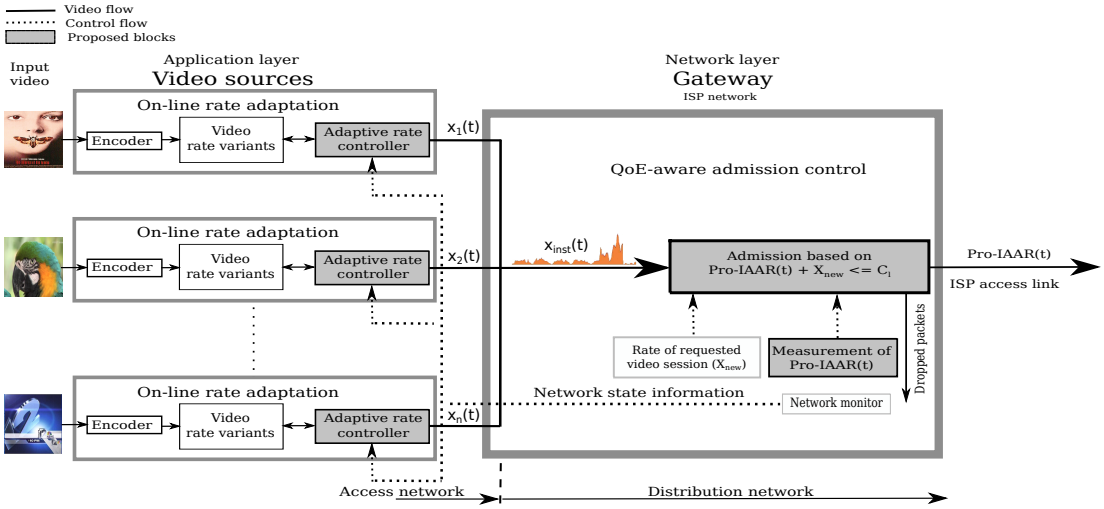


Figure 6.7: QoE-aware cross-layer architecture for video traffic

applications which require smooth sending rate such as video streaming (Floyd et al. 2008). The significance of TFRC for media applications has been growing remarkably (Lie & Klaue 2008). The rate controller selects a suitable video quality of available bit rates (video rate variants in Figure 6.7) for each GoP based on the information on the network state received from the network monitor. An open loop VBR controller requires access to both video content and network state information. The Explicit Congestion Notification (ECN) bit in the acknowledgement packet of the TFRC header is utilised for the purpose of network monitoring. The rate controller at the sender side reduces its transmission rate by selecting a lower video rate variant if ECN 1 is detected in the acknowledgement packet.

The rate controller switches to the next rate by selecting the next quantizer scale at the start of the next GOP. This may delay the new rate up to the duration of one GOP. A leaky bucket can be used to control the target bit rate and the allowed bit rate variability. It acts as a virtual buffer, therefore it does not introduce additional delay to video packets. Leaky bucket algorithms are widely used by rate controllers to control traffic to packet-switched and ATM-based networks (Hamdi et al. 1997).

The proposed QoE-aware traffic measurement algorithm introduced in Chapter 5 measures the network load and based on that, the QoE-aware admission control

Algorithm 2 Implementation of the QoE-aware cross-layer architecture for video admission

```
    Given C_l, n, α, and σ
 1: for Every video session request do
 2:     Compute μ_r(t) from Equation (5.3)
 3:     Compute β from Equation (5.10)
 4:     Compute ϵ from Equation (5.5)
 5:     Compute Pro-IAAR(t) from Equation (5.4)
 6:     c=2
 7:     x_new = Highest bit rate (QP = c)
 8:     if Pro-IAAR(t) + x_new ≤ C_l = True then
 9:         Session accepted with rate x_new
10:         Send the QP/c that satisfies accepted x_new, to the source
11:     else
12:         if c ≤ 31 then
13:             Increment c
14:             x_new = Next bit rate (QP = c)
15:             Goto line 8
16:         else
17:             Session rejected
18:         end if
19:     end if
20: end for
```

makes the decision. The new requested session will be admitted only if the sum of *Pro-IAAR* on the link plus x_{new} is less than or equal to C_l.

A video source prior to start transmitting, sends a request to the ISP gateway indicating its intended sending rate (highest bit rate) as well as other possible bit rates (30 bit rates in total). The gateway upon receiving the request calculates $\mu_r(t)$ using Equation (5.3), β using Equation (5.10), *Pro-IAAR(t)* using Equation (5.4) and checks the condition of Equation (5.7). The new session is accepted with its intended bit rate x_{new} if the condition meets. If the condition does not meet however, the gateway checks the next bit rate (from higher to lower) that satisfies the condition. The gateway acknowledges the potential source should any other bit rate meets the condition which then is adopted by the source. If non of the bit rates satisfies the condition however, the request is rejected. The video sources are able to switch to a higher bit rate after they have been successfully accepted when bandwidth becomes available. Since only the acceptance/rejection admission policy was the target of this study, post-acceptance bit rate switching was not addressed by our algorithm.

QoE is included into Algorithm 2 through parameter β which controls the total bitrate on a specific link based on the QoE of current sessions. The impact of β was explained in Chapter 5. On the other hand, the rate controller makes the architecture flexible by offering 30 different bit rates-with the preference from high to low-assuming that they do not cause noticeable artifacts.

Algorithm 2 is jointly implemented by the video sources and ISP gateway relying on the available communication messages of the TCP/IP protocol suite for showing the interest to send, notification of the sender and network monitoring as explained earlier in this section. It therefore does not demand additional requirements. The complexity of the algorithm is rated low assuming that each media content is encoded with 30 video rate variants. This assumption is justifiable for video streaming services and the dropping cost of storage on media servers. The pseudocode for the implementation of the proposed QoE-aware cross-layer architecture for video admission is summarised in Algorithm 2.

Using Big O notation metric, the complexity of Algorithm 2 is determined by counter c of the iteration loop in line 12 as well as fundamental operations in lines 2, 3, 4, 5, 6, 7, 8, 9, 10 and 17. This describes the worst-case scenario when the condition in line 8 is not satisfied. The time complexity of our algorithm is linear to the counter c, i.e.

$$T(c) = 10 + 1 + (c + 1) + 3c \tag{6.2}$$

$$T(c) = 12 + 4c \tag{6.3}$$

that is to say, $T(c) \sim \mathrm{O}(c)$. The space complexity of the algorithm such as memory requirement, is insignificant due to the large storage capacity of modern routers.

The proposed architecture addresses the issue of QoE degradation of video traffic in a bottleneck network by introducing a QoE-aware cross-layer architecture to

optimise the video quality. In particular, it allows video sources, at the application layer, to adapt to the network environment by controlling the transmitted bit rate dynamically; and the edge of network, at the network layer, to protect the quality of active video sessions by controlling the acceptance of new session through a QoE-aware admission control. Each of the on-line rate adaptation and QoE-aware admission control has been implemented and investigated separately in Chapter 3 and Chapter 5 respectively. In this chapter, the functionalities of both components are combined in our architecture.

6.4 Evaluation Environment

This section describes the settings of the evaluation environment for testing the performance of our architecture. Evalvid-RA (Lie & Klaue 2008) was used to implement an on-line rate adaptation from different encoded videos each with a valid range of QP from 2-31. A lower QP causes a higher bit rate and better quality. The description of the video sequences used in this chapter, as well as coding and network parameters, were the same as shown in Tables 3.1 and 3.2. To evaluate the performance of the proposed architecture for different video resolutions, QCIF and CIF videos were used in the simulation. Parameter β was experimentally found to be 0.9 for MAD sequence and 0.78 for Grandma sequence. It was also calculated using Equation (5.10). The values of coefficients (α and σ) were adopted from Chapter 5. Experimental and calculated β are illustrated in Table 6.4. In Chapter 5, we evaluated the robustness of our proposed measurement algorithm and its implementation in an environment where only VBR traffic were present. In this chapter, in addition to the VBR traffic, the link also accommodates FTP traffic. The objective was to have a more realistic scenario where other traffic exist in the same network along with the video traffic.

Table 6.4: Calculation of β

Video sequence	β **(Experimental)**	β **(Equation 5.10)**	α	σ	C_l**(Mbps)**	**mean** n
MAD (CIF)	0.9	0.84	-0.54	0.96	32	24
Grandma (QCIF)	0.78	0.775	-0.1	0.4	7	20

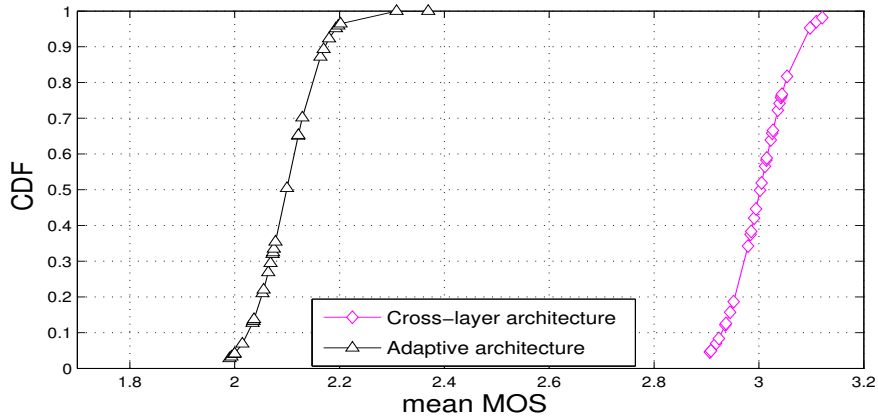
This also demonstrates how much video flows are affected by the background FTP flows.

The proposed QoE-aware architecture (referred to as *cross-layer architecture*) was compared to the *adaptive architecture* (defined in Chapter 3) using the topology shown in Figure 3.2. The gateway of the *cross-layer architecture* implements the proposed QoE measurement algorithm and admission control mechanism in addition to the rate adaptation of the video sources. NS-2 (NS-2 n.d.) was used to evaluate the performance of both architectures.

