QoE PREDICTION MODEL FOR MULTIMEDIA SERVICES IN INTELLIGENT TRANSPORT SYSTEM

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ABSTRACT

Vehicular ad hoc networks (VANETs), present an intriguing platform for applications like Intelligent Transportation System (ITS), Infotainment applications including but not limited to, live video streaming, file sharing, mobile office advertisements and even distributed computer games. These conceivable ITS and infotainment applications aspire to be a prevalent mode of communication among vehicles while on the road. However, Impact of such anticipated increased in communication among vehicles, is bound to have increased contention on communication links resulting in variable service quality for different applications. A mechanism is needed to manipulate the allocation of the network resources to meet these application traffic demands. Before now, the most prominent approach used to differentiate network traffic flow was Quality of Service (QoS). But then, QoS mainly focuses on objective measurement of network parameter such as jitter, throughput, loss and delay, but pay less attention to how users of the network perceived the service delivery quality. Studies have shown that the traditional QoS approach for evaluating network service quality is not sufficient, and so calls for a more exhaustive and comprehensive quality assessment approach that is not entirely based on network parameter measurement, but one that also include the end user perception of service quality. This quality assessment approach is known as Quality of Experience (QoE). Though, absolute QoE assessment requires a subjective approach, however, performing a subjective test to evaluate the quality of real-time multimedia services is expensive in terms of time and resources and hard to carry out in real-time. The process involves in subjective approach requires a controlled environment, such controlled environment is not realistic in a complex network environment such as VANETs. Therefore, the

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only practical solution during service operation is to apply an objective quality assessment model, which produces an estimate of the perceived quality without human involvement. Hence, in this thesis, a QoE prediction model that estimates the QoE of ITS multimedia services over VANETs objectively, was proposed. The proposed model is based on a state space approach and advanced statistics method, in conjunction with ordinal regression analysis, that estimates the perceived ITS multimedia service quality as a function of aggregated QoE influential factors. The multimedia/ITS distribution network was segmented into a theoretical explanation of three quality optimization component, to develop a QoE optimization function, which takes into consideration the service source quality, the network resource constraint and the human and context factors in defining the overall QoE. The result indicates to be promising, as the proposed model exhibits good predictive power that is coherent with the observed data.

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Abstrak:

Kenderaan pada masa akan datang dijangka menjadi sebahagian daripada Internet, sama ada dengan menjadi nod rangkaian, terminal rangkaian mudah alih atau sebagai sensor bergerak yang mampu memberikan maklumat alam sekitar, maklumat status kereta, streaming video, untuk menamakan adil beberapa. Sebuah kenderaan rangkaian ad hoc (VANETs) adalah teknologi yang dijangka mencapai jangkaan ini. VANETs, membentangkan satu platform menarik untuk aplikasi seperti Sistem Pengangkutan Pintar, aplikasi Inforia (ITS) termasuk tetapi tidak terhad kepada, live streaming video, perkongsian fail, iklan pejabat mudah alih dan permainan komputer walaupun diedarkan. ITS ini dapat difikirkan dan aplikasi infotainment bercita-cita untuk menjadi mod lazim komunikasi antara kenderaan semasa di jalan raya. Walau bagaimanapun, Kesan itu berharap dapat meningkatkan komunikasi di antara kenderaan, sudah pasti telah meningkat perbalahan pada pautan komunikasi menyebabkan kualiti perkhidmatan pembolehubah untuk aplikasi yang berbeza. Satu mekanisme diperlukan untuk memanipulasi peruntukan sumber-sumber rangkaian untuk memenuhi permintaan trafik permohonan. Sebelum ini, pendekatan yang paling menonjol yang digunakan untuk membezakan aliran trafik rangkaian adalah Kualiti Perkhidmatan (QoS). Tetapi kemudian, QoS terutamanya memberi tumpuan kepada pengukuran objektif parameter rangkaian seperti ketar, pemprosesan, kehilangan dan kelewatan, tetapi kurang memberi perhatian kepada bagaimana pengguna rangkaian yang dilihat kualiti penyampaian perkhidmatan. Kajian telah menunjukkan bahawa pendekatan QoS tradisional untuk menilai kualiti perkhidmatan rangkaian tidak mencukupi, dan sebagainya memerlukan pendekatan penilaian kualiti yang lebih lengkap dan menyeluruh, itu bukan sahaja dianggap sebagai pengukuran parameter rangkaian, tetapi satu yang juga termasuk persepsi pengguna akhir perkhidmatan kualiti. Pendekatan penilaian kualiti dikenali sebagai Kualiti Pengalaman (QoE). QoE tidak menggantikan QoS, tetapi sebaliknya,

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QoE meningkatkan QoS dengan menyediakan hujung-ke-akhir kuantitatif dikaitkan dengan persepsi pengguna, dan seperti aggrandized perspektif QoS semasa ke arah jangkaan pengguna akhir. Walaupun, penilaian QoE mutlak, memerlukan satu pendekatan yang subjektif, bagaimanapun, melakukan ujian subjektif untuk menilai kualiti multimedia masa nyata adalah mahal dari segi masa dan sumber. Begitu juga dengan prosedur yang melibatkan tidak sesuai untuk menilai perkhidmatan multimedia masa nyata seperti video melalui rangkaian pernah dinamik seperti VANETs. Oleh itu, satu-satunya penyelesaian yang praktikal semasa operasi perkhidmatan adalah untuk memohon model penilaian kualiti objektif, yang menghasilkan suatu anggaran kualiti dilihat dalam ukuran. Oleh itu, di dalam tesis ini, kami mencadangkan satu model ramalan QoE yang menganggarkan QoE perkhidmatan multimedia ITS lebih VANETs secara objektif. Model cadangan kami adalah berdasarkan kepada pendekatan keadaan ruang dan kaedah statistik awal, bersempena dengan analisis regresi ordinal, bahawa anggaran dilihat ITS kualiti perkhidmatan multimedia sebagai fungsi agregat QoE faktor berpengaruh. Kami dibahagikan / rangkaian pengedaran ITS multimedia, ke dalam penjelasan teori tiga kualiti komponen pengoptimuman, untuk membangunkan pengoptimuman fungsi QoE, yang mengambil kira kualiti sumber perkhidmatan, kekangan sumber rangkaian dan elemen manusia dalam mentakrifkan keseluruhan QoE. Hasilnya kami menunjukkan menjadi cerah, sebagai model yang dicadangkan mempamerkan kuasa ramalan baik yang koheren dengan data yang dicerap.

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LIST OF SYMBOLES AND ABBREVIATIONS

ASTM	American Society for Testing and Materials
β	Regression coefficient (parameters)
BIC	Bayesian information criterion
BNs	Bayesian Networks
BR	Bit Rate
CBR	Constant Bit Rate
CD	Codec
DOT	Department of Transportation
DSM	Dynamic Message Signs
DSRC	Dedicated Short-Range Communications
ε	Random error of a regression model
ε_i	Random error between a regression model and the i^{th}
E-2-E	End-to-End
EDCA	Enhanced Distributed Channel Access Mechanism
FR	Full Reference
$g(.)$	Cumulative logits distribution function
GLzM	Generalized Linear Model
GPRS	General Packet Radio Services
HTTP	Hyper Text Transfer Protocol
i	Index denoting different observation in a dataset
IP	Internet Protocol

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IPTV	Internet Protocol Television
IRTSS	Intelligent Road Traffic Signalling System
ITS	Intelligent Transportation System
ITU-T	International Telecommunications Union -Telecommunication
IVHS	Intelligent Vehicle-Highway Systems
J	Number of dependent/response variable categories
K	Number of independent/explanatory variables in a model
LL	Log Likelihood
Logit	Log of Odds
MAC	Medium Access Control
MANETs	Mobile Ad- Hoc Networks
Mbps	Mega bits per second
MCMC	Markov Chain Monte Carlo
ML	Maximum Likelihood
MOS	Mean Opinion Score
MPEG	Moving Picture Expert Group
n	Number of observations in a data sample
NITSA	National ITS Architecture
NR	Non Reference
NS-2	Network Simulator 2
PLR	Packet Loss Rate
PSNR	Peak Signal to Noise Ratio
QoE	Quality of Experience
QoS	Quality of Service

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RR	Reduce Reference
RSUs	Road Side Units
SQ	Service Quality
SPSS	Statistic Package for Social Science
TCP	Transmission Control Protocol
TQ	Transport Quality
UDP	User Datagram Protocol
UTE	User Terminal Environment
UVE	User Vehicle Environment
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VANETs	Vehicular Ad Hoc Networks
VBR	Variable Bit Rate
VIF	Variance Inflation Factor
VoIP	Voice Over Internet Protocol
WAVE	Wireless Access in Vehicular Environment
α	Threshold or intercept term
$\boldsymbol{x}$	Vector of independent/explanatory variables
x_i	Independent/explanatory variable from i^{th} observation
Y	Dependent/response variable
Y_{ij}	Cumulative response probability up to and including $Y = j$ at i^{th} Observation

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CHAPTER ONE: Introduction

1.1 INTRODUCTION

The advances in mobile ad hoc and wireless communication have presented a new potential for Intelligent Transportation System (ITS). Increasing attention has been centered on developing these technologies on vehicles in order to utilize them for improving driving conditions. By introducing short range communication means to vehicles, an ad hoc network of vehicles known as vehicular ad hoc networks (VANETs) is formed, allowing vehicles to communicate with one another, thereby exchanging vital information's regarding road conditions. VANETs is a unique type of Mobile Ad- Hoc Networks (MANETs), it differs from infrastructure based networks such as cellular networks on its demanded equipment to form a transportable network (Wahab, Otrok, & Mourad, 2013). VANETs makes use of the wireless technology such as 802.11p wireless standards, General Packet Radio Services (GPRS), as well as Dedicated Short-Range Communications (DSRC) (Z. S. Khan, Moharram, Alaraj, & Azam, 2014; Zeadally, Hunt, Chen, Irwin, & Hassan, 2012) to communicate with surrounding vehicles. Based on VANETs technology, a large number of safety related applications and non-safety applications have been implemented. Safety applications offer relevance traffic safety information to drivers while on the road, some good examples are: Intelligent Road Traffic Signalling System (IRTSS), collision warning, incident management cooperative (Nafi & Khan, 2012). While non-safety application offers information and entertainment for both drivers and passengers, e.g., Internet access, multiplayer games, multimedia applications, etc. A variety of relevant data such as weather information, tourist information, gas prices and parking space information can also be spread using this same procedure. These services, also known as infotainment

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(Chang & Hsiao, 2011), can offer unlimited opportunities for vehicle internet applications that can make the driver and passengers experience more pleasant.

In this dissertation, the attention focuses on the infotainment aspect of ITS/VANETs application, where the deployment of multimedia services such as Internet protocol TV (IPTV), TV, gaming application etc., over VANETs is proposed. However, to successfully deploy such multimedia services over VANETs, it's imperative to first overcome the major challenge involved in delivering an acceptable level of multimedia service quality to the end-users of these services. To ensure an acceptable level of multimedia service quality delivery over VANETs. The network must satisfy the perception quality requirement of real-time multimedia traffic known as Quality of Experience (QoE). Though, absolute QoE assessment requires a subjective approach (as QoE is influenced by multiple service factors, which by nature are subjective) (Maia, Yehia, & Errico, 2015; Menkovski, Exarchakos, & Liott, 2010; Sector, 2002). Performing a subjective test to evaluate the quality of real-time multimedia services is expensive in terms of time and resources and hard to carry out in real-time (Aguiar et al., 2014; Alreshoodi & Woods, 2013; Menkovski, Exarchakos, Liotta, & Sánchez, 2012; Zaric et al., 2010). Furthermore, the process involves in subjective approach requires a controlled environment, such controlled environment is not realistic in a complex network environment such as VANETs. Thus, the only practical solution during service operation is to apply an objective quality assessment model, which produces an estimate of the perceived quality in a measurement. Hence, in this thesis, a novelty QoE model that could estimate VANETs multimedia service QoE objectively was proposed and developed.

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1.2 MOTIVATIONS

VANETs present an intriguing platform for applications like Intelligent Transportation System (ITS), Infotainment applications including but not limited to live video streaming, file sharing, mobile office advertisements and even distributed computer games. These conceivable ITS and infotainment applications aspire to be a prevalent mode of communication among vehicles while on the road (Barba, Mateos, Soto, Mezher, & Igartua, 2012), (Bishop, 2000), (Papadimitratos, La Fortelle, Evenssen, Brignolo, & Cosenza, 2009). However, impact of such anticipated increase in communication among vehicles, is bound to have increased contention on communication links resulting in variable service quality for different applications. Therefore, a mechanism known as Quality of Service (QoS) is required to control the allocation of these network resources to application traffic such that will meet the application end to end quality demands. However, VANETs being characterized by high node mobility and frequent link break makes it difficult to provide an effective QoS that will meet the service quality requirements of this real-time multimedia traffic. In order to meet end to end service delivery requirements of ITS real-time multimedia services that will guarantee better service quality to end users, a quality service level control that maximizes the user's satisfaction and usage of network resources is required. Before now, the most prominent approach to assess the performance of a network end-to-end service quality delivery was QoS, which mainly focus on objective measurement of network parameter such as jitter, throughput, loss and delay but pay less attention to how users of the network perceived service quality (Reis, Chakareski, Kassler, & Sargento, 2010). Studies have shown that the traditional QoS approach for measuring network service quality is not sufficient (Gomes, Jailton, Moreira, & Abelem, 2009), (Fiedler, Hossfeld, & Tran-Gia, 2010), (Grega, Janowski, Leszczuk, Romaniak, & Papir, 2008), so calls for a more exhaustive and comprehensive quality assessment approach that is not entirely based on measuring network parameters but one that also includes measuring the end user perspective of network service quality. This quality assessment approach is known as Quality of Experience (QoE). QoE is a subjective measurement that actually measures users' perceived network service delivery quality (Moller, Engelbrecht, Kuhnel, Wechsung, & Weiss, 2009); QoE provides information regarding the delivered services from the user’s point of view and so, it is considered the most appropriate approach to measure network delivery service performance. Hence, QoE procedures can be explored to improve the accuracy of QoS control plane operations and to ensure smooth transmission of real-time multimedia traffic over all-IP networks. However, QoE does not replace QoS, but instead, QoE enhance QoS by providing an end-to-end quantitatively linked to user perception thereby aggrandizing the current quality of service (QoS) perspective towards end user expectations. QoS and QoE somehow have something in common, both are end-to-end dependant, but differs in principle, with QoS ensuring that the network delivered an end-to-end service quality, while QoE focused on how this qualitative end-to-end service delivered is being perceived by the end user. In practice, however, these two concepts seem to interweave in the sense that QoE is impacted by the performance of multiple QoS parameters along with user expectation and context. Significantly, there exists a correlation between these two concepts, as the best QoS practice may not necessarily warrant good QoE, but an efficient QoE must include the adoption of network QoS (Piamrat, Singh, Ksentini, Viho, & Bonnin, 2010). For example QoS may detect some problem in the transmission network that might not be detected by the user and consequently, measurement in an individual node may attest a satisfactory QoS, but the user may still experience objectionable QoE. Therefore, in order to provide the highest possible level of user satisfaction for real-time ITS multimedia services over VANETs, QoS and QoE are crucial metrics to be considered. Understanding the

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relationship between QoS and QoE will facilitate a quality service level control that maximizes the user's satisfaction and utilization of network resources. Therefore, it is pertinent and imperative to create a comprehensive framework/model that could address both the technical service performance (QoS) and user-centered quality (i.e., QoE). By combining the two concepts such that could secure an efficient network service management that will meet end user's expectation.

1.3 PROBLEM STATEMENT

Researchers over the year have made numerous attempt to developed a reliable QoE framework/model that could accurately and reliably evaluate end user's perception of multimedia service quality. Though, lots of innovative solutions had been proposed, but lots of open issues still exist. The main challenge faced by researchers in QoE assessment is the ambiguity that exists in defining the appropriate component for its mapping. QoE is a very complex concept, as it is influenced by numerous factors, and can be understood in diverse perspective that may result in different explanations, different techniques and different destination, depending on the background in which it is viewed. However, no matter the background or perspective in which the concept is viewed, the touchstone for assessing the QoE of any streaming media can be grouped into two broad approaches namely; the subjective and objective assessment approaches. Subjective approach involves a group of people to observe a video clips and thereafter provide a quality score, which is graded on a scale of 1 to 5 as recommended by ITU-T (Bergstra & Middelburg, 2006), where 5 is rated as the most excellent possible score. An example of this method is the mean opinion score (MOS) (Streijl, Winkler, & Hands, 2014). However, performing a subjective test is not suitable for assessing real-time traffic. Consequently, subjective assessment requires an enabling environment, and

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such a controlled environment is not practically feasible in a complex network environment such as VANETs. Objective assessment approach, on the other hand presents a more mathematical technique or model base on metrics that can be measured objectively and evaluate automatically, using a computer program. This approach is considered to be more suited for evaluating QoE of real-time multimedia traffic in networks with high mobility such as VANETs. The reason for this argument is based on the fact that the objective approach requires no human opinion nor does it require any controlled environment.

Most existing QoE assessment techniques in the literature are based on objective analysis using Full Reference or Reduce Reference approach of multimedia quality evaluation. Such procedures are not practically applicable to VANETs which network characteristics make it practically impossible to access any part of the reference video sequence, and so the only practical solution during service operation is to apply a No Reference assessment approach, which produces an estimate of the perceived quality with no need for any reference video sequence whatsoever. So, the question that sparked this research was whether there exist any novel QoE evaluation technique that can produce an optimum solution that will meet the need and the constraint imposed by unstable and uncertain networks such as VANETs. In the literature, only very few works adopted the No Reference method, and most are carried out in a mobile environment with a much more stable links than VANETs. QoE measurement and prediction may involve a large parameter comprising of several QoE parameters. Thus, selecting relevant parameters and to define the relationships between the parameters is usually nonlinear and hard to quantify. Furthermore, QoE evolves over time, by repeated use of service, thus, QoE measurement and prediction at a single point in time may not yield correct results and may have to be done over a longer period of time. This necessitates the development of novel QoE modelling techniques that could efficiently

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utilize selected relevant QoE parameters to model, measure and predict the users' QoE over time. So therefore, the challenge in this research work is on how to develop an objective QoE optimization function that can take into account both the network resource constraint and the human and contextual factors in determining the overall users' QoE.

1.4 RESEARCH OBJECTIVES

The objectives of this research are:

- To identify the optimum measuring metric, assessment methods and model to evaluate user perceived quality of ITS based multimedia services in VANETs
- To investigate the feasibility of applying multiple regression techniques in predicting multimedia quality of experience in a vehicular environment
- To develop an analytical model that quantifies the multimedia QoE influencing factors, and to establish a relationship between each individual factor as they collectively impact on the multimedia service QoE.
- To analyse the QoS parameters (such as jitter, packet loss, delay and throughput), as they reflect on the user perceived service quality (QoE) via simulation.
- To develop a comprehensive QoE predictive model for monitoring, optimizing and controlling the end to end streaming media quality that will guarantee an acceptable quality level of multimedia services in ITS.

1.5 SIGNIFICANCE OF RESEARCH

Vehicles in the near future are expected to become a portion of the Internet, either by being a network node, mobile network terminals or as a moving sensor capable of

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providing environmental information, car status information, streaming videos, to name just a few. Multimedia services such as Internet Protocol Television (IPTV) in vehicles will change automobiles into productive equipment that will keep commuters entertained during long distance travels. Real time video clips of nearby accidents or dangerous situations videos can offer drivers with first hand warning information, this will facilitate informed decision-making as to whether to continue or turn backward. A business person who needs to keep with the latest stock news or parent who want to keep their children entertained during an extended long distance trip, need not worry because live TV and video on demand are some of the features of the ITS infotainment. Thus, the findings in this research will provide insight and answers that could be used to fix the drawback currently experienced with the existing approach of QoE evaluation of real-time multimedia services. Furthermore, Since humans are the ones to watch the videos, it is pertinent that their distribution be done in a way that ensures that the provided quality is based on the end user subjective perception (i.e., QoE). The parameters that are under the service providers control are the QoS parameters but controlling these parameters alone does not lead to good QoE (see section 1.2). therefore, the ability to predict QoE will help multimedia-based service providers such as Alpine Electronics Inc., Denso Corp., Harman International Industries Inc. (Searl, 2014) , etc., in developing, presenting and managing real-time multimedia application over wireless and mobile networks, with the followings:

- Provide the understanding of the relationship between QoS and QoE such that could facilitate the adoption of a quality service level control that maximizes the user's satisfaction and usage of network resources.
- Empowering network engineers and network service providers in determining user's aspect of ITS multimedia application services that should be improved in order to enhance long term user experience

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- Assist in addressing both technical QoS and user-centric QoE in a manner that will insure an acceptable quality level of information exchange between vehicles in a VANETs system

1.6 RESEARCH SCOPE

Addressing the aforementioned research questions completely is a huge challenge, as QoE is a complex metric that relied on numerous parameter. All the same, in this thesis by multimedia service, we refer to audio visual services such as Internet Protocol Television (IPTV), and hence the term multimedia and IPTV as used interchangeably in this research could be deduced to mean an instance of ITS multimedia application. We narrow down the scope of the research by classifying QoE influencing factor into two categories: the technical and non technical factors. The technical factors comprised of factors that affect the multimedia quality at the service generation level and at the network transporting level. While, the non technical factors are those factors that can be directly or indirectly linked to the human subjective perception, such as context, gender, age, expectation, etc. To be exact, as it is exceedingly hard to leverage numerous factors that influences end user experience when viewing multimedia service. This thesis focuses mainly on the important influencing factors, which we categorize into three: at the service generation level, we consider two components, namely; the frame rate and bite rate. At the network transport level, factors considered are; bandwidth (i.e., throughput), packet loss and delay. Lastly, the human and contextual factors considered are; gender and social context (these three categories are addressed in more detail in chapter four).

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1.7 THESIS LAYOUT

This remaining chapters of this dissertation are organized in the following order:

CHAPTER TWO

Chapter two, presents the concepts of Intelligent Transportation System (ITS), highlight its applications, features and challenges. Discussion of the basic concepts, definitions and measurement criteria involved in the estimation of multimedia service QoE was also presented. Furthermore, the chapter presents the state-of-the-art objective QoE measurement, modelling and prediction techniques.

CHAPTER THREE

This chapter identifies the methodology and the steps adopted in the model development. Detail information regarding the process by which the model was built, the technique used to determine the adequacy of the model, analysis of the model potential problem, the solution to the analysed problem and the validation technique used to ascertain the generalisability of the developed model was also presented.

CHAPTER FOUR

Chapter four, provide detailed explanation of the QoE model architecture. The chapter also offers a detailed explanation of the QoS analytical deduction of the VANETs connectivity model, and the analytical model for the end-to-end QoS parameters. Furthermore, the results of the simulation conducted in NS-2 to deduce the sample data used in the regression analysis was also presented.

CHAPTER FIVE

This chapter presents the formulation, modelling, evaluation and validation of the QoE estimation model using the ordinal logistic regression analysis. Detailed description of the data used and preparation process and the applicability of the selected model to estimate the QoE of ITS multimedia services was also presented. The chapter also identifies the detail analysis of the simulation conducted using IBM Statistic Package for Social Science (SPSS) software package version 22.

CHAPTER SIX

Chapter six presents the conclusion and suggestion on possible research direction.

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CHAPTER 2: Background and Related Work

2.1 INTRODUCTION

This chapter first presents the concepts of Intelligent Transportation System (ITS), highlight their applications, features and challenges. The chapter also explains the basic definitions, concepts and measurement criteria involved in the estimation of multimedia service QoE, and presents the state-of-the-art objective QoE measurement, modelling and prediction techniques. In addition, the chapter presents an overview discussion on regression analysis as used in the development of the QoE prediction model.

2.2 OVERVIEW OF INTELLIGENT TRANSPORTATION SYSTEM

Intelligent Transport System (ITS) is the term used to describe the application of information and communication technology to improve and alleviate the transportation problem. ITS is an integrated, flexible and scalable technology that leverage the potentially transformative abilities of wireless technology to advance transportation safety, mobility and environmental sustainability (Singh & Gupta, 2015). The primary objective of Intelligent Transport System is to improve transportation outcome by offering modern services that connect with diverse ways of transit and traffic management, and to provide different users with better information that will ensure safer, more coordinated, 'smarter' use of transportation networks and to make transportation more efficient, green, safe, and seamless. As exemplified in figure 2.1, ITS envelops the whole scope of information technology as apply in transportation (transportation here refers to any of land, ocean and air means of transportation), these include control, communication and computation model, human interface, algorithms

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and database models. ITS advantages can be evaluated in terms of crash reduction, traffic congestion reduction, delays and travelling time reduction, air contamination and fuel consumption reduction and so on

Figure 2.1: An illustration of intelligent transportation system (Machan & Laugier, 2013)

A substantial part of ITS is based on the concept of vehicular ad hoc networks (VANETs) (Yu, Yi, & Tsao, 2012), where moving vehicles act as nodes in a network to create a mobile vehicular communication that include vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications (Xinping, Hui, & Chaozhong, 2012). Vehicles with these capabilities form an ad hoc network communication, commonly referred to as vehicular ad hoc networks (VANETs). In V2I communications, vehicles communicate with a fixed roadside access points known as road side units (RSUs), while in the V2V approach, vehicles are equipped with wireless communications solutions to directly communicate with adjacent vehicles without the demand for any

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RSUs. VANETs provides a unique kind of ubiquitous vehicle information sharing platform, where vehicles are able to send, receive, and relay, safety or infotainment data without necessarily requiring fixed infrastructure (C. Cheng & Tsao, 2014). In line with the connections between ITS and VANETs as outlined in this section, the term VANETs or ITS, as may be used interchangeably in this chapter and in this thesis in general, should be understood to signify the ITS that solely involve vehicles, which is popularly known as Vehicular Ad Networks or simply VANETs. Figure 2.2A illustrates a typical ITS/VANETs scenario as used in this dissertation and Figure 2.2B show VANET communication technology.

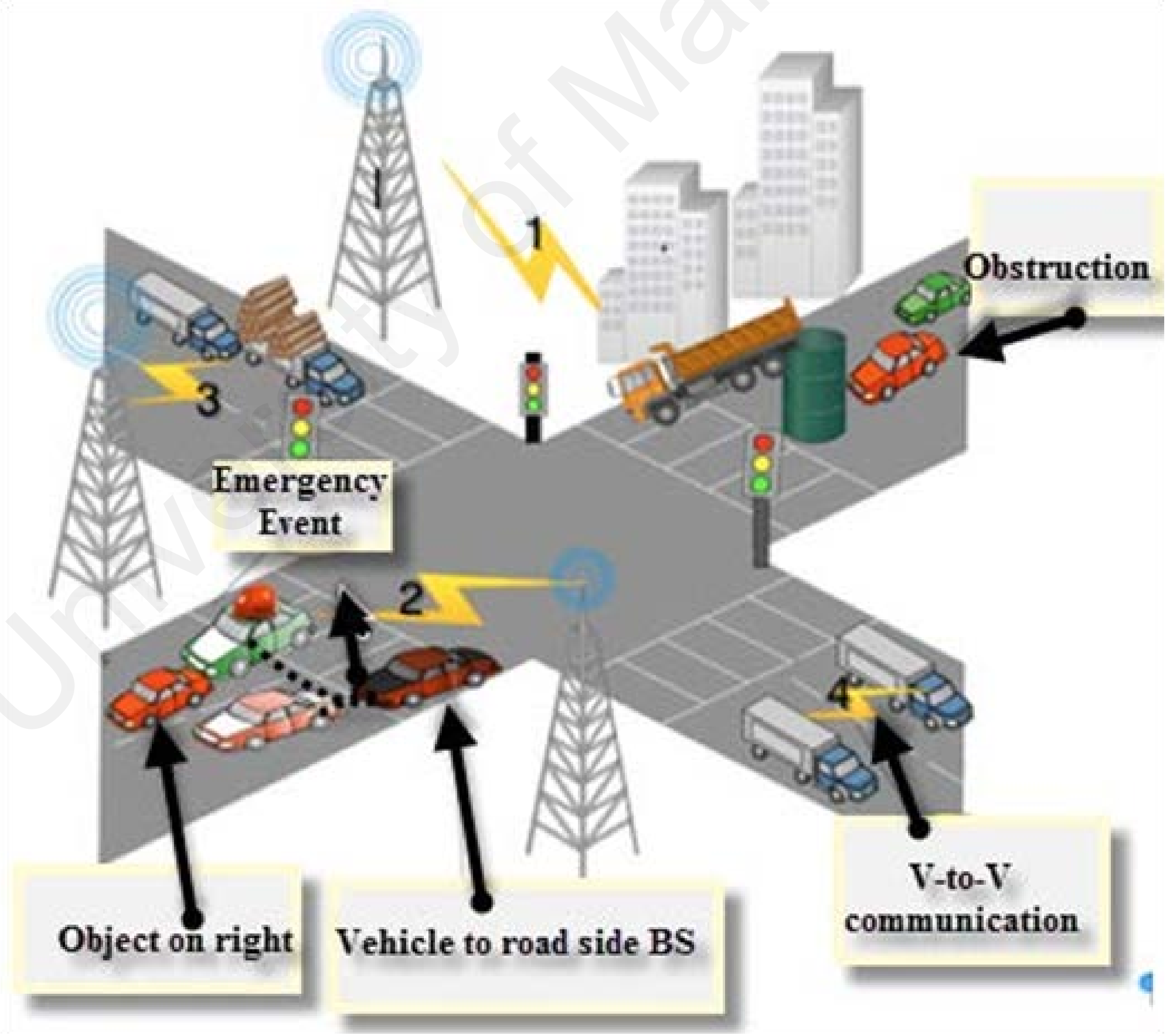

Figure 2.2A: Illustration of ITS/VANETs scenario

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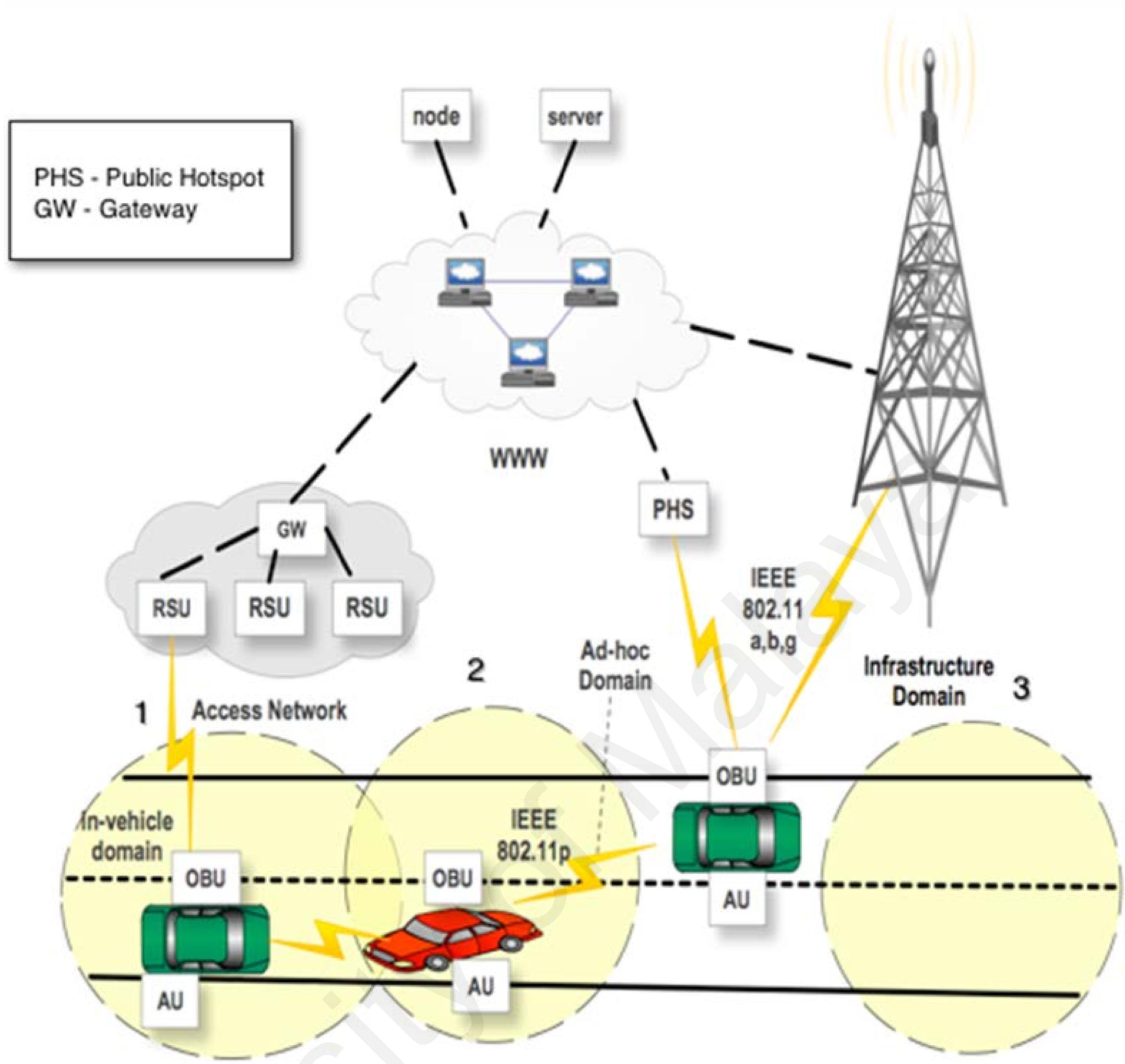

Figure 2.2B: VANETs communication technology

2.2.1 STANDARDS FOR WIRELESS ACCESS IN VANETs

The protocols that have been standardized for used in vehicular ad hoc network is the DSRC. US Department of Transportation (DOT) In 1996, together with some concerned parties, established a layout foundation that defined and integrate Intelligent Vehicle-Highway Systems (IVHS) (Uzcategui & Acosta-Marum, 2009). This framework was the master plan that had served as ITS initiatives for past 16 years. At first NITSA identified wireless communications as the key element for implementing many ITS services, but was later found out after a test of automated toll collection which later failed because the band used then was too small and polluted and could not bring to light the envision evolution of the IVHS communication. The frequency used then was between the range of 902 MHz to 928 MHz The need for a much functional bandwidth that will support ITS Dedicated Short-Range Communications (DSRC), was sort for but not until October 1999 before such request was granted (Uzcategui & Acosta-Marum, 2009). The ITS radio services DSRC-based acquire 75 MHz spectrum ranging from 5.85-5.925 GHz the frequency band consist of numerous channels as illustrated in figure 2.3. The ITSA recommended the adoption of the American Society for Testing and Materials (ASTM) standard which was established on the IEE 802.11 to be the single standard for used in the medium access control (MAC) and physical (PHY) layers of the DSRC draft, this was officially adopted by the FCC from 2003 to 2004 time frame (Uzcategui & Acosta-Marum, 2009). But later in 2004, the IEEE 802.11 task group took over the role started by ASTM to develop the improved version of the IEEE802.11 standard that will involve VANET environment. Today the IEEE802.11p together with IEEE160X collectively formed the standard recognized as Wireless Access in Vehicular Environment (WAVE) (Miao, Zheng, Zheng, & Zeng, 2014). The scope of the WAVE standards is to ascertain services, functionality at both the network and the transport layers, services that will support wireless connectivity between vehicles based devices with fixed roadside devices and vehicle with vehicle based devices, using the 5.9 GHz DSRC/WAVE channels. The protocol architecture defined by these standards is shown in Figure 2.5. WAVE architecture comprises of the following standards: IEEE 1609.1, IEEE 1609.2, IEEE 1609.3, IEEE 1609.4 and IEEE 802.11p (Ghandour, Di Felice, Artail, & Bononi, 2014).

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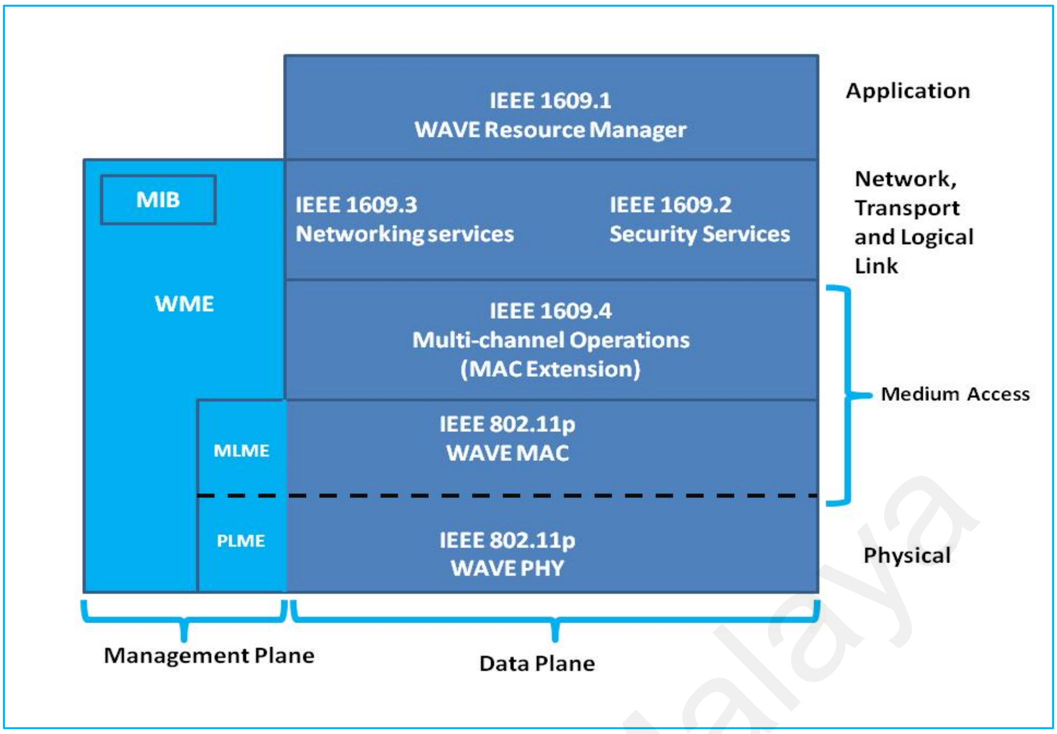

Figure 2.3: Wireless vehicular communication protocol standard family (Ghandour, et al., 2014).

As illustrated in Figure 2.3, the IEEE 802.11p specifies the standard for the Physical layer (PHY) and the Medium Access Control (MAC) layer. While the upper layers are define by the IEEE 1609 standard family. The proposed MAC layer IEEE 802.11p is a subset of the IEEE 802.11p. In order to provide for quality of service (QoS), the CBP in IEEE 802.11p utilizes the IEEE 802.11e enhanced distributed channel access mechanism (EDCA) to ensure the medium access priority. The IEEE 1609.1 defines the application known as the Resource Manager and uses the network stack for information interchange. The IEEE 1609.2 in concern with the security, also responsible for securing the message formatting, the processing, and the message exchanging. The IEEE 1609.4 defines the Channelization while IEEE 1609.3 defines the upper layers of the network stack (Ghandour, et al., 2014).

2.2.2 CHARACTERISTICS OF INTELLIGENT TRANSPORTATION SYSTEM

ITS is a network technology that makes use of moving cars as nodes connected such that each vehicle involve can receive and transmit messages to each other via radio frequency. But this kind of network is temporary, in the sense that vehicles that are involved in the network formation are only connected for a short period of time. This is due to their movement, which is characterized by high node mobility and frequent topology change. A typical ITS topology is illustrated in Fig. 1. There are two most prominent communication in ITS, Vehicle to Vehicle communication (V2V) and Vehicle to Infrastructure (V2I). In the V2V communication, vehicles interact with each other directly or through other vehicles in a multi hop fashion. On the other hand, communication in the V2I is possible through the support of roadside unit infrastructure. Nodes in the ITS environment are much more dynamic because most cars usually are at a very high speed and change their position constantly. The high mobility as well contributes to a dynamic network topology, while the links between nodes connect and disconnect very often. Furthermore, ITS has a potentially large scale which can include many participants and can extend over the entire road network. These unique ITS features pose a large challenge in offering an effective QoE for multimedia services in an ITS environment. Some of these characteristics are summarised as follows (Eze, Sijing, & Enjie, 2014):

- **High dynamic topology:** vehicles on the road moves with variable speed and their position changes frequently as a result of their speed and path choice, these scenarios make the topology of VANET to be highly dynamic.
- **Frequent disconnected Network:** the dynamic nature of the vehicular network results to frequent topology change, and as such, leads to frequent network

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disconnection. Especially in situations of low vehicle density the probability of network disconnection is high.

- **Energy and storage capacity**: unlike mobile ad hoc network that is constrained by limited power, ITS is characterized with abundant energy which usually comes from the vehicle battery and also possessed high storage and processing capability.
- **Interaction with on-board sensor:** it is usually presumed that nodes in ITS, are equipped with on-board sensor that can provide useful information to form a communication link and for use in the routing determination.
- **Numerous communication environments:** there are usually two modes of communication environment in ITS: the highway traffic scenario and the city traffic scenario. The later (city scenario) is said to be much more complex, while the highway scenario is considered to be much more straight forward and less complex as it is constrained with one-dimensional movement.

2.2.3 APPLICATION OF VEHICLE ITS

Vehicle Intelligent Transportation System application can be classified into two main categories namely: safety and comfort (Al-Sultan, Al-Doori, Al-Bayatti, & Zedan, 2014). Safety application aimed to improve the safety of drivers and passengers by making it possible for vehicles on the roads to exchange vital, relevant safety data through vehicle to vehicle communication or infrastructure to vehicle communication. Comfort applications, also known as infotainment, are ITS application that offers information and Entertainment for drivers and passenger, some examples of such entertainment applications include: IPTV, internet access, multiplayer games, video-on-demand, etc. Variety of relevant information such as weather data, tourist

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information, gas prices and parking space information can also be spread using this same procedure. These infotainment services can provide limitless opportunities for vehicle internet applications and Invehicle entertainment that can make the driver and passengers experience more enjoyable and less tiresome. Below in Figure 2.4A and 2.4B are representations of some available safety and comfort application in ITS (Mittal & Vashist, 2014).