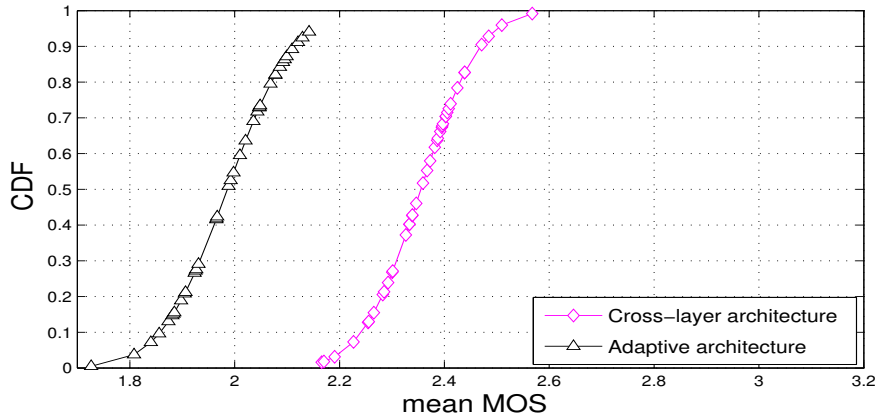
A maximum of 24 video sessions were competing for the capacity of a bottleneck link. The simulations with settings described in Table 3.2 run for 500 seconds. The simulation of the *cross-layer architecture* was configured so that new sessions were requested randomly within every second and would be accepted if enough bandwidth was available, i.e. the condition $Pro\text{-}IAAR(t) + x_{new} \leq C_l$ is satisfied. This procedure ensured that new sessions do not penalise active sessions and they receive sufficient resources. This results in an acceptable QoE. Whereas for the *adaptive architecture*, all sessions were admitted for each simulation run. For simplicity, the maximum number of competing sessions was limited to 24 sessions. The same video sequences (MAD and Grandma) described in Table 3.1 were encoded and decoded in the similar way as explained in Chapter 3. The quality of received videos from the simulation was evaluated as explained in Section 3.3 of Chapter 3. As mentioned in Chapter 3, the CDF of each metric was calculated as the mean of the 24 video flows over 30 simulation runs. As the *number of sessions* is controlled by β in addition to C_l, its value was set based on Equation (5.10).

6.5 Performance Evaluation of the Architecture

In Chapter 3, the performance of the video flows in the *adaptive architecture* was compared to the video flows in the *non-adaptive architecture* in terms of MOS, number of successfully decoded sessions, delay and jitter. In this chapter,



(a) MAD (CIF)



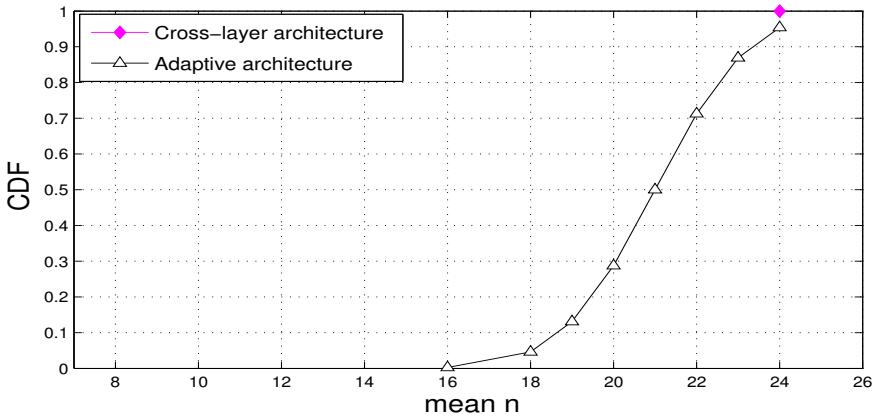
(b) Grandma (QCIF)

Figure 6.8: CDF of the mean MOS of the video flows in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

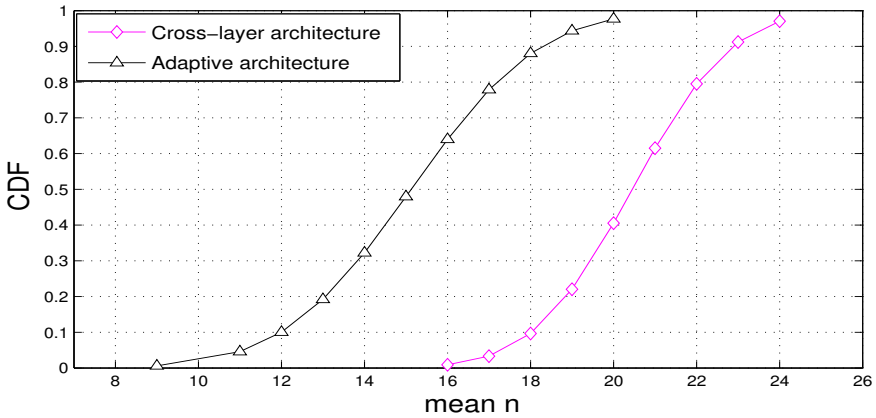
the performance of the video flows in the *cross-layer architecture* is compared to the video flows in the *adaptive architecture* using the same metrics. Finally, a comparison between the video flows in the *non-adaptive architecture*, *adaptive architecture* and *cross-layer architecture* is made.

6.5.1 *Cross-layer architecture* vs *Adaptive architecture*

The CDF of the mean MOS of the video flows in the *cross-layer architecture* and *adaptive architecture* for both resolutions are plotted in Figure 6.8. MOS enhancement of the video flows delivered through the proposed *cross-layer architecture* can be seen for both resolutions. The difference between the graphs



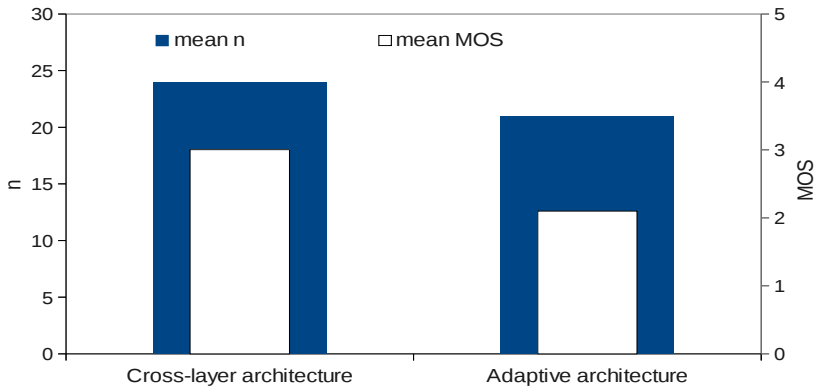
(a) MAD (CIF)



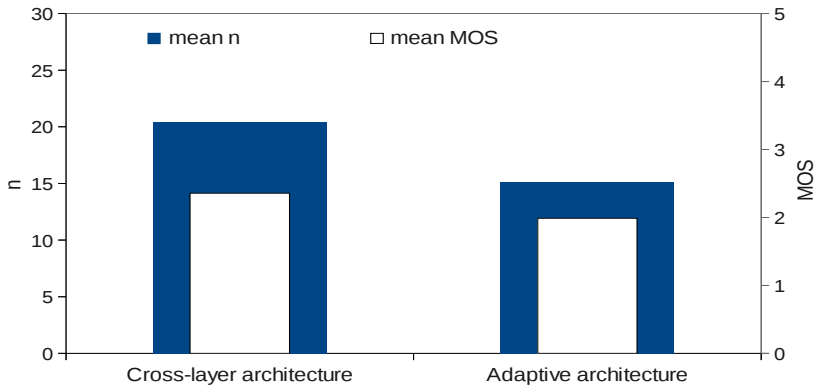
(b) Grandma (QCIF)

Figure 6.9: CDF of the mean *number of sessions* in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

shows that the result depends on the resolution. The mean MOS of the video flows in the *adaptive architecture* was enhanced by the *cross-layer architecture* from 1.98 to 2.35 for the QCIF resolution and from 2.09 to 3 for the CIF resolution. Although, the enhancement of the QCIF resolution is considered trivial, it is substantial for the CIF resolution as the MOS of the videos according to Table 2.1 (Stankiewicz et al. 2011), changes from bad to fair. Recalling from Chapter 3 that the maximum possible MOS for any multimedia services in practice is 4.5 (Thakolsri et al. 2009), this slight enhancement of the QCIF MOS by *cross-layer architecture* can still make a difference in today's huge number of video sessions over the Internet.



(a) MAD (CIF)

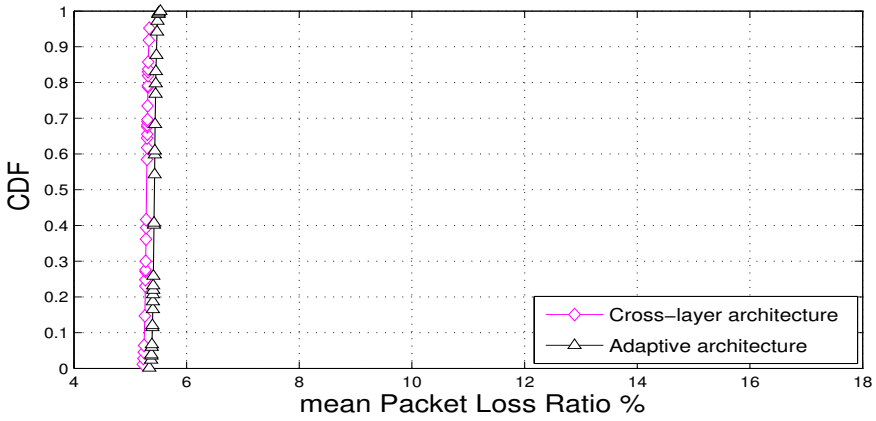


(b) Grandma (QCIF)

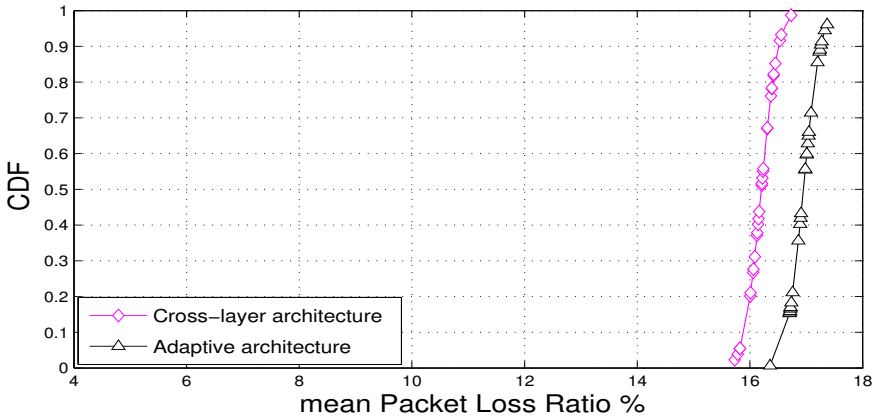
Figure 6.10: Mean MOS of the video flows and mean *number of sessions* in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

It is worthwhile mentioning that the performance of the proposed QoE-aware rate measurement algorithm and associated admission control were more pronounced in terms of MOS when they were evaluated among video flows only in Chapter 5. In this chapter, FTP traffic is included as a background traffic. Rate adaptation implemented by the video sources lets the video flows pay attention to the FTP flows by adapting their sending rates. This resulted in a lower MOS compared to the MOS of the video flows in Chapter 5 where FTP flows were not considered.