Figure 2.4A: Safety Application

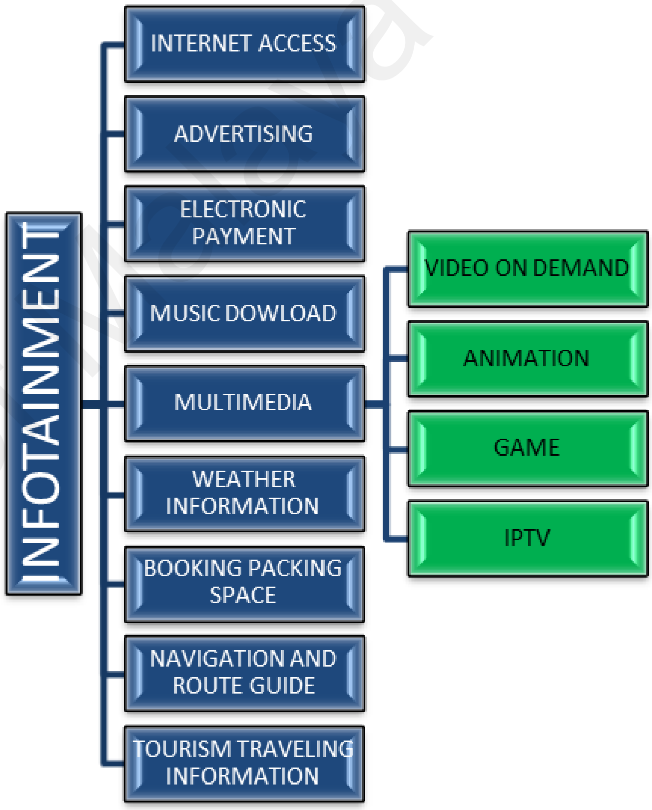

Figure 2.4B: Comfort Application

2.2.3.1 VANETs APPLICATIONS TO INTELEGENT TRANSPORT SYSTEM

Various researchers are working on vehicular network technology in order to create a more intelligent transportation system, transport system that could provide drivers with vital information regarding the road condition such as traffic congestion, accident, dangerous road curved etc. Some applications of Intelligent Transport System are stated below (Singh & Gupta, 2015).

- Road enforcement system- refers to an automatic enforcement system such as speed violation enforcement, traffic signal and automatic ticket offender detection. Using cameras and vehicle monitor devices to record vehicle violations.
- Automatic parking management- refers to the ability to monitor parking space availability and to communicate such information to the driver, this reduce frustration and congestion that could occur as the result of searching for a parking space.
- Information dissemination- dissemination of information to travellers has greatly improved thanks to ITS organization's operation. Travellers can now receive information regarding road conditions and other relevant information in numbers of ways, such as the dynamic message signs (DSM), the highway advisory radio, and the in-vehicle signing.
- Emergency vehicle notification system- when activated the device will set up an emergency call that carries data and voice message directly to any emergency point close by.
- Electronic payment and pricing- this includes toll collection, transit fare payment, packing fee payment and congestion pricing. All payment systems can be enabled in the vehicular system; this simplifies payment and greatly reduces congestion.
- Intersection collision warning- this system is designed to detect and warn drivers approaching intersections.

- On-board monitoring- this application using equipped in- vehicle diagnostics can track and report mechanical vehicle condition, safety and security information is easily made available to the driver immediately.

2.3 QUALITY OF SERVICE VERSUS QUALITY OF EXPERIENCE

QoS and QoE are terms often applied loosely and sometimes even used interchangeably, such that QoE in some instances may be used in situations where QoS would have been more appropriate and in some other cases, QoS may be applied in a context where QoE would have been more applicable. This is probably due to several reasons, one of which could be attributed to the fact that the boundaries between QoS and QoE not been distinctively understood. QoE is intrinsically a multi-disciplinary field and practitioners from different backgrounds see it, rather naturally, from different perspectives. For networking individuals, QoE is sometimes considered as a simple extension, or even a re-branding, of the well-grounded concept of QoS. But this is not really the case, as the two terms are not precisely the same, nor do they signify the same terminology, and they are simply not mutually-exclusive. Nevertheless, in a typical network environment, these two concepts may have similar definitions but are different in application. So therefore, an attempt is made here to try to bring to light some well accepted definition of these two concepts.

2.3.1 QUALITY OF SERVICE

Quality of service in any network, be it local area network, wireless network, mobile ad hoc network or vehicular network cannot be overemphasized. In computer network and other telecommunication packet switched networks, the term quality of service does not refer to the achieved service quality. Rather, it refers to the resource reservation control mechanisms, which is the ability to provide different priority to different application,

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users, or to guarantee a certain performance level to the flows of data. Quality of service, therefore, is the measure of service availability of a network and its transmission quality. Consequently, ITU-T E.800 in one of their recommendation, defined QoS as, "*the collective effect of service performance which determine the degree of satisfaction of a user of the service*" (cited by (Varela, Skorin-Kapov, & Ebrahimi, 2014)). The availability of service in a network environment, therefore, is a crucial fundamental element of QoS. To successfully implement QoS in any ITS network environment, the network infrastructure must be designed in a way that it will be highly available for users. (Wang & Lee, 2009). The transmission quality of multimedia service in VANET is determined by three major factors namely (i) minimum packet loss, (ii) jitter and (iii) delay (Oche, Noor, & Aghinya). Packet loss, jitter and delay can affect greatly the quality of streaming media at the final stage of the receiver, because any of these three mentioned parameters can create inadmissible gabs and a chasm in streaming video. QoS exclusively, is commonly applied to network traffic generated for multimedia applications such as: video, IPTV, Voice over Internet protocol (VoIP), streaming media, videoconferencing and online gambling.

2.3.2 QUALITY OF EXPERIENCE

In order to provide users with multimedia services that have acceptable quality, the factors that influence user's QoE must be well-thought-out. However, in this context, due to the inherent complexity of QoE, there are numerous facets to its definition. For instance, in (Le Callet, Moller, & Perkis, 2013), QoE is defined as "*the degree of delight or annoyance of the user of an application or services. It results from the fulfilment of his or her expectations with respect to the utility and/or enjoyment of the application or services in the light of the user's personality and current stat. In the*

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context of communication services, QoE is influenced by service, content, device, application and context of use". Authors in (K. Mitra, Zaslavsky, & Ahlund, 2014), defined QoE as *"a metric that depends on the underlying QoS along with a person's preferences towards a particular object or service where his/her preferences are defined by his/her personal attributes related to expectations, experiences, behaviour, cognitive abilities, object's attributes and the environment surrounding the person".* In the ITU-T p.10/G 100 (Rec, 2007), QoE is defined as *"the overall acceptability of an application or services, as perceived subjectively by the user"* which include end-to-end system effects and *"overall acceptability may be influenced by user expectation and context".* In (Weiss, Möller, Wechsung, & Kühnel, 2011), the authors define QoE as *"Degree of delight of the user of a service. In the context of communication services, it is influenced by content, network, device, application, user expectations and goals, and context of use".* What all these different definitions simply point out, is that the concept of QoE is still to be considered as an abstraction. As QoE of multimedia distribution services has never been set by a single monotone dimension, the notion of QoE extend to many different fields and often the meaning differ from one individual to some other individual. Undeniably, a user's perception of multimedia quality may be influenced by numerous factors, such as: frame loss, audio clarity, lip synchronisation during speech, content, display size and resolution, network bandwidth (Jelassi, Rubino, Melvin, Youssef, & Pujolle, 2012), delay as well as other human subjective factors such as: expectations, gender, context, and many more (Fu, Chiu, & Lei, 2010). In order to be consistent with the definition above, in this work, QoE of multimedia services is considered to include two quality perspective; the perception aspect which involves the user's subjective influence (i.e., the user perceived quality (UPQ)) as well as the quality influence as a result of the characteristic of the underlying network technology (QoS).

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2.4 MEASURING MULTIMEDIA QUALITY OF EXPERIENCE

There are two approaches defined in the literature for evaluating users' perceived quality of multimedia services: the subjective and objective methods.

2.4.1. SUBJECTIVE EVALUATION METHOD

Subjective test involves direct data collected from users in the form of ratings. Standardization bodies such as the ITU-T P.800 recommendation (Rec, 1996), presented a methodology for conducting a subjective test for multimedia applications. The recommendation also defines a method to measure users Quality of Experience based on a score scale known as the Mean Opinion Score (MOS) (Streijl, et al., 2014). MOS is widely used for assessing both voice and video quality, where human test subjects, grade their overall experience on the Absolute Category Rating Scale (ACR). This scale is made up of five alternative from which the users attest to, for instance, '5' could represent very good quality, '4' could represent good quality, '3', '2' and '1' could represent fair, poor and bad quality respectively (see illustration in figure 2.5).. Various problems might happen while getting a subjective test to assess media quality. Problem ranges from; large sample and space requirement to time and resources that will be needed in order to obtain credible results (Streijl, et al., 2014). Subjective test can be expensive and time consuming. Hence, subjective tests are mainly limited to major telecom providers. Furthermore, the native language of human subjects might not be same across test subjects and thus, the result obtained through a subjective test could be biased or may yet be incomplete . Several researchers (Karan Mitra, Zaslavsky, & Åhlund, 2014), over the years have also noted some flaws while adhering to the ITU-T P.800 recommended for conducting subjective test. The greatest difficulty with the MOS subjective results is that it computes only the average user rating. And mathematic

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operation such as the average computation and standard deviation cannot be given to the subjective rating because of the categorical nature of the subjective ratings. The human test subjects ranks the options on the categorical scale where the space between these choices cannot be known. Hence, mathematical operations cannot be applied. Furthermore, the procedure involves in subjective assessment is not suited for assessing real-time multimedia application such as video. Therefore, the only practical solution during service operation is to apply an objective quality assessment model, which produces an estimate of the perceived quality in a measurement.

Figure 2.5: An illustration of the Mean Opinion Score procedure

2.4.2 OBJECTIVE EVALUATION METHOD

The objective QoE evaluation method is the aspect of QoE assessment that is of optimum concern in this thesis and so it is discussed in a much more details. This QoE evaluation method, present a more mathematic technique or model that is based on metrics that can be measured objectively and evaluate automatic using computer program(s). The objective QoE measurement technique offers a better method to assess real-time multimedia application. The main advantage remains in the fact that the objective assessment can be performed quickly in order to support fine turning of network variables. Briefly, those methods are instrumental techniques that produce, from several measurements, results that approximate the rating that would be obtained by using subjective techniques. The objective QoE assessment technique can further be sub-classified into five categories (Karan Mitra, Zaslavsky, & Ahlund, 2013): Data Metrics or Packet-Layer Models, Picture metrics or Media-Layer Metrics, Parametric Planning Models, Packet or Bit-stream Layer model and Hybrid Models.

2.4.2.1 PARAMETRIC PLANNING MODELS

All the other four objective measurement models (i.e., Packet-Layer Models, Bit-stream Layer Model, Hybrid Models and Media-Layer Models) estimate subjective quality assessment as inputs (i.e., estimate media signals, packet information, bit-stream information, etc.). But the parametric-planning model estimates subjective quality based on network and terminal quality design and management parameters (e.g., coding bit rate, packet loss rate, etc.) inputs. While subjective quality assessment characteristics for each codec and system must be obtained and organized in a database in advance. This model has the advantage of very efficient desktop quality design at the service design stage.

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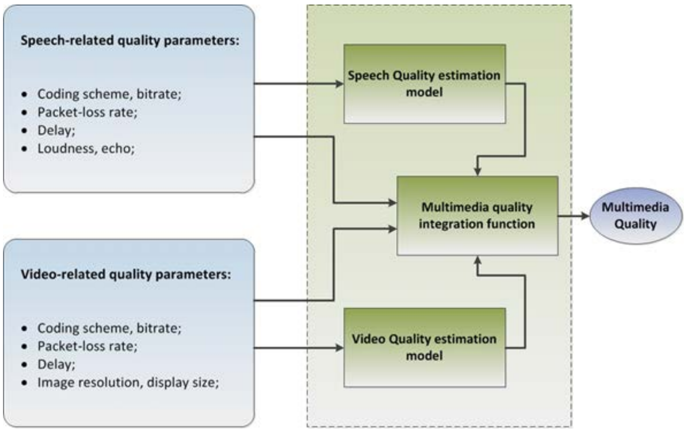

Figure 2.6: An illustration of Parametric Planning Models QoE assessment method (Coverdale, Moller, Raake, & Takahashi, 2011)

2.4.2.2 DATA METRICS OR PACKET-LAYER MODELS

This QoE assessment method, predict the QoE only from the Internet Protocol (P) and the RTP packet header information. Since media signals are not decoded as in the medium-layer model, the processing overhead is extremely light, which make this model very promising for “in-service quality management” enabling assessment of quality even while a service is being provided. Estimating quality without using media information, especially assessing video quality considering the content dependent, is inherently difficult. This means various kinds of system information must be obtained in advance: assumed attributes of content being handled, the codec being used, and so on.

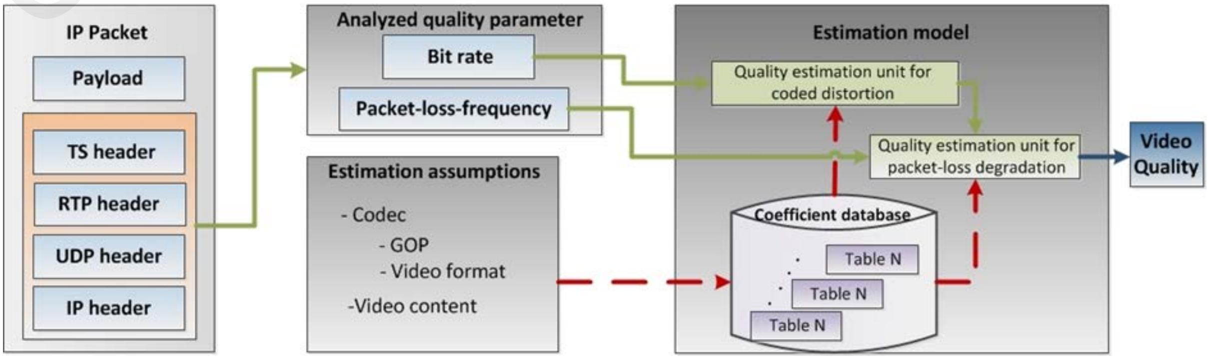

Figure 2.7: An illustration of Packet-Layer Models QoE assessment method

2.4.2.3 BIT-STREAM LAYER MODEL

The Bitstream-Layer QoE assessment method uses the coded bit-stream data (i.e., payload information) and information from the packet header in measuring the multimedia QoE. Because this method of QoE assessment have access to the payload information, it takes content dependence on video quality into account that is unavailable in the packet-layer model. This model is more computationally intensive than the packet-layer model, so CPU load must be considered before it is implemented on user terminal equipment. Note that the encrypted payload information must be decrypted, so the packet-layer and the bit-stream-layer must be used properly in accordance with the application service specifications.

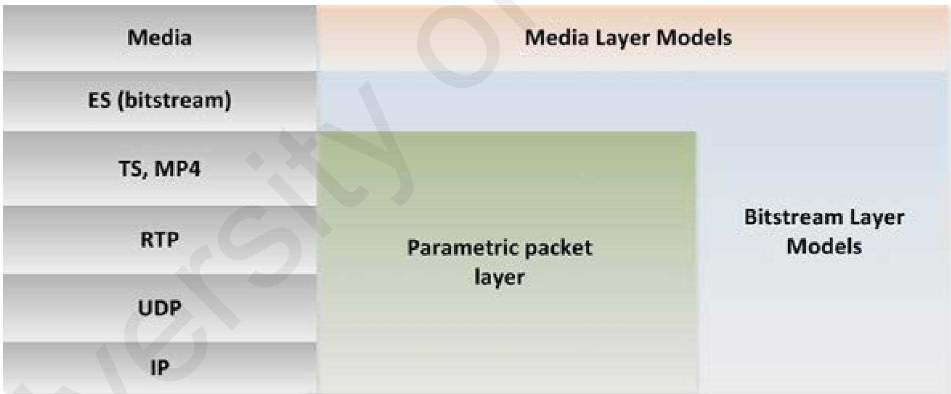

Figure 2.8: An illustration of Bitstream-Layer QoE assessment method

2.4.2.4 HYBRID MODELS

The Hybrid Models, combines two or more of the aforementioned assessment techniques, and therefore exploits information obtained during in-service quality management through estimation of simple, accurate subjective quality.

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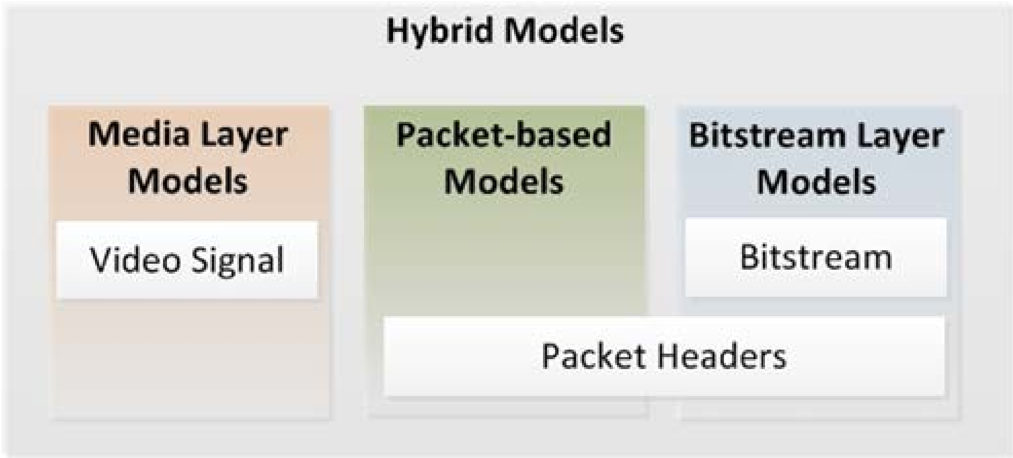

Figure 2.9: an illustration of Hybrid Models of QoE assessment method

2.4.2.5 PICTURE METRICS OR MEDIA-LAYER MODELS

The Media-Layer Models measure the fidelity of the multimedia signal, treating the multimedia signal just as the visual information it contains. It can account for the effect of distortions and content on the user's perceived quality. By modelling the features of the human vision system and its parts, with the intention to obtain a quality rating that has a high correlation to results that an evaluation with real viewer would have offered. The Picture Metrics or Media-Layer Models can further be separated into three: Full Reference (FR), Reduced Reference (RR) and No reference (NR), depending on the amount of reference signal available for the quality evaluation (Maia, Yehia, & de Errico, 2014):

2.4.2.5.1 FULL REFERENCE APPROACH

The Full Reference (FR) requires a complete copy of the undistorted video alongside the distorted one in order to assess the QoE. Some examples of the FR are the popular Peak Signal to Noise Ratio (PSNR) , Structural Similarity index (SSIM) (Chikkerur, Sundaram, Reisslein, & Karam, 2011). FR multimedia evaluation metrics are based on a frame-by-frame comparison between a the original video known as the reference video and the distorted video at the receiver end point, by measuring the degree of degradation suffered by the final delivered video. In order to determine the quality of the delivered video, both the source video and the received signal must be available for comparison.

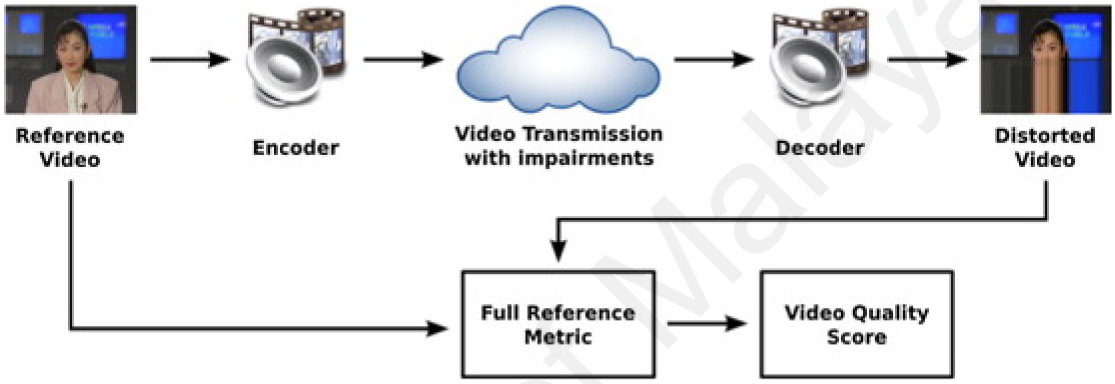

Figure 2.10: An illustration of Full Reference multimedia QoE assessment technique

2.4.2.5.2 REDUCE REFERENCE APPROACH

The Reduce Reference (RR) is an objective video quality assessment method that requires part of the original video. In the RR metric, a limited feature extracts from the original video, which is used to evaluate the quality of the distorted video. Reduce-Reference Image Quality Assessment (RR-IQA) proposed in (Rehman & Wang, 2012), Video Quality Assessment by Reduce Reference proposed in (Soundararajan & Bovik, 2013), are some few examples of the RR metric.

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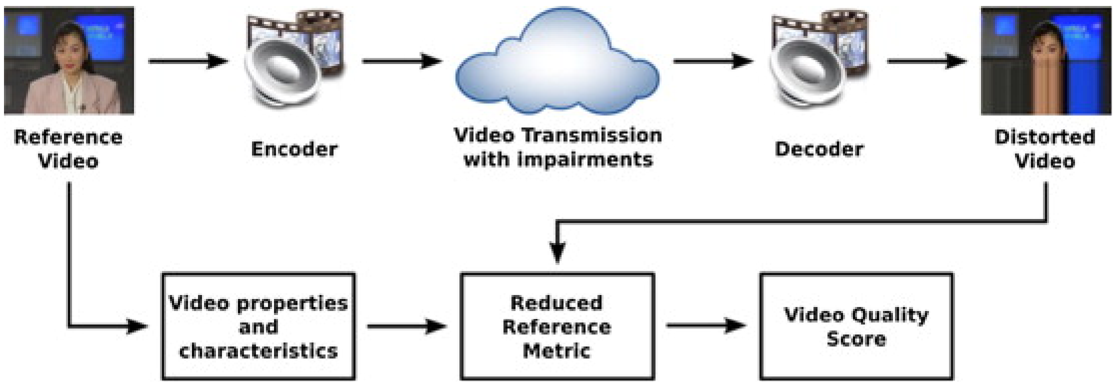

Figure 2.11: An illustration of Reduce Reference multimedia QoE assessment technique

2.4.2.5.3 NO REFERENCE APPROACH

The No Reference (NR) evaluates the multimedia quality blindly with no requirement of full or part of the original video content. This feature makes the NR quality assessment metric more suited for usage in real-time video streaming environment, and can also be used anywhere, in any existing compression system and transmission network where the original TV signal is not accessible. Some good examples of the NR are the Media Delivery Index (MDI) (Welch & Clark, 2006), and V-Factor (Winkler & Mohandas, 2008).

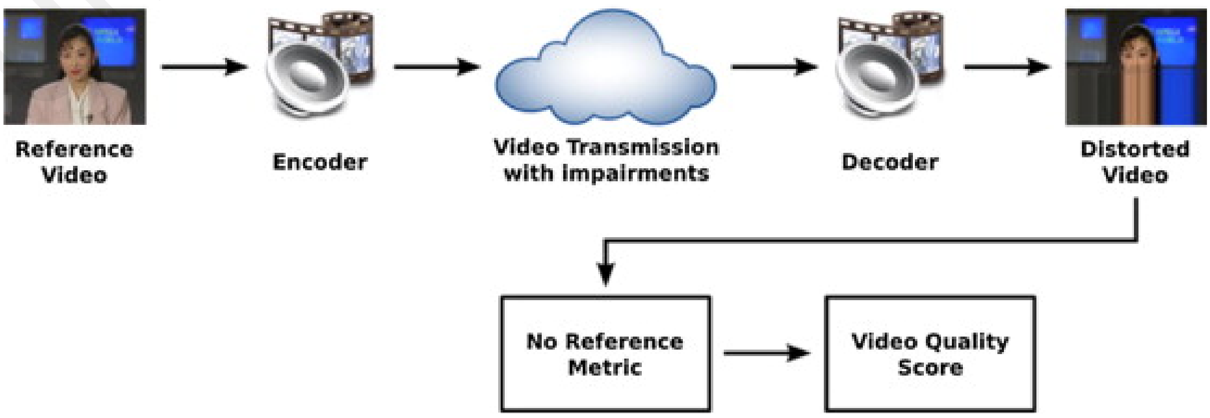

Figure 2.12: An illustration of No-Reference multimedia QoE assessment technique

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2.5 STATE-OF-THE-ART IN MULTIMEDIA QoE EVALUTION

The greatest challenge encountered by researchers in Quality of Experience (QoE) assessment is the ambiguity that exists in determining the appropriate factor for its mapping. QoE is a very complex concept, as it is influenced by numerous factors, and can be understood in diverse perspective that may result in different explanations, different techniques and different understanding. In an effort to alleviate these challenges, QoE researchers over the years have developed/proposed numerous objective assessment techniques. Thus, this section of this dissertation, presents some reviews on the state-of-the-art objective QoE measurement, modelling and prediction techniques as suggested in the literature.

Janowski and Papir (Janowski & Papir, 2009), in their work used Generalized Linear Model (GLZ) to predict QoE. GLZ is a general form of linear regression analysis, which can deal with both linear and non-linear data. Using the GLZ, the probability distribution of the user ratings was computed, based on the subjective tests involving 60 users. The authors, in their proposed model, used the GLZ to relate the probabilities of particular QoE levels to independent network and application explanatory variables in a statistical credible manner. They argued that the probability distribution of QoE categories would provide better understanding and detailed information about the users QoE ratings than just simply computing the numerical index such as the MOS. The most fitted model parameters were selected using the Bayesian information criterion (BIC), and in order to find the most probable predicted QoE rating with a little variation as possible, they utilized the maximum likelihood estimation to specify the set of values of the parameter vector that maximizes the likelihood function of the model given the set of explanatory variables. Their result was validated using the

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Chi-square test statistics, and the confidence interval test that measure the statistical accurateness of a prediction model.

Chen et al. in (K.-T. Chen, Tu, & Xiao, 2009), proposed a model named OneClick, to measure and predict QoE of multimedia applications such as voice over internet protocol (VoIP), video streaming and gaming. They adopted the Possion regression analysis (Possion regression is an aspect of the Generalize Linea Model), to formulate a model which was used to predict the users' QoE, based on user click rate. The user click rate was computed whenever the user(s) click their keyboard keys, which was considered to corresponding to the network QoS condition. Their work was validated via some experimental analysis, they performed two experimental case studies comprised of VoIP application such as; Skype, MSN messenger, AIM messenger and first person shooter game such as; Halo and Unreal Tournament. The authors argued that OneClick could be used to predict QoE in the case of unmeasured parameters such as background noise.

Kim et al. in (H.-J. Kim et al., 2008), proposed a method for QoE prediction based on a function of QoS parameters such as; delay, bandwidth, jitter and packet loss. At first, a normalized QoS value is computer based on what they identify as the linear weight sum of the QoS parameters. Once the QoS value was computed, it was then used in the determination of the QoE, using a scale of one to five. However, their method was limited to just QoS parameters which were treated independently and the failed to provide details on how the weight of each QoS parameter was determined.

Han, Bingjun, et al. in (Han, Zhang, Qi, Gao, & Yang, 2012), proposed a model name QoE Based Scheduling (QBS). QBS is a QoE video model which incorporated both the QoE environmental factors and equipment factors. The author argued that environmental factors and user equipment along with the underlying network QoS,

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collective impact on the users' QoE. Two QoS parameters, that is, throughput and bit rat were used in their analysis. The idea behind the proposed model was to examine the users' hardware and environmental parameters in order to adjust the demand for the network signal according the result obtained from the individual users' equipment and environmental parameters such that could meet the users' need. In their result, they observed that the users' satisfaction was improved by the QBS algorithm, more especially, for the resource constrained users. Consequently, they discovered that the surrounding environmental interference such as light, noise and shakings has great effect the level of users' QoE, as the influences of these environment parameters, in their result manifested in different users' QoE level. Thus, they came to a conclusion that a better QoE could be perceived when a high quality signal is delivered to high end devices with low environmental interference, and vice versa. However, in their conclusion, the author argued that the proposed algorithm will require further optimization and propose the inclusion of more QoS parameters and test should be conducted in numerous scenarios.

Mitra et al in (Karan Mitra, et al., 2013), proposed a context-aware approach named Context-aware QoE Modelling and Measurement (CaQoEM) for modelling, measuring and predicting users' QoE. Their model is based on Bayesian networks (BNs) and context spaces model. By using BNs, the relationships between context and QoE parameters and the relationships among QoE parameters can be determined in a simplified and in an efficient manner. The experts simply need to define the mapping casually by linking causes (e.g., context parameters). And so do not need to develop any precise mathematical or statistical model to determine the mapping between, context and the QoE parameters. The BNs can automatically handle linear and nonlinear relationship, can also handle both discrete and continuous variables. It also has the ability to map several QoE and context parameters to measure and predict users' QoE on a single scale.

Authors in (Chihani, Bertin, Collange, Crespi, & Falk, 2014), proposed a user centered QoE measurement technique on smart phone. In the proposed framework, a mobile application is used to measure end-user perceived quality of service (i.e., QoE) directly on the users' devices and the estimated QoE is sent directly to a service provider. They adopted multiple QoE parameters which include both network parameters and what they identify as the system parameters in their QoE estimation.

Author in (Reichl, Tuffin, & Schatz, 2013), proposed a QoE framework which is based on what they identify as layer approach, aimed at improving the QoE of mobile broadband network services. Their approach combined user studies obtained from 3 relevant performance indicators (i.e., the network performance, users experience characteristics and specific applications or services related performance indicators), to obtained accurate model for QoE estimation.

In (Mushtaq, Augustin, & Mellouk, 2012), a machine learning method was used to build a QoE prediction. They used a decision tree (DT) along with a Support Vector Machines (SVM) to build an objective QoE model which was used to compare with other machine learning methods such as: Random Forest, Neural Networks and Naïve Bayes. In their resolutions, the Random Forest was recorded to perform better when compared to the rest others

Fiedler et al. in (Fiedler, et al., 2010), proposed a QoE model known as the IQX hypothesis for quantitative mapping between QoS and QoE. The IQX hypothesis is based on the exponential relationship between QoS and QoE parameters. The model takes as input the QoS parameters such as packet loss and jitter to determine the user QoE for VoIP applications. In their study, the QoE is considered as the MOS, while the

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QoS was evaluated via three different criteria (packet loss, jitter, response and download times). They argue that the derived nonlinear regression equation can provide excellent mapping between QoS parameters and MOS for VoIP applications. They also tested their hypothesis for QoE related to web browsing by considering the weighted session time and delivered bandwidth. To validate their proposed model, the authors tested their model by comparing it with the logarithmic approximation in (Khirman & Henriksen, 2002). The result turn out to be of better quality than the logarithmic expression.

Song, Wei, and Dian W. Tjondronegoro in (Song & Tjondronegoro, 2014), propose an acceptable-based QoE model which they identified as A-QoE. In their work, they argued the current QoE prediction model has two setbacks: their insufficiency in considering the influencing QoE factors and the limited studies in the area of QoE models for acceptability prediction. Their proposed QoE model was developed using nonlinear regression statistical analysis, with five explanatory variables (i.e., Spatial resolution, frame rate, quantization parameters, bit rate and the resolution of the mobile device) which they identified as the QoE influencing factors. Their proposed model was compared with three well known objective video quality evaluation technique (PSNR, SSIM and VQM), the solution shows that their proposed model produces higher prediction accuracy and usage flexibility over the other three objective quality metrics.

The most prominent objective QoE model, is the E-model proposed by the ITU-T research group (ITU-T & Recommendation, 2005). It predicts the quality of voice conversation based on end device characteristics and the transport parameters. It is centred on an impairment factor fundamental, which presumed that the quality deterioration caused by the various elements, have a collective consequence on the communication quality. The result of the model is converted into a rating scale known as the R scale. This R rating, can as well be translated into MOS. Bingjun Han el al in

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(Han, et al., 2012) proposed a scheduling QoE algorithm known as QoE based scheduling (QBS), their proposed algorithm was developed with the inclusion of both the environment and equipment factors that influence user's QoE with respect to QoS in the network. Yet, in their work they only looked at throughput and bit rate. this research work could be considered as the extension of (ITU-T & Recommendation, 2005) and (Han, et al., 2012). Like the E-model, the proposed QoE prediction model in this thesis, also predicts the multimedia perceived quality based on the transport network parameters, equipment and the human factors, but unlike the E-model which was developed for voice impairment only, in this thesis the proposed model is device to cater for both voice and video over VANETs

2.6 AN OVERVIEW OF REGRESSION ANALYSIS

Regression analysis is a group of statistical tool for analysing and estimating the relationships among variables usually a depended variable and one or more independent variables (Draper & Smith, 2014). Regression is regarded as a supervised learning method in the field of pattern recognition and machine learning, which is employed to predict the continuous values of a target variable when input variable are given. There are two main classes of regression, the linear and nonlinear (Fahrmeir, Kneib, Lang, & Marx, 2013), and in general regression can be represented in the form of:

$$Y \approx f(x, \beta) + \varepsilon, \qquad 2.1$$

Where ε is regarded as the noise term, which is random and unobserved, but is assumed to be statistically independent; f is the regression function describing the relationship between the input variable x and the output variable Y. The input variable can be a scalar or a vector, while the output variable Y is usually a scalar. The unknown

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parameter β is a scalar if there is only one parameter or a vector if there are multiple parameters. Regression analysis which deals with one independent variable is known as simple regression, while that which deals with two or more independent variable is known as multiple regression. There are two general applications of multiple regression: prediction and explanation (Keith, 2014). When one uses multiple regression for explanatory purposes, that individual is exploring relationships between multiple variables in a way to throw illumination on a phenomenon, with a goal of generalizing the new understanding to a population. When multiple regression is applied for prediction, one is using a given sample to construct a mathematical expression that would optimally predict a particular phenomenon within a specific population. This is the aspect of multiple regression that is of optimum concerns of this study, as the goal of this study is to use the regression formulation to predict the end user perception of ITS multimedia quality (QoE). Table 2.1 presents a summary of state-of-the art in QoE measurement, modelling and prediction techniques that utilized regression analysis.

There are several alternative terminologies used in the literature for Y and X. Except otherwise stated, these different names of Y and X as may be used interchangeably in this thesis should be understood to be equivalent terms as illustrated in table 2.2.

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Table 2.1: Summary of state-of-the art in QoE measurement, modelling and prediction techniques that utilized regression analysis

Paper	Applications	Regression Technique(s)	QoE parameter(s)	Year
(Kaiyu, Yumei, & Lin, 2014)	Video	Linear regression	Multiple	2014
(Song & Tjondronegoro, 2014)	Video	Nonlinear regression	Multiple	2014
(Rao et al., 2014)	VoIP and Video	Generalized logistic regression	Multiple	2014
(X. Jiang, Pan, & Ye, 2014)	TV service	Polynomial regression	Multiple	2014
(De Pessemier, Martens, & Joseph, 2013)	Mobile Video	Multinomial regression	Multiple	2013
(H. Chen, Xin, & Xie, 2013)	Video	Regression tree model	Multiple	2013
(Balachandran et al., 2013)	Internet Video	Linear regression	Multiple	2013
(A. Khan, Sun, & Ifeachor, 2012)	Video	Nonlinear regression	Multiple	2012
(T. Jiang, Wang, & Vasilakos, 2012)	Multimedia	Nonlinear regression	Multiple	2012
(Shen, Liu, Qiao, Sang, & Yang, 2012)	Video	Nonlinear regression	Multiple	2012
(A. Khan, Mkwawa, Sun, & Ifeachor, 2011)	Video	Nonlinear regression	Multiple	2011
(Mok, Chan, Luo, & Chang, 2011)	Video	Logistic regression	Multiple	2011
(Fiedler, et al., 2010)	VoIP and web browsing	Exponential function	Multiple	2010
(Elkotob, Grandlund, Andersson, & Ahlund, 2010)	Multimedia	Linear regression	Multiple	2010
(Janowski & Papir, 2009)	FTP	Generalized linear model	Multiple	2009
(Menkovski, Oredope, Liotta, & Sánchez, 2009)	IPTV	Decision tree	Multiple	2009
(K.-T. Chen, Huang, Huang, & Lei, 2006)	VoIP	Cox regression	Multiple	2006

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Table 2.2: classifications of variables in regression

The Y variable	The *X* variable
Predictand	Predictors
Dependent variable	Independent variables
Explained variable	Explanatory variables
Response variable	Covariate/factor
Effect variable	Causal variables
Experimental variable	Design variable
Target variable	Control variables
Measured variable	Determinant
Outcome or output	Input
Regressand	Regressor

2.6.1 LOGISTIC REGRESSION

Logistic regression, is a statistical method which allows modelling ordinal and categorical dependent variables by using both numerical and categorical independent variables and provides an estimate of the probability associated with the different levels or categories of the dependent variable (Hosmer Jr, Lemeshow, & Sturdivant, 2013). Logistic regression is similar to multiple regression in the sense that the model utilizes a linear relationship; however, in logistic regression, a logit transformation is applied to the dependent variables. Depending on the level and characteristics of the dependent variable, logistic regression can be examined in three groups: binary logistic regression, multinomial logistic regression, and ordinal logistic regression. By replacing logit transformation with other link functions, such as probit function, other variants of ordinal regression can be obtained. In this section, detailed information on binary logistic regression, multinomial logistic regression and ordinal regression with proportional odd assumption methods will be presented.

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2.6.1.1 BINARY LOGISTIC REGRESSION

Binary logistic regression is applied to model the relationship between a dichotomous dependent variable. In other word, binary Logistic regression, is a statistical method which allows modelling of binary dependent variables (when the dependent variable has only two outcomes, i.e., when $Y = 2$) (Sreejesh, Mohapatra, & Anusree, 2014). Binary logistic regression is similar to multiple regression in the sense that the model utilizes a linear relationship; however, in binary logistic regression, a logit transformation is applied to the dependent variables. For a binary response variable Y, is denoted in two categories by $1\ and\ 0$, (which in common terms used as success/failure or yes/no). For example, binary logistic regression can be used to model opinion poll for voters' choice in a presidential election, where there are only two party systems (such as: democrat or republican). With the independent or predictors variables, such as: political ideology, level of education, annual income and religion affiliation. Or for a case where a yes or no is the required outcome, such as in drug usage, which require a yes for illegal usage and no for legal usage. Here the explanatory variables could also be educational background, employment status, marital status annual income, etc. The explanatory variables can be numerical, categorical or possibly both (i.e., mixture of categorical and numerical variables), which are believed to have effects on the dependent variable. If independent variables are numerical, they can be inserted straight into the logistic regression equation. But, if the independent variables are categorical, the variable need to be dummy coded (see section 3.3.3 for dummy coded variables). Broadly speaking, binary logistic regression assumes a binomial distribution for the dependent variable, and are recognized to be a particular case of the generalized linear models (McCullagh, Nelder, & McCullagh, 1989). The model can be expressed as follows:

For a single independent variable, the model is expressed as:

$$logit\ Y = log\left[\frac{P(Y=1)}{1-P(Y=1)}\right] = \alpha + \beta x \qquad 2.2$$

And for multiple explanatory variables:

$$logit\ Y = log\left[\frac{P(Y=1|x_1,\ldots x_k)}{1-P(Y=1|x_1,\ldots x_k)}\right] = \alpha + \beta_1 x_1 + \cdots + \beta_k x_k \qquad 2.3$$

Where, Y represent the dichotomous dependent variable; $x_1, \ldots x_k$ represent the independent variables; α is the threshold also known as the intercept term; $\beta_1, \ldots, \beta_k$ represent the regression coefficients of the respective independent variables; and k is the total number of independent variables used in the regression analysis. The logit function is specified as the logarithm of the odds ratio, that is $\left[\frac{P(y=1)}{1-P(y=1)}\right]$.

a) Assumptions of Binary Logistic Regression

The assumptions of logistic regression are as follows:

- Absence of high multicollinearity
- Absence of specification error (i.e., All relevant predictors should be contained in the model, and those that are irrelevant should be got rid of).
- Independent variables should have a summative response scale, interval or ratio level of measurement; however, dichotomous variables is also taken into account.

Categorical variables with more than one category levels can be dummy coded into dichotomous variables, thereby meeting the last assumption of the logistic regression above. For example, if there are, for example N level of categorical variable, $N-1$ dummy coded categorical variable is needed to be made.

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2.6.1.2 MULTINOMIAL LOGISTIC REGRESSION

Multinomial logistic regression is applied when the categorical dependent variable has more than two levels $(Y > 2\, levels\, of\ categories)$. Assuming the dependent variable is of N categories (i.e., $Y_1, \dots, Y_N$), one of the category is chosen as the reference category (the chosen reference category is mostly either the highest or lowest category). The remaining $N - 1$ are then applied to generate $N - 1$ logit, as illustrated in equation 2.4

$$ln\left[\frac{P(Y=j|x_1,\dots x_k)}{1-P(Y=j|x_1,\dots x_k)}\right] = \alpha_j + \beta_{j1}x_1 + \cdots + \beta_{jk}x_k \qquad 2.4$$

Where $j = 1, \dots, J - 1$ corresponding to the categories of the dependent variable; $x_1, \dots x_k$ are the explanatory variables; α_j is the threshold or intercept for category j; and $\beta_1, \dots, \beta_k$ are the regression coefficient of the respective explanatory variables defined for each dependent category j.

Multinomial logistic regression simultaneously estimates α and β values for each $J - 1$ logit equation (Agresti, 2013). Thus, a multinomial logistic regression with J categorical levels of the dependent variable and a total number of k independent variables is estimated as J−1 thresholds, and k (J−1) regression coefficients. The probabilities associated with each category of the independent variables can be obtained using equation 2.5 and 2.6

$$(Y_i = j|x_{i1}, \dots x_{ik}) = \pi_{ij}(\boldsymbol{x}_i)$$

$$P(Y_i = j) = \pi_{ij}(\boldsymbol{x_i}) = \frac{exp(\alpha_j+\beta_{j1}x_1+\cdots+\beta_{jk}x_k)}{\left[1+\sum_{j=1}^{J-1} exp(\alpha_j+\beta_{j1}x_1+\cdots+\beta_{jk}x_k)\right]} \quad for\ j = 1, \dots, J - 1 \qquad 2.5$$

$$P(Y_i = J) = \pi_{iJ}(\boldsymbol{x_i}) = \frac{1}{\left[1+\sum_{j=1}^{J-1} exp(\alpha_j+\beta_{j1}x_1+\cdots+\beta_{jk}x_k)\right]} \quad for\ j = J \qquad 2.6$$

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a) Assumptions of the Multinomial Logistic Regression

Multinomial logistic regression shares the same assumptions with the binary logistic regression. Multinomial logistic regression is an appropriate method to use when the categories of the dependent variable are not regulated. In other words, if there is an ordinal relationship between the categories of the dependent variable, multinomial cannot reflect the orderly nature of such categories. In such case, ordinal regression is used in order to reflect the ordinal nature of the dependent variable.

2.6.1.3 ORDINAL LOGISTIC REGRESSION

The ordinal logistic regression is an extension of the binary logistic regression, which is appropriate when the outcome variable levels is more than two categories and are ordered. Some authors also call it the ordered logistic regression or simply ordered logit model (Greene & Hensher, 2010), because it is the generalization of the logit model to ordered response categories. So, when the scale of a multiple category outcome is ordinal, rather than nominal, the ordinal logistic regression is used to describe the relationship between the outcomes known as the dependent variable and a set of independent variables. In contrast to the multinomial logistic regression, the ordinal logistic regression actually preserved the ordinal relationship among the different levels of the dependent variable. Since the categories of the dependent variable can be conveyed in an orderly way, different outcome categories can be considered at different levels of the dependent variable. Although, ordinal regression can reflect the ordinal features of the model outcome, it is more restrictive compared to the multinomial logistic regression, in terms of the assumption to fulfil. The substantive difference between ordinal regression and multinomial regression is the principle of the proportional of odds that it must satisfy. According to this assumption, the effects of the

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independent variables are constant between different tiers of the dependent variable. In other words, the regression coefficients of the explanatory variables do not change between different tiers of the response variable. For this reason, the ordinal logistic regression is also known as proportional odds model (McCullagh, 1980), as the probability values of different levels of the response variable, for a given setting of the explanatory variables, vary only due to the differences between the thresholds for each level of the response variable. Thus, the ordinal regression analysis can be expressed in a general form as:

$$ln\left(\frac{P(Y \leq j|\ x_1, x_2, \ldots, x_k)}{P(Y > j+1|\ x_1, x_2, \ldots, x_k)}\right) = \alpha_j + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 2.7$$

Where $j = 1, \ldots, J-1$ *corresponding to the categories of the response variable;* $x_1, \ldots x_k$ *are the explanatory variables;* α_j *is the threshold or intercept for category* j*; and* $\beta_1, \ldots, \beta_k$ *are the regression coefficient of the respective explanatory variables.*

The ordered logistic regression can be used to model the user perceived quality known as QoE, since it appropriately identifies relationships which are statistically significant between the explanatory variables and the ordered outcome. This also holds true for ordinal least square regression. However, an important dissimilarity with the ordinary least squares regression is that the ordinary logistic regression effectively determines the unequal difference between the ordinal classifications in the dependent variable. Because of this, the ordinary logistic regression is able to capture the qualitative difference between different levels of user perceive quality satisfaction of ITS multimedia services.

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a) Assumptions of the Ordinal Logistic Regression

As was stated earlier, the ordinal logistic regression is bound by the proportional odds assumption, which stated that the regression coefficients are assumed to be constant across all levels of the response variable. This assumption poses a restriction on the applicability of ordinal logistic regression compared to the multinomial logistic regression, where the effects of the explanatory variables are allowed to vary between different levels of the response variable. The assumption of the proportional odds can be tested on Statistic Package for Social Science (SPSS) by using the "Test of Parallel Line" assumption. This test compares -2 Log Likelihood value for a model in which the regression coefficients are allowed to vary, -2 Log Likelihood value of the model that satisfies the proportional odds assumption. A Chi-Square test is then applied to the likelihood ratios and if the result is significant, then the null hypothesis which states that the regression coefficients do not vary based on the levels of the response variable is rejected. Thus, in order to utilise the ordinal logistic regression, the test of parallel line result should be non-significant.

2.7. SUMMARY

Due to the stringent requirements for multimedia streaming and the highly dynamic topology of vehicular networks, the evaluation of ITS multimedia service QoE is extremely challenging. This chapter present related background by introducing basic definitions, concepts and measurement criteria related to multimedia streaming services in vehicular ITS. It was followed by a profound literature review on the state-of-the-art objective QoE measurement, modelling and prediction techniques as suggested in the literature. Finally, regression analysis as an appropriate statistical tool for QoE estimation was briefly discussed.

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CHAPTER THREE: Methodology

3.1 INTRODUCTION

This chapter identifies the methodology and the steps adopted in the development, derivation, formulation and validation of the QoE prediction model. The steps involve are as stated below:

- Model building
- Assumptions
- Potential model problem and solutions
- Model Adequacy
- Model evaluation
- Model validation

3.2 MODEL BUILDING

A desired model is a model that not only fits well with the observations, but also produces better predictions of future responses, and one that simply includes explanatory variables that contribute significantly to the model. This procedure of ascertaining the best set of explanatory variables for a regression model is known as model building. Building a model for QoE prediction is not an easy straightforward process. Analysts must have a prior knowledge of the variables to identify as independent or explanatory variable to be included in the model. The explanatory variable can be first order or second order terms, interaction terms, dummy variable or the combination of two or more terms. To build up the model, regression analysis was

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used to derive the QoE equation as a function of QoE influencing factors. The method of model building as used in this research, is separated into three steps, namely:

- The determination of population sample.
- The QoE space
- The QoE driven prediction model.

3.2.1 DETERMINATION OF POPULATION SAMPLE

Based on the study in (J. S. Kim & Dailey, 2008), the number of samples must be calculated so as to ensure a confidence interval of at least 95% and an error not greater than 5% (i.e., 0.05). Taking into consideration the following formula:

$$n = \frac{\left(z_1 - \frac{\alpha}{2}\right)^2}{a^2} . \left(\frac{s}{mean\ (x)}\right)^2 \qquad 3.1$$

Where n is the number of samples, $z_1 - \frac{\alpha}{2}$ is the $1 - \frac{\alpha}{2}$ percentile of the standard normal distribution, s is the expected standard deviation, mean (x) is the expected mean value, and a is the relative accuracy.

3.2.2 QoE SPACE

The foremost step in putting together the QoE framework is the foundation of a QoE space. A QoE space is a known characterization of expected QoE for various values of the k-parameters (i.e., numbers of QoE factors) that affect the QoE. In general, if one assumes k-parameters to influence the quality of multimedia service space, in the form of a k-dimensional vector P. Then the vector P could be written as follows:

$$P = [y_1, y_2, y_3, \ldots\ldots, y_i, \ldots\ldots y_k] \qquad 3.2$$

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Where $y_i, 1 < i < k$, represents the instantaneous value of the i^{th} parameter. Thus, the vector P provides the instantaneous state of the multimedia streaming in transit. Due to the dynamism of the ITS network, the parameter y_i will experience a constant change and so also will the vector P. The constant changing of the vector P, can be interpreted as the motion of a point in a k-dimensional QoE space. We argue that associated with every single point in this space is a QoE index, which signifies the quality of experience offered by the network to the users. Since the QoE space is a record of parameter values and measured QoE, a variety of parameters can be used to quantify multimedia perceived quality categorizations. For example, in this thesis, the parameter that was identified to influence the multimedia service user QoE are seven. And so seven-dimensional QoE space was built, which consist of parameters such as frame rate, bit rate, delay, packet loss, throughput, gender and social context (further detail is presented in section 4.4).

3.2.3 QoE-DRIVEN PREDICTION MODEL

The primary driving force of this study, is to look into the influences of the various QoE factors as they impact on the users' quality perception known as the QoE and to deduce a mathematical relationship between these QoE factors in order to be able to predict user possible QoE of ITS multimedia services. As it has already been discussed in chapter 2, QoE is expressed in terms of human perception which is limited. Humans perceive things imprecisely (i.e., human can not precisely say the quality of the video is 80 or 20, rather he or she can only say the quality of the video is bad, good or excellent). And so, in order to cope with this human limitation, ITU-T proposed the Mean Opinio Score (MOS) (P.800.2:, 2013), a discrete scale that represents a user perception of multimedia quality which is scaled from 1 to 5 (with 1 representing bad quality and 5 is considered to represent excellent quality) (Streijl, et al., 2014). Therefore, if the possible outcome of the QoE prediction is limited to 5 ordered categories, then it will be fair to presume that the errors involved will not be distributed normally. Consequently, the fact that multimedia traffic over a non reliable network such as VANETs, are prone to experience several distortions due to the unstable nature of the network channels. Such distortion could manifest into blur images, scene frozen, edge noise, etc. (see figure 4.6 in chapter 4). These distortions are not completely independent, as they can intermix and manifest in a lower quality multimedia services. In this perspective, ordinal logistic regression, emerges as the most suitable statistical technique to be used in developing the QoE prediction model. Hence, ordinal scale was proposed for the QoE outcome, and the explanatory variables (i.e., the QoE factors) are analysed using the logit link function of the ordered logit model. Since the relationship among the categories of the dependent variable is ordinal, by using the ordinal logistic regression, the ordinal relationship that exists among the different QoE outcome will be preserved. Consequently, the categories of the dependent variables can be expressed in an orderly manner, such that the different outcome categories can be viewed independently.

The central difference between ordinal regression and multinomial regression is due to the proportional odds assumption. According to this assumption, the effects of independent variables are constant between different levels of of the dependent variable (McCullagh, 1980). In other words, the regression coefficients of independent variables do not change between different tiers of the dependent variable. The probability values of different tiers of the dependent variable for a given setting of the explanatory variables vary only due to the differences among the thresholds for each level of the dependent variable. Hence, ordinal logistic regression equations have the following general form:

$$ln\left(\frac{P(Y \le j \mid x_1, x_2, \dots, x_k)}{P(Y > j+1 \mid x_1, x_2, \dots, x_k)}\right) = \alpha_j + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 3.4$$

Where, Y represend the dependent variable, $j = 1, 2, \dots, J-1$ correspond to ordered levels of the dependent variable that holds a total number of J Levels (the dependent variable is the QoE and in this case $J = 5$); α_j represent the threshold for the jth level of the dependent variable; $x_1, x_2, \dots, x_k$ represent the explanatory variables, which in this case are the QoE factors; and $\beta_1, \dots., \beta_k$ are the regression coefficients for the individual explanatory variables.

Thus, using equation 3.4 above, an ordinal variable Y can be associated with the QoE levels, such that $Y = 1$ if the quality is bad, $Y = 2$ if the quality is poor, $Y = 3$ if the quality is fair, $Y = 4$ if the quality is good and $Y = 5$ if the quality is very good.

3.2.3.1 PARAMETER ESTIMATION

Parameters in the ordinal logistic model are estimated using the maximum likelihood method. The idea behind the maximum likelihood estimation is to determine the value of the parameters which cause the highest probability that the observed data is most likely to have happened. It likewise offers an effective method for quantifying uncertainty by mean of the confidence interval. The method is considered to be flexible, can be applied to most models and diverse data types. In this study, however, since the ordinal scale was proposed to be used for the QoE predicted model, and the fact that the QoE prediction is limited to 5 ordinal categories (i.e., scaled from 1 to 5). The analysis was done using the multinomial distribution with logit link function of the ordinal logit model. And so the parameters are estimated using the maximum likelihood estimation method. The likelihood function for ordinal logit model is defined as in equation 3.4 (Balakrishnan & Cohen, 2014).

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$$\prod_{i=1}^{n}\left[\prod_{j=1}^{J}\left(P(Y_i \le j|\boldsymbol{x}_i)\right)^{y_{ij}}\right] = \prod_{i=1}^{n}\left[\prod_{j=1}^{J}\left(P(Y_i \le j|\boldsymbol{x_i}) - P(Y_i \le j-1|\boldsymbol{x}_i)\right)^{y_{ij}}\right] \quad 3.5$$

Where $i = 1,2,\ldots,n$ representing observation; j=1,..,J representing level of the dependent variable; y_{ij} indicates the outcome of the observation; $y_{ij} = 1$ if outcome of the observation i is equal to j and 0 if otherwise.

For a dependent variable with J levels, J-1 cumulative logit equations are handled simultaneously, if there are k independent variables in the model, there will be ok regression coefficients, and a J-1 intercept term.

3.2.3.2 SIGNIFICANCE OF THE MODEL

The significance of the model is determined by using the likelihood ratio method. The -2loglikelihood of the model is compared with the -2loglikelihood of the base model, which only has the intercept.

3.2.3.3 SIGNIFICANCE OF THE COEFFICIENTS

Wald statistic was used to determine the significance of the regression coefficients. As mentioned in chapter two, the Wald statistics are calculated as the square of the regression coefficients divided by its standard error. A chi-square test with 1 degree of freedom is applied to determine the significance of the explanatory variables.

3.2.3.4 QUALITATIVE AND QUANTITATIVE VARIABLES

In this study, the values of the independent variables (i.e., the QoE parameters) are of two data types: quantitative and qualitative. Some values of the QoE factors are

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quantitative and some others are qualitative. A variable value is considered quantitative, if the value of such variable is measurable in terms of numbers. That is to say, quantitative variables are those variables whose values or attributes can be measured on a continuous or quantitative scale. For example, in a city population; the number of people subsisting in a particular city can be quantified. This implies that population is a quantitative variable, the fact that its attribute is measurable in terms of numbers. While qualitative variables are those variables that take on values that are categorical in nature. Variables such as gender, which can either be male or female, person's religion (can be Christian, Hindu, Muslim, and so on). This kind of variables takes on the values that are in the form of names or labels and not in terms of number, but rather in term of description.

In chapter four, the multimedia service QoE factors were classified into technical and non-technical factors, where the technical factor was sub-categorized into network and service QoS factors and the non-technical factors as the human and contextual QoE factors (see section 4.2). The technical factors are quantitative measurable variables (their information can be measured and written down with numbers and they all have units of measurement). As discussed in chapter four, each of the technical parameters: packet loss, delay, throughput, frame rate, bit rate, and so on, are all continuous variables, the fact that one can choose a value between their minimum and their maximum values. While on the other hand, the non technical factors are qualitative variables, their values or information cannot be measured, rather they are categorical variables whose value can only be classified into a group. For example, gender can only be male of a female, social context in this study is classified as single (i.e., if the user viewing the multimedia service is alone in the vehicle) and group (i.e., situation in which there are two or more users in the vehicle that are watching the multimedia service).

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In this work, because there are both categorical variables and continuous variable, the emphasis is not simply the linear trends, but also, on the differences between the means of Y at each tier of the categories. This way, one will be able to explain or predict the variance of the independent variables in conditions of their linear combination of several reference functions. However, in order to be able to combine both continuous and categorical variable in the same regression analysis, the categorical variable need to be represented in a form that can be measured (i.e., converted to binary variable known as dummy, see section 3.2.3.5).

3.2.3.5 DUMMY VARIABLES

Most often, we are confronted with the demand to include nominally scaled variable (i.e., the qualitative variables) in a model, because they are associated to the dependent variables. For example, in this study, the dependent variable is not exclusively determined by the quantitative variables (throughput, packet loss, delay, bit rate, frame rate), but also by qualitative variables (, gender, social context, and so on). Though, the ordinal regression model can accommodate both continuous measurable variables and categorical variables. Nonetheless, in order to be able to combine both qualitative and qualitative variables in the same regression analysis, the qualitative variable need to be represented in a form that can be measured. In such situation, a tool known as Dummy variable need to be created. Dummy variables are variable in a regression model that takes on a finite number of values so that different categories of a nominal variable can be identified (Hayes & Preacher, 2014). They are sometime referred to as binary or dichotomous variables as they need just two values, usually 1 or 0, to indicate the presence or absence of a feature. Therefore, in the QoE prediction model, the qualitative variables are dummy coded as follows:

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For example; to account for a qualitative variable gender:

$$Gender = \begin{cases} 0 & if\ the\ subject\ is\ male \\ 1 & if\ the\ subject\ is\ female \end{cases} \tag{3.6}$$

And the variable social context, which depends on the Presence or no presence of co-viewers, is dummy coded as.

$$social\ context = \begin{cases} 0 & if\ single\ user \\ 1 & if\ in\ group\ (i.e.,\ more\ than\ one\ user) \end{cases} \tag{3.7}$$

When placing a dummy variable, the conclusion as to which variable is assigned the value 1 and which is assigned the value zero is completely arbitrary. For example, in $gender$ as shown above, the variables male, can take any value of 1 or 0. So, using 1 and 0 binary values to represent these qualitative variables is an arbitrary choice. However, the response function in this consequence will only have different elevation, depending on the gender used (note: in a linear regression model, the number of dummy variables is one less than the number of classes). Dummy variables are useful because they enable one to use a single regression equation to represent multiple groups. Which eliminates the need to write out separate equation models for every subgroup. The dummy variable act like a switch that turn various parameters on and off in an equation.

3.3 ASSUMPTIONS

When a researcher chooses to use the ordinal logistic regression for analyzing his/her data, part of the process involves checking to ensure that the data to be analyzed can actually be analyzed using the ordinal logistic model. This is required because it is only

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appropriate to analysed the data using ordinal logistic model if the data satisfy the assumptions required for ordinal logistic regression to yield a valid result. These assumptions are:

1. The dependent variable must be measured at the ordinal level.
2. The explanatory variables must either be continuous, categorical, ordinal or all the three.
3. Multicollinearity must not exist between the explanatory variables (multicollinearity is said to exist when there is a high similarities known as 'collinearity' among two or more explanatory variables in the regression model)
4. The proportional odds assumption must be satisfied (i.e., the assumption that the effects of the explanatory variables are the same across the different thresholds has to be met).

Assumption 1 and 2 were tested first, before assumption 3 and 4, the assumptions are tested in this order, because the level also represents the ease at which the violation of the assumptions can be correctable. For example, the violation of assumption one and two can easily be corrected, while the violation of assumption four would mean ordinal logistic regression is no longer a viable option for such analysis. Thus, in this thesis, the data that were to be used in developing the QoE prediction model were all examined to ascertain that they pass these assumption tests, otherwise, the solution obtained when running the regression analysis might not be valid.

3.4 POTENTIAL MODEL PROBLEM AND SOLUTIONS

When constructing an ordinal logistic model, analysts should be cautious of potential problems, many of which are instigated by the violation of assumptions. Some of these

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problems can be minimized, while others can be fixed to improve the accuracy of the model.

3.4.1 PROBLEM OF OUTLIERS AND LEVERAGE

As the name implies, an outlier is a data point or observation in an experiment that significantly deviates from the rest of the observation or data points. In a multiple regression analysis (such data point is considered as an unusual data, see figure 3.1). Such an unusual data can wreak havoc with least-squares approximations, unusual data in regression include outliers and high-leverage points. An observation that is both outlying and has high leverage is considered as an influential outlier, and the removal of such outlier can significantly alter the result of the model least square estimation. Outliers occur very frequently in real data, and they often go unnoticed because nowadays much data is processed by computers, without careful inspection or display. Outliers may be a result of keypunch errors, misplaced decimal points, recording or transmission errors to mention but only a few. Some outliers can be desirable while others are not. Desirable or true outliers, are those outliers that are not due to discernible error, such outliers may present a clue that may reveal interesting finding about the model being tested, may reveal a possible assumption violation, or observation that experience no substantial influence on the analysis outcomes. While false or undesired outliers are those due to discernible error, such outliers in our study are considered irrelevant and may be withdrawn from the regression model. An outliers with respect to the explanatory variables are known as leverage points. This kind of outliers also constitutes substantial influence in the regression model. There exist two kind of leverage points in regression analysis: good leverage point and the bad leverage point (Marubini & ORENtI, 2014).

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- Good leverage point: is the point that is considerably large or small among the values of the regressors but are not regression outliers. A good leverage point has limited effect on giving a distorted impression of how the majority of the points is associated, and their presence improves the precision of the regression coefficients.
- Bad leverage points: these are point situated farther from the regression lines, far from the stage in which the bulk of the points is centred (i.e., a regression outlier whose point is relatively far removed from the regression line). Observations that are relatively far from the centre of the regression space, have a potentially greater influence on the least-squares regression coefficients; such points are said to have high leverage.

In this work, in order to identify possible influential outliers, the diagnostic tool known as the cook's distance was used (simply identify as cook's D).

Given a regression $Y\ on\ (x_1, \ldots., x_k)$ using dataset $\left(y_i, x_{1j}, \ldots, x_{kj}\right), j = 1, \ldots, n, if$

$s =$ estimated root mean square error

$\hat{y}_j =$ regression estimation of the conditional mean $E\left(Y_j \left| x_{1j}, \ldots x_{kj}\right.\right)$,

$\hat{y}_j\ (i) =$ regression estimation of the conditional mean $E\left(Y_j \left| x_{1j}, \ldots x_{kj}\right.\right)$ with the

$i^{th}\ data\ point\ (y_i, x_{1i}, \ldots, x_{ki})$ removed, then the Cook's Distance for point i in an observation is given by:

$$D_i = \frac{\sum_{j=1}^{n}\left(\hat{y}_j - \hat{y}_j(i)\right)^2}{(k+1)s^2} = \frac{(B-B_i)^T X^T X(B-B_i)}{(k+1)s^2}, i = 1, \ldots, n \qquad 3.8$$

Naturally, D_i is the normalized measure of the influence of point i on all predicted mean values, $\hat{y}_j, j = 1, \ldots, n$. And B is the coefficient vector obtained, including the i^{th} observation and B_i is the coefficient vector obtained excluding the i^{th} observation. k is the number of coefficients, of which in this study is 6 and s is the estimated root mean

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square error. Therefore, to identify potential outliers we look at the dispersion of the Cook's Distance value to see if there is any clearly large value relative to the rest others. If the values are roughly of the magnitude $\frac{4}{(n-k-1)}$ or larger, we will consider such outliers worthy of further investigation.

It will be pertinent to point out here that, the procedure, adopted above is simply meant to identify spots that are suspicious from a statistical point of view. This does not imply that such points if identified should be removed automatically, as the removal of whatever data point in a regression model can be unsafe. Though the removal of outliers may improve the fitness of a regression, but caution must be taken to insure that such removal does not end up in destroying some of the most important information in the model. And so, it is advisable to investigate dictated outliers to see if there exists reasonable or convincing information about them that could warrant their removal. And before we draw such a conclusion (i.e., conclusion on removing any oulier), we first asked ourselves the following question:

- Do the outliers involve any particular attributes or conditions that is not relevant to the situation we are investigating?
- Do the outliers involve any possible measurement errors?

In order to resolve these queries, we performed two separate regression analysis. First analysis, we included the outliers in the regression and in the second analysis, we took out the outliers, and examined their specific influence on the outcomes. If through our investigation, such distinguish features in the outliers could not be determined, then, we could conclude to say the outliers possess no clear reason to get rid of. As an alternative, we will present the two solutions, and simply draw attention to the fact that

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the details of the points are questionable. All the same, if any, minor influence is dictated, then it may not matter whether or not they are omitted.

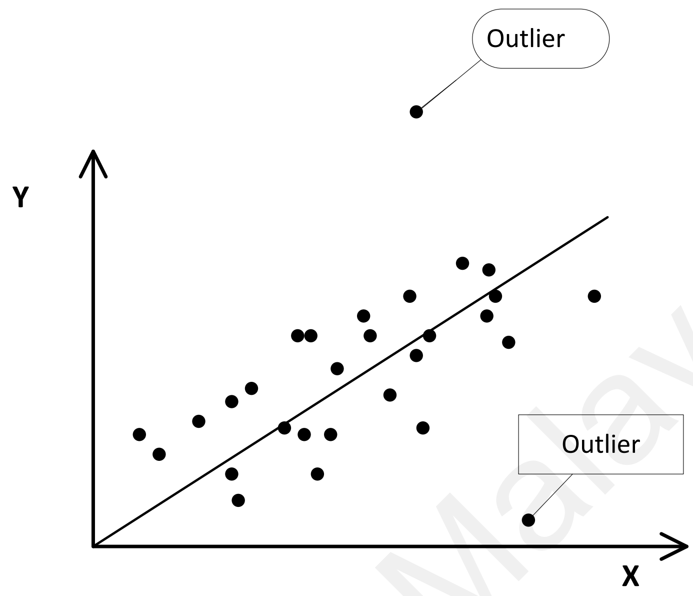

Figure 3.1: An example of outliers in a multiple linear regression model

3.4.2 PROBLEM OF MULTICOLLINEARITY

Multicollinearity is a state of affairs in which two or more independent variables in a regression model are extremely related such that they explain almost the same variability in the result or outcome. In such situation, the relationship among the independent variables are alleged to be 'collinear'. It is considered a safe practice, to first check for the presence of multicollinearity among all the explanatory variables to be included in a model before proceeding with the parameter estimation processes. Thus, the diagnostic information for multicollinearity in this thesis was obtained by generating the Tolerance and Variance Inflation Factor (VIF) values of all the explanatory variables used in the used in the QoE prediction model design. Tolerance and VIF are the two most important collinearity diagnostic factors that can be employed

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in regression to identify the existence of multicollinearity among explanatory variables (Draper & Smith, 2014). The calculation of these values (i.e., VIF and tolerance) is obtained through ordinary least square regression, because the values are similar to the general linear regression analysis. Tolerance measures the proportion of predictability of an explanatory variable that is not predicted by other explanatory variables in the regression model. while VIF measures how highly correlated each explanatory variable is with the other explanatory variables in the model. (VIF is $1/Tolerance$ and it is always equal to or greater than 1). It has been considered that a tolerance value below 0.20 is an indication of high multicollinearity (By Jeffery T. Walker, 2012) (the higher the Tolerance value, the more useful the explanatory variable is to the analysis, the lower the tolerance value, the higher the degree of collinearity). On the other hand, a VIF value greater than 5 is also commonly considered evidence of multicollinearity (Garson, 2012). In this thesis, the problem of multicollinearity is resolved by taking out one of the correlated independent variable in the model.

3.4.3 PROBLEM OF EXTRAPOLATION

Extrapolation in regression is the process of predicting the value of the dependent variable, beyond its original observed range, on the basis of its relationship with the independent variables. Using regression for prediction is correct only if the predicted data are from within the same range as the original input data. For instance, when one makes a linear regression equation to identify the relationship between a child's age, height and weight and then utilize the equation to input data from adults, this could result in the production of a completely false result. Extrapolation can be subject to high uncertainty with a high danger of producing meaningless results, if the assumed relationship is done outside the region of the actual data. Naturally, the characteristic of

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a particular method of extrapolation is limited by the assumption made by the method regarding the regression function. If the method assumes that the data are smooth, then a non-smooth regression function will be a poor generalization. The problem of extrapolation can be resolved by ensuring that input data does not extend beyond the range of the original observed data.

3.4.4 PROBLEM OF MISSING DATA OR VALUES

The trouble of missing information is perfectly common in nearly all research. Missing data can scale down the statistical power of a study and can produce biased estimates, leading to invalid conclusions. Numerous researchers one way or the other have been confronted with the problem of missing quantitative data at some period in their study, even in a well-design and controlled study, losing data are said to occur. Considering the expense of accumulating data, one cannot afford to start over or to wait until we have evolved a foolproof method of collecting and analysing data. In literature, there are diverse methods used by researchers in handling missing explanatory variable data in multiple linear regression, method such as: single-value imputation, available case analysis, complete case analysis (Hipp, Wang, Butts, Jose, & Lakon, 2015), (Chevret, Seaman, & Resche-Rigon, 2015) etc. However, the most common practice and easiest solution to apply is to utilize only those cases with complete information. Nevertheless, in this study, we chose to represent any missing data or information in our model with dummy variables to account for the missing data (dummy variable has been discussed briefly in section 3.2.3.5).

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3.5 MODEL EVALUATION

The evaluation of model adequacy is an essential step of the modelling process, because it ascertain how good a model fits the purpose for which it is being planned. It is constantly necessary to examine a regression model to assure that it offers an adequate approximation to the true system and to also verify that none of the regression assumptions are broken. Any model for predicting or estimation will give poor or misleading results if the accuracy of such model is not adequately examined. The most important diagnostic technique in determining model adequacy is to examine its goodness of fit (i.e., how well the model conforms to the given data).

3.5.1 MODEL GOODNESS OF FIT

When fitting a statistical model, the value of the dependent variable (such as the user's opinion score) is believed to be composed of two parts: systematic component and the nonsystematic or the stochastic component (Gordon, 2012). The systematic component is a mathematical function of the independent variables that characterise the given observed data among subjects within the independent variable of the model. Although the fit of the derived model can be roughly examined by comparing the model output to the observed data, the quantitative evaluation of the model fit is impossible with only the systematic component. The error component represents how much the model's output differs from the observed data. The process of examining the value of the error component is referred to as assessing the goodness of fit of the model. In practice the goodness of fit provides crucial information on how the model's output resembles the observed data from the experiment. In an ordinal logistic regression, the two most common methods used statistic in the literature to determine whether the observed data

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are well recognised by the fitted model, are the Pearson's Chi-sqare statistic and the Deviance statistic (Bhattacharyya & Bandyopadhyay, 2014).

The Pearson statistic is a quadratic alternative form of the Deviance test, and is often favoured over the residual deviance because of its moment estimator character. The anticipated value of the Pearson statistic depends merely on the first two moments of the y_i distribution, this makes the Pearson statistic to be more robust against mis-specification of the response distribution. However, in this study, the overall model fit was determined using both the Pearson's Chi-square and the Deviance goodness of fit test. This is to determine if the two different test statistics will lead to a similar outcome, if their p-values (significance value) are close, then it will be more appropriate to draw a conclusion that the sample approximation is in order. The two test statistic can be expressed empirically as follows:

Assuming N represent the ordinal response data of subjects with the cumulative logit model from k categorical covariates. A table such as the one shown in table 3.1, can be constructed for the observed cell counts and expected cell counts of the fitted model.

Table 3.1: Data classification for Deviance and Pearson Chi-square test

Covariates	Response				
	$Y=1$	$Y=2$	...	$Y=J$	Total
x_1	O_{11}	O_{12}	...	O_{1J}	N_1
x_2	O_{21}	O_{22}	....	O_{2J}	N_2
$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
x_k	O_{I1}	O_{I2}	...	O_{IJ}	N_I

The model-based expected frequency can then be computed using the expression:

$$E_{ij=}\sum_{i=1}^{N_i}\hat{p}_{ij} \qquad 3.9$$

Where $\hat{p}_{ij}$ is the predicted probability of individual in row i falling into the response category j. This will result in a table of expected counts corresponding to the observed count as exemplified in table 3.1. From these observed and expected frequencies, the Pearson chi-square x^2 and the Deviance D^2 can be obtained using the expression in equation 3. And 3.4 below.

Pearson chi-square:

$$x^2 = \sum_{i=1}^{k} \sum_{j=1}^{J} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \qquad 3.10$$

And Deviance:

$$D^2 = 2 \sum_{i=1}^{I} \sum_{j=1}^{J} O_{ij} ln \left(\frac{O_{ij}}{E_{ij}}\right) \qquad 3.11$$

If the model fit adequately, the value of both the Deviance and the Pearson Chi-square statistics will be low, but have high observed p-values (the higher the p-value the better the model fit). Otherwise, their p-value will be relatively low with each having very high statistical values.

3.5.2 CONFIDENCE INTERVAL TEST

The confidence interval is a standard method used to express the statistical accurateness of a prediction model. The expression in equation 3.12 was used in determining the confidence interval of the proposed model.

$$\hat{Y} \pm t \left[\left(v, 1 - \frac{1}{2\alpha}\right)\right] s\sqrt{\bar{u}_0{}^T S \bar{u}_0} \qquad 3.12$$

Where $\bar{u}_0$ is the column vector for a specific set of values of predictor variables, S is the variance-covariance matrix, s is the root mean square of the residual, v is the degree of freedom i.e., (n-p-1) and $1 - \frac{1}{2\alpha}$ is the confidence level, where α is the level of significance.

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3.5.3 PSEUDO R-SQUARE

Unlike in linear regression, where the coefficient of determination R-square is used to sum up the proportion of variance of the outcome that can be accounted for by the explanatory variables. In ordinal regression, it is not possible to compute the same R-square as applied in linear regression. As an alternative, three estimates, identified as the pseudo R-square are computed to determine the strength of association between the dependent variable and the explanatory variables. The three pseudo R^2 Statistics are:

- **Cox and Snell R-square**: The Cox and Snell's R-square is based on the log-likelihood for the model compared to the log likelihood for a baseline model. Nevertheless, with categorical outcomes, the maximum value of the Cox and Snell R-square is always less than 1 in theory, even for a perfect model (Field, 2013), .

$$R^2{}_{Cs} = 1 - \left(\frac{\boldsymbol{L}(\boldsymbol{B}^{(0)})}{\boldsymbol{L}(\hat{B})}\right) \qquad 3.13$$

- **Nagelkerke's R-square:** The Nagelkerke's R-square is an adjusted version of the Cox and Snell's R-square that adjusts the scale of the statistic to cover the full range from 0 to 1.

$$R^2{}_N = \frac{R^2_{CS}}{1-\boldsymbol{L}(\boldsymbol{B}^{(0)})^{2/n}} \qquad 3.14$$

- **McFadden's R-square:** The McFadden's R-square is another version, based on the log-likelihood kernels for the intercept only model and the full estimated model.

$$R^2{}_M = \left(\frac{\boldsymbol{L}(\hat{B})}{\boldsymbol{L}(\boldsymbol{B}^{(0)})}\right) \qquad 3.15$$

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Where $\boldsymbol{L}(\hat{B})$ is the log-likelihood function for the model with the estimated parameters and $\boldsymbol{L}(\boldsymbol{B}^{(0)})$ is the log-likelihood with the thresholds only, and n is the number of cases (sum of all weights).

Evenly, these three individual tests can offer reliable information as regards to the proportion of variation among the explanatory variables used in a model. Yet, what may constitute a good R-square value depends on the nature of the event and the explanatory variables. Nevertheless, a model with low pseudo R-square Values is an indication of a poor predictor outcome.

3.5.4 TEST FOR THE ASSUMPTION OF PROPORTIONALITY

In ordinal regression, instead of modelling the probability of an individual event like in the case of logistic regression, the consideration is in modelling the probability of an event along with all other events in the ordinal ranking. And so the concern of the ordinal regression is in the cumulative probabilities of the outcome rather than probability of separate groups. Therefore, the objective of a proportional odds model is to concurrently consider the effects of a set of explanatory variables across the successive cumulative splits in the response or outcome. To this end, a simplifying assumption that the effects of the explanatory variables are the same across the different thresholds has to be presumed; this is usually termed the "assumption of proportional odds" (in SPSS it is known as the "assumption of parallel lines"). Thus, before any conclusion is drawn on how well fit the model is, this assumption must be affirmed.

3.6 MODEL VALIDATION

Model validation is the process of finding out whether the mathematical model obtained from the regression analysis, possesses a satisfactory range of accuracy that is logical with the designated purpose of the model (Sargent, 2013). Model validation is one of

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the most significant facet of this dissertation. Validation, is the manner by which a model is assessed to ascertain its dependability, before it is put to use. In this thesis, The foremost measure is aimed at estimating the accuracy of point estimates of the prediction model, this first measure is conceptually divided into two: discrimination and calibration (Labarère, Bertrand, & Fine, 2014). The second step involved the determination of the stability and generalizability of the model, using the internal validation technique known as bootstrap (Efron & Tibshirani, 1994), (Steyerberg et al., 2010).

3.6.1 CALIBRATION

Model Calibration refers to the capability of a fitted model to produce an unbiased estimate of the outcomes. Recall that the model developed in this thesis is based on predicting QoE, of multimedia services. Still, before any conclusion can be drawn as to how well fitted the proposed QoE prediction model is, it is pertinent and imperative to ascertain how correctly the model is able to predict the QoE categories, based on the value of the explanatory variables. To verify how well the model predicts the final outcomes, a classification accuracy table was constructed, by cross-tabulating the predicted categories with the actual categories (the process is also known as confusion matrix) (Doyle et al., 2014).

3.6.2 DISCRIMINATION

Model Discrimination is the ability of the model to distinguish between the different QoE rating levels (i.e., the correct relative ranking of the predictive probabilities) (Petrie & Sabin, 2013). The model should be able to distinguish a bad user QoE outcome from a good, fair, poor or very good user QoE outcome. In other

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words, a model with good discriminatory ability should be able to single out the category with the highest probability of QoE value as the predicted category over category with lower probability value (i.e., being able to show the distinction between the QoE level with the highest predicted membership value over all other groups in the ordinal ranking).

3.6.3 BOOTSTRAPPING

The final result obtained after the estimation phase is a model that fits to the data the best from all considerations. This may not be sufficient since the interest here is not in modelling the data at hand, but rather in predicting the process behaviour. In the case of QoE subjective test as proposed in this research, the interest here is in predicting what would be the answer given by random service users if made to watch for example, a video clip while driving along highway or city environment. Thus, the model has to be corroborated, by testing if it offers the same solution for a data set that has not been applied to approximate the model. Such an additional data set is called a test set. It is also necessary that the test set differs from the set that is utilised to estimate the model (known as the "training set"). If the model generalizes the problem correctly, then the model answer should not differ statistically from the answers provided by the subjects in the test set. Nevertheless, since the fitted model in this thesis is not merely meant to be applied for computing the relative effect (i.e., odds ratio), but also to be used to forecast the chance of several QoE outcomes. It is important to ensure that the predicted probabilities are accurate in terms of agreement with observed proportions of events in a sample not used to produce the model. Such accuracy is said to be virtually guaranteed if such evaluation is implemented on the same sample that is used to fit the model (Guisan & Harrell, 2000). As reported in (Efron, 2003), bootstrap is considered to be the most efficient internal validation technique for logistic regression that could act

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exactly in such fashion. This is because bootstrap utilizes the complete data set from the same population in which they were produced for training and testing models while providing estimates of prediction error with relatively low variability and minimal bias (Efron & Tibshirani, 1997). Through re-sampling with replacement, the bootstrap allows one to estimate the optimism (bias) in whatever measure of predictive accuracy and, then, subtract the estimate of the optimism from the initial apparent measure to obtain a Bia-corrected estimate. The bias is the difference between the parameter estimate in the original sample and the bootstrap sample as reflected by the slope index is the measure of the amount of "optimism" (Halbesma et al., 2011), (Steyerberg et al., 2001). When the difference between the apparent and the bootstrap corrected (bias) value is too high (what is sometime called the optimism from over fitting), then the accuracy of the model should be severely questioned. Below are the steps undertaking to implement the nonparametric bootstrap on the estimated QoE prediction model:

1. The apparent predictive ability A was estimated using actual observed data used to fit the model.
2. N random samples were then drawn with replacement from the actual observed data to obtain a bootstrap sample
3. For each of the bootstrap samples, the model is fit to the bootstrap sample and the apparent predictive ability is then measured.
4. The test for the accuracy (t) of the measurement is obtained by comparing the bootstrap model with the actual observed sample.
5. The optimism or bias (b) in the predictive ability of the bootstrap model is then computed as $b = a - t$
6. A stable estimate of optimism as the mean optimism from the N bootstrap samples is then calculated as:

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$$b = \frac{\sum_{i=1}^{N} b_i}{N} \quad 3.16$$

7. The internal validated estimate of the predictive accuracy is then determined by subtracting the estimated optimism from the apparent predictive ability:

   $$V = A - b \quad 3.17$$

   Where a is the quantity of the individual bootstrap sample, b is the optimism in developed model, N number of bootstrap sample, t is the measured accuracy test and A is the apparent predictive ability

$$b = \frac{\sum_{i=1}^{N} b_i}{N} \quad 3.18$$

The bootstrap procedure (i.e., the step $1 - 7$), were performed automatically using IBM Statistic Package for Social Science (SPSS) software package version 22.

3.7 SUMMARY

This chapter described step-by-step the methodology undertook in this thesis to effectively model and predict the QoE of ITS based multimedia services. This includes the manner by which the proposed QoE model was formulated, the kind of test run to ascertain the model fit and the validation technique employed to ensure the generalizability of the proposed model. Ordinal regression analysis was adopted as the regression technique for the modelling, because of the ease at which it can be manipulated to model ordinal outcomes without altering the ordinal relationship that exists among the different outcome. However, this ease of use comes with a price, a price that the data being analyse must pass some assumptions required for the ordinal logistic regression to generate a valid result. Therefore, these suppositions were tested,

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before the final conclusion was drawn as to whether the choice of adopting the ordinal logistic regression was a feasible option. This chapter also stated clearly the steps that were taken to ensured that such assumptions were not broken. In conclusion, a taxonomy that recapitulates the methodology as adopted in the development of the proposed QoE prediction model is depicted in figure 3.2.