As the main target of this study is to optimise the *QoE-Session* trade-off, we can not consider the MOS of the video sessions alone. To account for this, the number of successfully decoded video sessions, was measured both for the *cross-layer architecture* and *adaptive architecture*. This is plotted for both resolutions



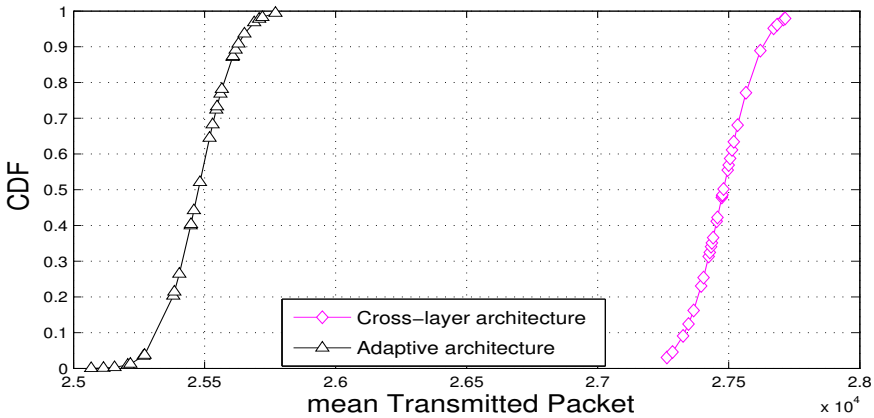
(a) MAD (CIF)



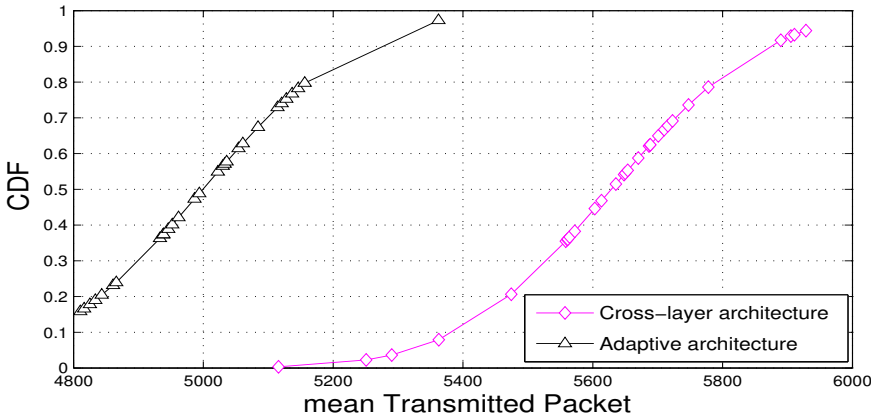
(b) Grandma (QCIF)

Figure 6.11: CDF of the mean packet loss ratio of the video flows in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

in Figure 6.9. Although, all 24 video flows in the *adaptive architecture* were active, an average of 15 QCIF and 21 CIF sessions were successfully decoded by the receivers. This is due to the fact that being adaptive, the video sources send data in a cooperative manner. Thus not all the video frames were sent into the network due to insufficient bandwidth and availability of other traffic (FTP) in the network. In contrast, an average of 20 QCIF and all 24 CIF videos sessions were successfully decoded when delivered on the *cross-layer architecture*. Although FTP flows were again available in this scenario, the video sessions were better managed by the proposed QoE-aware admission control *Pro-IBMAC* and therefore more sessions were accommodated.



(a) MAD (CIF)

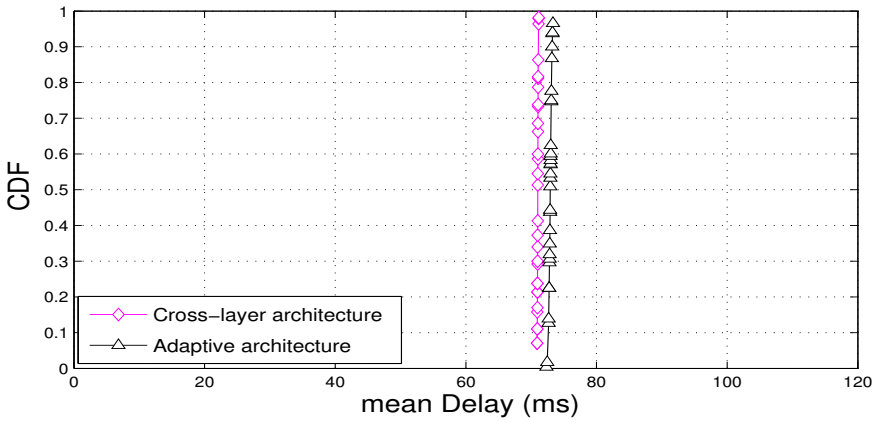


(b) Grandma (QCIF)

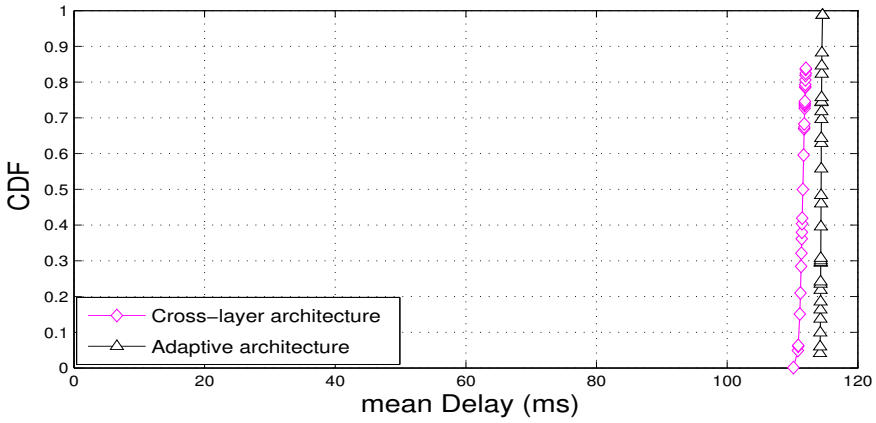
Figure 6.12: CDF of the mean transmitted packet of the video flows in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

It can also be noticed in Figure 6.9 that, in contrast to the video flows in the *adaptive architecture* which were more efficient for the QCIF resolution as discussed in Chapter 3, the *number of sessions* in the *cross-layer architecture* is not resolution dependent as 5 more QCIF and 3 more CIF sessions are accommodated by the *cross-layer architecture*. As stated in Chapter 3, due to each resolution's specific simulation settings, the mean MOS and mean *number of sessions* of the two resolutions were not compared to each other.

To compare the difference between the mean MOS of the video flows and mean *number of sessions* in the *cross-layer architecture* and *adaptive architecture* in a better way, both are plotted for both resolutions in the bar charts in Figure



(a) MAD (CIF)



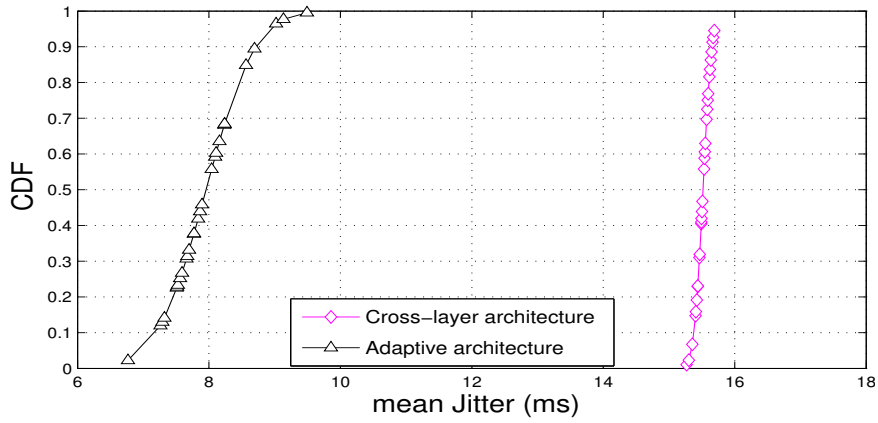
(b) Grandma (QCIF)

Figure 6.13: CDF of the mean delay of the video flows in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

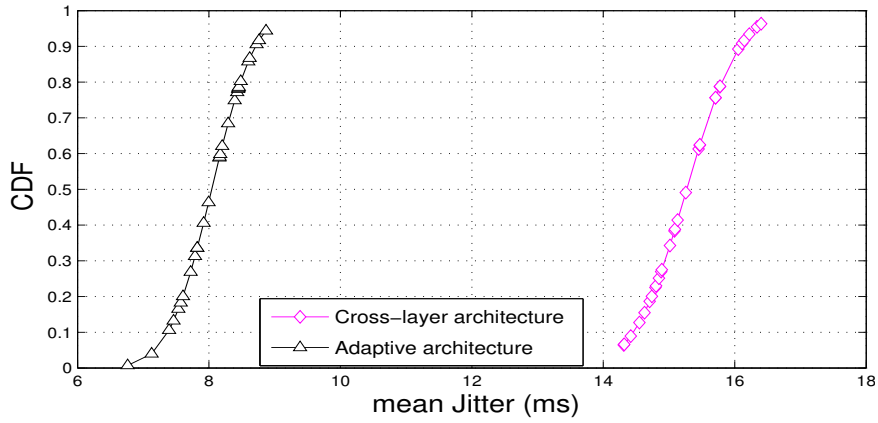
6.10. The white bars represent the mean MOS and blue bars represent the mean *number of sessions*.

Video streaming services are tolerant to packet loss to some extent. Error concealment in the decoder makes video to accept some tolerance of packet loss. We calculated the CDF of the mean packet drop ratio of the video flows in the *cross-layer architecture* and *adaptive architecture* and plotted them in Figure 6.11. Video flows delivered over the *cross-layer architecture* experienced less packet drop compared to the video flows in the *adaptive architecture*.

In contrast to the substantial difference in the mean MOS as shown in Figure 6.8, there is a small difference between the packet drop ratio of the video flows in the *cross-layer architecture* and *adaptive architecture* as can be seen in Figure



(a) MAD (CIF)

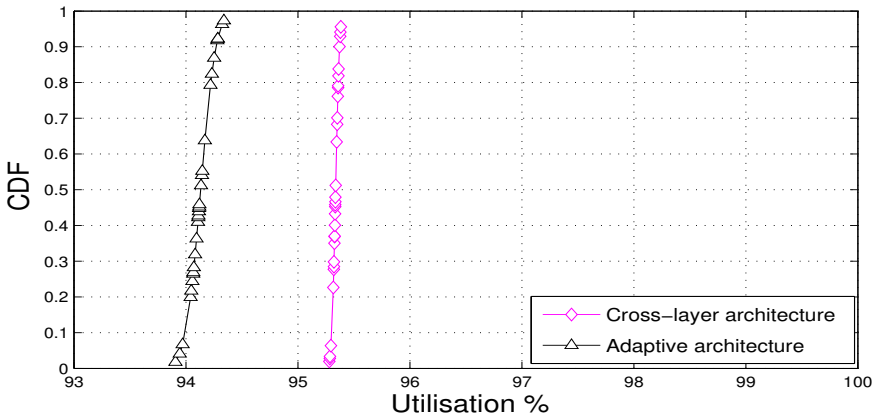


(b) Grandma (QCIF)

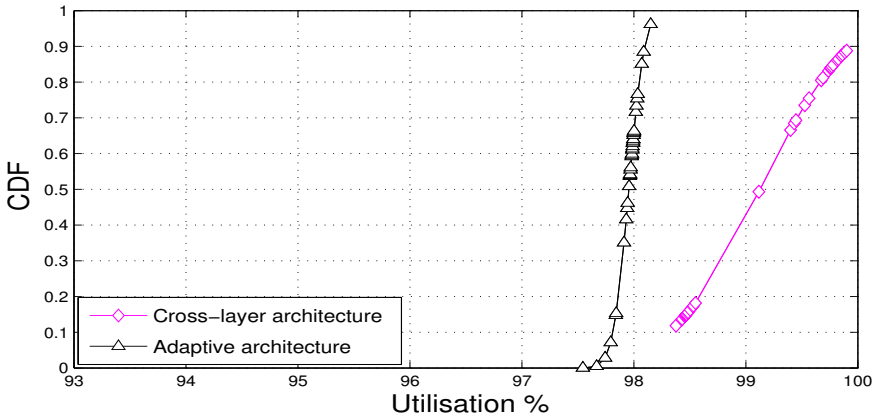
Figure 6.14: CDF of the mean jitter of the video flows in the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

6.11. However, these packets were dropped out of the total number of the transmitted packets. The CDF of the mean transmitted packet are shown in Figure 6.12 in which the difference between the number of packets transmitted by the video sources in each of the *cross-layer architecture* and *adaptive architecture* is evident. Therefore, a smaller ratio of the packet loss of the video flows out of a higher number of transmitted packets of the same video content in the *cross-layer architecture* compared to the *adaptive architecture* ensured a better quality (in terms of MOS) as discussed earlier in this section.

From Equation (3.2) and Figure 3.3, it is evident that a higher SBR provides a better MOS for the same packet drop ratio. Sending a higher number of video packets by the *cross-layer architecture* compared to *adaptive architecture* as shown in



(a) MAD (CIF)

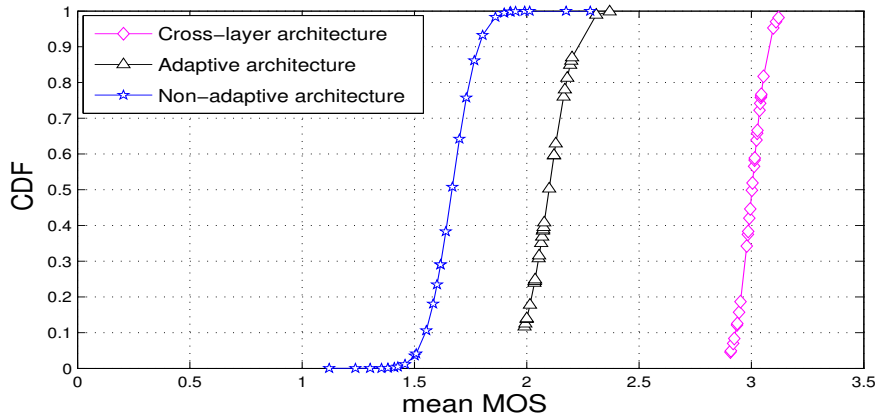


(b) Grandma (QCIF)

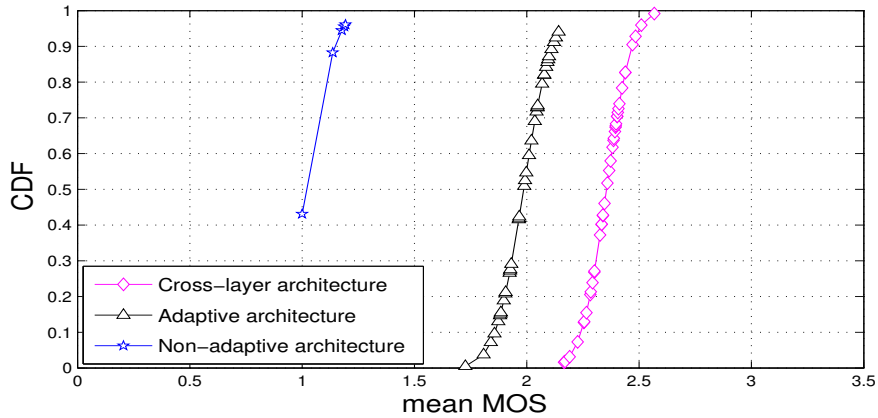
Figure 6.15: Utilisation of the *cross-layer architecture* and *adaptive architecture* for MAD and Grandma sequences

Figure 6.12 and a lower packet drop ratio as shown in Figure 6.11 over the same simulation time (500 seconds), indicates that the video content was sent with a higher bitrate, thus a better MOS was provided by the *cross-layer architecture*.

Video streaming applications have a lenient delay requirement. Depending on the application's buffering capabilities, 4 to 5 seconds delay is acceptable (Szigeti & Hattingh 2004). The CDF of the mean delay and mean jitter of the video flows for each of the *cross-layer architecture* and *adaptive architecture* are measured and depicted in Figures 6.13 and 6.14 respectively. The video flows in the *cross-layer architecture* experienced less delay and higher jitter compared to the video flows in the *adaptive architecture*. The mean jitter of the video flows in the *cross-layer architecture* is almost double of the video flows in the *adaptive architecture*.



(a) MAD (CIF)

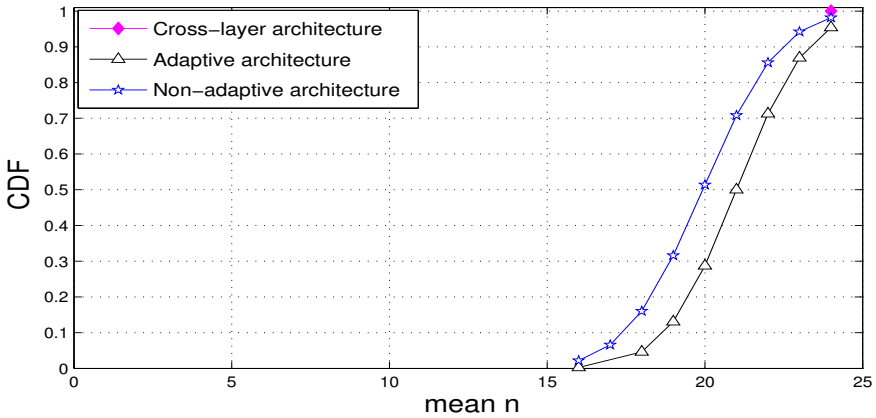


(b) Grandma (QCIF)

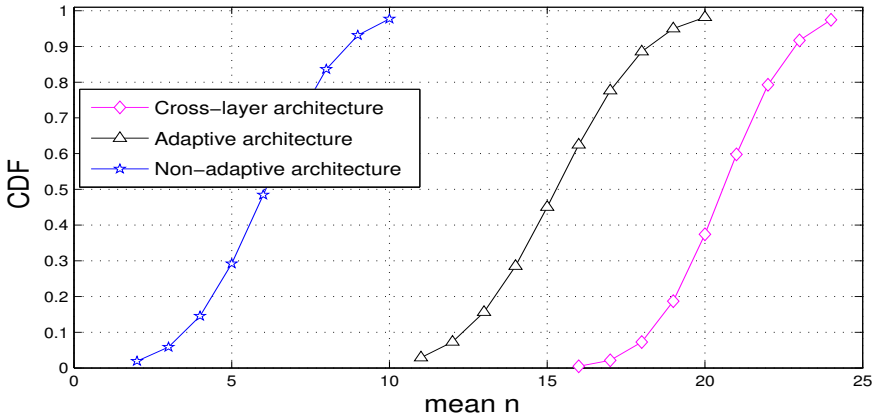
Figure 6.16: CDF of the mean MOS of the video flows in the *cross-layer architecture*, *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

However, there are no significant jitter requirements for streaming video (the target traffic of this study) (Szigeti & Hattingh 2004).

The *adaptive architecture* utilises the capacity of the bottleneck link less efficiently than the *cross-layer architecture* as can be observed in Figure 6.15. Please note that utilisation includes the FTP flows as well. It is calculated as the number of transmitted bits over the capacity of the link over the simulation period. Thus, the *adaptive architecture* leads to a high link utilisation: 94% for CIF and 98% for QCIF resolution. The utilisation for the *cross-layer architecture* increases to 95% for CIF and 99% for QCIF resolution. We can conclude that the utilisation



(a) MAD (CIF)



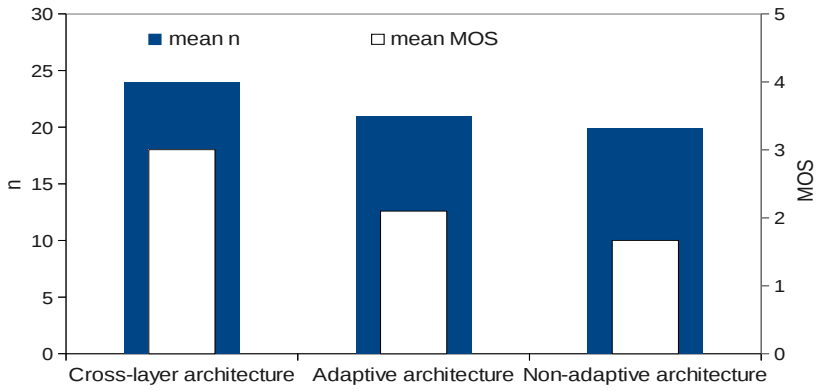
(b) Grandma (QCIF)

Figure 6.17: CDF of the mean *number of sessions* in the *cross-layer architecture*, *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

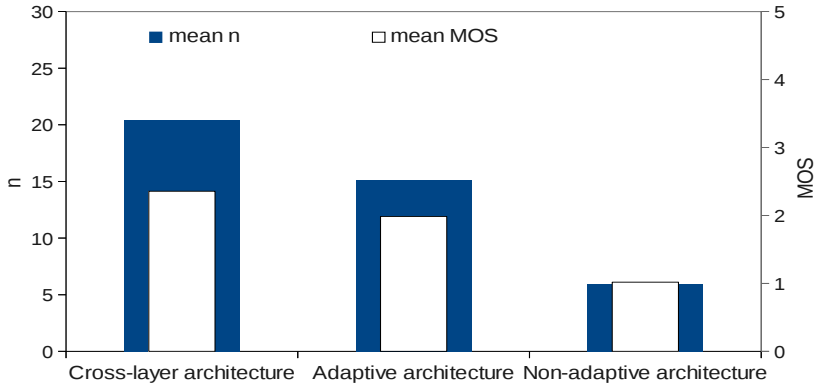
figures can not decide the performance of the two architectures for the video flows as it is calculated for video and FTP flows.

6.5.2 Comparison between *cross-layer architecture*, *adaptive architecture* and *non-adaptive architecture*

In this section, the video flows delivered over the proposed *cross-layer architecture* is compared to the video flows transmitted by each of the *adaptive architecture* and *non-adaptive architecture*. Figure 6.16 shows the CDF of the mean MOS of the video flows in the three architectures for both video resolutions. While,



(a) MAD (CIF)



(b) Grandma (QCIF)

Figure 6.18: Mean MOS of the video flows and mean *number of sessions* in the *cross-layer architecture*, *adaptive architecture* and *non-adaptive architecture* for MAD and Grandma sequences

there is an improvement of the mean MOS of the video flows in the *adaptive architecture* through adaptation of the sender rate compared to the video flows in the *non-adaptive architecture*, a higher value of the mean MOS of the video flows in the *cross-layer architecture* is observed.