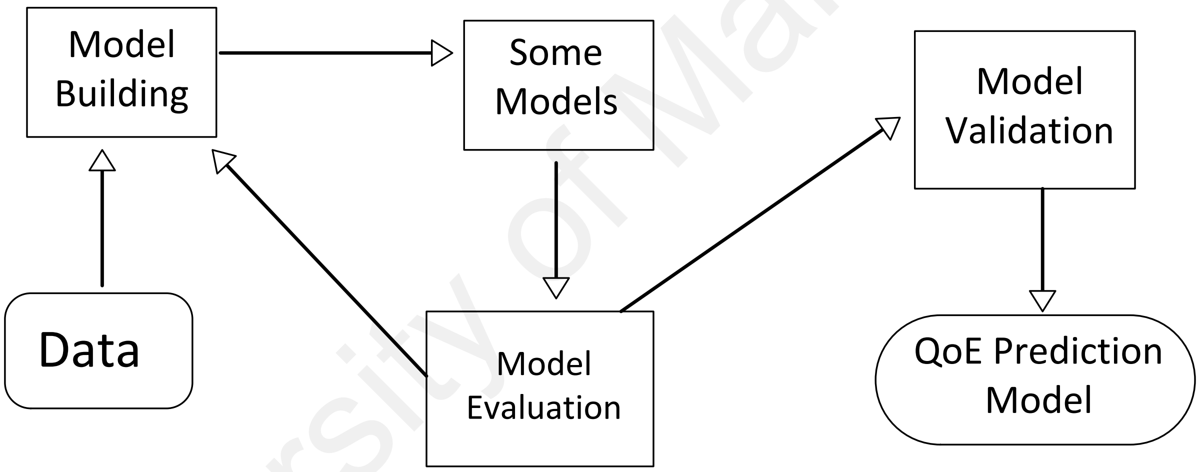

Figure 3.2: A taxonomy recapitulating the methodology as adopted in the development of the proposed QoE prediction model

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CHAPTER FOUR: Framework and Analytical Model

4.1 INTRODUCTION

The essential idea of this thesis is to report on development, evaluation and validation of QoE prediction model for ITS multimedia services, which was built using ordinal logistic regression analysis. This chapter provides detailed explanation of the model architecture (i.e., the framework), derived from the QoE influential factors. The framework has been developed utilizing the comprehensive set of metrics derive from both the technical objective network parameters and the subjective human QoE factors. The chapter also offers a detailed explanation of the QoS analytical deduction of the VANETs connectivity model, and the analytic model of the end-to-end QoS parameters. Furthermore, the results of the simulation conducted in NS-2 to deduce the sample data used in the regression analysis was also presented. Furthermore, in this chapter, Internet Protocol Television (IPTV) was used as the ITS multimedia service in this thesis. Except otherwise stated, the use of IPTV in this work is assumed to be an aspect of multimedia services. In that regard, the term IPTV and multimedia as may be employed interchangeably in this study should be interpreted as an application of ITS multimedia services.

4.2 MODELLING QoE IN VANETs

The ultimate goal of QoE assessment of any multimedia streaming services is in the satisfaction of its end-users quality perception of the services that is being delivered. This objective calls for an efficient management of underlying VANETs channel resources to support the adaptive nature of the network. However, unlike other mobile

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wireless ad hoc networks, VANETs is extremely vulnerable to noise, interference, multipath fading and has limited throughput, therefore results in high rate of packet loss and end-to-end delay variability. In addition to packet loss, delay, jitter and bandwidth availability, there are many other factors that undesirably affect the quality of media as perceived by the end-users. Factors such as channel conditions, users' device characteristics, environmental situation, context, coupled with human components, that may include user sensation, gender, age, expectation, etc. All these factors and many more events that occur during service transmission can greatly influence how IPTV media quality is being comprehended by the end users in a vehicular environment.

Accurate estimation of multimedia streaming QoE, will allow for control over the delivering quality and implementation of user centric management of services that focuses on managing the services based on the end user needs. Though, most parameter that influence QoE are subjective, but then subjective approach is considered unfeasible in a real time setting. Therefore, it’s pertinent to formulate metrics that can quantify these parameters as objective as possible. Once such metrics are put in place, network and service parameters can then be mapped into the metrics. This will permit the evolution of optimization functions, which can take into account the network resource constraint and the end users expectations. To develop such optimization functions, the multimedia/VANETs distribution network, was then segmented into a framework of three quality optimization component (see figure 4.1 and 4.2A and B). Each individual component and what it entails are discussed extensively in section 4.2.1, 4.2.2, and 4.2.3 respectively.

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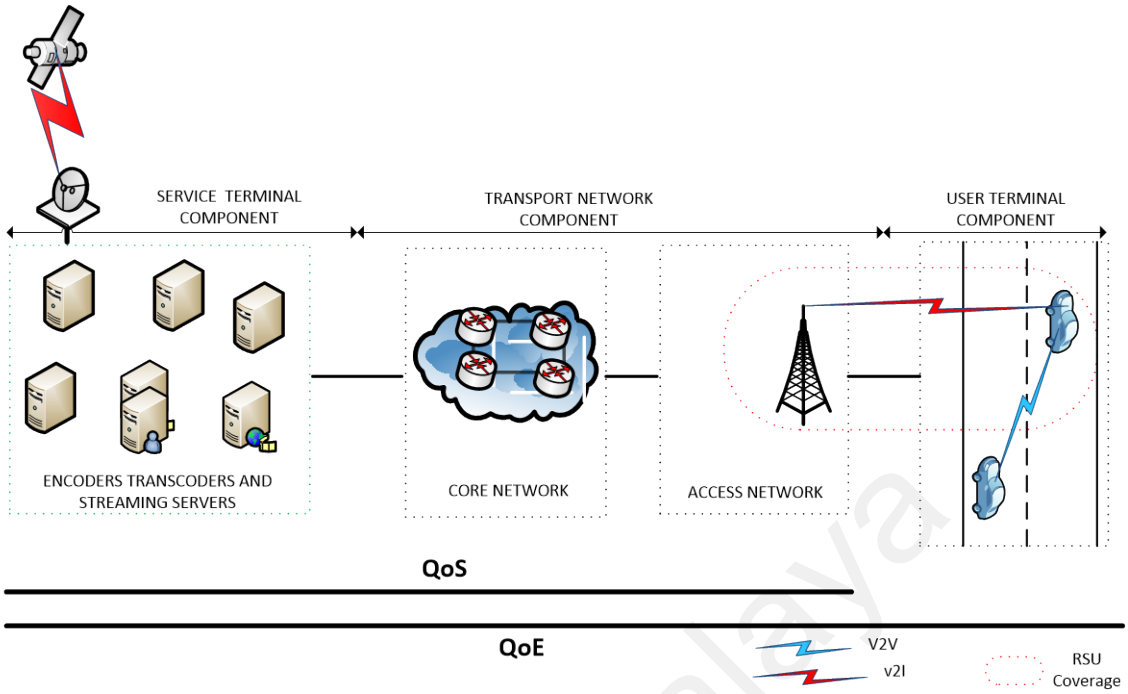

Figure 4.1: Application of Objective Quality Assessment Model in VANETs

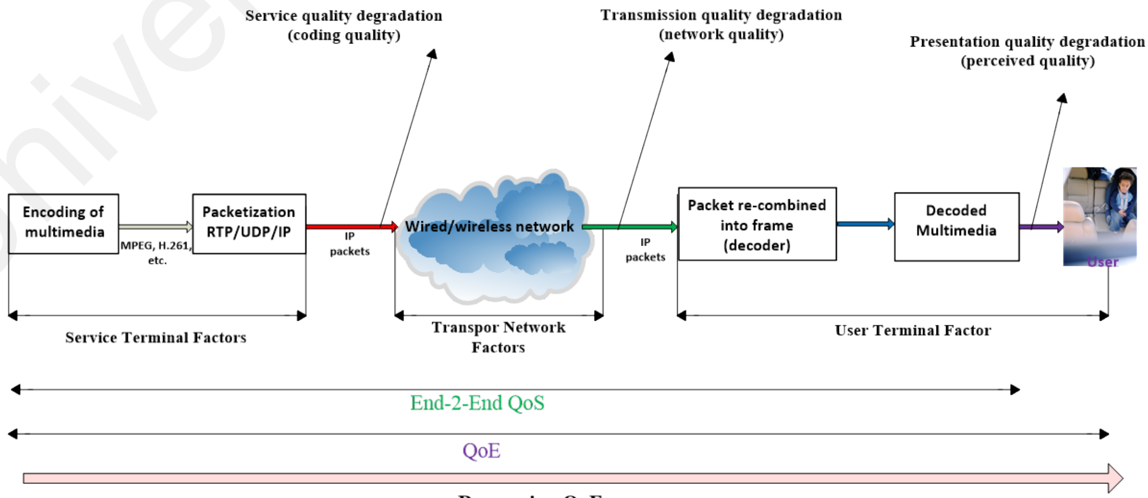

Figure 4.2A: Objective QoE Assessment Model for IPTV Services Over VANETs

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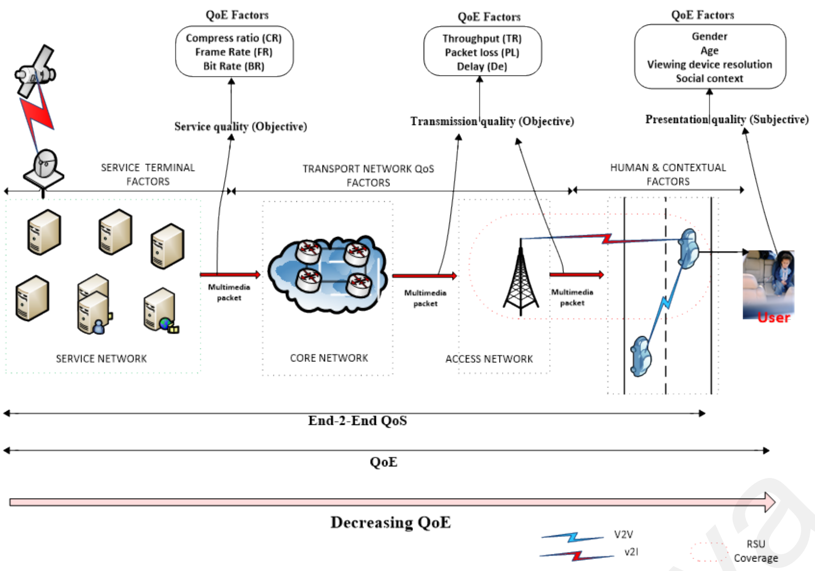

Figure 4.2B: QoE Influencing Parameters at the Different Levels of the Vehicular ITS Network

4.2.1 SERVICE TERMINAL OPTIMIZATION COMPONENT

This component involves parameters that determine the quality of the multimedia content, at the pre-transmission level (i.e., the quality of the IPTV content at the source). This includes the quality degradation that might be caused due to the encoding, compression and packetization of the raw signal. At this phase, the transmission quality of the services strongly depends on the method of encoding and the degree of compression. Broadly speaking, an increase in multimedia compression results in lower video quality, but a smaller data stream. Therefore, there is a tradeoff between the network bandwidth and the degree at which the picture is being compacted. Currently, there are numerous compression algorithms in use for encoding and decoding multimedia data stream such as: MPEG-2, H.264/MPEG-4 AVC, to name but a few. The quality degradation at this phase strongly depends on the selected encoding parameters and the adopted coding procedure, which are codec dependent. Codec dependent factors such as bit rates, frame rates, video resolutions, spatial resolution,

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content type quantization parameter, has great influence on the character of the media Perceptual quality.

4.2.2 TRANSPORT NETWORK OPTIMIZATION COMPONENT

This component involves parameters that determine the quality of the multimedia content at the transmission phase. This phase involves the distribution of the encoded and packetized multimedia signal across the underlying network, which in this case is VANETs. Under this phase, many factors can contribute to the degradation of the quality of the service, issues such as congestion in the underlying network, noise, bandwidth limitation, multipath fading, link failure (as in the case of VANETs where links experience frequent disconnection and reconnection due to the high node mobility), and many more. The quality degradation at the transmission phase are degradation that takes place during the service transmission over the network, and are network dependent. Network dependant factors such as: Bandwidth availability, package loss, delay and delay variation has a substantial influence on the quality of content delivered at the users' end.

4.2.3 USER TERMINAL OPTIMIZATION COMPONENT

This phase is the post-transmission stage, and involves parameters that influence the quality of the multimedia content at the end user's premises. Quality influencing factors under this phase include human components such as expectation, gender, age, environmental context, such as city or highways, and the characteristic of the vehicles involve, such as the vehicle velocity. User expectation, gender, age and context or

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environment in which the service is used can significantly impact the user's attitude towards his/her perception of the quality of service being delivered.

Each of the above mentioned optimization component is further split up into chunks of independent representative elements (see figure 4.5). These components are then normalized and aggregated using a statistical tool (multivariate regression analysis). Such that, their collection represents the resultant quality deterioration as a consequence of their independent induced impairment (independent implies that no overlap in the components and in their aggregation, (see figure 4.3). The result is a linear approximation of the collective effect of the different distortion introduces simultaneously to the raw multimedia content, from the point of generation to the point of presentation at the end user terminal. By combining these components in this manner, a flexible multimedia QoE mapping solution with high scalability and content/application independence is realized.

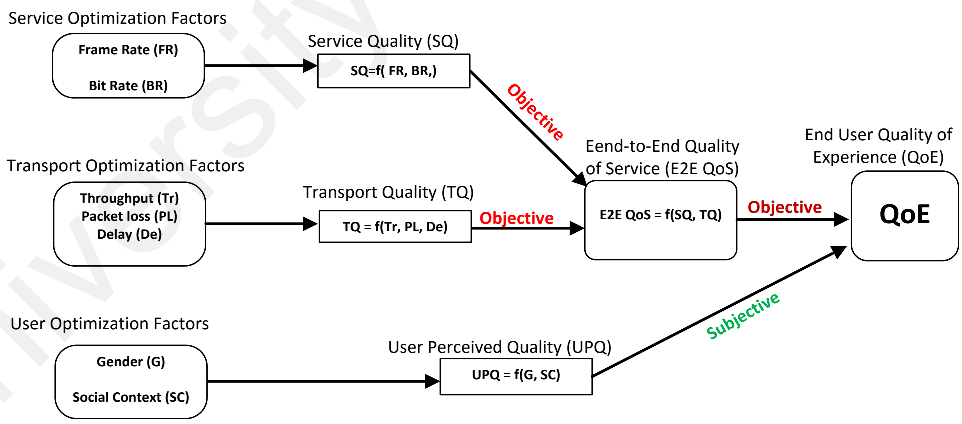

Figure 4.3: QoE/QoS parameter mapping solution

4.3 PARAMETER THAT IMPACT QoE OF ITS MULTIMEDIA SERVICES

Multimedia QoE is a complex metric that relied on numerous parameter. However, in this thesis (since our interest is in assessing Multimedia QoE in a vehicular environment), we classified Multimedia QoE parameters in two categories: the technical and non technical factors. The technical factors comprised of factors that affect the IPTV quality at the service generation level and at the network transporting level. While the non technical factors are those factors that can be directly linked to the human subjective perception, and they comprise of the context, gender and expectation, as illustrated in figure 4.4. Each of these factors can be further classified into other sub-parameters, as outlined in section 4.3.1 and section 4.3.2.

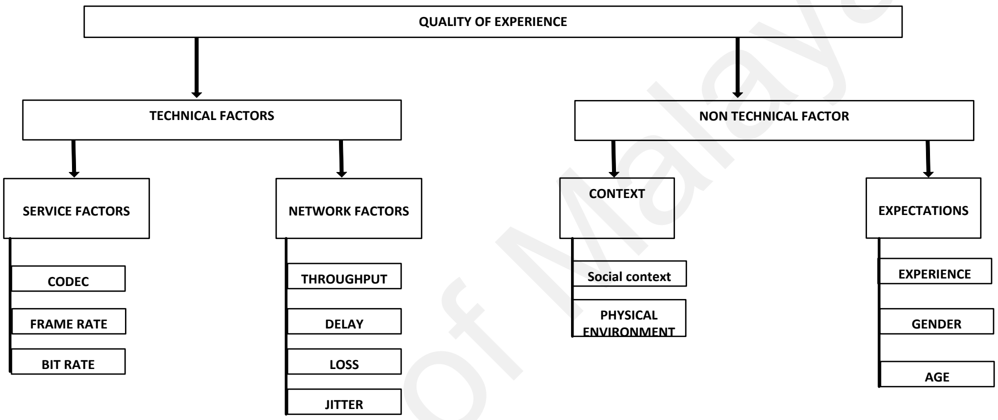

Figure 4.4: Technical and non-technical QoE influencing factors

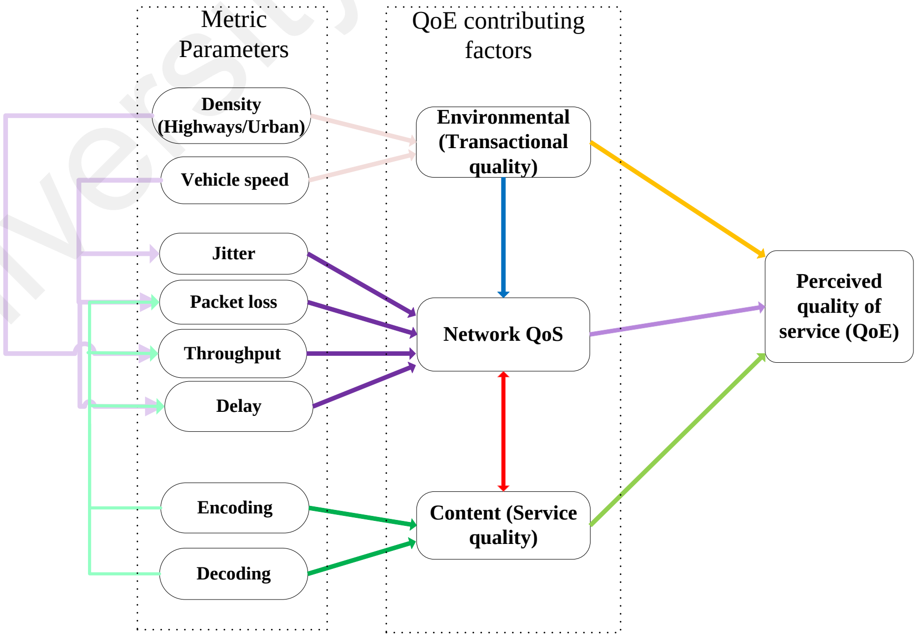

Figure 4.5: Relationship between technical (QoS) and non- technical factors as they affect the overall QoE

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4.3.1 TECHNICAL QoE FACTORS

Real-time multimedia services demand for resources is high, at both the source generating point and network level. Multimedia signal is usually compressed and coded at the source level, before being transmitted across the underlying network. This generates variable bit-rate streams that introduces variable processing requirements to process the different video frame sequence. A direct impact on the network resource is also obvious, since variable network bandwidth will be required to transmit the frames, which may have an effect on the bandwidth allocated to other streams (Gao, Chiu, & Lui, 2006). Effective distribution of multimedia traffic over VANETs requires that real-time constraints be respected or, at least, a QoS is guaranteed. Consequently, the architectures of multimedia QoE feasible solutions should define an integral set up of the different components, integrated in a manner that will ensure QoE-aware Multimedia transmission. The technical factor is further categorized into two sub components, namely: QoS network parameters and QoS service source parameters.

4.3.1.1 QoS NETWORK PARAMETERS

Key QoS network factors are packet loss, jitter and delay (Oche, Noor, & Jalooli, 2015). The impact of each individual or combined network parameters could lead to blockings, blurriness or even blackouts with different levels of quality degradation of video streaming.

- **Throughput:** The capacity per flow of a network is known as its throughput or bandwidth. It is determined by the traffic patterns and spatial parameters such as the network size, vehicle mobility and radio interaction. Unlike cellular or other mobile ad hoc networks whose capacity grows with network size, in

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VANETs, the network capacity decreases with size, as connectivity of the network is distributed linearly (i.e. road or highways) (Li, Blake, De Couto, Lee, & Morris, 2001), and are impacted by the forwarding property of the routing protocols and node mobility which introduce limitation in the spatial reuse of the radio spectrum. Thus, lowers the useful throughput that can be available per user pair.

- **Packet loss:** Packet losses have a direct effect on the quality of video presented to end users. As packet travel from source to destination, some packet may not get to their destination successfully. This may be caused by a lot of reasons, ranging from network congestion to packet corruption. Unlike connection-oriented network where lost packet can be resend using Transport Control Protocol (TCP), multimedia applications like any other real time traffic, is a connectionless application. And as a connectionless - oriented application, the audiovisual signal is transferred via user datagram protocol (UDP). There is no such guarantee that packet sent from one destination can get to the other end intact and so packet loss is inevitable. If too many packets is loss due to whatever reason, it becomes very difficult for the decoder to decode the multimedia stream. Thus, results in service quality degradation.

- **Jitter:** Jitter is another important network QoS parameter which has a great impact on video quality. It is defined as the variation in packet arrival times at the receiver's buffer. This happens due to the different path packets take to arrive at a destination. This result in frozen video scene or jerkiness. Nevertheless, this can be cancelled out or minimized to a negligible level, by increasing the buffer size at the receiver's end to delay the video playout time. However, increasing the buffer size could lead to increase in the level of delay

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tolerance that the playback can handle, as so care must be taken to ensure that the size of the buffer is not too large that could result in buffer underflow and not too small to avoid buffer overflow. Since any packet that arrive later than it buffering expiration time is considered a lost packet, and such packet drop by the application

- **Delay**: is the duration of time it takes for a packet sent from a source, to arrive at the receiver's end (destination). In a packet - based network, the path from a point of transmission to the destination point may not be the same as from destination back to the source. Because, as the packets are being forwarded from a one end to the other, packets may choose different paths as they travel from source to destination and destination back to the source, thereby arriving at different times and in many cases out of order. The packet needs to be reordered at the destination end, but then, for a real-time multimedia traffic such as IPTV, there is a specific needed time (threshold time) by which sent packets must arrive at the destination, any packet that fail to arrive at the destination at the threshold time is considered a loss packet, and such packet is dropped. If too many packets are dropped as a result of delay, this can strongly affect the quality of multimedia service as perceived by end users, since excessive delay can lead to scene freezing and loss of blocks of video.

4.3.1.2 QoS OF SERVICE SOURCE PARAMETERS

The quality of multimedia service being distributed across the network can be affected right at the source, i.e., at the IPTV head-end (see fig 1). The coding and the compression process usually creates a tradeoff between the quality of the video and the

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desired compression level. Some parameters at the source level that can considerably influence users' perceived quality are briefly outlined below:

- **Codec:** the term codec is a short form for compressor/decompressor. A codec is an algorithm used for compressing sound and video data when recoding and generating audiovisual content into digital format for transmission, and also used to decompress the produced content for playback at the end user's terminal. Each individual codec has a standard unique compression scheme for compressing data, and so, provide different level of video quality (i.e., some codec offers better quality at lower compression with minimum perceived quality loss over others). Therefore, the type of codec used to compress video content, has outstanding impact on the way users will perceive the video quality.

- **Bitrate or data rate:** This describes the rate at which bits are transferred from one end of a network to the other. It measures the amount of data transmitted per unit time. Bitrate considerably, can affect multimedia service QoE, in the sense that bitrate determines the amount of streaming data that can be transmitted over the network (Xu, Zhou, & Chiu, 2013), (Dobrian et al., 2011).

- **Frame rate:** is the number or sequence of images per second that is being transmitted or received. The higher the frame rate, the smoother the presentation of the motion in a video. The trade-off for higher quality, however, is that higher frame rate guarantees smoother and better quality video, but requires higher bandwidth which in this case is limited, due to the instability of the links in VANETs. In some instances, however, depending on the type of video content being transmitted (i.e., the type of multimedia services, whether it is a slow moving video such as a church service or video

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with a lot of movement, i.e. fast moving video, such as sport.), can affect the multimedia quality in a way that can influence the overall QoE. Slow moving video content such as a church service, instructional television, could still be broadcast with lower frame rate without compromising the quality. All the same, the greater the movement in a video, the higher the frame rate that will be needed to prevent image jerkiness or blurriness, thus, making frame rate an important deciding QoE factor. It is advisable to keep the frame rate at the lowest minimum possible level that could maintain better transmission quality for the type of IPTV content being transmitted.

4.3.2 NON TECHNICAL FACTORS

Nontechnical QoE factors such as human and contextual factors. Human factors refers to the individual characterictics of the user that may have influence in the way he/she perceived the quality of the multimedia content. Some example of human factors include: expectation, personal interest, demographic characteristics such as gender, age, etc., (Hyder, Crespi, Haun, & Hoene, 2012), (Murray, Yuansong, Lee, Muntean, & Karunakar, 2013). Contextual factors are related to the environment, social context, background, screen size, viewing distance, etc., in which the user consumes the multimedia content. In a vehicular network environment, some notable contextual QoE factors are: user location or user vehicle environment (i.e., city or highway environment), social context (in terms of whether the user watches the media clip alone or in company of other viewers), resolution (i.e., high or low resolution of the vehicle viewing display device), etc., (Karan Mitra, et al., 2014). In real vehicular environment, context can change dynamically while users vehicles are on-the-move. For example, at different user vehicle location (e.g., city or highways), QoS can vary, which in turn

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affect the QoE. Factors such as time-of-the-day, can help explain rise in network congestion leading to decrease in users' QoE. Furthermore, users social context changes through out the day leading to variation in QoE. For example, users' QoE may be affected if there are people nearby (Karan Mitra, et al., 2014).

However, in this thesis due to resource limitation, the nontechnical factors related data considered in the study is limited to two nontechnical factors; gender and social context (Zhu, Heynderickx, & Redi, 2015).

- Gender: Study in (Song, Tjondronegoro, & Docherty, 2011), show that gender plays a significant role in users expectation. In their work they observed that male frequent mobile video viewer expect higher video quality than the female counterparts. Study in (Sodergard, 2003), also shows that men have a more progressive attitude toward watching of digital television than women.

- Social Context: Research have shown that social context in terms of the presence or no presence of co-viewers (i.e., either alone as a single viewer or in company of others as group viewers) watching the multimedia content play an important role on how user perceived the quality of multimedia services . Study in (Zhu, et al., 2015) shows that better QoE is observed when multimedia is consumed in company of other viewers.

Remark #1: In VANETs, vehicles use numerous wireless access technologies to communicate with other vehicles and roadside base stations. This implies that VANETs protocols and techniques are similar to other mobile wireless network. The main significant difference between VANETs and other mobile wireless network is in the network topology, VANET topology changes fast due to the vehicle speed and density. Furthermore, unlike other mobile wireless network whose nodes moves randomly and are not constrained to a predefine road, VANETs node movement is regular and are

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constrained to a predefined road network. This property of VANETs highlights a simple fact that the application services and human subjective futures as applied to mobile wireless is the same in all wireless networks and the only difference is the network conditions and the associated constraints. Though, the notion of user performance is central to QoE because QoE is based on actual user experience, but it should also be noted that the underlying network has the potential to help or hinder the process and outcomes of the human behavior that will determine user satisfaction. Therefore, the subjective data that might be collected in different ways for laboratory and field test, and for different services and usage situations is applicable to any wireless network as long as the unique features and constraints of the network in question is considered. Furthermore, recent study (Casas, Gardlo, Seufert, Wamser, & Schatz, 2015), have shown that lab subjective QoE results are highly applicable to real live setting, as lab subjective QoE results shown no significant different from empirical QoE results obtained from a real live network setting. To this end, further step was taken in this direction to map the obtained subjective QoE data to the large scale realistic VANETs scenario experimental data obtained in section 4.6, where the unique VANETs features and constraints such as speed and density are taken into consideration in the determination of the network layer considers parameters.

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Table 4.1: Definition of Symbols

Notation	Description	Notation	Description
β	Signal attenuation between receiver and transmitter	θ	Quality of Service exponential
d	Interval between receiver and transmitter	$D(W)$	Normalized packet delay
α	Path loss exponential	$\beta(t)$	Attenuation variation in a given time interval
μ	Mean number of nodes per kilometre	$\beta(\underline{x})$	Attenuation variation with respect to distance
λ	Wavelength	β_{max}	Maximum possible attenuation
φ	Transmitting rate	$x(x_i, x_j)$	Probability that two nodes are connected
l	Message length (in bit)	$B(W)$	Throughput as a function of cumulated load
R	Data rate	m_{gr}	Message generation rate (in s^{-1})
s	Source traffic	AV_N	Average number of hops
$\underline{s}$	Traffic vector	$\beta_p(d)$	Average path loss within a given distance
β_p	Average path loss	R_{Sr}	Receiver Signal
β_s	A parameter that determines the effect of both $\beta(t)$ and $\beta(\underline{x})$	$P_l(W)$	Probability of packet loss as a function of cumulated load
A	Set of sender hyperarcs	$D(t)$	Delay experience by a packet at a given time
A'	Set of receiver hyperarcs	W_i	Cumulated load at node (V_i) collision domain
d_0	Reference distance	W_j	Cumulated load at node (V_j) collision domain
T_r	Transmission range	$\underline{W}$	Cumulated load vector
d_n	Non-line of sight distance (NLOS)	$Ç(G)$	Connectivity matrix
d_l	Line of sight distance (LOS)	$G \coloneqq (v, E)$	Network graph
α_l	Path loss along LOS	$H \coloneqq (v, A)$	Hypergraph
α_n	Path loss along NLOS	$S(t)$	Service delivered by a channel
T_p	Transmission power	sup_t	The least upper constrained in a variable time
P_s	Probability of successful packet transmission	$\Psi(t)$	Service curve at a given time
τ	Discrete time interval	T_h	Threshold time
R_S	Receiver sensitivity	$p_s(W)$	Probability of a successful packet delivery

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4.4 ANALYTICAL MODEL OF THE NETWORK QoS PARAMETERS

End-to-End QoS support for quality multimedia deployment over VANETs demands for a simple and accurate channel model. Unlike wire networks, whose channel capacity is constant, VANETs uses wireless infrastructure whose channels relies upon arbitrary factors such as: co-channel interference, multipath fading, and so many more. Significant research performed on real-time multimedia traffic over high speed vehicular networks (Luan, Ling, & Shen, 2012), showed that in order to sustain high quality delivery of real-time rich multimedia traffic, it is necessary for the underlying networks to support high data rate and better connectivity. An accurate estimate of VANETs link connectivity will ensure that QoS provisioning of multimedia traffic over it link is optimal with respect to the channel properties. By understanding these properties of VANETs link connectivity, one can appropriately manage traffic to ensure that specific QoS targets on packet delay are met. In this context, we account for the fundamental influence factor that affect the radio propagation in a VANETs; such as path loss, and multipath fading. By deriving a comprehensive mathematical formulation of the relevant factors that define the dynamic connectivity of vehicular ad hoc networks. The analysis, pave way for modelling the transmission probability, the connectivity, the capacity per flow (throughput), packet loss and packet delay. This analytical deduction, demonstrates how multimedia QoS can be realized in an arbitrarily connected VANETs to support qualitative multimedia services. Table 4.1, contains all relevant information regarding the meaning and definition of all the symbols employed in the analytical model.

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4.4.1 CONNECTIVITY MODEL

In a communication network, two or more network nodes are considered to be connected, if there exist a means by which data can be transmitted between them. In wireless networks, the radio signal R_{Sr} from a receiver must exceed a certain threshold R_S (known as the receiver sensitivity) in order for the message transmitted to be successfully detected and decoded. This means that two nodes are said to be connected if $R_{Sr} \geq R_S$ at the receiver end. Let T_p be the transmission power and β be the attenuation of the wireless signal between the transmitting and the receiving nodes by adopting the radio channel model in (Gozalvez, Sepulcre, & Bauza, 2012), we can derive the wireless signal attenuation as:

$$\beta = 10\, log_{10}\left(\frac{P_t^{(lin)}}{R_{Sr}^{(lin)}}\right) = 10\, log_{10}\left(P_t^{(lin)}\right) - 10\, log_{10}\left(R_{Sr}^{(lin)}\right) \qquad 4.1$$

$$therefore\ \beta = T_p - R_{Sr_r} \qquad 4.2$$

β is the attenuation caused as a result of physical effect that diminished the power density of the electromagnetic wave as it travels through space, it's a function of the transmitter position, the receiver and the environmental influence. β is measured in decibel (dB).

Let the maximum possible attenuation margin between T_p and R_S be given as β_{max}. From Eq. 4.2 the maximum possible attenuation therefore will be

$$\beta_{max} = T_p - R_s \qquad 4.3$$

Given two nodes i and j, the probability that the two nodes are connected if place in distinct position $\underline{x}_i$ and $\underline{x}_j$, will depend on the degree of attenuation between them which must be less than β_{max}.

The probability that the attenuation between the nodes is below β_{max}, and the formulation that channel model is a function of nodes' physical positions is:

$$x(x_i, x_j) = P(\beta(x_i, x_j) \leq \beta_{max}) \quad 4.4$$

More precisely, let us define $x(x_i, x_j)$ to be the probability that node A can transmit messages to node B and B can transmit to A (i.e., the transmission channel is reciprocal).

$$x(x_i, x_j) = x(x_j, x_i) \quad 4.5$$

The most obvious effect of attenuation is path loss which relates to the interval between a transmitter and a receiver.

Let *d* be the interval between the sender and the receiver i.e., $d = || \; x_i, x_j ||$

As proposed in (Gozalvez, et al., 2012), the received power deteriorates equilaterally with the distance:

$$\beta_f(d) = 20 log_{10} \frac{4\pi d}{\lambda} \quad 4.6$$

Where λ is the wavelength. Note however that, Eq. 4.6 is only valid if the distance *d* is in the far-field of the transmitting antenna.

To account for a situation in which parts of the wave front are reflected or absorbed as a result of obstacles, we adopted the long distance pathloss model in (Fernández, Rubio, Reig, Rodrigo-Peñarrocha, & Valero, 2013). Considering the shadowing component such as vehicles and other surface that eflect wave in a VANETs environment make this model suitable to be used in vehicular networks. Therefore, Eq. 4.6 can then be extended by introducing a path loss exponential α:

$$(d) = \beta_r(d_0) + 10\alpha \; log_{10} \frac{d}{d_0} \quad = 20 log_{10} \frac{4\pi d_0}{\lambda} + 10\alpha \; log_{10} \frac{d}{d_0} \quad 4.7$$

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Eq. 4.6 and Eq. 4.7 are homologous for $\alpha = 2$, but, in a situation in which part of the wave front is reflected or absorbed, higher value of α is used; in case such as city environments where there are lots of obstacles such as buildings, treestc.

Where $\beta_p(d_0)$ is the average path loss distance within a reference distance (d_0).

The transmission range T_r with respect to the maximum possible attenuation $(\beta_{max}), that\ is,$ the distance at which the received signal is just greater or equal to the receiver sensitivity Eq. 4.3 (the distance is commonly denoted as the radio range):

$$T_r = d_0 \left(\left(\frac{\lambda}{4\pi d_0} \right)^2 10^{01\beta_{max}} \right)^{1/\alpha} \qquad 4.8$$

Where d_0= reference distance in meters and $\lambda =$ wavelength in meters

For a long distance, T_r is independent of the actual positions of the transmitter and receiver. And so applying the dual-slope model as proposed in (L. Cheng, Henty, Bai, & Stancil, 2008), we can deduce a more realistic T_r by considering static obstacles such as buildings or other fixed object in the environment whose properties as regards to position, shape, is known. Given the position of both the transmitter and the receiver on the part of the object's position, the Line Of Sight (LOS) distance of the wave transmission can be considered to be, when $d_l \leq d$ and the Non-Line-Of-Sight (NLOS) to be $d_n = d_l$ segment of the wave propagation. And so Eq. 4.7 can be re-written as:

$$\beta_p(d) == 20log_{10} \frac{4\pi d_0}{\lambda} + 10\alpha_l\ log_{10} \frac{d_l}{d_0} + 10\alpha_n\ log_{10} \frac{d}{d_l} \qquad 4.9$$

Where d_l is the distance that the waves propagate without hitting the obstacle or object (i.e., LOS distance), d_n is the NLOS distance, α_l is the path loss on the path d_l and α_n is the path loss on the path d_n. Originally, Eq. 4.8 had been proposed to model attenuation in cellular system. Nevertheless, research in (L. Cheng, et al., 2008)

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demonstrated that it can be successfully used to model V2V channels. And so going by equation 4.9, we can deduce that the radio range $T_r(d_l)$ as a function of the length d_l of the LOS segment, which depends on the static object properties surrounding the transmitter. And so Eq. 4.8 can be re-written as:

$$T_r(d_l) = d_l \left(\left(\frac{\lambda}{4\pi d_0}\right)^2 \left(\frac{d_0}{d_l}\right)^{\alpha_l} 10^{01\beta_{max}} \right)^{1/\alpha_n} \qquad 4.10$$

And so therefore, the possibility that two nodes are connected is equal to:

$$x(\underline{x}_i, \underline{x}_j) = \begin{cases} 1 & ||\, x_i - x_j||\ \le\ r(d_l) \\ o & ||\, x_i - x_j||\ > r(d_l) \end{cases} \qquad 4.11$$

However, a realistic vehicular environment involves numbers of dynamic and static obstacle such as buildings, trees, pedestrians, vehicles to mention but a few. Whose properties as regards to their positions, shapes, etc. are unknown. Receivers placed in various positions, but at a fixed distance with respect to one another will have different attenuation equal to $\beta(\underline{x})$. So also, is the receiver at fixed position with respect to the movement of the objects, will experience an attenuation that varies over time denoted as $\beta(t)$.

$$\beta_{ps}(d) = \beta_p(d) + \beta_s \qquad 4.12$$

In Eq. 14, β_s is introduced as an additional parameter to cater for the effect of both $\beta(\underline{x})\ and\ \beta(t)$. Therefore, the probability that node A and B are connected is determined by the probability that $\beta_s \le \beta_{max} - \beta_p(d)$

Therefore

$$x(\underline{x}_i, \underline{x}_j) = \int_{-\infty}^{\beta_{max} - \beta_p(d)(||\, x_i - x_j||\,)} f_{\beta_s}(\beta_s) d\beta_s \qquad 4.13$$

But $f_{\beta_s}(\beta_s) = \frac{1}{\sqrt{2\pi\sigma}} exp\left(\frac{{\beta_s}^2}{2\sigma^2}\right)$ Under the assumption that the propagation wave experience numerous attenuation along its path, and substituting into Eq. 4.13:

$$x(\underline{x}_i, \underline{x}_j) = \frac{1}{2} + \frac{1}{2} erf\left(\frac{\beta_{max} - \beta_p(d)(||x_i - x_j||)}{\sqrt{2\sigma}}\right) \quad 4.14$$

In this research work, we referred to both RSU and vehicle as a node, with RSU label as a stationary node at a specified position and vehicles as mobile clients. In this system we assumed that all vehicles on the road are equipped with an omnidirectional antenna of radio transmission range T_r . Assuming that V represent connected vehicular ad hoc network, and $V = \{v_1, \dots v_n\}$ as a designate sets of nodes (i.e., sets of radios) with n = | v| be the number of elements in the set. And the sets of connections between the nodes be E, then we can show that nodes v_i and v_j are connected by the equation:

$$\text{Tuple } (v_i, v_j) \epsilon\, E \quad 4.15$$

In Eq. 4.4, we defined connectivity between two node v_i and v_j due to the attenuation between them. Attenuation itself depends on the physical positions of the two nodes, $\underline{x}_i$ and $\underline{x}_j$, as well as on their radio environment, described by a means of an appropriate channel model, $x(\underline{x}_i, \underline{x}_j)$.

Note that the channel model determines the probability that a connection exists between two nodes. Consequently, a pair of nodes is either connected or not; therefore we define the connection probability obtained from the channel model as the average over an infinite amount of realization:

$$P((v_i, v_j) \in E) = x(\underline{x}_i, \underline{x}_j) \quad 4.16$$

And so, a connectivity matrix $Ç(G) = (c_{ij})^2$ of a network's graph $G \coloneqq (v, E)$ can be used in place of the network graph to describe connectivity, where

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$$c_{ij} = \begin{cases} 1 \; if \; (v_i, v_j) \in E \\ 0 \quad\quad else \end{cases} \quad 4.17$$

$(c_{ij})^2$, is based on our assumption that VANETs links are bidirectional (i.e. that if node v_i is connected to node v_j, node v_j also connects to node v_i). Because of this assumption the connectivity matrix is symmetrical, which means:

$$c_{ij} = c_{ji} \quad 4.18$$

However, contrary to a fixed network, where individual links may be technically realized as dedicated links, VANETs due to its broadcast nature, allows a sent message to be picked up or received by all neighboring nodes at the same time. Therefore, when studying vehicular ad hoc network connectivity, it is vital that we consider their representation as a hypergraph H, i.e., a generalized graph in which edges are arranged as pairs of sets (hyperarcs), rather than tuples (as in Eq.4.15)

And so as a hypergraph, $H \coloneqq (v, A)$.