Moreover, the proposed *cross-layer architecture* accepts and delivers a higher *number of sessions* compared to the other two architectures (*adaptive architecture* and *non-adaptive architecture*). This can be observed in Figure 6.17. The bar chart in Figure 6.18 illustrates the difference in the mean MOS of the video flows and mean *number of sessions* between all three architectures for both resolutions.

6.6 Summary

Mechanisms proposed for optimising QoE of video traffic were surveyed in detail in this chapter and the challenges of achieving this objective were discussed. A QoE-aware cross-layer architecture for video traffic was also proposed. A rate-adaptation and QoE-aware admission control are the two main components of the architecture. The performance of the *cross-layer architecture* was analysed and compared to two other architectures (*adaptive architecture* and *non-adaptive architecture*). Extensive simulations results have shown that the *cross-layer architecture* can provide improvements both in terms of mean MOS, and higher number of successful decoded video sessions. Also, it utilised the bottleneck link more efficiently.

The next chapter concludes this study and outlines work to be done in this area in the future.

Chapter 7

Conclusions and Further Work

This chapter briefly highlights the contributions the study has made. It then concludes the outcomes of this research and finally elaborates on future work.

7.1 Summary of Contribution

This study has addressed the issue of QoE degradation of video traffic. The results and outcomes of the study have contributed to the research community in the area of QoE optimisation of video sessions. The following specific objectives have been addressed:

An Overview of QoE for Video Streaming Service

Chapter 2 has presented the background of QoE as well as motivations for introducing this metric. Various parameters identified by researchers which affect QoE were explained. The need for QoE-driven quality models was explained and a classification of video models was made. Standard and non-standard quality metrics, as well as subjective test methodologies, were discussed.

An Investigation of the Impact of Adapting SBR on QoE

Chapter 3 surveyed works which recommend rate adaptation for the improvement of video quality. This aspect was investigated by formulating a relationship

between SBR and QoE, then evaluated by doing extensive simulations. The performance of video sources that adapt their sending rates was compared to those which send without reacting to the network condition in terms of MOS, number of successful sessions, delay and jitter for QCIF and CIF resolutions.

A Comparison Between the Instantaneous and Average Aggregate Video Rates

Chapter 4 investigated the suitability of the average aggregate rate as an alternative to instantaneous rate for video traffic. A mathematical model to quantify the probability relationship between the two rates was presented. Simulation results did not show a significant difference between the rates however, the average was found to be lower than instantaneous for a small number of video flows and the difference increased for fast moving video contents or longer measurement time windows.

A Proposed QoE-Aware Rate Measurement Algorithm for Video Traffic

The results of Chapter 4 motivated the researcher to seek a more suitable means of video rate measurement. Our novel algorithm found the upper limit of the video total rate that can exceed a specific link capacity without the QoE degradation of ongoing video sessions. The tunable parameter β of the algorithm defines the exceedable limit. When implemented in an admission control procedure of CIF videos and compared to the calculated rate-based admission control, the proposed algorithm maintained a better QoE of a higher number of video sessions.

A QoE-aware cross-layer architecture for the optimisation of video traffic

Chapter 6 presented the proposed QoE-aware cross-layer architecture for video traffic. The architecture deploys the rate measurement algorithm proposed in Chapter 5 and rate adaptation capability of video applications. The proposed *cross-layer architecture* was found to outperform the *non-adaptive architecture* and *adaptive architecture* by providing a higher mean MOS, number of successful decoded video sessions, and link utilisation with less mean delay and packet loss. However, the video flows in the *cross-layer architecture* experienced higher jitter

compared to the video flows in the other two architectures. The rise of jitter in the *cross-layer architecture* however, is not considered a concern as there are no significant jitter requirements for streaming video (the target traffic of this study) (Szigeti & Hattingh 2004).

A Survey of QoE Optimisation Mechanisms

This aspect was covered in Chapter 6 by categorising mechanisms proposed for QoE optimisation of video traffic in the last 10 years. Comparisons of various mechanisms of each category were made. Challenges in optimising QoE of video traffic and motivations for further work were explained.

7.2 Conclusions

Adapting the sending rate of video applications improves the QoE of a higher number of successfully admitted video sessions compared to video traffic that is sent without rate adaptation. This enhancement in QoE and the *number of sessions* does not come at the cost of delay and jitter. However, the QoE of active video sessions in a bottleneck link degrade continually with the increase of the *number of sessions* due to accepting every new session.

Video traffic measurement based on the instantaneous or average rate over a time window is not an efficient method to classify video flows as there is not a notable difference between these rates, except for a small number of video flows, long measurement time window or fast moving contents such as sports.

The proposed QoE-aware measurement algorithm is a more efficient method of video rate measurement compared to algorithms that calculate the rate over a time window. It accounts for QoE for a higher number of admitted video sessions. Parameter β can be tuned by the ISPs for a better utilisation of resources and provision of services to end users. The model of β can be developed further to

include delay and applied to realtime video traffic.

The proposed video traffic measurement algorithm and *cross-layer architecture* were evaluated for the QCIF and CIF video resolutions. The results showed that the architecture outperforms the *adaptive architecture* and *non-adaptive architecture*. Based on the results, it also can be applied to other video resolutions.

The proposed QoE-aware *cross-layer architecture* is recommended for video transmission. It maintains the QoE of a higher number of successfully adaptive decoded video sessions compared to the *adaptive architecture* and *non-adaptive architecture*. It provides a notable enhancement in QoE and link capacity utilisation without compromising delay.

7.3 Further Work

Accounting for various degradations and factors is a challenging task for objective video quality models. In recent years, there has been a growing interest in the development of advanced objective video quality models that can closely match the performance of subjective video quality evaluation. Cross-layer designs must consider more relevant parameters to gain a better optimised outcome.

The first step of QoE optimisation is to measure QoE in an accurate way. Current QoE estimation models are limited to specific video resolutions and coding schemes. Thus, finding a prediction model that can estimate the quality for as wide as possible video formats and coding is required. As per the recommendation of ITU, any attempt for QoE modelling has to consider objective modelling of measurable technical performance and subjective testing with people (Brooks & Hestnes 2010). More intelligence fairness techniques are useful to avoid penalising the same user in the case of insufficient resources where some traffic needed to be dropped.

In Chapter 4, the impact of the measurement time window $k\tau$ was demonstrated without providing guidelines for the setting of the window, thus proper setting is an interesting topic for further work. The MOS metric from (Gross et al. 2004) was used as a measure of QoE in this study. Other metrics, such as *SSIM*, will further validate the results of this study in future work.

The model of β proposed in Chapter 5 did not include delay as a parameter. Since, real-time video streaming services tolerate a certain limit of delay, the model can be further extended to include delay as another variable to bound the functionality of the algorithm within an acceptable limit of delay. Furthermore, the model can be re-structured relying on subjective testing rather than simulation data only as the later does not represent direct perception of users.

Two different scenes (MAD and Grandma) and resolutions (QCIF and CIF) were used in the evaluation of the proposed architecture however, both clips are considered similar content types as the movement of the video scenes are limited to head and shoulder. Evaluating the architecture with a greater variety of video contents, such as sport, will be an interesting area of future research. Developing Algorithm 2 further in order to include post-acceptance bit rate switching is another interested area of future research.

Finally, simulation, mathematical modelling, subjective testing and statistical analysis were used in this study as means of evaluation and validation. Implementing the architecture in a real testbed environment will reflect a more realistic scenario.

Bibliography

Adzic, V., Kalva, H. & Furht, B. (2012), 'Optimizing video encoding for adaptive streaming over HTTP', *Consumer Electronics, IEEE Transactions on* **58**(2), 397–403.

Aguiar, A. C. C. (2008), Multi-user multi-flow packet scheduling for wireless channels, PhD thesis, Technichen Universit Berlin.

Ameigeiras, P., Ramos-Munoz, J. J., Navarro-Ortiz, J., Mogensen, P. & Lopez-Soler, J. M. (2010), 'QoE oriented cross-layer design of a resource allocation algorithm in beyond 3G systems', *Computer Communications* **33**(5), 571–582.

Ammar, D., Begin, T., Guerin-Lassous, I. & Noirie, L. (2011), Evaluation and comparison of MBAC solutions, *in* 'Local Computer Networks (LCN), 2011 IEEE 36th Conference on', pp. 215–218.

Ammar, D., Begin, T., Guerin-Lassous, I. & Noirie, L. (2012), KBAC: Knowledge-based admission control, *in* 'Local Computer Networks (LCN), 2012 IEEE 37th Conference on', pp. 537–544.

Auge, J., Oueslati, S. & Roberts, J. (2011), Measurement-based admission control for flow-aware implicit service differentiation, *in* 'Teletraffic Congress (ITC), 2011 23rd International', pp. 206–213.

Blake, S., Black, D., Carlson, M., Davies, E., Wang, Z. & Weiss, W. (1998), 'An architecture for differentiated services'.

Breslau, L., Jamin, S. & Shenker, S. (2000), Comments on the performance of measurement-based admission control algorithms, *in* 'INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE', Vol. 3, pp. 1233–1242.

Brooks, P. & Hestnes, B. (2010), 'User measures of quality of experience: Why being objective and quantitative is important', *Network, IEEE* **24**(2), 8 –13.

Calyam, P., Ekici, E., Lee, C.-G., Haffner, M. & Howes, N. (2007), 'A GAP-model based framework for online VVoIP QoE measurement', *Journal of Communications and Networks* pp. 446–456.

Camara, J., Moreto, M., Vallejo, E., Beivide, R., Miguel-Alonso, J., Martinez, C. & Navaridas, J. (2010), 'Twisted torus topologies for enhanced interconnection networks', *Parallel and Distributed Systems, IEEE Transactions on* **21**(12), 1765–1778.

Casetti, C., Kurose, J. & Towsley, D. (1997), A new algorithm for measurement-based admission control in integrated services packet networks, *in* W. Dabbous & C. Diot, eds, 'Protocols for High-Speed Networks V', IFIPThe International Federation for Information Processing, Springer US, pp. 13–28.

Cavusoglu, B. & Oral, E. A. (2014), 'Estimation of available bandwidth share by tracking unknown cross-traffic with adaptive extended Kalman filter', *Computer Communications* **47**(0), 34–50.

Chen, C., Zhu, X., de Veciana, G., Bovik, A. & Heath, R. (2015), 'Rate adaptation and admission control for video transmission with subjective quality constraints', *Selected Topics in Signal Processing, IEEE Journal of* **9**(1), 22–36.

Chen, X., Chen, M., Li, B., Zhao, Y., Wu, Y. & Li, J. (2013), 'Celerity: a low-delay multi-party conferencing solution', *Selected Areas in Communications, IEEE Journal on* **31**(9), 155–164.