A hyperarc is a pair of a set of senders s and a set of receiver R:

$$a = (s_a, R_a) \in A) \quad 4.19$$

$$s_a \cap R_a = \emptyset \quad 4.20$$

The kind of relationships that exist between the nodes in vehicular network is one-to-many relation, but can be viewed in two angles:

- Each individual sender has a set of receiving nodes, which can be represented by an associated hyperarc from the one sender to sets of recipients. Thus, the set of sender hyperarcs A is given by:

$$\forall v_i \in v: (\{v_i\}, R_i) \in A \quad 4.21$$

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- Each receiver has a set of senders that it receives from, this can be represented by an associated hyperarc from the set of senders to the receiver denoted as A'. And so, the set of the receive hyperarcs A' is:

$$\forall v_j \in v: \left(S_j, \{v_j\}\right) \in A' \qquad 4.22$$

The cardinality of the vertex and edge sets is:

$$|A| = |A'| = |v| \qquad 4.23$$

And so, we can now transform the conventional network representation of $G \coloneqq (v, E)$ into $H \coloneqq (v, A)$, where:

$$\forall_a = (\{v_i\}, R_i) \in A: \left(v_i, v_j\right) \in \varepsilon \; if \; v_j \in R_i \qquad 4.24$$

$$\forall_{a'} = \left(s_j\{v_j\}\right) \in A': \left(v_i, v_j\right) \in \varepsilon \; if \; v_i \in S_i \qquad 4.25$$

Assuming, i is a row index and j a column index of the connectivity matrix $Ç$. According to the definition of connectivity in Eq. 4.14, c_{ij} is 1 if v_i can transmit to v_j. Therefore, a 1 in a row i indicates membership in R_i, the rows of the connectivity matrix can thus be understood as a representation of the set of send hyperarc A. On the other hand, a 1 in a column j indicates membership in s_i, thus, the columns represent the set of receiving hyperarcs A'.

Considering the VANETs link symmetry, Eq. 4.18 can now be rephrased as:

$$\forall_{vi} \in v: (\{v_i\}, R_i) \in A, (s_i, \{v_i\}) \in A': R_i = S_i \qquad 4.26$$

Assuming the traffic that is generated by a node is represented as v_i and the subsequent traffic transmitted in the network as s_j "(Source) traffic". This term refers to the traffic for which v_i is the actual source. Generically, let m_{gr} be the message generation rate in s^{-1}, l the message length in bit, and R the data rate at which the message is sent. Then the sourced traffic s can be express as:

$$s = m_{gr} \;. \frac{l}{R} \tag{4.27}$$

In VANETs, the channels in the network are known to be shared between all the vehicles (i.e., nodes) in the network (as Wireless networks share a common medium). Thus, it will be relevant to recognize that there exist segments of the network that are determined with nodes that are in range with one another, which uses the different network segments. As a rule, we define the vehicular wireless network segments according to the sets of receiving hyperarcs $A\,'$, and henceforth refers to these segments as the collision domains. This means that, at a node $v_j \in v$, the medium will be shared among v_j and all other nodes that v_j can receive from (i.e., the nodes in the set s_j). And so we will denote the accumulated sourced traffic of nodes that share the same segment as the cumulated load W. Consequently, we will denote W_j as the cumulated load of nodes v_j Collision domain, and W_i to be the cumulated load at the nodes $v_i{}'s$ collision domain. So therefore W_j Could be expressed as:

$$W_j = s_j + \sum_{v_i \in s_j} s_i$$

$$W_j = s_j + \sum_{i=0}^{N} c_{ij}.\, g_i \tag{4.28}$$

Assuming vector $\underline{s}$ is the source traffic vector and s_i the drawn traffic from the network by which node v_i is the source. We can deduce the aggregate traffic offer to the medium at every respective node's collision domain (i.e., the vector that represents the cumulative load) as:

$$\underline{W} = Ç^T \underline{s} + \underline{s} \tag{4.29}$$

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Assuming that each node v_i has the chance to inject into the network a certain volume of traffic equivalent to s_i. By multiplying the source vector $\underline{s}$ with the connectivity matrix will results in the load vector $\underline{1}$:

$$\underline{W} = (\text{Ç}^T + \underset{\sim}{\mathrm{I}})\underline{s} \tag{4.30}$$

$\underline{W}$ is therefore the vector that will from henceforth serve as the aggregate traffic offered at the respective node's collision domain (i.e., the vector that represents the cumulative load of a collision domain). For example, given a signal range of nodes B, C, D and F. We can distinguish the network in hypergraph as:

$$V = \{\mathrm{a, b, c, d, e, f, g, h, i, j, k, l}\}$$

$$A = \left\{\begin{matrix} (\{a\},\{b\}),(\{b\},\{a,c\}),(\{c\},\{b,d,e,f\}),(\{d\},(c,e,f\}),(\{e\},\{c,d,f,g\}),(\{f\},\{c,d,e,i\}), \\ (\{g\},\{e,h\}),(\{h\},\{g\}),(\{i\},\{f,j,k\}),(\{j\},\{i,k,l\}),(\{k\},\{i,j\}),(\{l\},\{j\} \\ ) \end{matrix}\right\}$$

$$A' = \left\{\begin{matrix} (\{b\},\{a\}),(\{a,c\},\{b\}),(\{b,d,e,f\},\{c\}),(\{c,e,f\},\{d\}),(\{c,d,f,g\},\{e\}),(\{c,d,e,i\},\{f\}),(\{e,h\},\{g\}), \\ (\{g\},\{h\}),(\{f,j,k\},\{i\}),(\{i,k,l\},\{j\}),(\{i,j\},\{k\}),(\{j\},\{l\}) \end{matrix}\right\}$$

The load on the collision domain of node B,C,D and F can be deduced by adding up the traffic source of the nodes that are senders to them:

$$W_b = s_a + s_b + s_c$$

$$W_c = s_b + s_c + s_d + s_e + s_f$$

$$W_d = s_c + s_d + s_e + s_f$$

$$W_e = s_c + s_d + s_e + s_f + s_g$$

$$W_f = s_c + s_d + s_e + s_f + s_i$$

And the load vector $\underline{W}$ in matrix form can be deduced from the connectivity matrix Ç and the source vector $\underline{s}$ as follows:

$$\begin{bmatrix} W_a \\ W_b \\ W_c \\ W_d \\ W_e \\ W_f \\ \vdots \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 & \cdots & 0 & \cdots \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & \cdots & 0 & \cdots \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 & \cdots & 0 & \cdots \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & \cdots & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots \end{bmatrix}}_{(\c{C}^T + \underset{\sim}{I})} \cdot \begin{bmatrix} S_a \\ S_b \\ S_c \\ S_d \\ S_e \\ S_f \\ S_g \\ \vdots \\ S_i \\ \vdots \end{bmatrix} \qquad 4.31$$

4.4.2 QoS PARAMETERS ANALYTICAL MODEL

The QoS parameters throughput, packet loss and packet delay are dimensions that depend not only on the physical layer implementation of the vehicular wireless technology, but more so, on the MAC layer implementation: the manner in which the wireless nodes actually access the channel has a significant impact on these parameters. All MAC protocols have to make a tradeoff between maximum throughput, ease of implementation, fairness and so on. The actual performance of a protocol may depend on a number of further parameters such as size of nodes that share the medium, the message length, the message prioritization, resource allocation, susceptible to interference, etc. However, the key factor that determines the performance of a MAC protocol is the possibility that a packet sent from a source (i.e., a transmitter) to a receiver(s) is successfully delivered. Aside the protocol dependent parameters mentioned above, the most influential parameter is obviously the cumulated load (i.e., the totality of the individual offered traffic) in a collision domain (see Eq. 4.30).

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4.4.2.1 AVERAGE THROUGHPUT

In order to calculate the average throughput offer by the vehicular networks, we assumed that the capacity per flow of data (a flow is as defined in (Zhang & Fang, 2009), is a set of IP packets going through network during a certain time interval), is proportional to the ratio of the network capacity to the concurrent rate of flows (i.e., underlying network cumulative load). The throughput (B_w) for a flow is thus deduced as $\frac{N_c}{W}, where\ N_c$ Is the technological bandwidth and W is the average amount of communication passing through a node which is a function of cumulative load. The throughput B_w of the protocol is thus the ratio of the network capacity N_c and the cumulated load W.

$$B_w = \frac{N_c}{W} \qquad 4.32$$

The quantity of current flows in a vehicular network depends on the partial reusability of the topology of the network, since nodes in VANETs forms a chain of communication (Ducourthial, Khaled, & Shawky, 2007). Let μ be the mean number of nodes for each kilometre, T_r be the range of the wireless signal, φ the transmitting rate of the nodes and AV_N be average number of hops involve in the communications, then Eq. 4.32 can be re-written as:

$$B_w = \frac{N_c}{\mu\varphi T_r AV_N} \qquad 4.33$$

However, in a given communication, throughput $B_w < \alpha \frac{N_c}{\mu\varphi T_r AV_N}$. Where α is the factor that account for the bandwidth usage. Study in (Franceschetti, Migliore, & Minero, 2009), postulates that, the throughput measure in a sequence of nodes decreases with an increase in the number of nodes. Thus, the capacity per flow is equivalent to the

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rate of emission e (assuming the average numbers of packets generate per second is N, then, $e = N * packet\ size * 8\ bits/s$)

$$B_w \leq min\left(e, \frac{N_c}{\mu\varphi T_r AV_N}\right) \quad 4.34$$

4.4.2.2 PACKET LOSS PROBABILITY

Assuming p_s is the possibility that a packet is successfully transmitted from a sender to a receiver. A perfect protocol would transport every packet successfully ($p_s = 1$), until the cumulated load W exceeds the capacity N_c of the network channel. The probability of packet loss as an affair of the cumulative load $pl(W)$, is complementary to the success probability $p_s(W)$:

$$pl(W) = 1 - p_s(W) = 1 - \frac{B_w(W)}{W} \quad 4.35$$

Where $B_w(W)$ is the capacity per flow of vehicular network (i.e., the throughput as a function of the cumulative load).

4.4.2.3 AVERAGE PACKET DELAY

The delay that a packet experiences is determined by two factors: 1) the amount of time that the packet has to queue before the MAC literally gets to access the channel, 2) the number of necessary retransmission until successful delivery, as every retry adds to the delay that the packet experiences. Let us denote the average time until the channel is accessed as τ. Then, we can determine the delay $D(t)$ experience by a packet at time t, until the transmission is successful as:

$$D(t) = p_s(\tau + (1 - p_s)).2\tau + p_s(1 - p_s)^{\,2}.3\tau + p_s(1 - p_s)^3.4\tau + \cdots$$

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$$= \tau p_s . \sum_{n=0}^{\infty} (1 - p_s)^n \, (n + 1)$$

$$D(t) = \frac{\tau}{p_s} \quad 4.36$$

The average normalized packet delay, as a function of the cumulated load, is then:

$$D(W) = \frac{u}{B_w(W)} = \frac{1}{p_s(W)} \quad 4.\ 37$$

However, as a well known fact, multimedia traffic such as IPTV have a stringent QoS requirement, as packets exceeding their delay constrained are considered a loss and discarded. Consequently, recalling from Wu et al (Wu & Negi, 2003), where they extended the concept of the deterministic service curve $\Psi\ (t)$ of a wired network to a statistical version for wireless networks, stipulated as the pair $\{\Psi(t), \varepsilon\}$ Where ε is the probability of violating a QoS condition. This proposed service curve satisfies:

$$sup_t \; pr\{S(t) < \Psi(t)\} \leq \varepsilon \quad 4.\ 38$$

Where $S(t)$ is the service delivered by a channel, and sup_t the least upper constrained with variable t. For a given value of ε a non zero service curve $\Psi(t)$ can be ensured. This implies that the arriving process that will be served by the channel service $\Psi(t)$ with a limited violation possibility ε could be guaranteed. Similarly, adopting the effective capacity theorem (Wu & Negi, 2003), which stipulates that, for a continuing arrival and service process, the probability that the length of the queue $Q(t)$ in a given time *t* will exceed a required threshold T_h, decreases exponentially with increase in T_h:

$$sup_t \; pr\{Q(t) \geq T_h\} \approx \alpha e^{-\theta T_h} \quad 4.\ 39$$

Where θ is a positive real number known as the QoS exponential, and the probability that the queue is not empty is given as $\alpha = pr\{Q(t) > 0\}$

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Assuming D_m is the maximum delay constrained, then , the probability that the delay $D(t)$ exceeds the maximum delay constrained D_m is:

$$sup_t \, pr\{D(t) \geq D_m\} \approx \alpha e^{-\theta D_m} \qquad 4.40$$

The QoS exponential θ plays a major role in the IPTV QoS assurance, as it associates the network capacity with the QoS performance and shows the rate at which QoS violation probability degrades. A large θ results in a lesser delay, that is to say a rigorous QoS assurance can be insured guaranteed and vice versa. To be more specific, as $\theta \to \infty$, implies that the network can no longer tolerate any delay, likewise as $\theta \to 0$, implies that the network will not be able to cater for the delay constraint.

Remark #2: To provide a pre-defined QoS for VANETs multimedia traffic, it is necessary for network designers to specify at least one of the following QoS parameters:

- Maximum tolerable average packet loss: using Eq. 4.35, the traffic limit $\widehat{W}$ for the candidate MAC mechanism can be determined.
- Maximum tolerable average delay: with Eq. 4.37, the traffic limit $\widehat{W}$ can be determined.

If the cumulated load $\underline{\mathrm{W}}$ in all the collision domains is lower than the persistent load limit $\widehat{W}$, the desired QoS is achieved. From Eq. 4.30, the QoS criterion is thus:

$$\widehat{W}\underline{1} \leq (\text{Ç}^T + \underset{\sim}{\mathrm{I}})\underline{s} \qquad 4.41$$

As we have identified in the previous section, it should be noted that the traffic vector $\underline{s}$ encompasses all IPTV traffic generated by each individual node (i.e., unicast, multicast, and broadcast traffic) bearing in mind the broadcast nature of the vehicular network medium.

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To satisfy the QoS criteria given a current network connection Ç, a control algorithm ought to be designed to determine the traffic vectors in Eq. 4.41, such that:

- Will ensure that the load in each collision domain is constrained by: $\forall i : W_i \leq \widehat{W}$,
- Maximizes the traffic s_i that might be injected by each node,
- Allocates the number of traffic sourced in a way that will satisfy the fairness benchmark between contending nodes.

This section outlined how QoS provisioning based on a network connectivity can be achieved. The basis for the calculation is the connectivity matrix Ç that describe the communication relations between n networked nodes. Assuming $x(\underline{x}_i, \underline{x}_j)$ denote the channel function, taking the physical positions $\underline{x}_i, \underline{x}_j$ as parameters of two vehicles v_i, v_j in the environment. Using the connectivity matrix Ç from Eq. 4.4 and Eq. 4.17. Essentially, two vehicles v_i and v_j are connected if they are located within each others' radio ranges; if they are located further apart, implies that they are not connected. Therefore, the probability that the respective entry in the connectivity matrix is one is determined by the channel mapping:

$$Ç = (c_{ij}), c_{ij} \epsilon \{0,1\} \qquad 4.42$$

$$P(c_{ij} = 1) = x(x_{i,} x_j) \qquad 4.43$$

It was as well esterblished here that the QoS criterion is satisfied if the injected traffic is dimensioned such that each entry in the load vector W_i does not exceed a certain pre-defined threshold $\widehat{W}$.

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4.5 IMPLEMENTATION

Developing a VANETs in practical application is too costly, therefore, to test and to evaluate the protocol simulators are used. Several communications network simulators already exixt to provide a platform for testing and evaluating VANETs protocols, such as NS2, OPNET, NCTUNest, OPNET ++, etc. In this thesis, the following simulation tools were used:

- Simulation of Urban Mobility (SUMO) (Krajzewicz, 2010), is an open source, highly portable, microscopic, multi-modal road traffic simulation tool design to handle large road networks. It is script based tool which help users to creat a road topology with realistic vehicles movement.
- Mobility model generator for vehicular network (MOVE) (Karnadi, Zhi Hai, & Kun-chan, 2007), is a java based tool with graphic user interface (GUI) and is built on top of micro traffic simulator SUMO. It has the facity to generate real world mobility model for VANETs simulation. It has a set of GUI that makes it easier to create a real world simulation scenario. Output obtained by move is a trace file which can be further used by NS-2.
- Network Simulator version 2 (NS2) (McCanne & Floyd, 1999), is an object oriented, discrete event driven network simulator developed at UC Berkeley written in C++ and Object-oriented Tool Command Language (OTCL). NS2 is an event-driven simulation tool which provide substantial support for the simulation of TCP, UDP, routin and multicast protocols over wired and wireless networks.

The vehicular network scenario as used in this thesis was created using SUMO and MOVE. The road topology was created using the Map Editor component of MOVE and vehicles movement were generated using the MOVE Vehicle Movement Editor. The

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vehicle editor allows for the specification of the several properties of vehicle routes such as; number of vehicles in a specific route, vehicle departure time, vehicle origin and destination, vehicle speed, etc. the output generated by MOVE is the mobility trace file which hold all relevant data regarding real-world vehicle movements.

To create a realistic VANETs file, the open street map of Petaling Jaya, Malaysia, was downloaded where the partial streets of Petaling Jaya were extracted using MOVE and SUMO. A grid view map of Petaling Jaya (PJ) with total area of 652m X 752m was created using the Java OpenStreatMap Editor. The use of PJ open street map paves the way to explore a more sophisticated VANETs topology that include both highway and urban area in the simulation experiment. Three procedures were used in order to execute the traffic simulation in this partially used area. These procedures are listed below:

1. The mobility file of the map from Open Street Map (OSM) was generated. Most of the road was retained in the map for satisfactory simulation results. The tag depiction of the properties of the streets in OMS was reviewed. A manual correction of the intersection values is done so that the simulation results at appropriate location can be presented. For example, OSM output has to be reformatted and manually updated to match the formats required by NS2. In doing so, special attention is given to the intersection, redefining locations by using alternate coordinates. Subsequently, the anticipated element of the map was determined and exported in an OSM file.
2. Outset of traffic flows for the generated partial map is obtained after the removal of the redundant objects from the anticipated specifics, and after identifying the end-nodes.
3. The network is then simulated through NetConvert.

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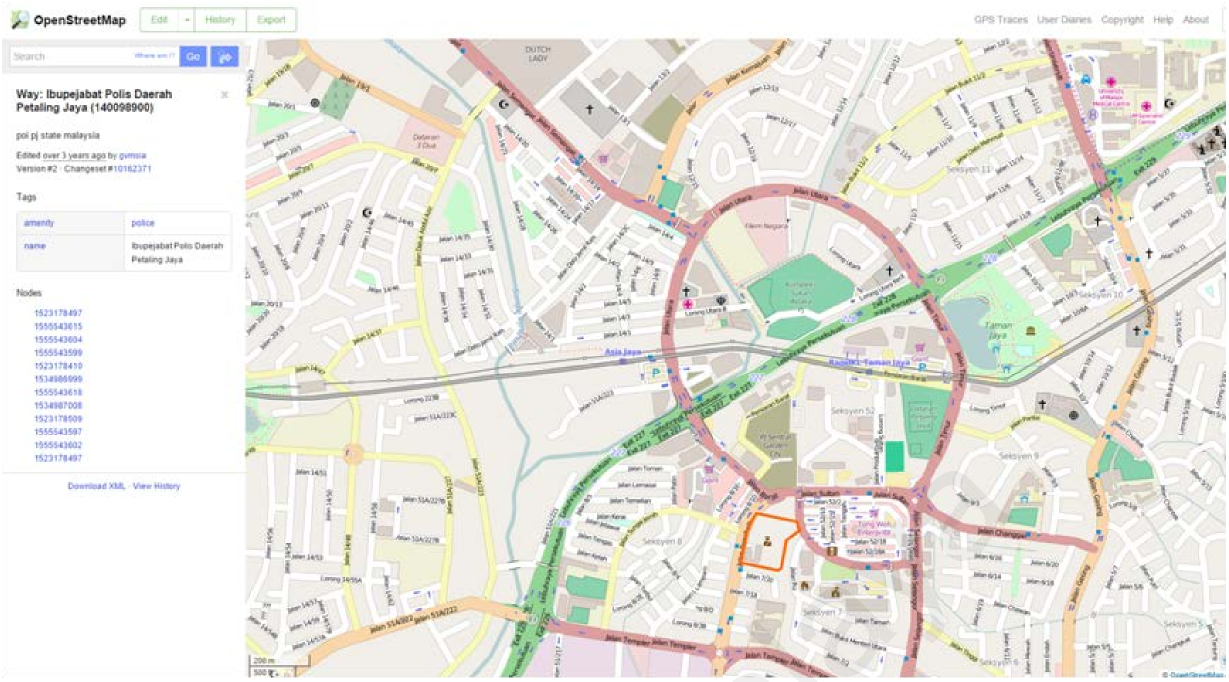

Figure 4.7: Petaling Jaya map using OpenStreetMap

Figure 4-7 shows an Open Street Map of PJ city, which was downloaded from google earth. The same map was imported to OSM. The imported OSM image is provided in figure 4.8. OSM provides the required system with the longitude and latitude data from the PJ partial street map. The longitudes provided by OSM are mapped onto the necessary coordinate with aspired origins in the 2D area (OpenStreatMap). Recalculating the 2D coordinates in the first quadrant of the plane is done by manually shifting the geometric origins to the desired location using the MOVE map configuration editor. The mathematical equation in 4.43 was used to determine the interpreted coordinates (X,Y) in the first quadrant.

$$X = x + a; Y = y + b \qquad 4.43$$

Where

(x,y) are the 2D coordinates before shifting the plane.

(a,b) are the origin of destination

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(X,Y) are the new 2D coordinates after shifting the plane.

The data extracted from the OSM database are compiled into an XML structure file named as (map-9. osm. xml). map-9.osm.xml, comprises of all data primitives, such as roads, intersections and relations. All the intersections generated in OSM are identified by their longitude and latitude values. The minimum bound latitude and longitude; maximum bound longitude and latitude of the values of the partial PJ city map are shown below.

- minlat=" 3.10052"   Maxlat=" 3.09804"
- minlon="-101.64725"   maxlon="-101.64304"

The standard Maximum and minimum bounds of the region were obtained through OSM. The above set of points defines the polygon zones of roads, and the metadata embedded within map-9.osm.xml file helps the stream of signal rules on roads with other characteristic objects. The extracted OSM data is then manually fed into the map intersection editor to be configured. At the next stage, the significances of the street vehicles are defined using the MOVE's road editor. The significances of the street are defined in order to provide one or more lane setups. The depiction of the street is studied in road editor which includes attributes such as number of lanes, average speed and the road priority. For simplicity, a system of default streets was adopted and their attributes are as follows:

- Default number of lanes: 2
- Default speed (m/s): 20m/s or 72km/h
- Default priority (%):80%
- Subsequently, the configured map is created as a final map (map-9.net.xml).

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Figure 4.8: Petaling Jaya extracted streets map

The last map produced (map-9.net.xml) is used in the next stage for the experimental traffic simulation with SUMO. By engaging SUMO and GUI, the representation of traffic infrastructure was then observed. The mobility traces obtained by SUMO is exported into NS2 using the TraceExporter. The two simulators are then launched simultaneously with ns2 acting as the client application and the SUMO as the server application. NS2 reads from the previously generated mobility trace and sends commands to SUMO via TraCI to execute the simulation steps in order to stay synchronized in time. Figure 4.9 shows the flows of the simulation

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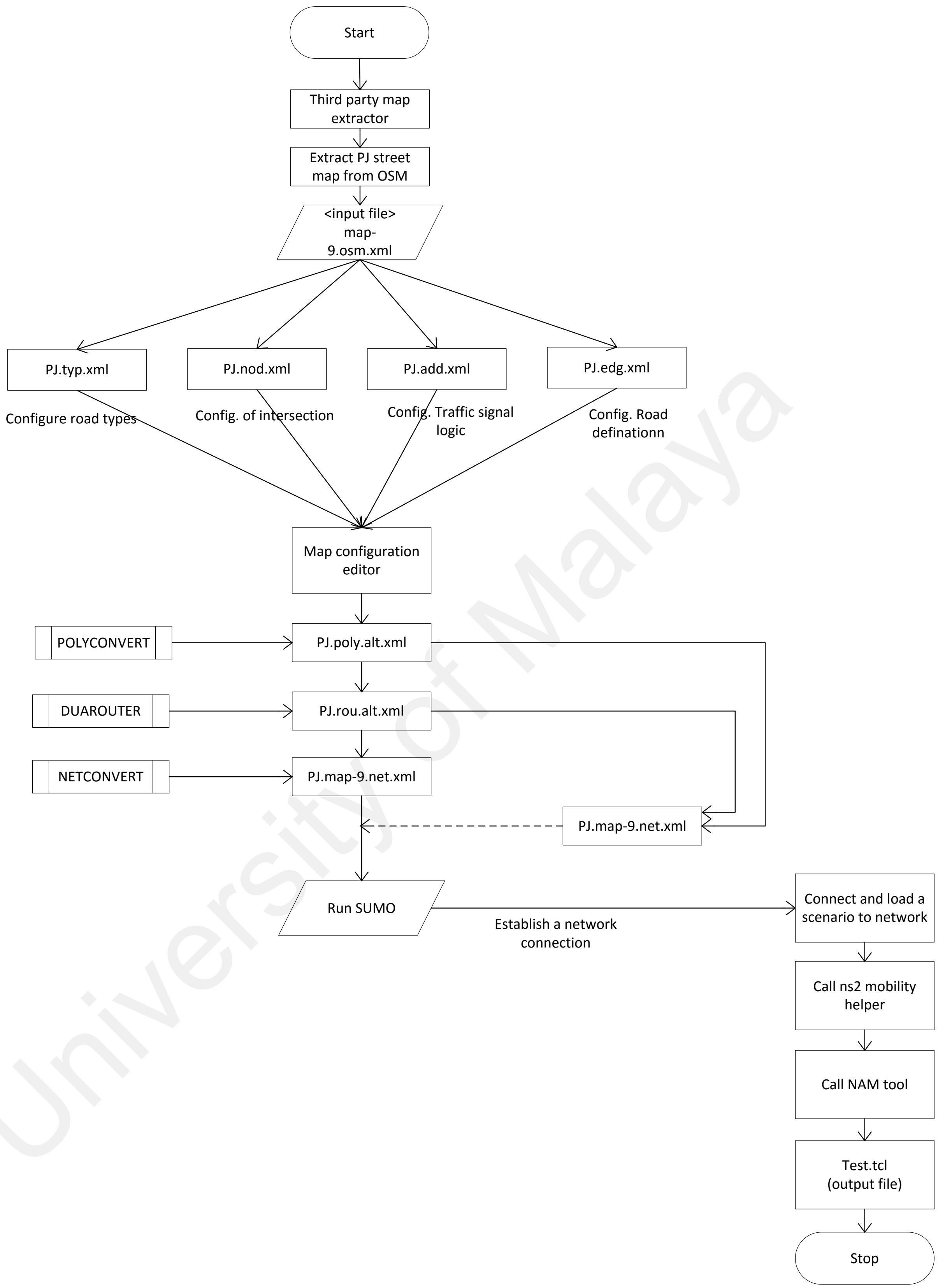

Figure 4.9: Flow of simulation of the generated mobility and traffic file as input to NS2

4.6. SIMULATION AND RESULTS

To determine the feasibility of the model, series of simulation was conducted using the NS2. In order to generate multimedia (i.e. IPTV) traffic analogous to the one transmitted over a real IP network, MPEG-4 video traces data was used. MPEG-4 video traces data is freely available on the Internet (the trace file is created by group of researchers at the Technical University Berlin in the year 2000) (Reisslein). Similarly, to simulate multimedia scenario as realistic as possible (i.e IPTV real scenario where different users watch different TV program simultaneously), the combination of four different video traces (Formular 1, Jurassic Part 1, ARD News, Soccer) of YUV:MP4 format was concurrently streamed to generate an aggregated multimedia traffic (the four video traces are simulated to be movies and TV program, see Figure 4.7). Each video clip starts at a random selected time of 0.3 second. All relevant information regarding the four video traces as used in the simulation is detailed in (table 4.2). Each frame in the MPEG-4 trace file used in this simulation is breake down into multiple packets fragments equal to 552 Mb, and transmit into the network following the RTP/UDP/IP packetization guideline and the MTU constraint as stated in (Fraunhofer & Kim, 2011). Each simulation was run for 200 seconds, and the traffic source uses User Datagram Protocol (UDP) for transferring Constant Bit Rate (CBR) flow without acknowledgement. Both RSU and vehicle are referred to as nodes, with RSU label as a stationary node at a fixed position and vehicles as mobile nodes. In this system, it was assumed that all vehicles on the road are equipped with wireless capability that complies with IEEE 802.11e standard, for V2V and V2I communications. The underlying network is built purely as an ad hoc network and the communication mode is a hybrid VANETs communication. Due to the mobility of vehicles and the limited transmission range of the RSU. Hybrid VANETs scenario, was employed (see Figure 2.2A), where vehicle within the RSU transmission range, act as a relay node by

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relaying traffic to vehicles outside the RSU transmission range via V2V communication, and those vehicles within the RSU transmission range connect directly in a one-hop manner. All vehicles are capable of supporting computational and storage resources. In the simulation both highway and city environment was considered (figure 4.910 and 4.11), a variable speed of 0 when the vehicles are stationary to 20 m/s (i.e., 72km/h) when vehicle are moving was also identified. Three traffic density situations were considered: sparse mode with 5 vehicles, medium mode with 15 vehicles and dense mode with 30 vehicles. The wireless access standard used is the IEEE 802.11e. DSRC PHY and MAC layer were implemented using standard set by ASTM and the data rate set to 1Mbps. All other parameters as used in the simulation are detailed in table 4.3

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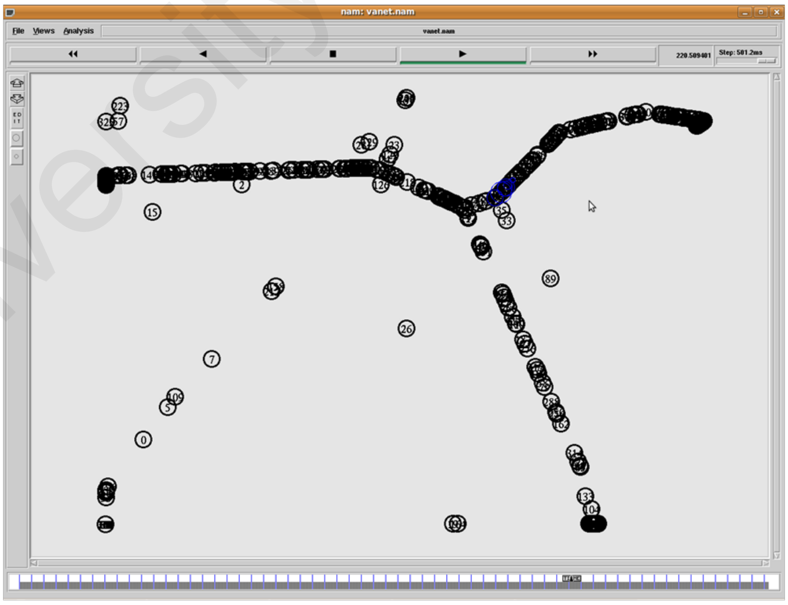

Figure 4.10: Petaling Jaya highway movement traces on network animation (NAM)

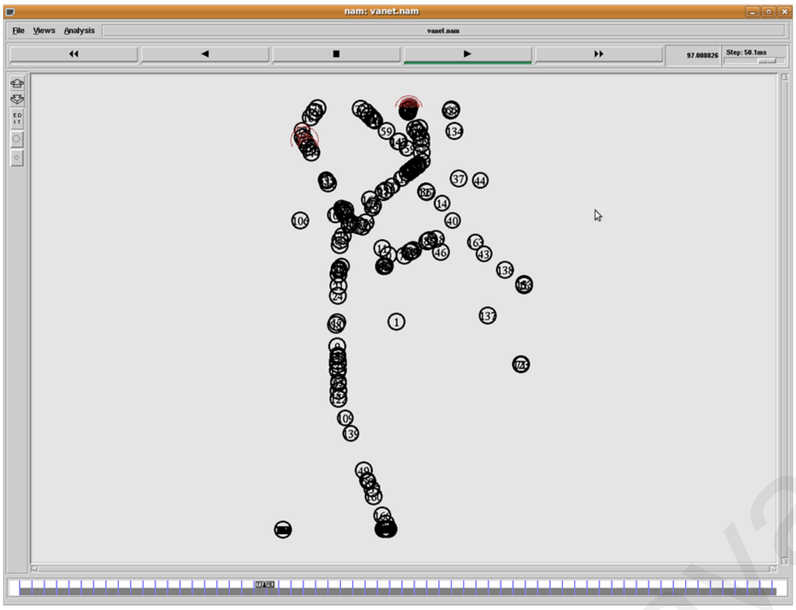

Figure 4.11: Petaling Jaya city movement traces on network animation (NAM)

Table 4.2: Frame statistic of MPEG-4 traces (Reisslein)

Trace	Compress. Ratio YU:MP4	Mean Frame Size (Kbyte)	Mean Bit Rate (Mbps)	Peak Bit Rate (Mbps)
Formular 1	9.10	4.20	0.84	2.90
Jurassic Part 1	9.92	3.8	0.77	3.30
ARD News	10.52	3.6	0.72	3.4
Soccer	6.87	5.5	1.10	3.6

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Table 4.3: Simulation Parameters

Parameter	Value
Antenna Type	Omni Antenna
MAC Protocol	IEEE 802.11E
Simulation time	200 seconds
Ad Hoc Routing protocol	AODV
Transmission Range	250m
Protocol	UDP
Packet size	552 MB
Radio Propagation	Two Ray Ground
Traffic	CBR
Traffic density	5, 15 and 30
Node speed	0m/s, 5m/s, 10m/s, 15m/s and 20m/s

In this experiment, the considered assumptions were as stated below:

- Each node has buffer capability to buffer packets when packets need to wait for transmission.
- No packet is lost in the expanse of the wired segment of the network connection path
- Vehicles on the road are mobile nodes with wireless ability capable of supporting large computational and memory resources.
- The power supply was considered not to be a problem because the engine of the vehicle should be able to supply adequate power for computation and whatever should need power to operate effectively.

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Advance on demand vector routing protocol (AODV) was utilized for the routing between nodes and the MAC used for the node is IEE 802.11Ext. The investigation of the system performance was done based on three key performance factors, which are throughput; latency or packet delay and packet loss rate. To make the design as realistic as possible, the video transmission QoS parameters were evaluated through a series of simulations. In each simulation, the impact of each individual metric as it affects the quality of video packet delivery was investigated.

4.6.1. THROUGHPUT

In this experiment, the aim is to ascertain that the underlying VANETs, given its characteristics, has the ability to support multimedia traffic such as IPTV, at higher speeds under different traffic scenarios. Using NS-2, the capacity per flow of vehicular network was determined by measuring the network throughput along a uniform unidirectional traffic stream. To measure the throughput, the network capacity w estimated via three network scenarios; ((a) scenario with 5 nodes in sparse mode, (b) scenario with 15 nodes in medium mode and (c) scenario with 30 nodes in dense mode). In order to estimate the maximum available throughput, a VBR traffic flow was allowed into the network., This is to ensure that the whole available bandwidth along the route between the origin and destination is dedicated to the transmission. Figure 4.12, shows the average throughput with respect to speed for the three vehicle density scenario. It could be observed that throughput is higher in the scenario with the lowest vehicle density scenario (i.e., node 5) in all the speed level; This implies that the average rate by which quality IPTV traffic can be delivered is greater with low vehicle density than high density. It was observed that the throughput dropped as the vehicle speed increases and the rate at which it drops is higher in the denser scenario (30 nodes) than the sparse or

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medium scenario. This also implies that the higher the vehicle density the greater the throughput dropped with increased vehicle speed. The dropped in throughput as a result of vehicle speed and density is caused by VANETs broadcast storm issue and the frequent link instability. As the vehicle density increases, so also is the amount of broadcast messages. However, Impact of such excessive broadcasts originating from vehicles as the density increases are bound to have increased contention on communication links resulting in signal contention, collision, interference and signal impairment, in consequence downgrade the capacity per flow of the network. This situation conformed with the expression in equation 4.34. Consequently, the increased in vehicle speed causes' link instability and rapid signal level fading. Thus, causing the drop in throughput, and so the higher the velocity, the greater the impact of fading on the amount of data transferred. In conclusion, throughput is greatly impressed by speed and vehicle density, with a lower vehicle density leading to higher data rate, which is greatly reduced by vehicle speed.

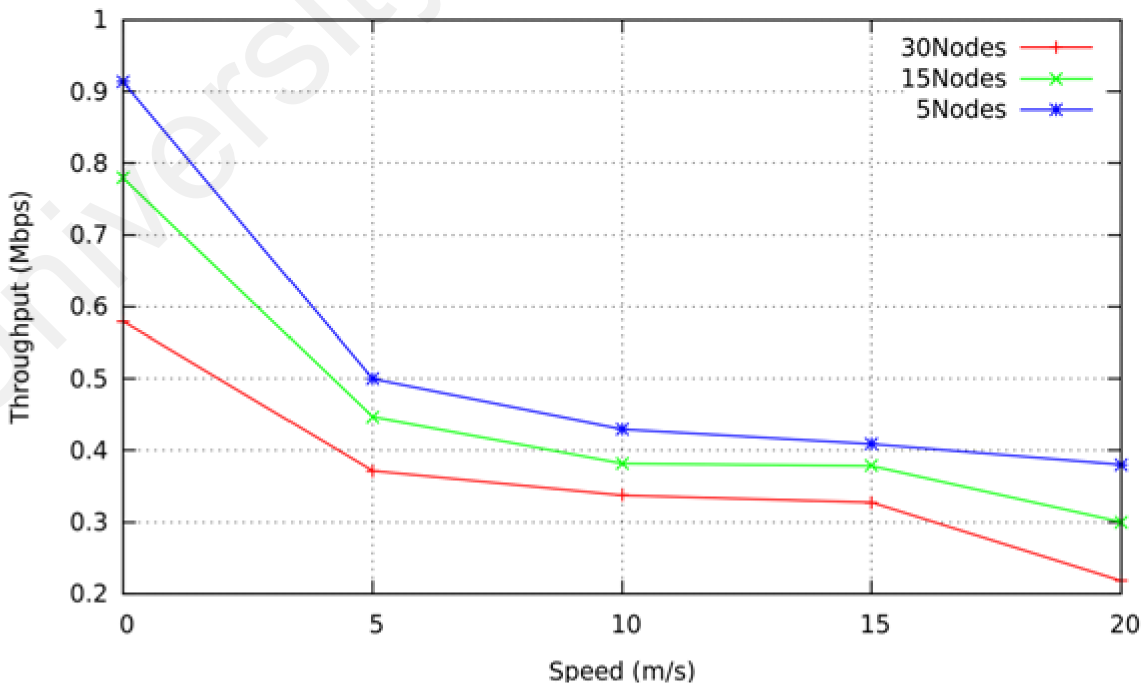

Figure. 4.12: Average Throughputs of 3 Different Vehicle Density scenarios Vs Speed

4.6.2 PACKET LOSS RATE

Figure. 4.13A, shows the average number of packet drop over a simulation period of 200 seconds for varying vehicle speed and node density. It could be observed from the graph that the packet loss, increases as the speed and the number of the vehicle increased. Though, at speed $\leq 10\, m/s$ the average loss rate of the three density scenarios remains constant (i.e., the percentage loss of all the three vehicle density scenarios is uniform and minimal within the speed limit $\leq 10\, m/s$.). This could be attributed to fewer link disconnection as a result of even nodes distribution at that speed, and so buffer overflow or buffer underflow is less. However, at the speed $> 10 m/s$ the packet loss can be observed to increase significantly, with the 30 nodes can be observed to be higher than all the other density scenarios. This could be attributed to the varying speed of the vehicle. As the vehicle speed increases, the pace at which nodes move away from the transmission range increases rapidly. And as the density increases, the number of nodes competing to access the channel and the amount of transmissions also increase, thereby, increasing the packet loss probability due to collisions. This result conformed with Eq. 4.6 of the proposed model, which illustrate that the received power deteriorates equilaterally with the distance. Hence, the drop in signal strength results in an increasing packet loss. Furthermore, the result in Fig. 4.9A, satisfy the loss model in section 4.4.2.2. As the node density increases, the number of transmissions in a collision domain also increased correspondingly, thus increasing the cumulative load W (i.e., as more traffic is being injected, the source vector $\underline{s}$ increases and an increase in $\underline{s}$ result in W being increased, see Eq. 4.30). Consequently, an increase in W is an indication that the number of nodes relaying messages have increased, which signifies the increasing number of nodes competing to access the available channel, thus, increasing collision. The increase in collision decreases the success probability $p_s(W)$ (see section 4.4.2.2). The decrease in $p_s(W)$ intensifies the rate of packet loss, and an increase in packet loss

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decreases the possibility of reproducing IPTV traffic streaming with reliable quality as the probability of transporting packet successfully decreases. Thus, the data in Figure 4.13A suggested that quality of IPTV traffic streaming over VANETs is influenced by both node (vehicles) density and node speed and that the speed of 10 m/s can be presumed to be the critical speed. Therefore, the quality of IPTV traffic will deteriorate if vehicle speed exceeds the critical speed of $10m/s$, and the rate of deterioration increases linearly with increasing node density. This implies that within the speed $\leq 10\ m/s$ where the aggregate packet loss ratio is below 12% (see Figure. 4.13B), PTV service can be deployed with packet loss that can support enough video rate with reliable quality. However, at vehicle speed higher than 10 m/s, some problem will occur while reproducing an IPTV stream without any special technique (special technique such as: buffering, error concealment) due to the high packet loss rate

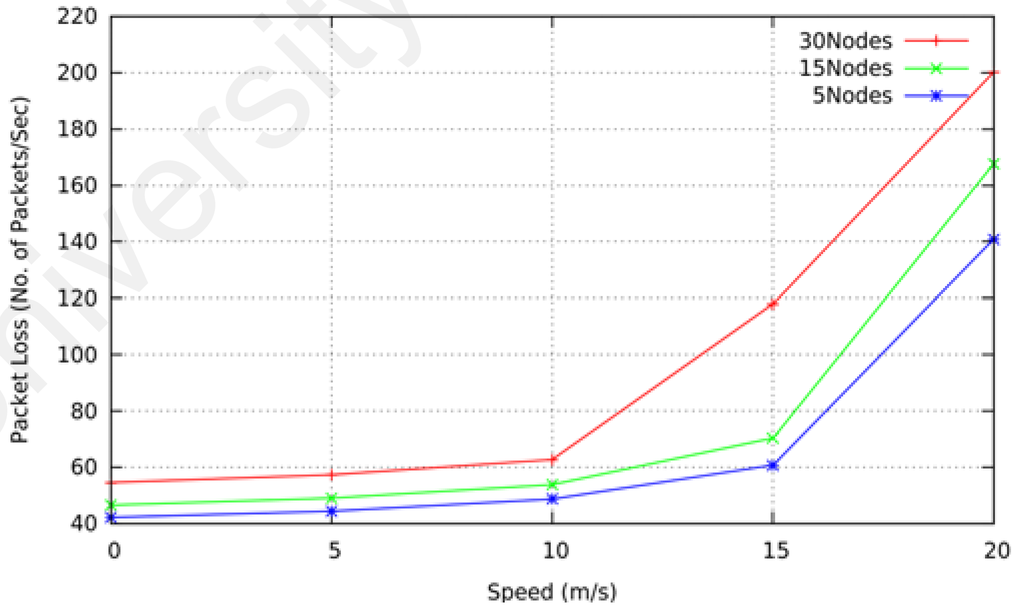

Figure 4.13A: Average Packet Losses of 3 Different Vehicle Density scenarios Vs Speed.