Chen, X., Hwang, J.-N., Lee, C.-N. & Chen, S.-I. (2014), 'A near optimal QoE-driven power allocation scheme for scalable video transmissions over MIMO

systems', *Selected Topics in Signal Processing, IEEE Journal of* **PP**(99), 1–1.

Chendeb Taher, N., Ghamri Doudane, Y., El Hassan, B. & Agoulmine, N. (2014), 'Towards voice/video application support in 802.11e WLANs: a model-based admission control algorithm', *Computer Communications* **39**, 41–53.

Cherif, W., Ksentini, A., Negru, D. & Sidibe, M. (2011), A PSQA: efficient real-time video streaming QoE tool in a future media internet context, *in* 'Multimedia and Expo (ICME), 2011 IEEE International Conference on', pp. 1–6.

Chikkerur, S., Sundaram, V., Reisslein, M. & Karam, L. (2011), 'Objective video quality assessment methods: A classification, review, and performance comparison', *Broadcasting, IEEE Transactions on* **57**(2), 165–182.

Cisco documentation (2014*a*), Cisco visual networking index: Forecast and methodology 2013-2018, Cisco white paper.

Cisco documentation (2014*b*), Cisco visual networking index: global mobile data traffic forecast update, 2013-2018, Cisco white paper.

Debono, C., Micallef, B., Philip, N., Alinejad, A., Istepanian, R. & Amso, N. (2012), 'Cross-layer design for optimized region of interest of ultrasound video data over mobile WiMAX', *Information Technology in Biomedicine, IEEE Transactions on* **16**(6), 1007–1014.

Deng, C., Ma, L., Lin, W. & Ngan, K. N., eds (2015), *Visual signal quality assessment; quality of experience QoE*, Springer.

Dobrian, F., Sekar, V., Awan, A., Stoica, I., Joseph, D., Ganjam, A., Zhan, J. & Zhang, H. (2011), 'Understanding the impact of video quality on user engagement', *SIGCOMM Comput. Commun. Rev.* **41**(4), 362–373.

Duong, T., Zepernick, H.-J. & Fiedler, M. (2010), Cross-layer design for integrated mobile multimedia networks with strict priority traffic, *in* 'Wireless Communications and Networking Conference (WCNC), 2010 IEEE', pp. 1–6.

Eardley P., E. (2009), Pre-Congestion Notification (PCN) architecture, RFC 5559, IETF.

El Essaili, A., Schroeder, D., Steinbach, E., Staehle, D. & Shehada, M. (2014), 'QoE-based traffic and resource management for adaptive HTTP video delivery in LTE', *Circuits and Systems for Video Technology, IEEE Transactions on* **PP**(99), 1–1.

Erdelj, M. (2013), Mobile wireless sensor network architecture: applications to mobile sensor deployment, PhD thesis, Universit des Sciences et Technologie de Lille.

Ernst, J. B., Kremer, S. C. & Rodrigues, J. J. (2014), 'A survey of QoS/QoE mechanisms in heterogeneous wireless networks', *Physical Communication* **13, Part B**(0), 61–72. Special Issue on Heterogeneous and Small Cell Networks.

Escuer, P. J. P. (2014), Analysis and evaluation of in-home networks based on HomePlug-AV power line communications, PhD thesis, Universidad Politcnica de Cartagena.

ETSI STF 354 (n.d.), 'Guidelines and tutorials for improving the user experience of real-time communication services'. [Online] `http://portal.etsi.org/stfs/STF_HomePages/STF354/STF354.asp`, accessed on: Nov. 5th, 2015.

FFMPEG Multimedia System (2004). [Online] `http://ffmpeg.mplayerhq.hu/`, accessed on: Nov. 5th, 2015.

Fiedler, M., Zepernick, H.-J., Lundberg, L., Arlos, P. & Pettersson, M. (2009), QoE-based cross-layer design of mobile video systems: Challenges and concepts, *in* 'Computing and Communication Technologies, 2009. RIVF '09. International Conference on', pp. 1–4.

Floyd, S. (1996), Comments on measurement-based admissions control for controlled-load services, Technical report. [Oline] `http://www.icir.org/floyd/admit.html`, accessed on: Nov. 7th, 2015.

Floyd, S., Handley, M., Padhye, J. & Widmer, J. (2008), TCP friendly rate control (TFRC): protocol specification, RFC 5348, IETF. [Oline] `https://www.ietf.org/rfc/rfc3448.txt`, accessed on: Nov. 7th, 2015.

Frost, V. & Melamed, B. (1994), 'Traffic modeling for telecommunications networks', *Communications Magazine, IEEE* **32**(3), 70–81.

Fu, B., Munaretto, D., Melia, T., Sayadi, B. & Kellerer, W. (2013), 'Analyzing the combination of different approaches for video transport optimization for next generation cellular networks', *Network, IEEE* **27**(2), 8–14.

Gibbens, R. J. & Kelly, F. P. (1997), Measurement-based connection admission control, *in* '15th International Teletraffic Congress Proceedings'.

Goudarzi, P. (2012), 'Scalable video transmission over multi-hop wireless networks with enhanced quality of experience using Swarm intelligence', *Signal Processing: Image Communication* **27**(7), 722–736.

Goudarzi, P. & Hosseinpour, M. (2010), 'Video transmission over MANETs with enhanced quality of experience', *Consumer Electronics, IEEE Transactions on* **56**(4), 2217–2225.

Gross, J., Klaue, J., Karl, H. & Wolisz, A. (2004), 'Cross-layer optimization of OFDM transmission systems for MPEG-4 video streaming', *Computer Communications* **27**(11), 1044–1055.

Group, V. Q. E. (2008), 'VQEG multimedia project: Final report'.

Guerrero, C. D. & Labrador, M. A. (2010), 'On the applicability of available bandwidth estimation techniques and tools', *Computer Communications* **33**(1), 11–22.

Gurses, E., Akar, G. B. & Akar, N. (2005), 'A simple and effective mechanism for stored video streaming with TCP transport and server-side adaptive frame discard', *Computer Networks* **48**(4), 489–501.

Hamdaoui, B. & Ramanathan, P. (2007), 'A cross-layer admission control framework for wireless ad-hoc networks using multiple antennas', *Wireless Communications, IEEE Transactions on* **6**(11), 4014–4024.

Hamdi, H., Roberts, J. & Rolin, P. (1997), 'Rate control for VBR video coders in broad-band networks', *Selected Areas in Communications, IEEE Journal on* **15**(6), 1040–1051.

Hoeffding, W. (1963), 'Probability inequalities for sums of bounded random variables', *Journal of the American Statistical Association* **58**(301), 13–30.

Hu, H., Zhu, X., Wang, Y., Pan, R., Zhu, J. & Bonomi, F. (2012), QoE-based multi-stream scalable video adaptation over wireless networks with proxy, *in* 'Communications (ICC), 2012 IEEE International Conference on', pp. 7088–7092.

ITU-R Recommendation BT.500-12 (2009), 'Methodology for the subjective assessment of the quality of television pictures', International Telecommunication Union.

ITU-R Recommendation BT.500-13 (2012), 'Methodology for the subjective assessment of the quality of television pictures', International Telecommunication Union.

ITU-R Recommendation BT.710-4 (1998), 'Subjective assessment methods for image quality in high-definition television', International Telecommunication Union.

ITU-T Document FG IPTV-IL-0050 (2007), 'Definition of quality of experience (QoE)'.

ITU-T Recommendation G.107 (2015), 'The E-model: a computational model for use in transmission planning', International Telecommunication Union.

ITU-T Recommendation G.1070 (2012), 'Opinion model for video-telephony applications', International Telecommunication Union.

ITU-T Recommendation J.144 (2001), 'Objective perceptual video quality measurement techniques for digital cable television in the presence of a full reference', International Telecommunication Union.

ITU-T Recommendation J.343 (2014), 'Hybrid perceptual/bitstream models for objective video quality measurements', International Telecommunication Union.

ITU-T Recommendation P.564 (2007), 'Conformance testing for voice over IP transmission quality assessment models', International Telecommunication Union.

ITU-T Recommendation P.800.1 (2006), 'Mean Opinion Score (MOS) terminology', International Telecommunication Union.

ITU-T Recommendation P.862.1 (2003), 'Mapping function for transforming P.862 raw result scores to MOS-LQO', International Telecommunication Union.

ITU-T Recommendation P.910 (1998), 'Subjective audiovisual quality assessment methods for multimedia applications', International Telecommunication Union.

ITU-T Recommendation P.910 (1999), 'Subjective video quality assessment methods for multimedia applications', International Telecommunication Union.

ITU-T Recommendation P.910 (2008), 'Subjective video quality assessment methods for multimedia applications', International Telecommunication Union.

ITU-T Recommendation P.920 (2000), 'Interactive test methods for audiovisual communications', International Telecommunication Union.

Ivesic, K., Skorin-Kapov, L. & Matijasevic, M. (2014), 'Cross-layer QoE-driven admission control and resource allocation for adaptive multimedia services in LTE', *Journal of Network and Computer Applications* **46**(0), 336–351.

Jamin, S., Danzig, P. B., Shenker, S. J. & Zhang, L. (1997), A measurement-based admission control algorithm for integrated services packet networks, *in* 'IEEE/ACM Transactions on Networking', pp. 56–70.

Jamin, S., Shenker, S. & Danzig, P. (1997), Comparison of measurement-based admission control algorithms for controlled-load service, *in* 'INFOCOM '97.

Sixteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Driving the Information Revolution., Proceedings IEEE', Vol. 3, pp. 973–980.

Jiang, Y., Emstad, P., Nevin, A., Nicola, V. & Fidler, M. (2005), Measurement-based admission control for a flow-aware network, *in* 'Next Generation Internet Networks, 2005', pp. 318–325.

Joskowicz, J., Sotelo, R. & Lopez Ardao, J. (2013), 'Towards a general parametric model for perceptual video quality estimation', *Broadcasting, IEEE Transactions on* **59**(4), 569–579.

Ju, Y., Lu, Z., Zheng, W., Wen, X. & Ling, D. (2012), A cross-layer design for video applications based on QoE prediction, *in* 'Wireless Personal Multimedia Communications (WPMC), 2012 15th International Symposium on', pp. 534–538.

Khalek, A., Caramanis, C. & Heath, R. (2012), 'A cross-layer design for perceptual optimization of H.264/SVC with unequal error protection', *Selected Areas in Communications, IEEE Journal on* **30**(7), 1157–1171.

Khan, A., Sun, L. & Ifeachor, E. (2009*a*), 'Content-based video quality prediction for MPEG4 video streaming over wireless networks', *Journal of Multimedia* **4**(4).

Khan, A., Sun, L. & Ifeachor, E. (2009*b*), Content clustering based video quality prediction model for MPEG4 video streaming over wireless networks, *in* 'Communications, 2009. ICC '09. IEEE International Conference on', pp. 1–5.

Khan, A., Sun, L. & Ifeachor, E. (2010), 'Learning models for video quality prediction over wireless local area network and universal mobile telecommunication system networks', *Communications, IET* **4**(12), 1389–1403.

Khan, A., Sun, L. & Ifeachor, E. (2012), 'QoE prediction model and its application in video quality adaptation over UMTS networks', *Multimedia, IEEE Transactions on* **14**(2), 431–442.

Khan, A., Sun, L., Ifeachor, E., Fajardo, J., Liberal, F. & Koumaras, H. (2010), 'Video quality prediction models based on video content dynamics for H.264 video over UMTS networks', *International Journal of Digital Multimedia Broadcasting* **2010**.

Khan, A., Sun, L., Jammeh, E. & Ifeachor, E. (2010), 'Quality of experience-driven adaptation scheme for video applications over wireless networks', *Communications, IET* **4**(11), 1337–1347.

Khan, S., Duhovnikov, S., Steinbach, E. & Kellerer, W. (2007), 'MOS-based multiuser multiapplication cross-layer optimization for mobile multimedia communication', *Adv. MultiMedia* **2007**(1), 6–6.

Khan, S., Peng, Y., Steinbach, E., Sgroi, M. & Kellerer, W. (2006), 'Application-driven cross-layer optimization for video streaming over wireless networks', *Communications Magazine, IEEE* **44**(1), 122–130.

Kim, D. & Chung, K. (2012), 'A network-aware quality adaptation scheme for device collaboration service in home networks', *Consumer Electronics, IEEE Transactions on* **58**(2), 374–381.

Kim, T. & Ammar, M. (2005), 'Optimal quality adaptation for scalable encoded video', *Selected Areas in Communications, IEEE Journal on* **23**(2), 344–356.

Koo, J. & Chung, K. (2010), MARC: Adaptive rate control scheme for improving the QoE of streaming services in mobile broadband networks, *in* 'Communications and Information Technologies (ISCIT), 2010 International Symposium on', pp. 105–110.

Laghari, K. & Connelly, K. (2012), 'Toward total quality of experience: a QoE model in a communication ecosystem', *Communications Magazine, IEEE* **50**(4), 58–65.

Lambrecht, C. V. D. B. & Verscheure, O. (1996), Perceptual quality measure using a spatio-temporal model of the human visual system, *in* 'Int. Soc. Opt. Eng. (SPIE)', Vol. 2668, pp. 450–461.

Latré, S. (2011), Autonomic QoE management of multimedia networks, Phd dissertation, Universiteit Gent.

Latré, S. & De Turck, F. (2013), 'Joint in-network video rate adaptation and measurement-based admission control: Algorithm design and evaluation', *Journal of Network and Systems Management* **21**(4), 588–622.

Latré, S., Klaas, R., Wauters, T. & DeTurck, F. (2011), 'Protecting video service quality in multimedia access networks through PCN', *Communications Magazine, IEEE* **49**(12), 94–101.

Latré, S., Simoens, P., De Vleeschauwer, B., Meerssche, W., Turck, F., Dhoedt, B., Demeester, P., Berghe, S. & Lumley, E. (2009), 'An autonomic architecture for optimizing QoE in multimedia access networks', *Computer Networks* **53**(10), 1587–1602.

Latré, S., Vleeschauwer, B., Meerssche, W., Schepper, K., Hublet, C., Leekwijck, W. & Turck, F. (2011), 'PCN based admission control for autonomic video quality differentiation: Design and evaluation', *J. Netw. Syst. Manage.* **19**(1), 32–57.

Lee, G., Kim, H., Cho, Y. & Lee, S.-H. (2014), 'QoE-aware scheduling for Sigmoid optimization in wireless networks', *Communications Letters, IEEE* **18**(11), 1995–1998.

Li, D. & Pan, J. (2010), 'Performance evaluation of video streaming over multihop wireless local area networks', *Wireless Communications, IEEE Transactions on* **9**(1), 338–347.

Li, M., Chen, Z., Tan, P. H., Sun, S. & Tan, Y.-P. (2015), 'QoE-aware video streaming for SVC over multiuser MIMO-OFDM systems', *Journal of Visual Communication and Image Representation* **26**(0), 24–36.

Li, Y. (2014), A quality guaranteed video dissemination protocol over urban vehicular Ad Hoc networks, PhD thesis, University of Ottawa.

Lie, A. & Klaue, J. (2008), 'Evalvid-RA: trace driven simulation of rate adaptive MPEG-4 VBR video', *Multimedia Systems* **14**, 33–50.

Lima, S., Carvalho, P. & Freitas, V. (2007), 'Admission control in multiservice IP networks: Architectural issues and trends', *Communications Magazine, IEEE* **45**(4), 114–121.

Liu, C., Bouazizi, I. & Gabbouj, M. (2011), Rate adaptation for adaptive HTTP streaming, *in* 'Proceedings of the Second Annual ACM Conference on Multimedia Systems', MMSys '11, ACM, New York, NY, USA, pp. 169–174.

Liu, J., Rosenberg, C., Simon, G. & Texier, G. (2014), 'Optimal delivery of rate-adaptive streams in underprovisioned networks', *Selected Areas in Communications, IEEE Journal on* **32**(4), 706–718.

Lu, Z., Lin, W., Ong, E., Yang, X. & Yao, S. (2003), PQSM-based RR and NR video quality metrics, *in* 'Int. Soc. Opt. Eng. (SPIE)', Vol. 5150, pp. 633–640.

Lubben, R., Fidler, M. & Liebeherr, J. (2014), 'Stochastic bandwidth estimation in networks with random service', *Networking, IEEE/ACM Transactions on* **22**(2), 484–497.

Ma, X., Li, F., Hu, F. & Liu, X. (2012), 'A hybrid channel assignment strategy to QoS support of video-streaming over multi-channel Ad Hoc networks', *Journal of Systems and Software* **85**(2), 300–308. Special issue with selected papers from the 23rd Brazilian Symposium on Software Engineering.

Maallawi, R., Agoulmine, N., Radier, B. & ben Meriem, T. (2014), 'A comprehensive survey on offload techniques and management in wireless access and core networks', *Communications Surveys Tutorials, IEEE* **PP**(99), 1–1.

Mathieu, B., Ellouze, S., Schwan, N., Griffin, D., Mykoniati, E., Ahmed, T. & Prats, O. (2011), 'Improving end-to-end QoE via close cooperation between applications and ISPs', *Communications Magazine, IEEE* **49**(3), 136–143.

Menth, M., Lehrieder, F., Briscoe, B., Eardley, P., Moncaster, T., Babiarz, J., Charny, A., Zhang, X., Taylor, T., Chan, K.-H., Satoh, D., Geib, R. & Karagiannis, G. (2010), 'A survey of PCN-based admission control and flow termination', *Communications Surveys Tutorials, IEEE* **12**(3), 357–375.

Menth, M. & Lehrieder, L. (2012), 'Performance of PCN-based admission control under challenging conditions', *Networking, IEEE/ACM Transactions on* **20**(2), 422–435.

Miller, R. G. & Brown, B. W. (1997), *Beyond ANOVA: basics of applied statistics*, Chapman & Hall.

Moller, S. & Raake, A., eds (2014), *Quality of experience advanced concepts, applications and methods*, Springer.

Moore, A. W. (2002), Measurement-based management of network resources, PhD thesis, University of Cambridge.

Nam, S. Y., Kim, S. J., Lee, S. & Kim, H. S. (2013), 'Estimation of the available bandwidth ratio of a remote link or path segments', *Computer Networks* **57**(1), 61–77.

Nam, S. Y., Kim, S. & Park, W. (2012), 'Analysis of minimal backlogging-based available bandwidth estimation mechanism', *Computer Communications* **35**(4), 431–443.

Nam, S. Y., Kim, S. & Sung, D. K. (2008), 'Measurement-based admission control at edge routers', *Networking, IEEE/ACM Transactions on* **16**(2), 410–423.

Navarro-Ortiz, J., Ameigeiras, P., Lopez-Soler, J., Lorca-Hernando, J., Perez-Tarrero, Q. & Garcia-Perez, R. (2013), 'A QoE-aware scheduler for HTTP progressive video in OFDMA systems', *Communications Letters, IEEE* **17**(4), 677–680.

Nevin, A. (2010), The uncertainty of decisions in measurement based admission control, PhD thesis, Norwegian University of Science and Technology.

Nevin, A., Jiang, Y. & Emstad, P. (2008), Robustness study of MBAC algorithms, *in* 'Computers and Communications, 2008. ISCC 2008. IEEE Symposium on', pp. 1040–1046.

NS-2 (n.d.), *The Network Simulator*. [Online] http://www.isi.edu/nsnam/ns/, accessed on: May 28, 2015.

Ohm, J.-R. (1999), 'Bildsignalverarbeitung fuer multimedia-systeme'.

Ohm, J.-R. (2004), *Multimedia communication technology*, Vol. 1, Springer.

Oyman, O. & Singh, S. (2012), 'Quality of experience for HTTP adaptive streaming services', *Communications Magazine, IEEE* **50**(4), 20–27.

Papadimitriou, P. & Tsaoussidis, V. (2007), 'SSVP: A congestion control scheme for real-time video streaming', *Computer Networks* **51**(15), 4377–4395.

Piamrat, K., Ksentini, A., Bonnin, J. & Viho, C. (2009), Q-DRAM: QoE-Based dynamic rate adaptation mechanism for multicast in wireless networks, *in* 'Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE', pp. 1–6.

Piamrat, K., Ksentini, A., Viho, C. & Bonnin, J. (2008), QoE-aware admission control for multimedia applications in IEEE 802.11 wireless networks, *in* 'Vehicular Technology Conference, 2008. VTC 2008-Fall. IEEE 68th', pp. 1–5.

Piamrat, K., Viho, C., Bonnin, J. & Ksentini, A. (2009), Quality of experience measurements for video streaming over wireless networks, *in* 'Information Technology: New Generations, 2009. ITNG '09. Sixth International Conference on', pp. 1184–1189.

Pinson, M. & Wolf, S. (2004), 'A new standardized method for objectively measuring video quality', *Broadcasting, IEEE Transactions on* **50**(3), 312–322.

Politis, I., Dounis, L. & Dagiuklas, T. (2012), 'H.264/SVC vs. H.264/AVC video quality comparison under QoE-driven seamless handoff', *Signal Processing: Image Communication* **27**(8), 814–826.

Qadir, Q. M., Kist, A. A. & Zhang, Z. (2015*a*), 'Mechanisms for QoE optimisation of video traffic: a review paper', *Australasian Journal of Information, Communication Technology and Applications* **1**(2), 1–18.

Qadir, Q. M., Kist, A. A. & Zhang, Z. (2015*b*), 'A novel traffic rate measurement algorithm for quality of experience-aware video admission control', *Multimedia, IEEE Transactions on* **17**(5), 711–722.

Qadir, Q. M., Kist, A. A. & Zhang, Z. (2015*c*), 'The probability relationship between video's instantaneous and average aggregate rates', *Multimedia Tools and Applications* pp. 1–16.