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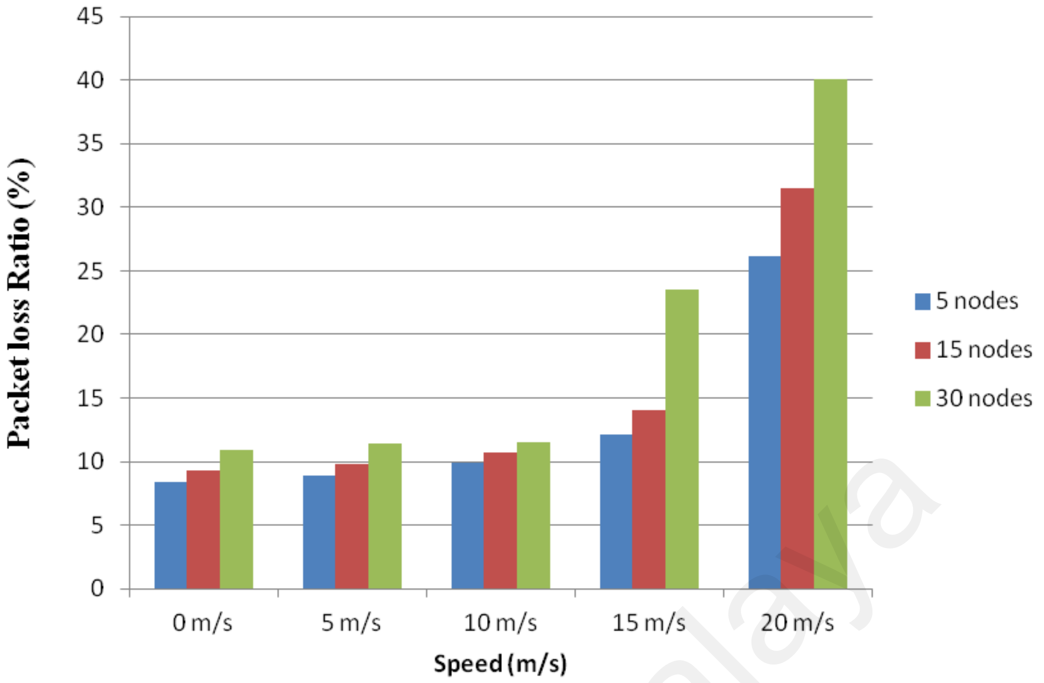

Figure 4.13B: Percentage loss ration as vehicle speed and density increases

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4.6.3 PACKET DELAY

Figure 4.14, illustrate the average delay for three different vehicle scenarios with regard to speed. It could be observed that packet delay increases as the vehicle speed get higher, and in some cases the packet delay decreases even when the speed increased. This is could be attributed to the number of handoff. Packet delay depends on the number of handoff, as can be observed in Figure 4.14, the scenario with 30 nodes was affected more, this is due to the fact that the scenario contained more nodes, as such, more handover were expected to occur. Depending on the number of handover, the packet delay can increase or decrease as the vehicle speed increases. The increased in the end to end delay as the vehicle speed gets higher could also be attributed to high propagation delay. As the vehicle speed increases, so also is their distance apart. And as the inter vehicle gaps widen, the stability of the link is affected (as the higher the gap between vehicles the lesser the transmission range and the higher the probability of link disconnection). In order to reconnect a broken link that might be caused as a result of the enlarge inter vehicle gap, vehicles will need to catch up with other vehicles ahead to reconnect, and this takes time. During the catch up period in VANETs, the routing protocols employ a strategy known as Carry-and-forwarding, a situation where node forwarding packets hold the packet for a next optimum hop yet to be available (Saleet et al., 2011), by buffering the packets and transmit it in a later available opportunity. However, for real-time multimedia traffic such as IPTV, there is a specific needed time (threshold time) by which these packets must be buffered. And so, depending on the stability of the link, the threshold time can decrease or increase. With an increase in threshold time, resulting in the decrease in the delay probability and decrease in the threshold time given rise to high delay probability (see Eq. 4.39, section 4.4.2.3). Consequently, in figure 4.14, as the vehicle density increases, the delay could be observed to have intensified. The reason could be attributed to the increasing number of transmissions competing to access the limited available network link (As higher vehicle density implies increase in the number of nodes relaying messages). Thereby increasing the amount of time required for packets to queue before the MAC to literally get to access the channel. Thus, increasing the likelihood of a delay exceeding the maximum delay constraint (see Eq. 4.40, section 4.4.2.3). The result in figure 4.14, implies that the average delay of multimedia services such as IPTV increases as the traffic load and node mobility increases. However, depending on the inter vehicle distance and the number of nodes involved in the communication, the delay could decrease slightly even when the vehicle speed increases (this situation could be observed in figure 4.10, between the speed 5 m/s and 10 m/s). In figure 4.14, It could be notice that within the speed ranging from 5 m/s to 10 m/s, the scenario with the node density of 15 experiences a slight reduction in delay even when the vehicle speed increases, while the 5 node scenario experience a stable with an insignificant increase in delay within the

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same speed limits (i.e., speed ≥ 5m/s and speed = 10 m/s). This situation conforms to the delay model in section 4.4.2.3 Eq. 4.39. Consequently, at this same speed limit (i.e., speed ≤ 10 m/s), in section 4.5.2 (packet loss experiment) a minimal packet loss was also observed. Therefore, it will be fair to conclude that the threshold speed in which IPTV services with reliable quality can be feasible, is the speed limit ≤ 10 m/s. As long as this speed limit of 10 m/s is not exceeded, reliable IPTV can quality be assured.

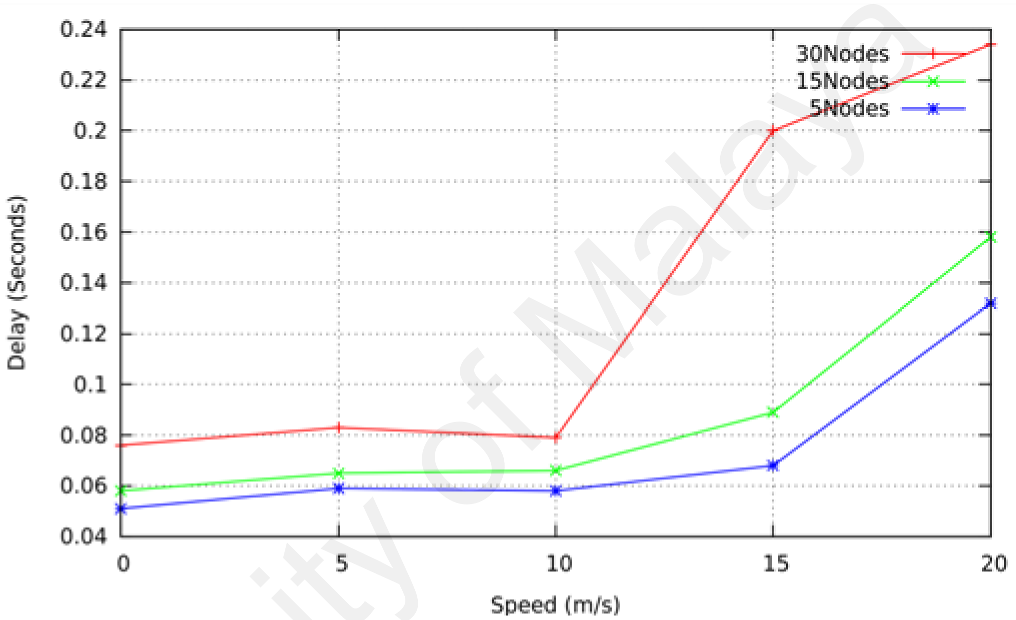

Figure 4.14: Average Delays for 3 Different Vehicle Density scenarios Vs Speed

4.7. SUMMARY

It is often very difficult to understand the factors that influence the quality of multimedia services (such as IPTV, video, etc.), from the users' point of view, and this difficulty increases in a vehicle ITS scenario due to the high dynamism experienced by the network channels. In ITS context, there is no reference signal to compare with each impairment, turning the estimation of the quality perceived by the users a very

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challenging task. The difficulty in the maximization of the perceived quality increases, therefore reducing or not optimizing the users' experience. This chapter presented the requirements for the assessment system architecture/framework. The framework has been developed by utilizing the comprehensive set of metrics derived from both the technical objective network parameters and the subjective human QoE parameters. This was followed by a comprehensive description of the QoE prediction architecture/framework with discussion on the details as well as the specification of each module and components. Furthermore, an empirical derivation of the QoS parameters was presented. In conclusion, a series of simulated experiment of the set of QoS parameters under study were presented, as well as their impact on the quality of multimedia service delivery.

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CHAPTER FIVE: Multimedia QoE Prediction Modelling

5.1 INTRODUCTION

This chapter presents the formulation, modelling, evaluation and validation of the QoE estimation model using the ordinal logistic regression analysis. The explanatory variables (i.e., the QoE factors) have an ordinal structure, therefore, ordered logit model with the proportional odds assumption was selected to model the QoE estimation. Since the applicability and accuracy of the QoE prediction model depend highly on the datasets used, a detailed description of the data used and preparation process was first expounded. Secondly, the applicability of the selected model to estimate the QoE of ITS multimedia services was also presented. This chapter also identifies the detail analysis of the simulation conducted using IBM Statistic Package for Social Science (SPSS) software package version 22 (Wagner III, 2014). The analysis of the result obtained, the test for model goodness-of-fit, test for proportional odds assumption and the validation techniques employed to ascertain the predictive accuracy and the generalizability of the model were also presented. Finally, recall in chapter two, the ordinal logistic regression was elaborated to be known as ordered logistic regression or simply ordered logit model because it is the generalization of the logit model to ordered response categories. Consequently, the ordered logit model is as well recognised to be cumulative logit model (Agresti, 2010), because it is used to model cumulative probabilities. Some author also refers to the cumulative logit model as a proportional odds model (McCullagh, 1980), because in cumulative model, the intercepts are the only portion of the model that depend on the category level the explanatory variables do not. In line with these connections, the term proportional odds, ordered logistic regression, cumulative model and ordered logit model as may be used interchangeably in this

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chapter, should be understood to signify the ordinal logistic model with the proportional odds assumption.

5.2 DATA DESCRIPTION AND PREPARATION

The dataset used for the estimation of the QoE prediction model are of two kinds: the technical QoE factor dataset and the nontechnical QoE factor dataset.

- Technical QoE factors dataset: As stated in chapter 4 section 4.3.1, the teqnical QoE factors are classified into two: QoS network parameters and QoS service source parameters. The dataset of the QoS network parameters are obtain via simulation experiment (see chapter 4 section 4.6 for details). The information obtained from the experiment in chapter four are data that represent the simulated results of the end-to-end QoS parameters (i.e., the observed values for the end-to-end throughput, end-to-end packet lost and end-to-end delay). The result represent the values of the quantitative continuous explanatory variables which constitute three out of the five quantitative explanatory variables used in the development of the QoE prediction model. While the dataset for the QoS service source parameters (i.e., the bite rate and frame rate dataset) are obtained from Image and video quality assessment data base. The database is created by the Image and Video Communication research group of the Institut de Recherche en Communications et Cybernétique de Nantes (IRCCyN). The dataset are freely available on the Internet at (IVC Team Database). Detailed description of the characteristics and statistical breakdown of distribution of the quatitative variables datasets as used in the QoE modelling is presented in section 5.2.1 and 5.2.3 respectively.
- Non technical QoE factors dataset: The human and contextual QoE factors are the non technical QoE factors adopted in the QoE modelling. These variables are

qualitative variables, which are intrinsically subjective. Just as previously stated, it is not feasible to perform subjective test of real-time multimedia service in VANETs. Therefore, empirical subjective QoE assessment dataset were obtained from TUD QoE database (i_QoE dataset, 2015). This database contains subjective QoE dataset created by the Multimedia Computing Reseach Group of Technical University of Delf (TUD) and are made available to the research community to be use for experiment that involves both image and video quality evaluation. Since the human and contextual QoE factors adopted in this thesis are gender and social context, only the subjective dataset relevant to these two qualitative wariables were collected. Detailed description of the characteristics and statistical analysis of distribution of the qualitative variables datasets as used in the QoE modelling is presented in section 5.2.1 and 5.2.2 respectively.

5.2.1 CHARACTERISTICS OF THE DATASET

Table 5.1 gives the description of all the variables used in the development of the QoE prediction model. The dependent or response variable is the QoE level, which is ranked 5 levels in descending order from very good quality to bad quality. The explanatory variable are separated into two categories, category 1, represent the continuous variable (i.e., the QoS parameters) classified as covariates and category 2, represent the the human and contextual QoE parameters, they are classified as factors. Table 5.2 illustrates the statistic description of the variables. These descriptions include the standard deviation, range, mean, minimum and maximum values of all the variables use in the model development.

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Table 5.1: Description of the variables used for the QoE prediction model development

Variable	Description	Type	Value	Definition
QoE	User quality perception level	Ordinal	5	Very good quality
			4	Good quality
			3	Fair quality
			2	Poor quality
			1	Bad quality
Objective QoE factors				
Throughput	Average End-to-end throughput	Continuous	Measured in Megabits per second (Mbps)	
Loss	Average End-to-end packet loss	Continuous	Measurement is in number of packets per second (Npps)	
Delay	Average End-to-end delay	Continuous	Measured in seconds (S)	
Bite Rate	The amount of data transmitted per unit time	Continuous	Measured in Kilobite per second (Kbps)	
Frame Rate	Number or sequence of images per second that is being transmitted or received	Continuous	Measured in number of frames per second (Fps)	
Subjective QoE factors				
Gender	Users biological Sex	Nominal	0	Male
			1	Female
Social Context	Presence or no presence of co-viewers	Nominal	0	Single
			1	Group

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Table 5.2: Statistic description of the variables used to develop the QoE prediction model

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
End to End Throughput	200	68.8400	2.5000	71.3400	26.951550	15.4345900	1.156	.172
End to End Delay	200	2.0890	.0310	2.1200	.709720	.5794441	1.022	.172
End to End Packet loss	200	24.6351	6.1500	30.7851	16.123264	7.3134501	.896	.172
Gender	200	1	0	1	.38	.487	.498	.172
Social_Context	200	1	0	1	.56	.498	-.244	.172
Bite_Rate	200	500.00	12.00	512.00	141.7500	132.06093	.973	.172
Frame_Rate	200	23.00	6.00	29.00	14.9780	6.04407	.525	.172
Valid N (listwise)	200							

5.2. 2 DISTRIBUTION OF THE QUALITATIVE EXPLANATORY VARIABLE

The qualitative explanatory variables are: gender and social context. The dataset of these two factor variables is sorted into two parts. For example, gender is categorized accoding to the users biological Sex, which is either male or female. The percentage of gender as used in the model design is exemplified in figure 5.1. In the case of the social context factor, it is categorized according to whether the user watched the multimedia service alone in the vehicle or watched in company of others (i.e., in the Presence or no presence of co-viewers). The situation were the user is alone is considered ‘single’ (i.e., single viewer) and when in company of others is regarded as ‘group’ (i.e., the user is in company of other viewers). Figure 5.2 shows the percentage distribution of the social context categories (i.e., single or group) as used in the model design. Furthermore, the cumulative percentage of the two qualitative variables (i.e., gender and social context) were also observed and the result is shown in figure 5.3 and 5.4. The two separate curves as could be observed in figure 5.3 and 5.4, represent the curves for male and female users and that of the single and group users respectively. These plots, help one to visualize the pattern of the data in order to gain insight on how the expected result would look like prior to the model design. For instance, let consider the case in figure 5.3, where the users' QoE rating is “bad” a bigger percent of male compared to the female user were observed below the “QoE is bad” rating. This could be attributed to the fact that it is the first response and so the cumulative percentage was just the observed percentage of the response. However, it could be noted further that despite additional percentages (i.e., moving upward to the 100% point where the two courses must run across), the cumulative percentage of the male users still continue to be higher than the one of female users. In this kind of situation, one should expect a negative coefficient for such explanatory variable because is an indication that low quality rating is more when the user is not a female. The same is applicable to social context, negative coefficient should be expected for the explanatory variable and low quality rating will be more when the user watching the video is not in company of other viewers (i.e., if the viewer is alone watching the video).

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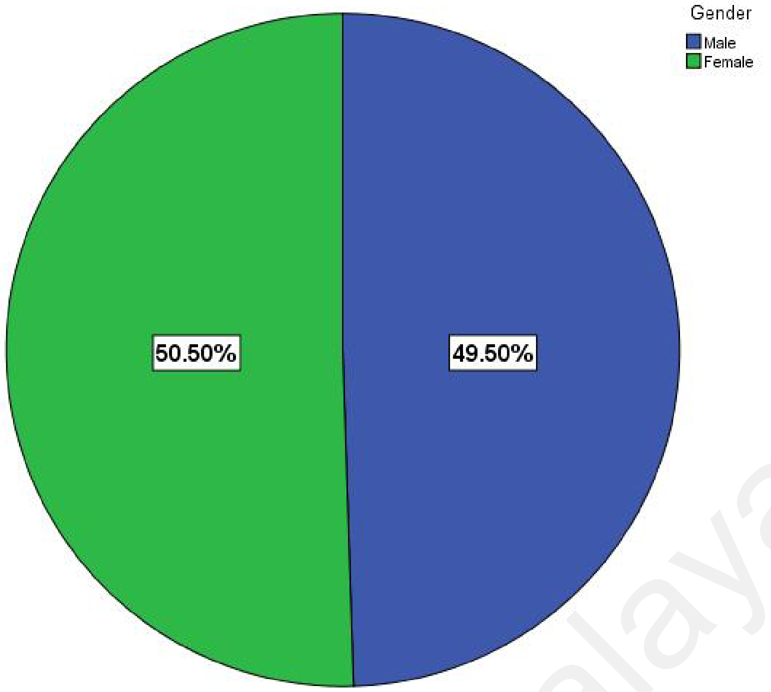

Figure 5.1: percentage distribution of gender dataset

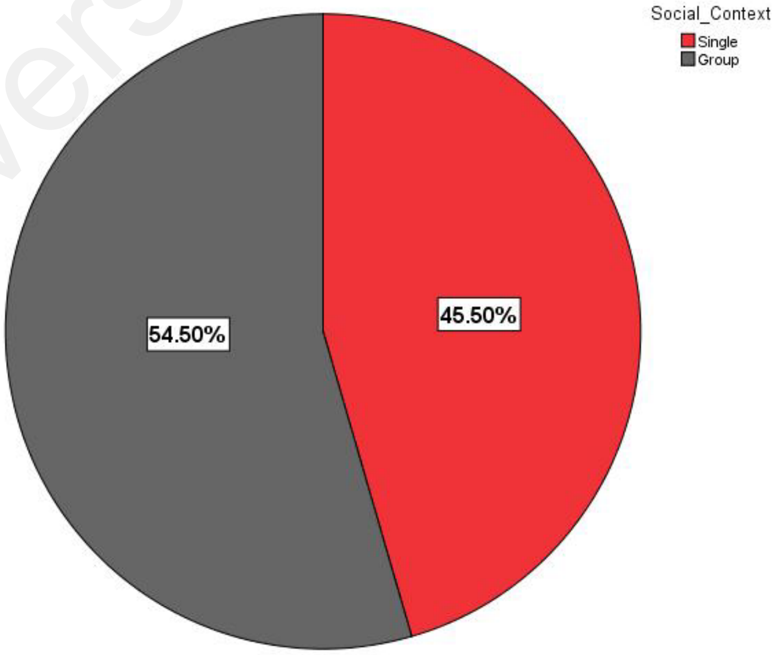

Figure 5.2: percentage distribution of the social context dataset

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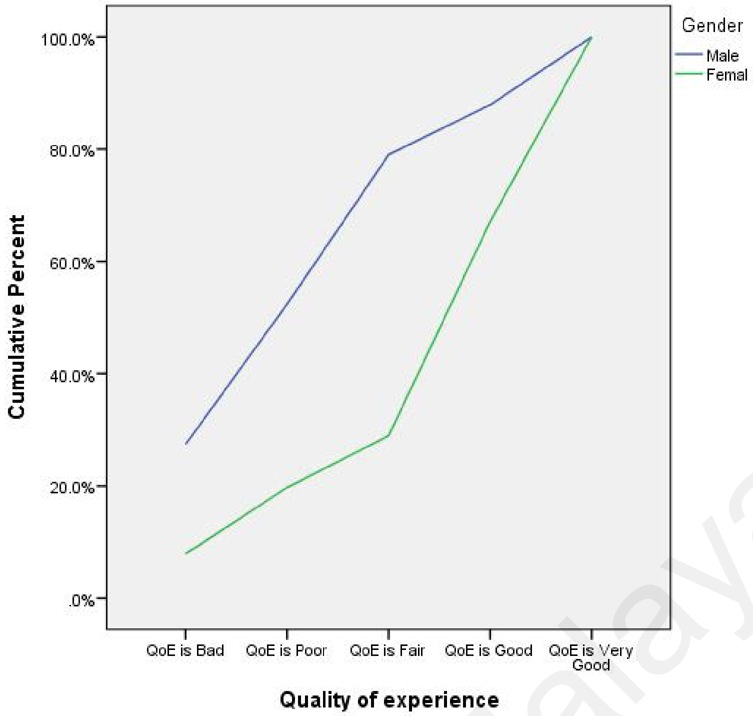

Figure 5.3: Cumulative percentage distribution of gender dataset

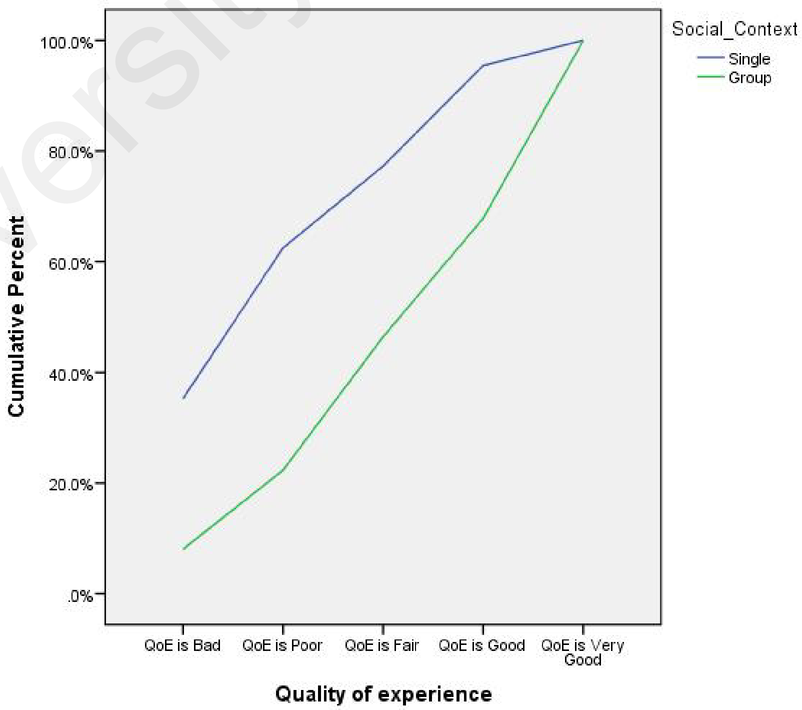

Figure 5.4: Cumulative percentage distribution of social context dataset

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5.2.3. DISTRIBUTION OF THE QUANTITATIVE EXPLANATORY VARIABLES DATASET

Figure 5.5, 5.6, 5.7, 5.8 and 5.9, illustrates the distribution of the quantitative explanatory variables dataset for 200 observations $(n = 200)$ as used in the development of the QoE prediction model. As shown in the figures, the distribution of all the five variables is positively skewed (i.e., the long tail is on the right side of the peak). This shows that the observed data are not normally distributed, which justifies our used of logit in place of probit as the linearization (link) function (probit assumes that the errors are distributed normally whereas logit assumed that the errors are not distributed normally but according to a logistic distribution). Since, the form of the probability histogram is asymmetric and discrete sideways. The normal distribution would be a useless approximation of such configuration.

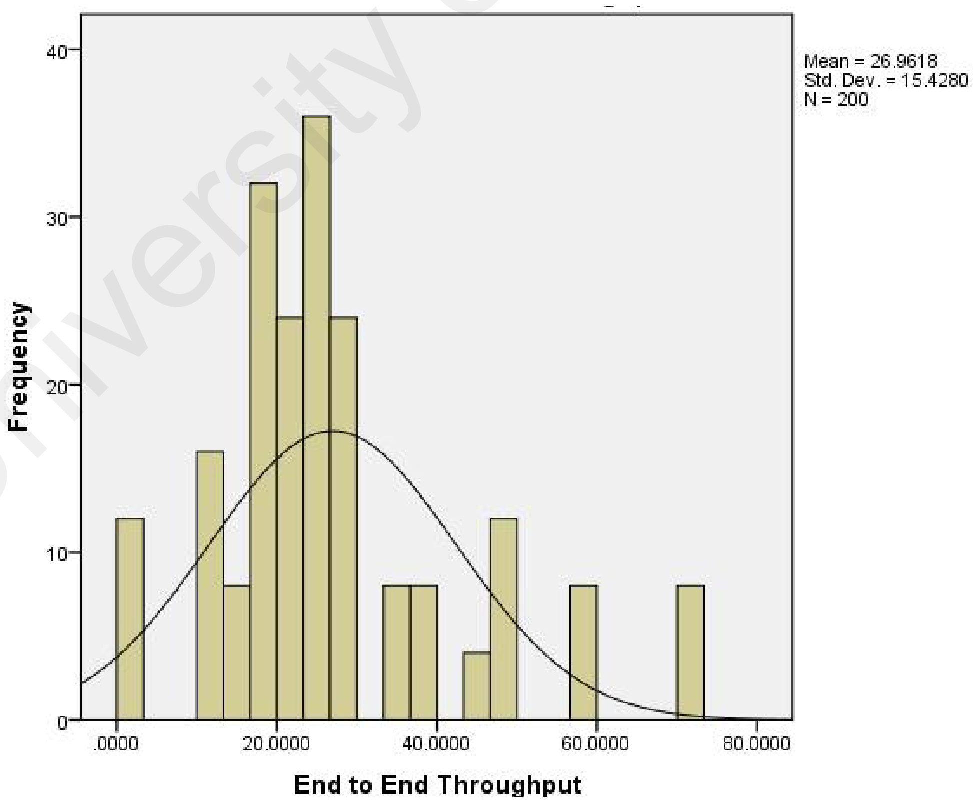

Figure 5.5: Distribution of end-to-end throughput dataset

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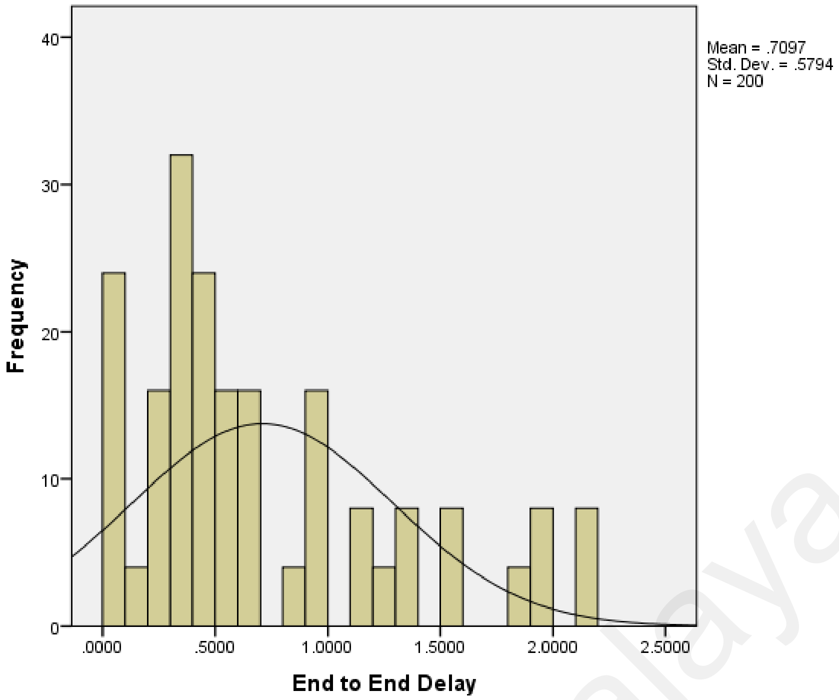

Figure 5.6: Distribution of end-to-end delay dataset

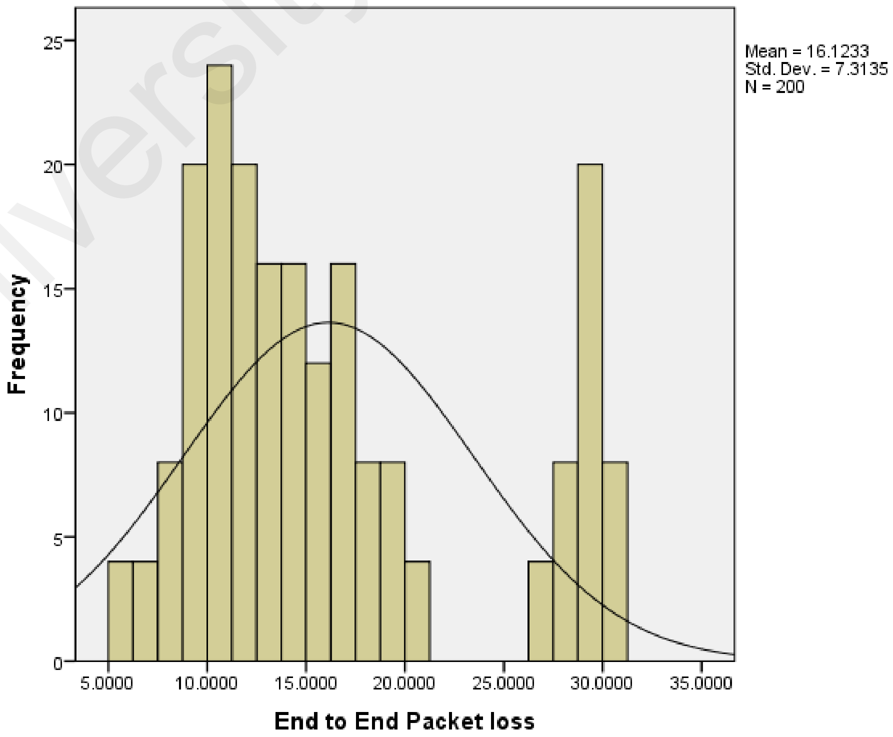

Figure 5.7: Distribution of end-to-end packet loss dataset

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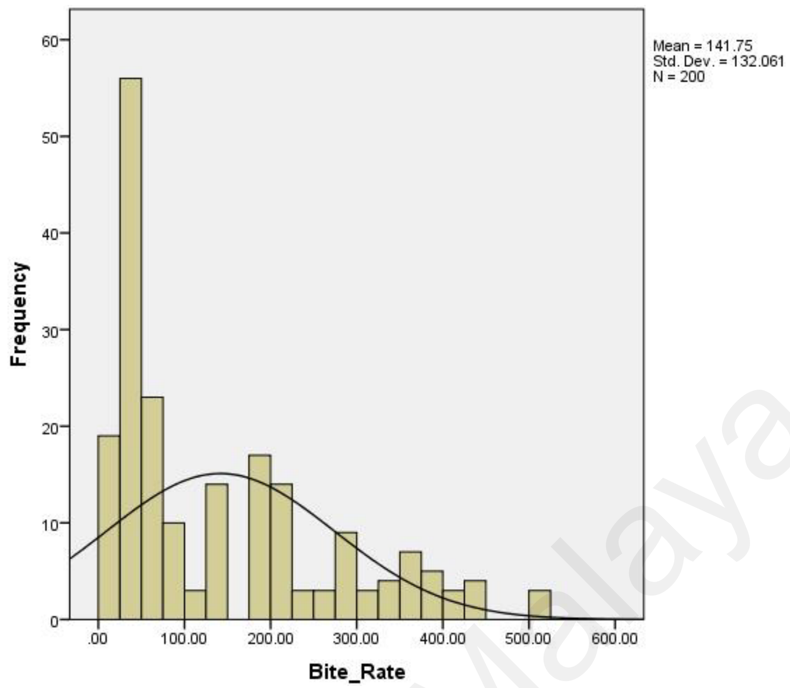

Figure 5.8: Distribution of bite rate dataset

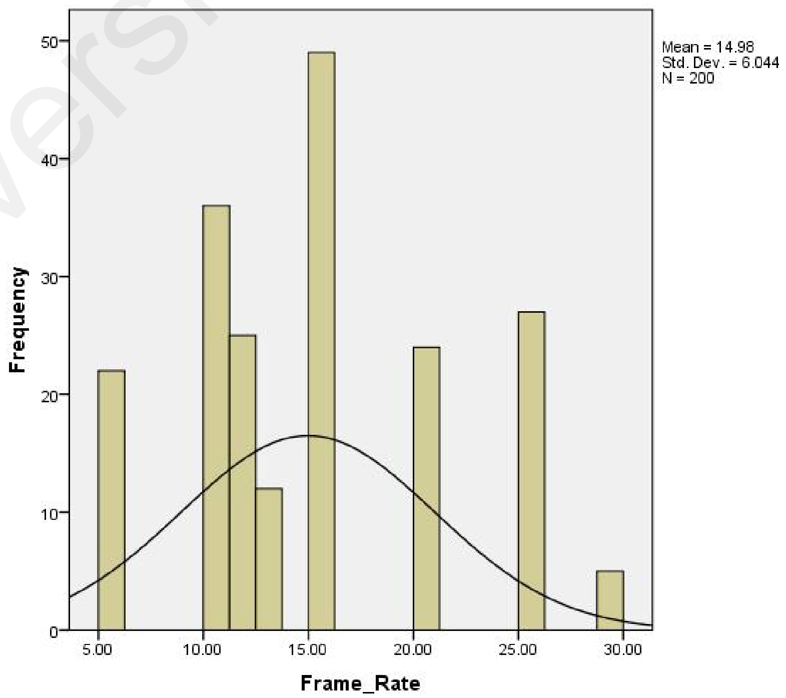

Figure 5.9: Distribution of frame rate dataset

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5.3 MODEL GENERAL SPECIFICATION

The ITS multimedia services QoE prediction model being considered in this thesis is one that accommodates discrete choices, one that supports multiple, ordered outcomes for users' satisfaction such as very good, good, fair, poor and bad (i.e., 5 categories). This analysis requires a method such as the ordinal logistic regression, which impacts categorical values to each of the choices involved and hence, is suitable for the analysis of ordinal data. The dependent variable specifies the degree of user quality perception known as the QoE. For example, assuming a series of observations $Y_i, for\ i = 1, \ldots\ldots, n$, of the outcomes of the multiple choices, from a categorical distribution of size j (there are j possible choices). Along with each observation Y_i, is a set of k observed values $x_{1,i}, \ldots\ldots x_{k,i}$ of the explanatory variables (i.e., the QoE factors). Using these observations, the QoE for each individual user can be modelled as a linear function of the explanatory variables. As in the present study, an ordinal variable Y_i can be associated with the QoE levels, such that $Y_i = 1$ if the quality is bad, $Y_i = 2$ if the quality is poor, $Y_i = 3$ if the quality is fair, $Y_i = 4$ if the quality is good and $Y_i = 5$ if the quality is very good. Thus, a low value of Y_i is associated with a lower degree of user quality perception and a high value Y_i is associated with a higher degree of user quality perception. It should also be noted that the ordinal nature of these outcomes does not imply that the outcome associated with, for example, $Y_i = 1$ is twice as strong as that associated with $Y_i = 2$ in terms of how the users perceived the multimedia quality. It is likewise assumed that each of these outcomes is mutually exclusive independent and collectively exhaustive. In this thesis, the user perceives quality (i.e., the QoE level) is classified in terms of five satisfaction levels (i.e., there are 5 possible answers). Thus, the user(s) response is considered to be a discrete multinomial distribution. As a consequence, the regression is the probability of each possible outcome. Assuming Y represent the categorical response variable with

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$j = 1, \ldots, J$ ordered classifications. And considering a response variable of QoE given by ordering categories, with higher values belonging to higher user satisfaction (see illustration in equation 5.10).

$$Y = \begin{cases} 1 = & quality\ is\ bad \\ 2 = & quality\ is\ poor \\ 3 = & quality\ is\ fair \\ . & \\ . & \\ . & \\ 5 = & quality\ is\ very\ good \end{cases} \qquad 5.10$$

The probability for the realization of user outcome say $Y = j$, given X, can be defined by the expression $\pi_j(x) = P_r(Y = j|X)$. For $j = 1, 2, \ldots$.,J, and $\pi_j(x)$ is the probability that a score j is rated by human users.

When the scale of a multiple choice outcome is ordinal (i.e., ordered, like the case of Y in equation 5.10 above), rather than nominal, the ordered logit regression also known as the cumulative logic is used to describe the relationship between the outcome and a given set of explanatory variables. Using the ordered logit model or cumulative logit model, one could model the probability that user's score is less or equal to score j (where $j = 1, 2, \ldots$.,J). Assuming, Y is an ordinal variable with categories $j = 1, 2, \ldots$.,J, a number of $J - 1$ logit is established to obtain the cumulative probabilities. Table 5.3, describes the probabilities and cumulative probabilities of each individual j category of the possible QoE outcome.

Table 5.3: Cumulative probabilities of individual j categories

QoE of j Categories	Probabilities	Cumulative Probabilities
1	π_1	$y_1 = \pi_1$
2	π_2	$y_2 = \pi_1 + \pi_2$
$\vdots$	$\vdots$	$\vdots$
$J = 5$	π_J	$y_J = \pi_1 + \cdots + \pi_J$

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This implies that:

$$P(Y \le j) = \pi_1 + \cdots + \pi_j, \quad where\ j = 1, 2, \ldots, J-1 \qquad 5.2$$

And so, the cumulative logit which is the logit of the cumulative probabilities is given by:

$$logit[P(Y \le j|x)] = \ log\left[\frac{P(Y \le j|x)}{1-P(Y \le j|x)}\right] = log\left[\frac{\pi_1(x)+\cdots.+\pi_j(x)}{\pi_{j+1}(x)+\cdots.+\pi_J(x)}\right] \qquad 5.3$$

Given a collection of explanatory variables, the cumulative logit can be used to make prediction for $J-1$. In this case, however, $J-1 = 4$ cumulative probabilities, since $J = 5$ $(i.e.,\ 5\ QoE\ categories)$. Each cumulative logit of the model has its own threshold/intercept (α_j). The threshold α_j, is increasing in j (since $P(Y \le j)$ increases in j for fixed x), and the logit is an increasing function of this probability. Due to the nature of the cumulative logit, each logit for the model have the same effect on the regression coefficient β, but different threshold α_j. All the same, the transformed model is linear in the parameters, which entails that the effects of explanatory variables on the logarithm of the odds are additive (when an outcome is dichotomous, one model the odds, or more specifically, the natural (base e) log of the odds, which is referred to as "logits" of the model distribution) (Wolf, Slate, & Hill, 2015). For a 5 point user opinion scale, the choice and definition of response categories (opinion scale), is either arbitrary or subjective. It is essential that when modelling users' responses, the nature of the users' responses should not be determined by the number of choice or response categories. Such considerations lead to modelling the dependence of the response on the explanatory variables by means of ordered logit model with the proportional odds assumption, where the cumulative probabilities are related to the independent variables through a linear predictor and a link function g. The ordered logit model with the proportional odds assumption also known simply as a proportional odds model. The proportional odds model is a class of generalized linear model (GLzM), which extends logistic regression to handle multiple response variables. The proportional odds model, under the ordinal linear regression framework, provides a more flexible structure to incorporate linear effects, nonlinear effects as well as random effects to construct a more complex model suitable for modelling different data sets. Since there are 5 possible QoE prediction possibilities, the distribution of the user response is therefore considered to be a discrete multinomial distribution. As a consequence, the QoE prediction model is the probability of each possible answer from "very good" to "Bad" computed as a function of the distortion assessment of the QoE factors (i.e., end-to-end QoS parameters plus the human factors). So the collective impact of the end-to-end QoS parameters and the human factors on the variable log(QoE) is linear. Hence, the proportional odds prediction model can be applied to expresses the value of the response variables as a linear function of more than one explanatory variable. This can be expressed empirically as:

$$g(\mu_j) = \alpha_j + \beta_1 x_1 + \cdots + \beta_k x_k \qquad 5.4$$

$where\ \mu_j = P(Y \leq j)\ \ for\ j \geq 2$

The expression in Equation 5.4, extends the logistic regression to allow for a multinomial distribution, as a case of generalized linear model. It predicts variables with various types of probability distributions by fitting the linear predictor function of the above form to some sort of arbitrary transformation of the expected value of the variables.