Qadir, S. & Kist, A. (2013*a*), Quality of experience enhancement through adapting sender bit rate, *in* 'TENCON Spring Conference, 2013 IEEE', pp. 490–494.

Qadir, S. & Kist, A. A. (2013*b*), Video-aware measurement-based admission control, *in* 'Telecommunication Networks and Applications Conference (ATNAC), 2013 Australasian', pp. 178–182.

Qadir, S., Kist, A. A. & Zhang, Z. (2014), QoE-aware cross-layer architecture for video traffic over Internet, *in* 'Region 10 Symposium, 2014 IEEE', pp. 522–526.

Qadir, S., Kist, A. A. & Zhang, Z. (2015*d*), Optimization of quality of experience for video traffic, *in* 'The 22nd ICT'.

Qiu, J. & Knightly, E. (2001), 'Measurement-based admission control with aggregate traffic envelopes', *Networking, IEEE/ACM Transactions on* **9**(2), 199–210.

Qualinet (2013), Definitions of quality of experience, Qualinet white paper, European network on Quality of Experience in multimedia systems and services. [Online] `http://www.qualinet.eu/images/stories/QoE_whitepaper_v1.2.pdf`, accessed on: Nov. 5th, 2015.

Rengaraju, P., Lung, C.-H., Yu, F. & Srinivasan, A. (2012), 'On QoE monitoring and E2E service assurance in 4G wireless networks', *Wireless Communications, IEEE* **19**(4), 89–96.

Ries, M. & Nemethova, O. (2008), 'Video quality estimation for mobile H.264/AVC video streaming', *Journal of Communications* **3**(1), 41–50.

Riley, M. & Richardson, I. (1997), *Digital video communications*, Artech House.

Roberts, L. (2009), 'A radical new router', *Spectrum, IEEE* **46**(7), 34–39.

Rodriguez-Escalona, S. S. (2011), A rate control algorithm for scalable video coding, Phd dissertation, Universidad Carlos III De Madrid.

Rugelj, M., Sedlar, U., Volk, M., Sterle, J., Hajdinjak, M. & Kos, A. (2014), 'Novel cross-layer QoE-aware radio resource allocation algorithms in multiuser OFDMA systems', *Communications, IEEE Transactions on* **62**(9), 3196–3208.

Schwarz, H., Marpe, D. & Wiegand, T. (2007), 'Overview of the scalable video coding extension of the H.264/AVC standard', *Circuits and Systems for Video Technology, IEEE Transactions on* **17**(9), 1103–1120.

Seeling, P., Reisslein, M. & Kulapala, B. (2004), 'Network performance evaluation using frame size and quality traces of single-layer and two-layer video: a tutorial', *Communications Surveys Tutorials, IEEE* **6**(3), 58–78.

Shabdanov, S., Mitran, P. & Rosenberg, C. (2012), 'Cross-layer optimization using advanced physical layer techniques in wireless mesh networks', *Wireless Communications, IEEE Transactions on* **11**(4), 1622–1631.

Singhal, C., De, S., Trestian, R. & Muntean, G.-M. (2014), 'Joint optimization of user-experience and energy-efficiency in wireless multimedia broadcast', *Mobile Computing, IEEE Transactions on* **13**(7), 1522–1535.

Staelens, N., Moens, S., Van den Broeck, W., Marien, I., Vermeulen, B., Lambert, P., Van de Walle, R. & Demeester, P. (2010), 'Assessing quality of experience of IPTV and video on demand services in real-life environments', *Broadcasting, IEEE Transactions on* **56**(4), 458–466.

Stankiewicz, R., Cholda, P. & Jajszczyk, A. (2011), 'QoX: what is it really?', *Communications Magazine, IEEE* **49**(4), 148–158.

Szigeti, T. & Hattingh, C. (2004), *End-to-end QoS network design: Quality of service in LANs, WANs, and VPNs (Networking Technology)*, Cisco Press, Indianapolis, IN, USA.

Taboada, I., Liberal, F., Fajardo, J. O. & Ayesta, U. (2013), 'QoE-aware optimization of multimedia flow scheduling', *Computer Communications* **36**(1516), 1629–1638.

Takahashi, A., Hands, D. & Barriac, V. (2008), 'Standardization activities in the ITU for a QoE assessment of IPTV', *Communications Magazine, IEEE* **46**(2), 78–84.

Tan, K. (2013), Design and implementation of spectrum-aware wireless multimedia communication system, PhD thesis, University of California.

Thakolsri, S., Khan, S., Steinbach, E. & Kellerer, W. (2009), 'QoE-driven cross-layer optimization for high speed downlink packet access', *Journal of Communications* **4**(9), 669–680.

Tommasi, F., Melle, C. & Luca, V. D. (2014), 'OpenSatRelaying: a hybrid approach to real-time audio-video distribution over the Internet', *Journal of Communications* **9**(3), 248–261.

Vadakital, V. & Gabbouj, M. (2011), 'Prediction and transmission optimization of video guaranteeing a bounded Zapping-Delay in DVB-H', *Broadcasting, IEEE Transactions on* **57**(2), 231–245.

Van der Auwera, G., David, P. & Reisslein, M. (2008), 'Traffic and quality characterization of single-layer video streams encoded with the H.264/MPEG-4 advanced video coding standard and scalable video coding extension', *Broadcasting, IEEE Transactions on* **54**(3), 698–718.

Volk, M., Sterle, J., Sedlar, U. & Kos, A. (2010), 'An approach to modeling and control of QoE in next generation networks [next generation Telco IT architectures]', *Communications Magazine, IEEE* **48**(8), 126–135.

Wang, Z., Bovik, A., Sheikh, H. R. & Simoncelli, E. P. (2004), 'Image quality assessment: from error visibility to structural similarity', *Image Processing, IEEE Transactions on* **13**(4), 600–612.

Wang, Z. & Li, Q. (2007), 'Video quality assessment using a statistical model of human visual speed perception', *J. Opti. Soc. America A (Optics, Image Sci., Vision)* **24**(12), B61B69.

Wang, Z., Lu, L. & Bovik, A. C. (2004), 'Video quality assessment based on structural distortion measurement', *Signal Processing: Image Communication* **19**(2), 121–132.

Wang, Z., Simoncelli, E. & Bovik, A. (2003), Multiscale structural similarity for image quality assessment, *in* 'Signals, Systems and Computers, 2004. Conference Record of the Thirty-Seventh Asilomar Conference on', Vol. 2, pp. 1398–1402.

Watson, A. B., Hu, J. & Mcgowan, J. F. (2001), 'Digital video quality metric based on human vision', *Journal of Electronic Imaging* **10**(1), 20–29.

Weller, D. & Woodcock, B. (2013), 'Bandwidth bottleneck [data flow]', *Spectrum, IEEE* **50**(1), 80–80.

Wojcik, R., Domzal, J. & Jajszczvk, A. (2013), Enhanced measurement-based admission control for flow-aware networks, *in* 'Computing, Networking and Communications (ICNC), 2013 International Conference on', pp. 922–926.

Wright, S. (2007), 'Admission control in multi-service IP networks: a tutorial', *Communications Surveys Tutorials, IEEE* **9**(2), 72–87.

Xu, Y., Deng, J. & Nowostawski, M. (2013), Quality of service for video streaming over multi-hop wireless networks: admission control approach based on analytical capacity estimation, *in* 'Intelligent Sensors, Sensor Networks and Information Processing, 2013 IEEE Eighth International Conference on', pp. 345–350.

Xu, Y., Yu, C., Li, J. & Liu, Y. (2014), 'Video telephony for end-consumers: measurement study of Google+, iChat, and Skype', *Networking, IEEE/ACM Transactions on* **22**(3), 826–839.

Yerima, S. Y. (2013), 'Implementation and evaluation of measurement-based admission control schemes within a converged networks QoS management framework', *CoRR* **abs/1311.1435**.

Yuedong, X., Altman, E., El-Azouzi, R., Haddad, M., Elayoubi, S. & Jimenez, T. (2014), 'Analysis of buffer starvation with application to objective QoE optimization of streaming services', *Multimedia, IEEE Transactions on* **16**(3), 813–827.

Zhang, J. & Ansari, N. (2011), 'On assuring end-to-end QoE in next generation networks: challenges and a possible solution', *Communications Magazine, IEEE* **49**(7), 185–191.

Zhang, W., Wen, Y., Chen, Z. & Khisti, A. (2013), 'QoE-driven cache management for HTTP adaptive bit rate streaming over wireless networks', *Multimedia, IEEE Transactions on* **15**(6), 1431–1445.

Zhang, X., Xu, Y., Hu, H., Liu, Y., Guo, Z. & Wang, Y. (2013), 'Modeling and analysis of Skype video calls: Rate control and video quality', *Multimedia, IEEE Transactions on* **15**(6), 1446–1457.

Zhao, M., Gong, X., Liang, J., Wang, W., Que, X. & Cheng, S. (2014), 'QoE-driven cross-layer optimization for wireless dynamic adaptive streaming of scalable videos over HTTP', *Circuits and Systems for Video Technology, IEEE Transactions on* **PP**(99), 1–1.

Zheng, K., Zhang, X., Zheng, Q., Xiang, W. & Hanzo, L. (2015), 'Quality-of-experience assessment and its application to video services in LTE networks', *Wireless Communications, IEEE* **22**(1), 70–78.

Zhou, L., Yang, Z., Wen, Y., Wang, H. & Guizani, M. (2013), 'Resource allocation with incomplete information for QoE-driven multimedia communications', *Wireless Communications, IEEE Transactions on* **12**(8), 3733–3745.

Appendix A

Proof of Equation (5.5)

Using Equation (5.1), Equation (4.2) can be written as follows

$$Pr\{IAAR(t) \geq \mu_r(t) + n\epsilon\} \leq \delta. \tag{A.1}$$

Equation (5.4) is defined as a new variable which is equal to right hand side part ($\mu_r(t) + n\epsilon$) of the probability relationship in Equation (A.1).

ϵ given by Equation (5.5) satisfies the probability condition ($IAAR(t) \geq \mu_r(t) + n\epsilon$) in Equation (A.1). Below is the proof assuming $\beta = 1$

Substituting Equation (5.5) into Equation (5.4), we obtain

$$\mu_r(t) + n\epsilon = n\mu_r(t). \tag{A.2}$$

Since we have all enrolled sessions active at any time (none ON/OFF sessions), each individual session has the same probability. Thus $p_1(t) = p_2(t) = ... = p_n(t) = 1/n$.

Equation (5.3) can be simplified as below

$$\mu_r(t) = x_1(t)p_1(t) + ... + x_n(t)p_n(t) = x_1(t)\frac{1}{n} + ... + x_n(t)\frac{1}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i(t). \quad \text{(A.3)}$$

Substituting Equation (A.3) into Equation (A.2), we get

$$\mu_r(t) + n\epsilon = \sum_{i=1}^{n} x_i(t) = IAAR(t). \quad \text{(A.4)}$$

Equation (A.4) satisfies the probability condition of Equation (A.1) regardless of the quantity (δ) of the probability out of this relationship.