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5.4 MULTIMEDIA QoE PREDICTION MODEL FORMULATION

The model described in this thesis involves a single response variable Y, known as the dependent variable and six independent variables known as explanatory variables (note: response variable is the QoE predicted value, while the explanatory variables are the QoE influence factors). Suppose there is n population of users (i.e., the size of users whose opinion was to be taken). Let Y_i be a categorical response for observation i with J categories. It is assumed that the observed probability Y_i falls into the jth category with a probability $\pi_{ij},\ where\ j = 1, \dots, J$. Suppose Y_i follows a multinomial distribution with trial size 1, the corresponding probability mass function for Y_i could be expressed as:

$$f\left(Y_i\,; \pi_1, \dots, \pi_J\right) = \pi_{i1}^{y_{i1}} \dots \pi_{ij}^{y_{ij}} \dots \pi_{iJ}^{y_{iJ}}, \sum_{j=1}^{J} \pi_{ij} = 1 \qquad 5.5$$

Where $\left(y_{i1}, \dots, y_{iJ}\right)$ is an indicator vector with $y_{ij} = 1$, if Y_i falls into the jth category and $y_{ij}{}' = 0, for\ any\ j \neq j'$. Therefore, the probability Y_i falling into jth category can be calculated as $P(Y_i = j) = \pi_{i1}^{0} \dots \pi_{ij}^{1} \dots \pi_{iJ}^{0} = \pi_{ij}$**.** Correspondingly. The possibility that the response Y_i falls into lower than or equal to the jth category can be calculated by summing up j mutually exclusive π_{ij} values:

$$P(Y_i \leq j) = P(Y_i = 1) + \cdots + P(Y_i = j) = \pi_{i1} + \cdots + \pi_{ij} \qquad 5.6$$

To build the QoE prediction model under the proportional odds assumption of the ordered logit model, it is essential to connect the probabilities $\left(\pi_{i1}, \dots \pi_{iJ}\right)$ to the explanatory or independent variables $\boldsymbol{x_i}$. Let y_{ij} be a function of probabilities $\left(\pi_{i1}, \dots \pi_{iJ}\right)$, suppose a monotone, differentiable link function $g(.)$ Connects y_{ij} to the linear component $\alpha_j + \boldsymbol{x_i'\beta}$ such that:

$$g^{-1}\left(y_{ij}\right) = g^{-1}\left(P(Y_i \leq j|\boldsymbol{x})\right) = \alpha_j + \boldsymbol{x_i'\beta}, \quad j = 1, \dots, J-1 \qquad 5.7$$

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Where y is the user's opinion score (one of j possible score can be assigned to rate the quality of the multimedia service), j is a specific QoE score, J is the total number of possible user responses (i.e., quality categories, which in this case is 5), $\boldsymbol{x_i}\ is\ k \times n$ vector of the distortion level (i.e., the parameters that collectively affect the QoE), $\boldsymbol{\beta}\ is\ a\ k \times 1$ vector of the model coefficient and g^{-1} Is the normalization function which in this case is the logit link function. The probability $P(Y \leq j|\boldsymbol{x})$ is conditional probabilities that ensure that a user opinion score is not higher than $j = 1, \ldots, J - 1$ with respect to the QoE factors. This generalisation allows a more effective modelling of the five-point scale user opinion score with relaxed requirements on the normality and the scale of the experiment data.

For more flexibility, the QoE responses $y_1, \ldots y_n$, can be written in matrix notation as:

$$g(\mu_i) = g\big(E(y_i)\big) = X_i'\beta \qquad 5.8$$

Where

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix}$$

And the fitted values:

$$\hat{\mu}_{n\times 1} = \begin{bmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \\ : \\ . \\ \hat{\mu}_n \end{bmatrix} = \begin{bmatrix} g^{-1}(\hat{\eta}_1) \\ g^{-1}(\hat{\eta}_2) \\ : \\ . \\ g^{-1}(\hat{\eta}_n) \end{bmatrix} = \begin{bmatrix} g^{-1}\big(x_1\hat{\beta}\big) \\ g^{-1}\big(x_2\hat{\beta}\big) \\ : \\ . \\ g^{-1}\big(x_n\hat{\beta}\big) \end{bmatrix}$$

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Where

$$\boldsymbol{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \text{is the vector of the responses (i.e., the predicted QoE)}$$

$$\boldsymbol{g}[\mathbb{E}(\boldsymbol{Y})] = \begin{bmatrix} g[\mathbb{E}(y_1)] \\ g[\mathbb{E}(y_2)] \\ \vdots \\ g[\mathbb{E}(y_n)] \end{bmatrix}, \text{is the vector of the function of terms } \mathbb{E}(y_i)$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, \text{is the vector of the regression coefficients}$$

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}, \text{is a matrix representing the values of the QoE factors}$$

$\boldsymbol{Y}$ is $n \times 1$ random vector, $\boldsymbol{\beta}$ is a $k \times 1$ vector of the model parameters and $\boldsymbol{x}$ is $k \times n$ matrix values of the QoE factors. For the QoE prediction model in this thesis, k represent the number of QoE factors (i.e., the number of explanatory variables in the model), and n represent the number of observations.

5.4.1 APPLICATION OF THE ORDERED LOGIT REGRESSION IN MODELLING QUALITY OF EXPERIENCE

The proportional odds assumption of the ordered logit model procedure assumes a specific error distribution; therefore a natural way of deriving the values of the unknown parameters is through the maximum likelihood estimation (MLE). The likelihood indicates the chance that the model can predict the observed data (e.g., subjective

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ratings) given the explanatory variables (e.g., the QoE factors). For a QoE response variable (Y) that is of J categories, the Probability for j category is given by $P(Y = j) = \pi_j \quad for\, j = 1, \dots J$. The cumulative probability for Y is the probability that Y falls at or below a particular point. Recall from equation 5.2, for outcome category j, the cumulative probability is $P(Y \leq j) = \pi_1 + \cdots + \pi_j \quad for\, j = 1,2, \dots, J-1$, where $P(Y \leq 1) \leq P(Y \leq 2) \leq \cdots \leq P(Y \leq J) = 1$.To derive the cumulative probabilities for each possible j outcome, given $j = 1,2, \dots, J-1$:

(Note here that the concern is for $j = 1,2, \dots, J-1$ *and not* $j = 1,2, \dots, J$ *because* $y_J = P(Y \leq J)$ *is always* $= 1$*, and so needed not to be included in the probability determination).* Assuming observation Y are statistically independent of each other: Then the odds of the first j cumulative probabilities i:

$$odds\left(P(Y \leq j)\right) = \frac{P(Y \leq j)}{1 - P(Y \leq j)} = \left[\frac{\pi_j}{1-\pi_j}\right] \quad for\, j = 1, \dots, J-1 \tag{5.9}$$

The proportional odds are the log of odds of the cumulative probabilities. And so, the log of cumulative odds or the logit of the sequence of $j = 1, \dots, J-1$ cumulative probabilities can be defined as:

$$L_1 = log\left[\frac{\pi_1}{1-\pi_1}\right] = \log\left(\frac{\pi_1}{\pi_2 + \cdots + \pi_J}\right) \tag{5.10}$$

$$L_2 = log\left[\frac{\pi_2}{1-\pi_2}\right] = \log\left(\frac{\pi_1 + \pi_2}{\pi_3 + \pi_4 \dots + \pi_J}\right) \tag{5.11}$$

$$\vdots$$

$$L_{J-1} = log\left[\frac{\pi_{J-1}}{1-\pi_{J-1}}\right] = \log\left(\frac{\pi_1 + \pi_2 + \cdots \pi_{J-1}}{\pi_J}\right) \tag{5.12}$$

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Note that in the above equation, the last category (i.e., $y = J$) was not included, because being the highest category it will always hold a cumulative probability of 1.0 (as no category falls above it).

For J possible ordinal outcomes, the ordered logit model with the proportional odds assumption makes use of $J - 1$ predictions, each corresponding to the accumulation of probability across successive categories. Thus, given a set of k explanatory variable denoted by a vector $\boldsymbol{x_i}$ ($\boldsymbol{x_i} = x_{i1,}x_{i2,} \dots, x_{ik}$), in order for one to relate the logit to the k explanatory variables, the above cumulative logit (equation 5.10 - 5.12), could be rephrased as:

$$ln\left(\frac{\pi_1}{1-\pi_1}\right) = \alpha_1 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 5.13$$

$$ln\left(\frac{\pi_2}{1-\pi_2}\right) = \alpha_2 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 5.14$$

$$\vdots$$

$$ln\left(\frac{\pi_{J-1}}{1-\pi_{J-1}}\right) = \alpha_{J-1} + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad 5.15$$

And so, the ordered logit model equates the logit transformation to the linear component. In so doing, the following hold for $y_{ji} = P(Y \le j)$ for each unit of i and each category $j = 1,2, \dots, J - 1$

$$P(Y_i \le j|\boldsymbol{x_i}) = \begin{cases} g(\alpha_1 + \boldsymbol{x}_i'\boldsymbol{\beta}) & Y_i = 1 \\ g\left(\alpha_j + \boldsymbol{x}_i'\boldsymbol{\beta}\right) - g\left(\alpha_{j-1} + \boldsymbol{x}_i'\boldsymbol{\beta}\right) & 1 < Y_i \le J - 1 \\ 1 - g\left(\alpha_{J-1} + \boldsymbol{x}_i'\boldsymbol{\beta}\right) & Y_i = J \end{cases} \qquad 5.16$$

Where $g(.)$ is the cumulative logits distribution function

It is assumed here, that the probability of observing a state j of dependent variable y depends on the vector of coefficients $\boldsymbol{\beta}$, associated with the explanatory variables $\boldsymbol{x}$

and the jth threshold values α_j. Assuming the individual pair of y and x is represented by y_i and x_i, then, for every y_i, the probability of observing a particular j state is dependent on x_i. Let represent this reliance with the expression $P(y_i = j|x_i)$. Given this, the cumulative logits associated with the probability that a response falls in jth category can be exponentiated to arrive at the estimated cumulative odds and then utilized to determine the estimated cumulative probabilities (i.e., the predicted probability) (del Pino & Ruiz-Gallardo, 2014), (Christensen, 2014).

$$P(Y_i = 1|\boldsymbol{x_i}) = \frac{exp(\alpha_1+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_1+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} \quad 5.17$$

$$P(Y_i \leq 2|\boldsymbol{x_i}) = \frac{exp(\alpha_2+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_2+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} - \frac{exp(\alpha_1+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_1+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} \quad 5.18$$

$$\vdots$$

$$P(Y_i \leq j|\boldsymbol{x_i}) = \frac{exp(\alpha_j+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_j+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} - \frac{exp(\alpha_{j-1}+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_{j-1}+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} \quad 5.19$$

$$P(Y_i = J|\boldsymbol{x_i}) = 1 - \frac{exp(\alpha_{j-1}+\beta_1 x_{i1}+..+\beta_k x_{ik})}{1+exp(\alpha_{j-1}+\beta_1 x_{i1}+\cdots+\beta_k x_{ik})} \quad 5.20$$

Where α_j Signify the threshold or intercept; $\boldsymbol{\beta}$ is a $k \times 1$ vector representing the coefficients associated with the vector of explanatory variables $\boldsymbol{x_i}$ **(**note: the explanatory variables in this case are the QoE influencing parameters**)**. Under the proportional odds assumption, $\boldsymbol{\beta}$ has the same effects for each $g(y_j)$, but $\boldsymbol{\beta}$ does not depend on j, this implies that the relationship between $\boldsymbol{x}$ and Y is independent of the categories. The model intercept terms vary for each of the equations and satisfies the condition $\alpha_1 < \alpha_2 < \cdots < \alpha_{j-1}$.

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5.4.2 ANALYTICAL DEDUCTION OF THE MAXIMUM LIKELIHOOD

We employ maximum likelihood estimation (MLE) to compute model coefficients and use the Interactive weighted least square method to solve the optimization problem. For the QoE prediction model, since the underlying users opinion is categorical (i.e., user in group i can have a response which falls into one of possible j multinomial categories). Supposing, $y_{ij} = 1$ if user QoE is in level j and 0, if otherwise. And assuming each user QoE level is mutually independent of other users QoE, such that $\boldsymbol{Y}_i = (Y_{i1}, \dots, Y_{iJ})'$, and the J multinomial distribution categories are ordered (it should be noted that $J = 5$ in this case). Assuming also that the multinomial totals for the Y_i is equal to m_i:

$$y_i = (y_{i1}, y_{i2,} \dots, y_{iJ})', \sum_{j=1}^{J} y_{ij} = m_i \qquad 5.21$$

Let r_{ij} be the probability for the jth category of the ith multinomial vector, with $\sum_{j=1}^{J} r_{ij} = 1$, that is:

$$r_i = (r_{i1}, r_{i2}, \dots, r_{iJ})', \sum_{j=1}^{J} r_{ij} = 1 \qquad 5.22$$

Where $= 1, \dots, n, \;\; and\; j = 1, \dots J - 1 \dots$

Then, the likelihood function for observing y_i will be:

$$l_i(\pi_i|y_i) \propto \sum_{j=1}^{J} y_{ij} log(r_{ij} - r_{ij-1}) = \sum_{j=1}^{J-1} y_{ij} log(r_{ij} - r_{ij-1}) + y_{iJ} log[1 - r_{iJ-1}] \quad 5.23$$

Thus

$$\frac{\partial l_i(\pi_i|y_i)}{\partial r_{ij}} = \frac{y_{ij}}{r_{ij} - r_{ij-1}} - \frac{y_{ij+1}}{r_{ij+1} - r_{ij}} = \frac{y_{ij}}{\pi_{ij}} - \frac{y_{ij+1}}{\pi_{ij+1}}$$

$$= \left(\frac{1}{\pi_{ij}} + \frac{1}{\pi_{ij+1}}\right) z_{ij} - \frac{z_{ij-1}}{\pi_{ij}} - \frac{z_{ij+1}}{\pi_{ij+1}}$$

$$= \left(\frac{1}{\pi_{ij}} + \frac{1}{\pi_{ij+1}}\right)\left(z_{ij} - m_i r_{ij}\right) - \frac{\left(z_{ij-1} - m_i r_{ij-1}\right)}{\pi_{ij}} - \frac{\left(z_{ij+1} - m_i r_{ij+1}\right)}{\pi_{ij+1}}$$

Where $z_{ij} = y_{i1} + y_{i2} + \cdots + y_{ij}$.

By introducing the formulation in matrix notation,

$$\frac{\partial \boldsymbol{l}}{\partial \boldsymbol{r}_i} = \boldsymbol{m_i} \boldsymbol{\Gamma_i^-} (\boldsymbol{z}_i - \boldsymbol{m}_i \boldsymbol{r}_i) \qquad 5.24$$

Where

$$\boldsymbol{\Gamma_i^-} = \frac{1}{m_i} \begin{bmatrix} \pi_{i1}^{-1} + \pi_{i2}^{-1} & -\pi_{i2}^{-1} & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ -\pi_{i2}^{-1} & \pi_{i2}^{-1} + \pi_{i3}^{-1} & \pi_{i3}^{-1} & \cdots & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -\pi_{ij}^{-1} & \pi_{ij}^{-1} + \pi_{ij+1}^{-1} & -\pi_{ij+1}^{-1} & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & 0 & -\pi_{ij-1}^{-1} & \pi_{iJ-1}^{-1} + \pi_{iJ}^{-1} & 0 \\ 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 & 0 \end{bmatrix}$$

And

$$z_i = \left[z_{i1} \quad z_{i2} \ldots z_{iJ}\right]'.$$

And so

$$\frac{\partial l}{\partial r} = \boldsymbol{M} \Gamma^- (z - \mu_r)$$

Where

$$\Gamma^- = diag[\Gamma_i^-] = \begin{bmatrix} \boldsymbol{\Gamma_1^-} & 0 & \cdots & 0 \\ 0 & \boldsymbol{\Gamma_2^-} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{\Gamma_n^-} \end{bmatrix} \qquad 5.25$$

$$z = [z_1' \ z_2' \ldots z_n']'$$

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$$\mu_r = [(m_1 r_1)', (m_2 r_2)' \dots (m_n r_n)']$$

It should be noted that:

$$\frac{\partial l_i(\pi_i|y_i)}{\partial r_{ij}} = \frac{y_{ij}}{\pi_{ij}} - \frac{y_{ij+1}}{\pi_{ij+1}} = \left(\frac{y_{ij}}{\pi_{ij}} - \frac{y_{iJ}}{\pi_{iJ}}\right) - \left(\frac{y_{ij+1}}{\pi_{ij+1}} - \frac{y_{iJ}}{\pi_{iJ}}\right)$$

$$= \frac{\partial l_i(\pi_i|y_i)}{\partial \pi_{ij}} - \frac{\partial l_i(\pi_i|y_i)}{\partial \pi_{ij+1}}$$

Expressing the maximum likelihood estimate approach using the proportional odds model

$$log\left(\frac{r_{ij}(x_i)}{1-r_i(x_i)}\right) = \theta_j + x_i\beta \qquad 5.26$$

We can rewrite the model as

$$log\left(\frac{y_{ij}}{1-y_{ij}}\right) = \alpha_j + \boldsymbol{x}_i'\boldsymbol{\beta} \qquad 5.27$$

Where

α_j is the intercept of jth category, $\boldsymbol{\beta}$ is a $k \times 1$ vector of regression coefficient associated with the explanatory variables $\boldsymbol{x_i}$. We can rewrite y_{ij} as a function of the linear components and each probability $\pi_{ij}(\boldsymbol{x_i})$ can be computed as the difference between two adjacent y_{ij} values as:

$$\pi_{ij}(\boldsymbol{x_i}) = y_{ij} - y_{ij-1} = P(y_i \leq j|\boldsymbol{x_i}) - P(y_i \leq j-1|\boldsymbol{x}_i) \qquad 5.28$$

But recall from eq. 5.17

$$P(Y_i \leq j|\boldsymbol{x_i}) = \frac{exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)}{1 + exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)}$$

Therefore

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$$\pi_{ij}(\boldsymbol{x_i}) = \frac{exp(\alpha_j+\boldsymbol{\beta}'\boldsymbol{x_i})}{1+exp(\alpha_j+\boldsymbol{\beta}'\boldsymbol{x_i})} - \frac{exp(\alpha_{j-1}+\boldsymbol{\beta}'\boldsymbol{x}_i)}{1+exp(\alpha_{j-1}+\boldsymbol{\beta}'\boldsymbol{x}_i)} \qquad 5.29$$

For any given category j, the partial derivative of $\pi_{ij}(\boldsymbol{x_i})$ with respect to $\boldsymbol{\beta_j}$ can be derived as:

$$\frac{\partial\pi_{ij}(\boldsymbol{x_i})}{\partial\boldsymbol{\beta_j}} = \boldsymbol{x_{ij}}\left[P(y_i \le j|\boldsymbol{x_i})\left(1 - P(y_i \le j|\boldsymbol{x_i})\right) - P(y_i \le j-1|\boldsymbol{x_i})\left(1 - P(y_i \le j-1|\boldsymbol{x_i})\right)\right]$$

$$= \boldsymbol{x_{ij}}\left[\frac{exp(\alpha_j+\boldsymbol{\beta}'\boldsymbol{x}_i)}{\left(1+exp(\alpha_j+\boldsymbol{\beta}'\boldsymbol{x}_i)\right)^2} - \frac{exp(\alpha_{j-1}+\boldsymbol{\beta}'\boldsymbol{x}_i)}{\left(1+exp(\alpha_{j-1}+\boldsymbol{\beta}'\boldsymbol{x}_i)\right)^2}\right] \qquad 5.30$$

For two extreme categories when $j = 1$ that is $j = minimum$, the intercept $\alpha_{min} = -\infty = \alpha_0 = 0$ this implies that:

$$\frac{exp(\alpha_0 + \boldsymbol{\beta}'\boldsymbol{x_i})}{\left(1 + exp(\alpha_0 + \boldsymbol{\beta}'\boldsymbol{x_i})\right)^2} = 0$$

And when $j = J$, that is when $j = maximum$, the intercept $\alpha_{max} = \infty = \alpha_J = 1$, this also implies that:

$$\frac{exp(\alpha_J + \boldsymbol{\beta}'\boldsymbol{x_i})}{\left(1 + exp(\alpha_J + \boldsymbol{\beta}'\boldsymbol{x_i})\right)^2} = 1$$

Thus

$$\frac{\partial\pi_{iJ}(\boldsymbol{x_i})}{\partial\boldsymbol{\beta_j}} = \boldsymbol{x_{ij}}\left(\frac{exp(\alpha_{J-1} + \boldsymbol{\beta}'\boldsymbol{x_i})}{\left(1 + exp(\alpha_{J-1} + \boldsymbol{\beta}'\boldsymbol{x_i})\right)^2}\right)$$

And

$$\frac{\frac{\partial\pi_{iJ}(\boldsymbol{x_i})}{\partial\boldsymbol{\beta_j}}}{\pi_J(\boldsymbol{x_i})} = \boldsymbol{x_{ij}}\left(\frac{exp(\alpha_{J-1} + \boldsymbol{\beta}'\boldsymbol{x_i})}{1 + exp(\alpha_{J-1} + \boldsymbol{\beta}'\boldsymbol{x_i})}\right)$$

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So therefore, for user i, with $(y_{i1}, \dots y_{ij})$ being the multinomial distribution of the response, where $y_{ij} = 1$ once user opinion is in category j. For mutual exclusive independent observations with respect to the explanatory variable vector $\boldsymbol{x_i}$, the likelihood function for n observation for user i, is determined as in equation 5.31:

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}; \boldsymbol{x}) = \prod_{i=1}^{n} f(\boldsymbol{x}_i; \boldsymbol{\alpha}, \boldsymbol{\beta}) = \prod_{i=1}^{n} \left(\prod_{j=1}^{J} \pi_j(\boldsymbol{x_i})^{y_{ij}} \right) \qquad 5.31$$

Using the proportional odds model, the maximum likelihood estimation can further be written as:

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}; \boldsymbol{x}) = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left(P(Y_i \le j | \boldsymbol{x}_i) \right)^{y_{ij}} \right]$$

$$= \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left(P(Y_i \le j | \boldsymbol{x_i}) - P(Y_i \le j-1 | \boldsymbol{x}_i) \right)^{y_{ij}} \right]$$

Recall from equation 5.2 and 5.29

$$P(y_i \le j | \boldsymbol{x_i}) - P(y_i \le j-1 | \boldsymbol{x}_i) = \pi_{ij}(\boldsymbol{x_i})$$

and

$$\pi_{ij}(\boldsymbol{x_i}) = \frac{exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)}{1 + exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)} - \frac{exp\left(\alpha_{j-1} + \boldsymbol{\beta}'\boldsymbol{x}_i\right)}{1 + exp\left(\alpha_{j-1} + \boldsymbol{\beta}'\boldsymbol{x}_i\right)}$$

Therefore

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}; \boldsymbol{x}) = \prod_{i=1}^{n} \left[\prod_{j=1}^{J} \left(\frac{exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)}{1 + exp\left(\alpha_j + \boldsymbol{\beta}'\boldsymbol{x_i}\right)} - \frac{exp\left(\alpha_{j-1} + \boldsymbol{\beta}'\boldsymbol{x}_i\right)}{1 + exp\left(\alpha_{j-1} + \boldsymbol{\beta}'\boldsymbol{x}_i\right)} \right)^{y_{ij}} \right] \qquad 5.32$$

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The estimation of the model parameters is obtained by setting the above derivatives to zero and solving the resultant equations simultaneously. Unfortunately, there are no closed form solutions for these equations. Thus, the only solutions is by applying numerical optimization methods such as Newton-Raphson method or Fisher' Scoring method, also known as Iterative Reweighted Least Squares (IRLS). In this thesis, we utilize the Iterative Reweighted Least Squares, using the IRLS, the second derivatives of the log likelihood function was derived as follows:

The above equation can be expressed in matrix form as,

$$X'W_t\left(Z_t - X\hat{\beta}_{t+1}\right) = 0 \tag{5.33}$$

Where

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}$$

$$\boldsymbol{W}_t = \begin{bmatrix} w_{t1} & 0 & \cdots & 0 \\ 0 & w_{t2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{tn} \end{bmatrix}$$

And

$$\boldsymbol{Z}_t = \begin{bmatrix} z_{t1} \\ z_{t2} \\ \vdots \\ z_{tn} \end{bmatrix}$$

Then the maximum likelihood estimate at the $(t+1)'th$ interaction is

$$X'W_tZ_t = X'W_tX\hat{\beta}_{t+1} \Leftrightarrow \hat{\beta}_{i+1} = (X'W_tX)^{-1}\, X'W_tZ_t \tag{5.34}$$

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Note that $\hat{\beta}_{t+1}$ can be thought as weighted least squares estimate with weight matrix W_t and covariate X and the response vector Z_t. Therefore, $\hat{\beta}_t, t = 0.1, 2, \dots, n$ can be generated by

$$\hat{\beta}_1(X'W_tX)^{-1}X'W_0Z_0$$

$$\hat{\beta}_2(X'W_tX)^{-1}X'W_1Z_1$$

$$\vdots$$

$$\hat{\beta}_{t+1}(X'W_tX)^{-1}X'W_tZ_t$$

$$\vdots$$

The weight matrix W_t is reweighted (i.e., changed) at each iteration. Thus, $\hat{\beta}_t, t = 0.1, 2, \dots, n$, can also refer to as iterative reweighted least squares estimation.

We can proceed by initially assigning some value to β,

$$\hat{\beta}_0 = [\hat{\beta}_{01}\ \hat{\beta}_{02} \dots . \hat{\beta}_{0k}]'$$

Then

$$\hat{\eta}_{0i} = \hat{\beta}_{01}x_{i1} + \hat{\beta}_{02}x_{12} + \dots + \hat{\beta}_{0k}x_{ik}, \ \ \hat{\mu}_{0i} = [g^{-1}(\eta_i)]_{\beta=\hat{\beta}_0} = g^{-1}(\hat{\eta}_{0i}) \qquad 5.35$$

$$z_{0i} = \hat{\eta}_{0i} + \left[(y_i - \hat{\mu}_{0i})\frac{\partial \eta_i}{\partial \mu_i}\right]_{\beta=\hat{\beta}_0} = \hat{\eta}_{0i} + (y_i - \hat{\mu}_{0i})\left(\frac{\partial \eta_i}{\partial \mu_i}\right)_{\beta=\hat{\beta}_0} \qquad 5.36$$

The interactive weight can then be derived as:

$$w_{0i} = \left[\frac{1}{V_i\left(\frac{\partial \eta_i}{\partial \mu_i}\right)^2}\right]_{\beta=\hat{\beta}_0} = \left[\frac{1}{b''(\theta_i)\left(\frac{\partial \eta_i}{\partial \mu_i}\right)^2}\right]_{\beta=\hat{\beta}_0} = \frac{1}{b''(\hat{\theta}_{0i})}\left[\frac{1}{\left(\frac{\partial \eta_i}{\partial \mu_i}\right)^2}\right]_{\beta=\hat{\beta}_0}$$

Where

$$b^{i}(\theta_i) = \mu_i \Leftrightarrow \theta_i = (b')^{-1}(\mu_i)$$

$$\hat{\theta}_{0i} = [(b')^{-1}(\mu_i)]_{\beta=\hat{\beta}_0} = (b')^{-1}(\mu_{0i})$$

Therefore

$$Z_0 = \begin{bmatrix} z_{01} \\ z_{02} \\ \vdots \\ z_{0n} \end{bmatrix}, \quad W_0 = \begin{bmatrix} w_{01} & 0 & \cdots & 0 \\ 0 & w_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{0n} \end{bmatrix} \qquad 5.37$$

And

$\hat{\beta}_1(X'W_0X)^{-1}X'W_0Z_0$, Can be generated.

Following this same procedure $\hat{\beta}_t,\ t = 2, \ldots, n$ can also be generated.

5.5 DEVELOPING THE MULTIMEDIA QOE PREDICTION MODEL

The procedure of estimating the parameters of ordinal logistic regression analysis is very complex. However, in this day and age, the complexity can easily be managed using a computer program. At present, there are numerous software packages capable of fitting ordinal regression models. Software such as: SAS, MATLAB, R, etc. However, in this thesis, the QoE prediction model was developed using the Polytomous Universal Model (PLUM) procedure available in IBM Statistic Package for Social Science (SPSS) software package version 22 (Meyers, Gamst, & Guarino, 2013). PLUM is capable of fitting different types of ordinal models, as it provides opportunity for one to specify any of five different link functions, as well as scaling parameters. Since the data in this study are ordinal, the logit link function was chosen to run the ordinal regression analyses. The default and currently the only optimization method implemented in the

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PLUM function is the Fisher Iterative Reweighted Least Square (IRLS). And thus, the model parameters were estimated using the IRLS inbuilt in the PLUM function of the SPSS ordinal regression procedure. Based on the data as described in section 5.2, the regression to be estimated is:

$$Y_{ij} = \alpha_j + \beta_1 \text{E2E Delay}_i + \beta_2 \text{E2E Packet loss}_i + \beta_3 \text{E2E Throughput}_i + \beta_4 Gender_i + \beta_5 \text{Social Context}_i + \beta_6 \text{Bite Rate}_i + \beta_7 \text{Frame Rate}_i + \varepsilon_i \quad 5.38$$

The coefficient (β) in front of each independent variable determines the strength and direction of correlation between the explanatory variables and dependent variable Y (these coefficients generally are not known, but their values can be estimated using a regression analysis). α_j is called the intercept term (i.e., the value of Y at the point where all the independent variables are equal to zero). And ε_i, is known to be the error term, which specifies the stochastic variation. However, when dealing with order categorical data, ε_i is assumed to be logistically distributed across all observations. Specifically, in this thesis, ε_i is considered to be a random variable with cumulative distribution g, where $g(Y) = e^Y/1 + e^Y$. Let represent the explanatory variables as:

x_1 = E2E Delay

x_2 = E2E Packet loss

x_3 = E2E Throughput

x_4 = Gender

x_5 = Social Context

x_6 = Bite Rate

$x_7 = Frame\ Rate$

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Where

$$x_4 = \begin{cases} 1 & \textit{if} \text{ gender is female} \\ 0 & \textit{if otherwise} \end{cases} \quad 5.39$$

$$x_5 = \begin{cases} 1 & \textit{if} \text{ social context is group} \\ 0 & \textit{if otherwise} \end{cases} \quad 5.40$$

The human and contextual aspect of the QoE factors are intrinsically nominal (i.e., made up of two categories, but do not have any intrinsic order). Therefore, the nominal variables are evaluated solely in terms of whether the individual users belong to certain distinct category or not (e.g., female or male and group or single users). Thus, the equation that links each QoE response Y_i and the set of distortion as a result of the QoE factors (i.e., the explanatory variables) $x_1, x_2, \ldots., x_7$ has the form of:

$$g^{-1}[P(Y_i \leq j|\boldsymbol{x}_i)] = logit[P(Y \leq j|x)] = \alpha_j + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \quad 5.48$$

$$For\ j = 1, 2, \ldots. J - 1 \quad and\ i = 1, \ldots, n. \quad where\ J = 5, \text{k} = 7 \text{ and n} = 200$$

The letter i represent individuals (i.e., the users) while the latter J represent the QoE categories, g^{-1} is a logit link function which transforms the cumulative probability of the QoE rating to be at or below a given categorical level; $j = 1, \ldots \ldots J - 1$, indicates the user perception level. α_j is the threshold of jth category, condition on the level of each user perception level j; $\beta_1, \beta_2, \ldots, \beta_7$ are the regression coefficients of the respective explanatory variables, they are estimated by the maximum likelihood method. As could be observed, the $\beta's$ do not have j subscript, this is because β has the same effect on x for each of the $j = 1, \ldots, J - 1$ cumulative logits and do not depend on the number of response categories (proportional odds assumption) (Thomas, 2014). x_1, x_2, x_3, x_6, x_7 are the covariates or continuous variable (i.e., the end-to-end QoS parameters); while x_4 and x_5 are factors defined for the human and contextual QoE components (i.e., the qualitative QoE factors). Eq. 5.48, postulates that at the point

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$(x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, x_{i6}, x_{i7})$, (i.e., the ith row of the data matrix), the expected value, which in this case is the QoE prediction or opinion score is equal to the linear function of the six explanatory variables (note: explanatory variables are the QoE influence factors, see chapter 4 for details). In vector form, the explanatory variables describing observation i can be expressed as $\boldsymbol{x}_i$, the effect of $\boldsymbol{x_i}$ is the same for all $j-1$. $\boldsymbol{\beta}_k$ is a vector of weighs (or regression coefficients) corresponding to the number of parameters k, the effects of β is invariant to the choice and number of response categories. While, $(\boldsymbol{y}_{ij},)$ is the score associated with assigning observation i to category j. In discrete choice theory, observations usually represent individuals and outcomes represent choices (Train, 2009). Therefore, the QoE scores in this thesis are assumed to be the utility associated with person i choosing outcome j (by utility, we mean user perception/satisfaction).

When SPSS is used to estimate the effects of explanatory variables on the odds of being at or below a certain category, the effects of explanatory variables are subtracted from the thresholds instead of adding as used in equation 5.17 – 5.20 and equation 5.45. This is done so that the sign of the coefficient will have the usual meaning (i.e., if the derived coefficients are positive, the increase in x will be associated with the probability of increase in y and if they are negative, the increase in x will be associated with the probability of decrease in y) (Elliott & Woodward, 2015). Since SPSS is the statistic software used in this thesis to estimate the regression coefficients, the cumulative probability given in equation 5.17 is now rephrased as:

$$P(Y_i = 1|\boldsymbol{x_i}) = \frac{exp[\alpha_j - (\beta_1 x_{i1} + .. + \beta_k x_{ik})]}{1 + exp[\alpha_j - (\beta_1 x_{i1} + .. + \beta_k x_{ik})]} \qquad 5.49$$

Thus, the probability of the outcome being j can be computed by taking the differences between the cumulative probabilities:

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For $j = 2, .., 4$

$$P(Y_i = j|\boldsymbol{x_i}) = \frac{exp[\alpha_j-(\beta_1 x_{i1}+..+\beta_k x_{ik})]}{1+exp[\alpha_j-(\beta_1 x_{i1}+..+\beta_k x_{ik})]} - \frac{exp[\alpha_{j-1}-(\beta_1 x_{i1}+..+\beta_k x_{ik})]}{1+exp[\alpha_{j-1}-(\beta_1 x_{i1}+..+\beta_k x_{ik})]} \qquad 5.50$$

And for $j = 5$ (i.e., $j = J$)

$$P(y_i = J|\boldsymbol{x_i}) = 1 - \frac{exp[\alpha_{J-1}-(\beta_1 x_{i1}+..+\beta_k x_{ik})]}{1+exp[\alpha_{J-1}-(\beta_1 x_{i1}+..+\beta_k x_{ik})]} \qquad 5.51$$

Since the likelihood of the ith observation depends on the particular value of j that is being observed. Then, for each j value of the ordered response, the product of all observations for which $y_i = j$ is taken and the likelihood is determined using equation 5.52:

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}; \boldsymbol{x}) = \prod_{i=1}^{200}\prod_{j=1}^{5}\left(P(y_i \leq j|\boldsymbol{x}_i)\right)^{y_{ij}} \qquad 5.52$$

Where $y_{ij} = 1$ if $y_i = j$, and 0 if otherwise. The y_{ij} define a set of J dummy variables. And for the cumulative logit model, the log-likelihood is expressed in terms of the model quantities:

$$logL = Log_e P(Y_1, \dots, Y_J) = \sum_{i=1}^{200}\sum_{j=1}^{5} y_{ij} log\left[g\left(\alpha_j + \boldsymbol{\beta x_i'}\right) - g\left(\alpha_{j-1} + \boldsymbol{\beta x_i'}\right)\right] \qquad 5.53$$

The slope coefficient vector $\boldsymbol{\beta}$ are identical for each of the $J-1$ cumulative logits, but the intercept differs. And due to the ordinal nature of the QoE response, the slope coefficient vectors $\boldsymbol{\beta}$ is interpreted as, the change in the logarithm of an odds ration (i.e., the cumulative odds ratio for a unit change in its associated QoE factors). The value of $\alpha_1, \dots, \alpha_{J-1}$ and $\boldsymbol{\beta}$ that maximize the $Log_e P(Y_1, \dots, Y_J)$ was then determined using the SPSS statistic software.

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5.5.1 CHECKING FOR OUTLIERS AND MULTICOLLINEARITY

Before constructing the model, a frequency analysis and normal probability plot was carried out to visually inspect the pattern of the data distribution and to check if there exist any outliers that could affect the result of the regression analysis. The findings, as shown in figure 5.10A, 5.10B, 5.10C, 5.10D and 5.10E, show no sign of outliers. However, the S-like shape pattern made by the data around the baseline is an indication that the data are not normally distributed. This result further supports the choice of using ordinal logistic regression for the development the QoE prediction model.

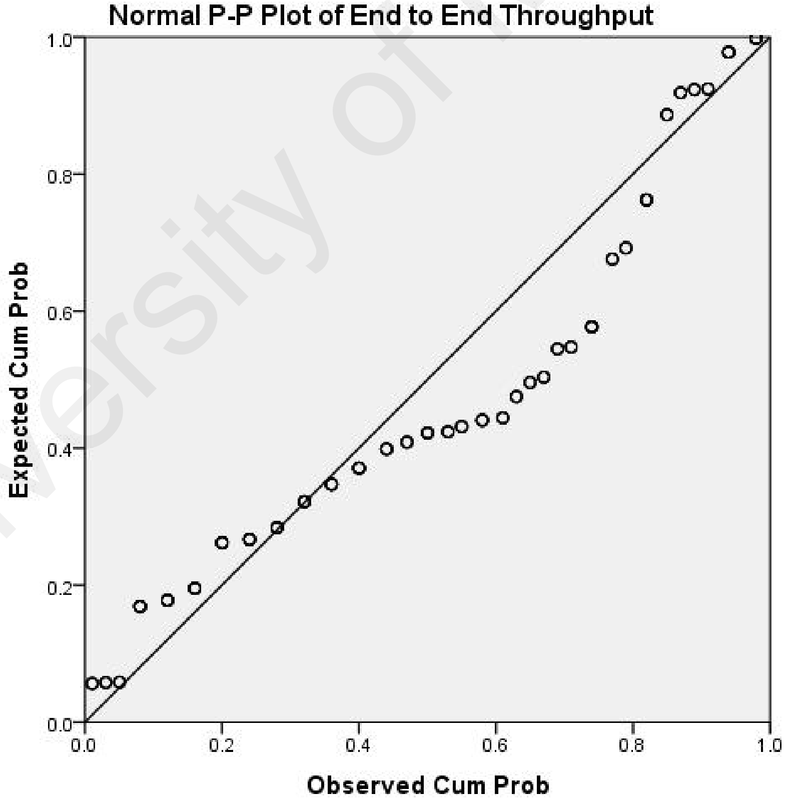

Figure 5.10A: Normal P-P Plot of End to End throughput

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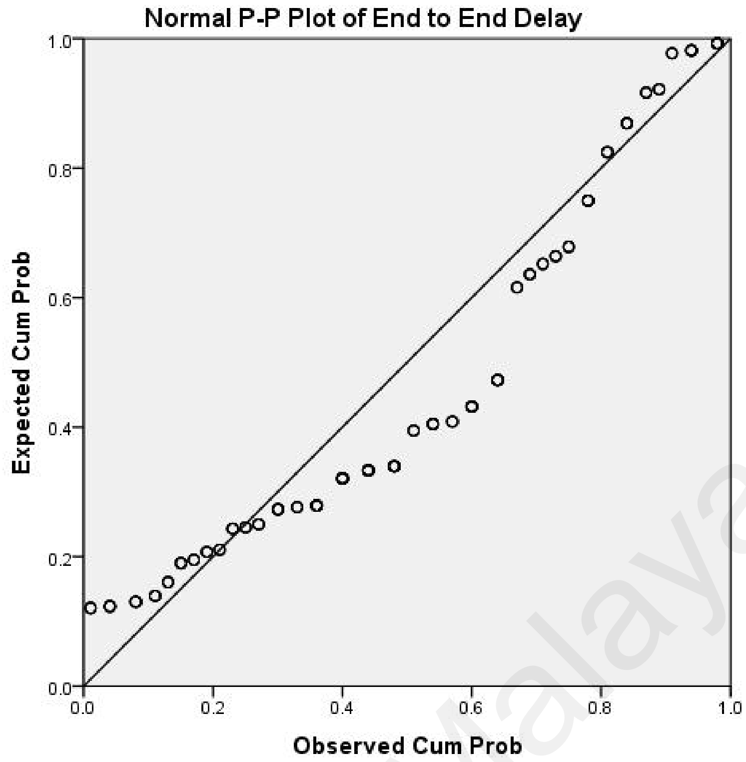

Figure 5.10B: Normal P-P Plot of End to End Delay

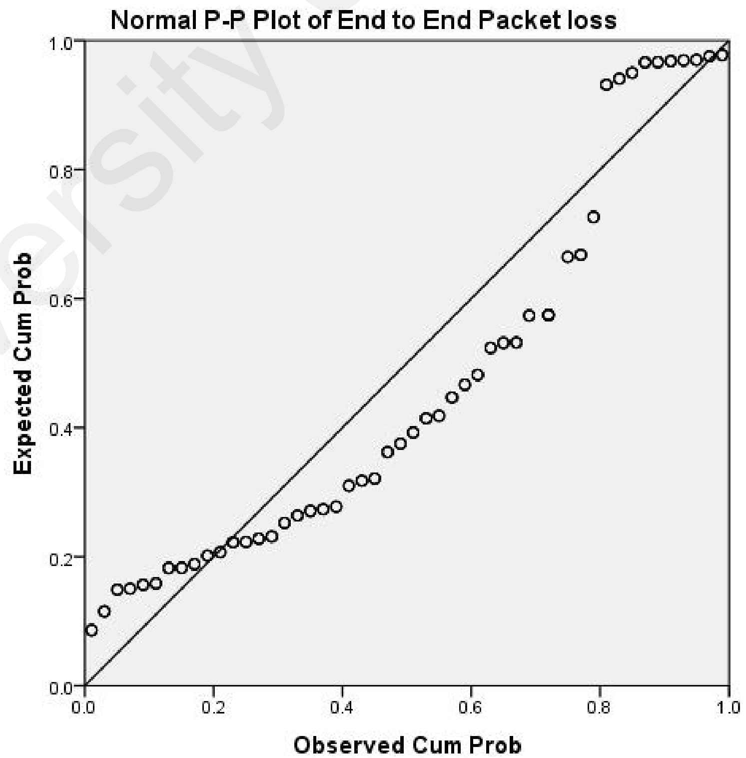

Figure 5.10C: Normal P-P Plot of End to End packet loss

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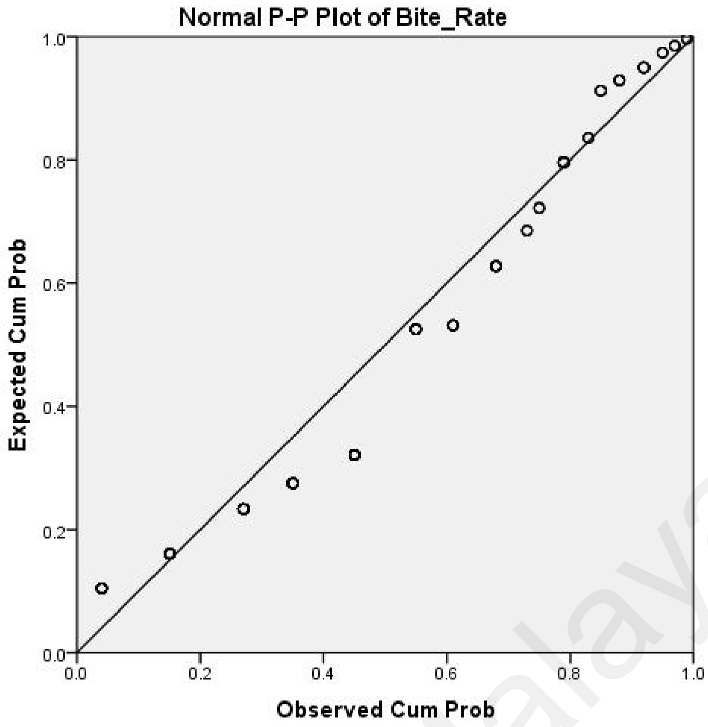

Figure 5.10D: Normal P-P Plot of bite rate

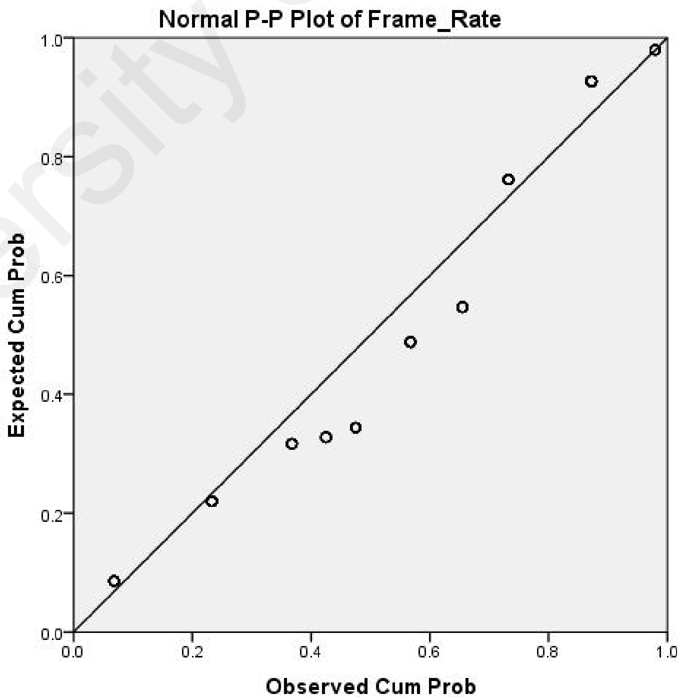

Figure 5.10E: Normal P-P Plot of frame rate

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Furthermore, a test of multicollinearity amongst the independent variables was also conducted, where the tolerance and the variance inflation factor (VIF) values were examined. The result for the Tolerance and VIF are shown in table 5.4. As could be observed in the table, the results of the test show very high tolerance values for all the explanatory variables, all the values are greater than 0.2 (see tolerance in section 3.4.2). On the other hand, the VIF values of all the explanatory variables are all relatively small; with each individual value less than 2.5 (see VIF in section 3.4.2). The results in table 5.4 clearly do not present any evidence of multicolinearity amidst the explanatory variables in the model.

Table 5.4: Tolerance and the variance inflation factor

Model		Collinearity Statistics	
		Tolerance	VIF
1	End to End Throughput	.533	1.877
	End to End Delay	.727	1.376
	End to End Packet loss	.697	1.435
	Gender	.839	1.191
	Social_Context	.830	1.205
	Bite_Rate	.450	2.224
	Frame_Rate	.516	1.937

5.5.2 TEST OF OVERALL MODEL FIT

Before proceeding with the analysis of the effects of the model explanatory variables, there is the need to verify the overall model fit (i.e., the significance of the model coefficients). This is to find out whether the inclusion of the explanatory variables improves the ability of the model to predict the QoE level outcomes or not. This was done by comparing the log-likelihood (LL) value of the intercept only model (i.e., a model without the explanatory variable), against the general or final model (i.e., a model that includes all the explanatory variables). The chi-square likelihood ratio test,

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based on -2LL ratio is applied to assess the significance of the overall model fit. A good fitting model will exhibit a p-value ≤ 0.05 (Dodge, 2014), allowing for the rejection of the null hypothesis that the model without predictors is as good as the model with predictors. Table 5.5 reveals that chi-square statistics are significant ($p - value = 0.000$. The significant Chi-Square statistic indicates that the general model provides a substantial improvement over the baseline intercept-only model. This essentially proves that the model will produce a better prediction than when one just guessed based on the marginal probabilities of the outcome categories. This is a good sign, however, what one should really be more concern with is knowing how much better by evaluating the observed data to test how consistence the observed data is with the fitted model (see table 5.6 for Significance of Model parameters).

Table 5.5: Model fitting information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	643.775			
Final	130.412	513.363	7	.000

5.5.2.1 SIGNIFICANCE OF MODEL PARAMETERS

To assess the contribution the individual explanatory variable made to the fitness of the model (i.e., the significance of the mode parameter). The Wald statistic was used in this thesis to test the significance of the QoE prediction model. Wald statistics is the ratio of the square regression coefficient to its standard error and is asymptotically distributed as a chi-square distribution (Agresti, 2013). Going by the result obtained after the test (as shown in table 5.6), the result attests that the model parameters are all relevant to be included in the model design. As could be observed in the table, all the explanatory variables are shown to be highly significant (i.e., the p-values of the variables are less than 0.05).

Table 5.6: Test for the effects of model parameters

Source	Type III		
	Wald Chi-Square	df	Sig.
Throughput	29.883	1	.000
Delay	41.414	1	.000
Loss	42.574	1	.000
Bite_rate	15.292	1	.000
Frame_Rate	15.053	1	.000
Gender	23.949	1	.000
Social_Context	11.485	1	.001

5.5.3 ESTIMATION OF THE MODEL COEFFICIENTS

The parameter estimates as shown in table 5.7, specifically offers vital information regarding the relationship that exists between the explanatory variable and the dependent variable (i.e., the QoE level). The part labelled threshold in table 5.7, is the section that holds the information regarding the regression constant also known as "cut point or threshold" (α_j). The cut point depend only on the probability of the category which is being predicted, as such, the value of the explanatory variable does not affect the threshold part of the model. There are four thresholds in this model, each representing the cutpoint of the four QoE categories (the ordered logit model estimate $J - 1$ cumulative probabilities, and there are 5 QoE categories, hence, $5 - 1 = 4$). The estimate labelled location is the section that hold the information regarding the coefficients of the model explanatory variables. That is the coefficients for: throughput, delay, loss bite rate, frame rate, social context and gender. As shown in table 5.7, the coefficients for all the parameters appear to be highly significant, which shows that they all have significant influence in the prediction of the user quality perception (i.e., the

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result of the QoE prediction model outcome). As could be noted in the table, the parameters; throughput, bite rate and frame rate, all has positive coefficient. This means that a positive relationship exists between these three parameters and the ordinal outcome (i.e., the QoE levels). A positive relationship implies that an increase in any of the three parameters will lead to an increase in the probability of user rating being at the higher QoE levels. Delay and loss on the other hand has a negative relationship with the ordinal outcome, therefore, an increase in any of the two parameters will result in poorer QoE. In other word, an increase in throughput, bite rate and frame rate will increase the probability of better quality perception (i.e., the probabilities of users' quality perception to be at the categories of "Good" and Very Good" is on the increase), while an increase in loss or delay will decrease the probability of good quality perception (i.e., the probabilities of users' quality perception to be at the lower categories such as "Poor" or "Bad" increases). For gender, male compared to female has a higher probability of perception rating to be in the lower QoE categories. The same is applicable to social context, since the two factors presented to all have a negative $\beta's$ values (i.e., the β of all the two factors are negative, which suggests their individual odds ration values is less than one) (Keith, 2014). Furthermore, by taking the exponential (i.e., the odds ratio) of the estimated coefficient of each individual parameter in table 5.7, the degree at which the individual factor affects the QoE can be determined. For example a unit gain in throughput will result in an increment in the odds of users' perception rating to be at a higher category of the QoE level by 1.256 ($i.\ e.,\ exp.(0.228) = 1.256$). On the other hand, a unit increase in packet loss will result in an increment in the odds of users' perception rating being in a lower category of the QoE level by 0.523 ($i.\ e.,$ $exp.(-0.649) = 0.523$).

Table 5.7: Model parameter estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[QoE = 1]	-18.042	2.916	38.276	1	.000	-23.757	-12.326
	[QoE = 2]	-8.611	1.698	25.707	1	.000	-11.939	-5.282
	[QoE = 3]	-3.188	1.343	5.634	1	.018	-5.820	-.555
	[QoE = 4]	4.841	1.661	8.492	1	.004	1.585	8.097
Location	Throughput	.228	.042	30.173	1	.000	.147	.309
	Delay	-6.374	.992	41.272	1	.000	-8.319	-4.430
	Loss	-.649	.099	42.671	1	.000	-.844	-.454
	Bite_rate	.014	.004	15.366	1	.000	.007	.021
	Frame_Rate	.254	.065	15.128	1	.000	.126	.382
	Gender	-3.216	.653	24.242	1	.000	-4.496	-1.936
	Social_Context	-1.741	.515	11.427	1	.001	-2.751	-.732

5.6 MODEL EVALUATION

The evaluation of model adequacy is an essential step of the modelling process, because it ascertain how good a model fits the purpose for which it is being planned. It is constantly necessary to examine a regression model to assure that it offers an adequate approximation to the true system and to also verify that none of the regression assumptions are broken. The most important diagnostic technique in determining model adequacy is to examine its goodness of fit (i.e., how well the model conforms to the given data).

5.6.1 MODEL GOODNESS OF FIT

The Goodness-of-fit of a model, is a test used to evaluate how good a model describes the dependent variable in the model, it involves the examination of the model to see how near the values predicted by the model are to the observed values. In practice the goodness of fit provides crucial information on how the model's output resembles the observed data from an experimentation. It is also a useful tool for examining the

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effectiveness of the model design. Pearson Chi-Square and Deviance goodness of fit statistics are two most common methods used in the literature (Lee, 2013), (Bhattacharyya & Bandyopadhyay, 2014), (Perera, Sooriyarachchi, & Wickramasuriya, 2014), to determine whether the observed data are well recognised by the fitted model. These statistics are intended to test whether the observed data are inconsistent with the fitted model. If they are not (i.e., if the p-values are large), then one could conclude that the data and the model predictions are similar, which implies that the model adequately fit the observed data. Table 5.8, shows the result obtained from SPSS for the goodness-of-fit test, the table contains information regarding the Pearson's Chi-square statistic and the Chi-square statistic based on Deviance. As could be observed from the table, the Chi-Square values for both the Pearson and the Deviance are high, with the Pearson equal to 177.032 and Deviance equal to 130.412. Both are equally significant ($i.e., each\ having\ the\ P - value\ =$ 1.000). This outcome indicates that the QoE prediction model could be considered as rationally good.

Table 5.8: Model goodness of fit

	Chi-Square	df	Sig.
Pearson	177.032	561	1.000
Deviance	130.412	561	1.000

5.6.1.1 PSEUDO R-SQUARE

As could be observed in table 5.9, all the three pseudo R-square are relatively high, with the Nagelkerke's R-square being 0.962, indicating that approximately 96.2% of the variation is explained by the estimated model.

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Table 5.9: Pseudo R-square

Cox and Snell	.923
Nagelkerke	.962
McFadden	.797

5.6.1.2 TEST FOR THE ASSUMPTION OF PROPORTIONALITY

Using the SPSS PLUM, the test for parallel line assumption was carried out, and the result is shown in table 5.10. The row labelled null hypothesis in table 5.10, contains -2 log-likelihood (-2LL) values for the constrained model (i.e., the model that assumes the lines are parallel), while the row labelled General contains -2LL value of the full model. The column labelled Chi-square shows the value of the difference between the -2LL of the Null Hypothesis and the General. If the lines or planes are parallel, the observed significance for the change will be high (i.e., greater than a p-value of 0.05) (Dolgun & Saracbasi, 2014), (Weisburd & Britt, 2014). As could be noted in the table, the test for parallel assumption is reasonable, the result shows a non-significant evidence ($P - value\ =\ 1.000 > 0.05$), indicating that the odds are proportional across the response variable. Hence, the proportional odds assumption is satisfied for the QoE prediction model. Therefore, the null hypothesis that the lines are parallel is upheld, since the result in the table suggested that the model's assumption of parallel lines is not violated in the complete model.

Table 5.10: Test for the assumption of proportional odds

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	130.412			
General	129.974	.438	21	1.000

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5.7 MODEL VALIDATION

Model validity refers to the stability and the rationality of the regression coefficients, the acceptability and usability of the fitted model function, and the ability to generalize inferences drawn from the statistical analysis. As stated earlier in chapter three (section 3.6.1 – 3.6.3), the proposed QoE model was evaluated using two steps. The foremost measure is aimed at estimating the accuracy of point estimates of the prediction model. This first measure is conceptually divided into two: discrimination and calibration. The second step involved the determination of the stability and generalizability of the model using the bootstrapping approximation procedure.

5.7.1 CALIBRATION

Table 5.11, shows the classification accuracy of the predicted categories and the observed QoE categories. The row represents the predicted response category, while the column represents the observed category. The diagonal element represents the correct classification cases (showed in percentage), whereas the off-diagonal elements represent misclassifications. As could be observed from the table the overall accuracy of the model is 98% that is $(100 + 95 + 97.5 + 97.5 + 100)/5 = 98\%$). The crosswise of the table indicates the percentage of accurate predictions. To further show the level of the model accuracy, a histogram of the percentage of classification error was also obtained. Figure 5.11A, illustrates the correctly classified cases, as well as the wrongly classified cases. As could be observed in the chat, category 5 and 1 has all their cases successfully and correctly classified (i.e., 100% with no error). Category 2, correctly classified 38 cases out of 40 cases (i.e., 95% of cases in categories 2 were predicted correctly, 5% wrongly classified). Category 3 and 4, correctly classified 39 cases out of 40 cases (i.e., 97.50% of cases in categories 3 and 4 were predicted correctly, only

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2.5% were wrongly classified). The relatively low classification error exhibited by the model indicates that the model fits the data adequately well. Consequently, figure 5.11B presents a graphical representation of the estimated classification probability of the predicted category versus estimated classification of the probability of the observed QoE category. As shown in the graph, the trends among the various levels were in agreement. The compliance between the predicted QoE response category with the observe values was also checked, a quantile-quantile probability plot (Q-Q plot) was employed to determine whether the QoE cumulative predicted response categories approximates the observed cumulative category adequately. Figure 5.12A and 5.12B shows the result obtained from the Q-Q plot. As could be observed in the figures (i.e., 5.12A and 5.12B), the plotted points of the two cases exhibit similar patterns of data distribution and they all fit the baseline with no distinct deviance. The fact that the observe QoE frequency and the predicted probabilities are in agreement over the entire range, further ascertained the reliability of the predictive capability of the fitted QoE prediction model.

Table 5.11: Cross tabulation of predicted QoE categories with the actual QoE categories

			Predicted Response Category					
			QoE is Bad	QoE is Poor	QoE is Fair	QoE is Good	QoE is Very Good	Total
Quality of experience	QoE is Bad	Count	40	0	0	0	0	40
		% within Quality of experience	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	QoE is Poor	Count	1	38	1	0	0	40
		% within Quality of experience	2.5%	95.0%	2.5%	0.0%	0.0%	100.0%
	QoE is Fair	Count	0	1	39	0	0	40
		% within Quality of experience	0.0%	2.5%	97.5%	0.0%	0.0%	100.0%
	QoE is Good	Count	0	0	1	39	0	40
		% within Quality of experience	0.0%	0.0%	2.5%	97.5%	0.0%	100.0%
	QoE is Very Good	Count	0	0	0	0	40	40
		% within Quality of experience	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%
Total		Count	41	39	41	39	40	200
		% within Quality of experience	20.5%	19.5%	20.5%	19.5%	20.0%	100.0%

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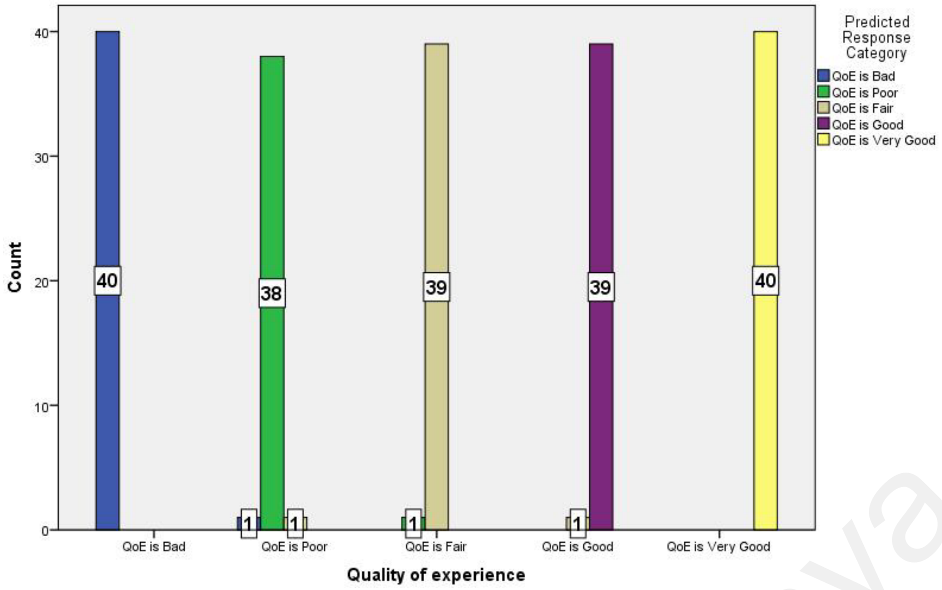

Figure 5.11A: Percentage of predicted error

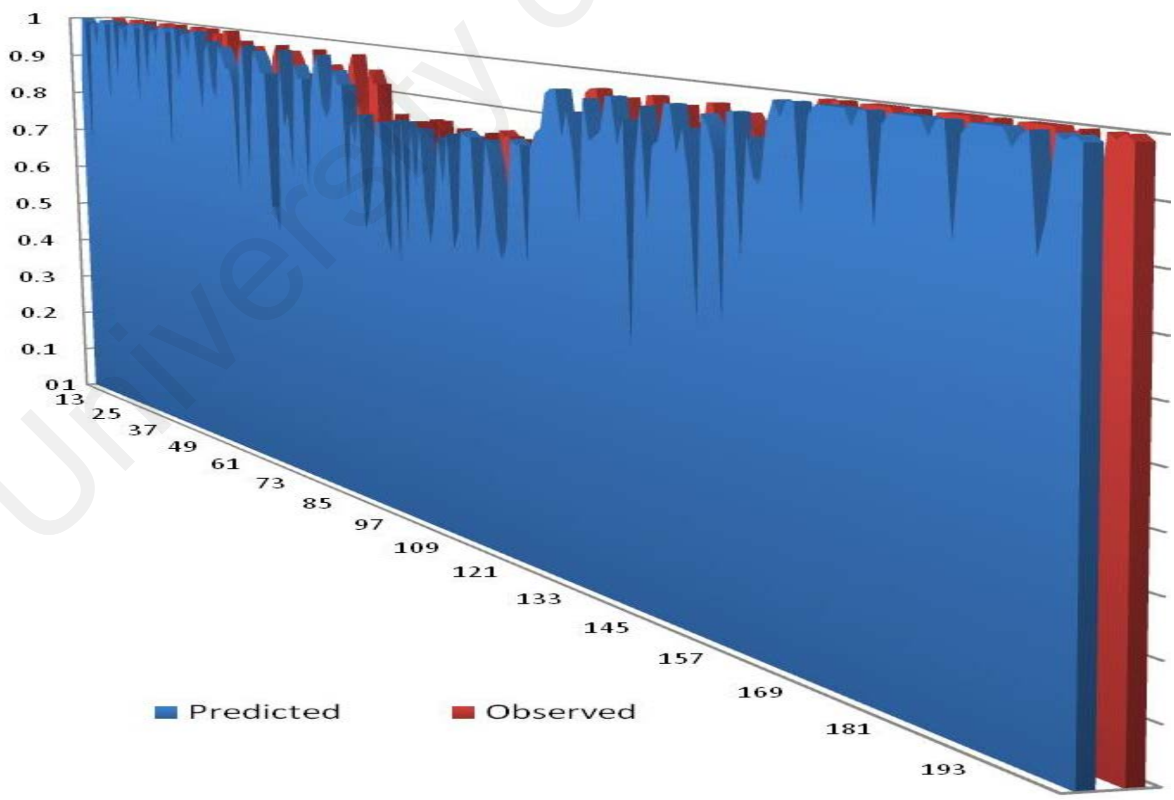

Figure 5.11B: Estimated classification of predicted QoE VS estimated classification of Observed QoE

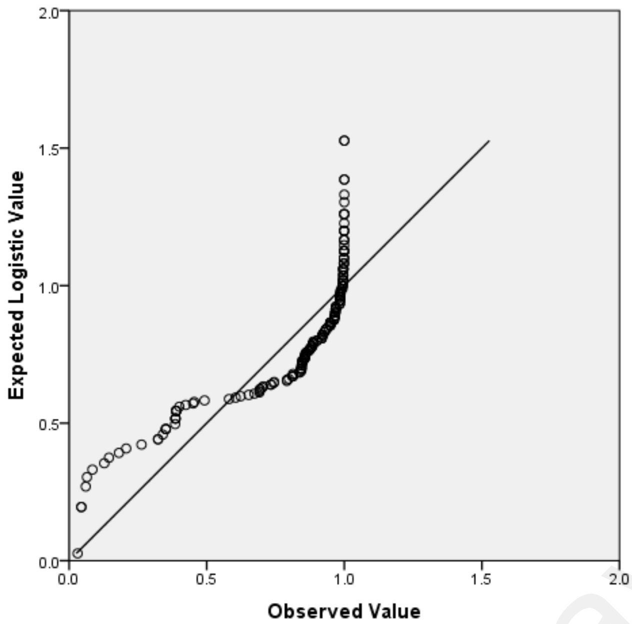

Figure 5.12A: Logistic Q-Q Plot of estimated classification probability for the QoE category

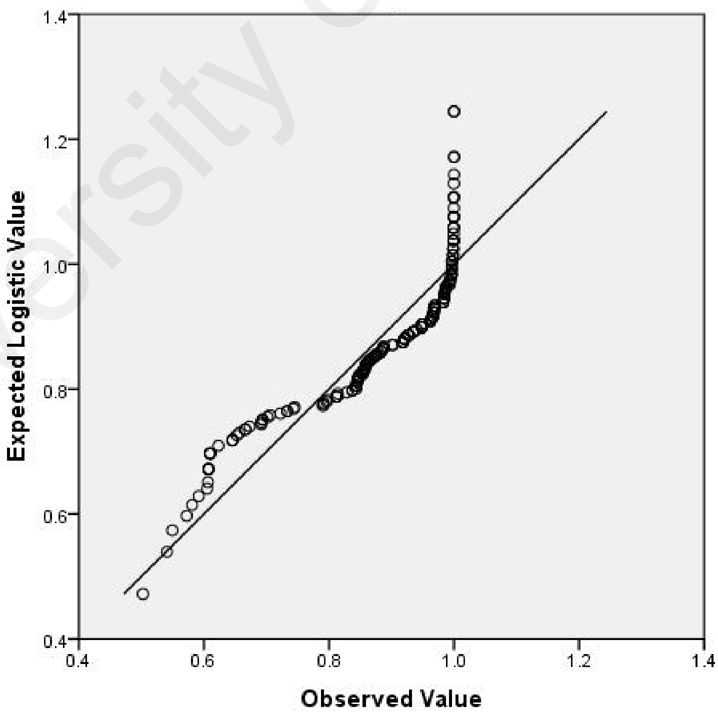

Figure 5.12B: Logistic Q-Q Plot of estimated classification probability for the predicted QoE category

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5.7.2 DISCRIMINATION

Figure 5.13A up to 5.13E shows the discriminatory ability of the QoE prediction model. As could be noted in the figure, the model was able to distinguish between category with the highest predicted probability value over the ones with lower predicted probability values. For example, in figure 5.13A, when QoE is bad, the model was able to establish the distinction among the QoE category, as shown in the figure, the QoE category 1 is shown to have the highest estimated cell frequency compared to the rest four QoE categories. This discriminating ability of the model may well be observed in figure 5.13B, 5.13C, 5.13D and 5.13E, for response category 2, 3, 4 and 5 respectively.

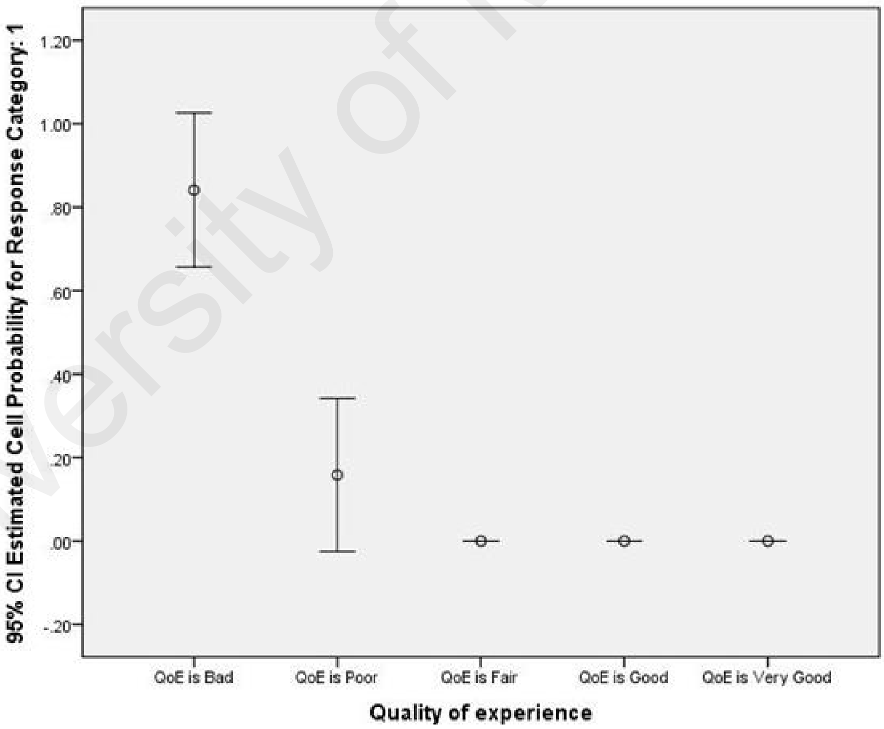

Figure 5.13A: Discriminating ability of QoE category rating equal to one

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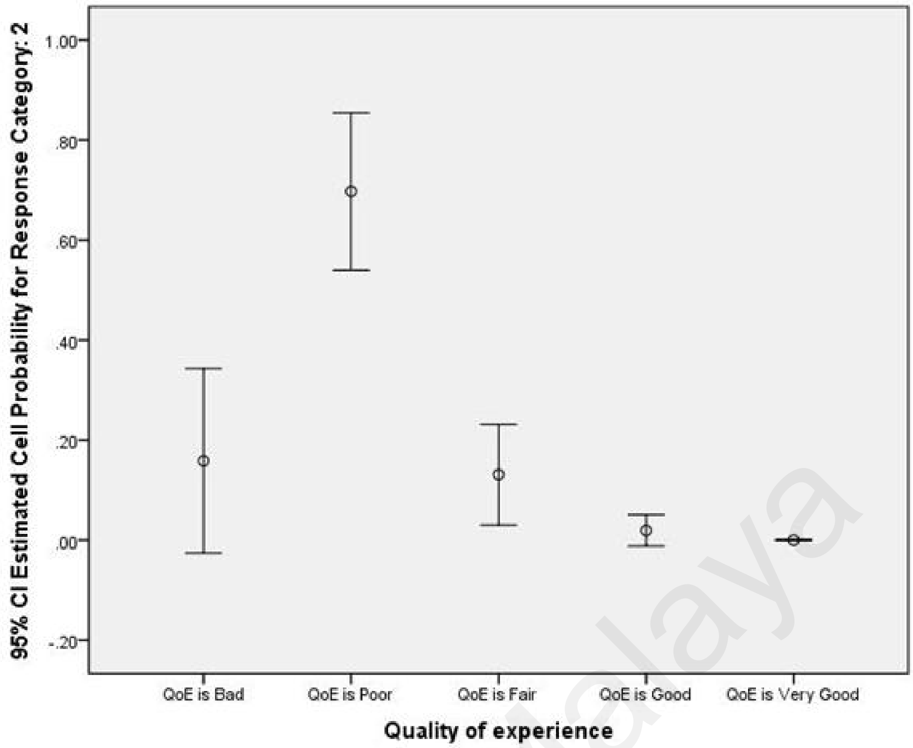

Figure 5.13B: Discriminating ability of QoE category rating equal to two

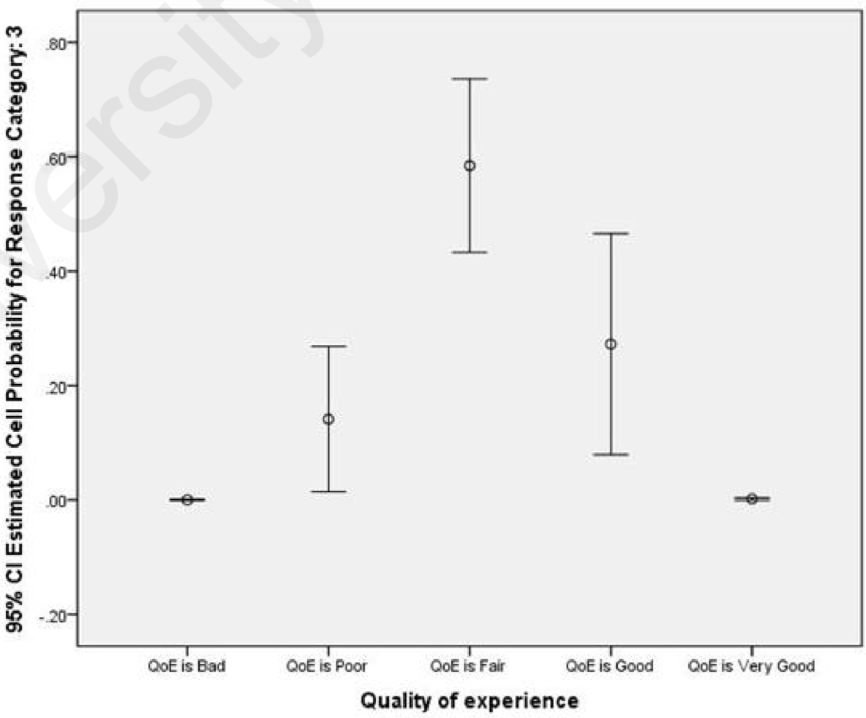

Figure 5.13C: Discriminating ability of QoE category rating equal to three

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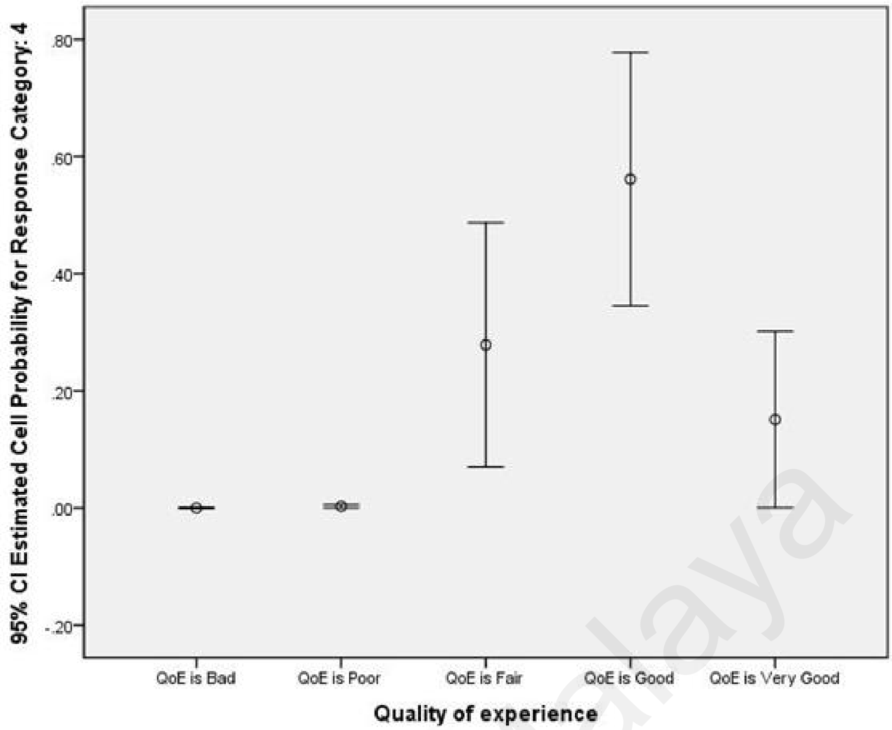

Figure 5.13D: Discriminating ability of QoE category rating equal to four

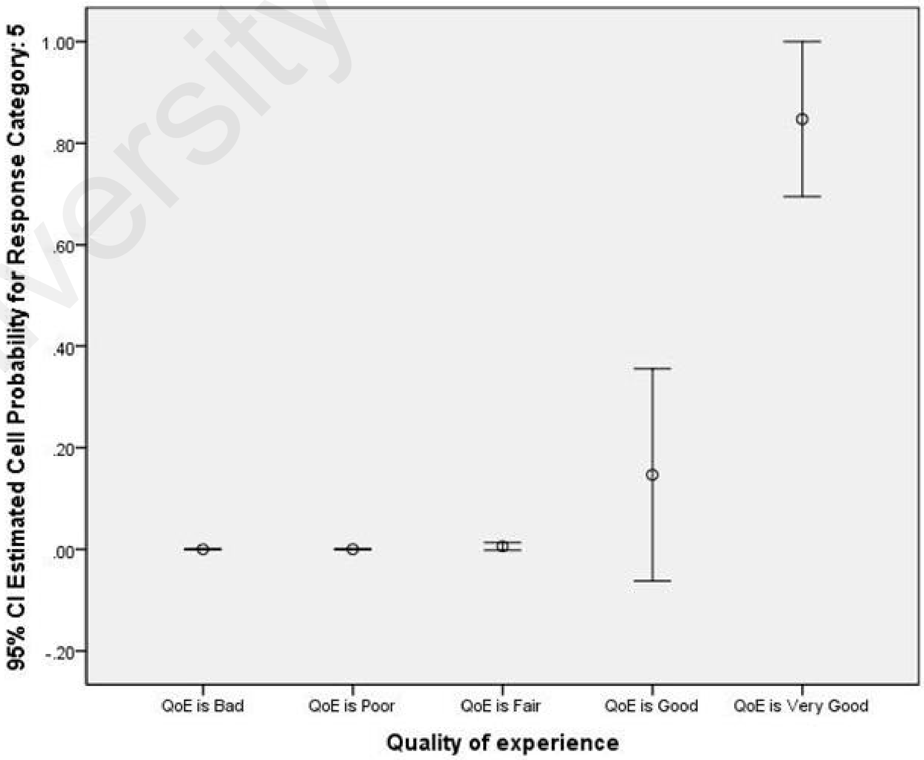

Figure 5.13E: Discriminating ability of QoE category rating equal to five

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5.7.3 BOOTSTRAP INTERNAL VALIDATION

The bootstrap procedure is a means of estimating the statistical accuracy of the data in a single sample. It mimics the process of selecting many samples when the population is too small to handle differently. And so, samples are generated from the original observed data, by copying its many number of times (just like in Monte Carlo Simulation). The samples can then be taken at random and descriptive statistics can be calculated or regressions can extend for each sample. The results generated from the bootstrap samples can be treated as if they were the results of the actual sampling from the original population.

To validate the predictive accuracy of the proposed QoE prediction model, the bootstrapping internal validation procedure was adopted. To be specific, the nonparametric bootstrap method was used, because of its capability to produce an unbiased value of the model performance estimator even when the proof set is not available or when the data set is too small or not enough to set aside a test data set (Gude, Mitchell, Ausband, Sime, & Bangs, 2009). Thus, using the bootstrap tools in SPSS statistical package, 1000 bootstrap samples of the original observation were re-sampled with replacement (sample with replacement means every observation has an equal probability of being selected and observations can be selected more than once). For each of these samples, the ordinal logistic regression was run to obtain the values of the regression coefficients. The empirical distribution of the resulting coefficients and the standard error was then examined. Table 5.12 shows bootstrap estimates from the 1000 bootstrap samples of the QoE prediction model. As could be noted in the bootstrap results in table 5.12, the model shows similar coefficient values with the result in table 5.7. Consequently, the standard error of the bootstrap estimate in table 5.12 could also be observed to have a negligible difference to the result in table 5.7 (The standard error of the bootstrap estimate is the amount of variability in the regression coefficients if a repeated sample of size n is repeatedly taken and replaced x times). Thus, by comparing the standard error obtained from the original model and the bootstrap estimated model. It could as well be noted that the highest standard error difference between the two models is 0.158, which is exhibited by the explanatory variable ‘delay’. The explanatory variable delay experienced a standard error of 0.834 in the bootstrap observation, and 0.992 standard error in the original observation (see the standard error of explanatory variable delay in table 5.7 and 5.12). By comparing these two values, the upshot is a difference of 0.158. Similarly, the amount of optimism (i.e., the bias) could be observed to be relatively low (see table 5.12). This results are genuinely significant, as it establishes the sufficiency of the proposed QoE prediction model to fit adequately with the observed data.

Table 5.12: Bootstrap internal validation for 1000 bootstrap samples

			Bootstrap[a]			
					BCa 95% Confidence Interval	
		Estimate	Bias	Std. Error	Lower	Upper
Threshold	[QoE = 1]	-18.042	-1.250	2.470	-21.571	-16.986
	[QoE = 2]	-8.611	-.584	1.822	-11.696	-6.844
	[QoE = 3]	-3.188	-.162	1.630	-6.675	-.329
	[QoE = 4]	4.841	.484	2.076	.655	11.039
Location	Throughput	.228	.019	.043	.116	.399
	Delay	-6.374	-.505	.834	-7.534	-6.194
	Loss	-.649	-.043	.074	-.747	-.638
	Bite_rate	.014	.002	.004	.006	.028
	Frame_Rate	.254	.016	.076	.110	.468
	Gender	-3.216	-.268	.762	-4.489	-2.527
	Social_Context	-1.741	-.168	.537	-2.770	-1.173

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

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5.8 QoE PREDICTION RATE

Because the QoE prediction model attempt to predict cumulative probabilities rather than category membership, two steps are necessary in order to determine predicted categories. First, for each situation, the probabilities must be estimated for each category. Second, these probabilities must be utilized to select the most likely outcome category for each instance. The probabilities themselves are estimated by using the predictor values for each case in the model equation and taking the inverse of the link function. The result is the cumulative probability for each group, conditional on the pattern of predictive values in the case. The probabilities for individual categories can then be derived by taking the differences of the cumulative probabilities for the groups in an orderly manner. In other words, the probability for the first category is the first cumulative probability; the probability of the second category is the second cumulative probability minus the first cumulative probability; the probability for the third category is the third cumulative probability minus the second cumulative probability; in that order. For each case, the predicted outcome category is simply the category with the highest probability, given the predictor values for that case. For example, the probability of a user to perceive a certain QoE level can be predicted by calculating probabilities associated with each condition state using the QoE prediction equations (see equation 5.38) and by comparing the resultant probability values. In order to compute the probability of a QoE level to be in a certain category, first, the explanatory variables and parameter estimated need to be entered into the QoE prediction equation, to compute the odds ratio. In the second step, the obtained odds ratio values are then used to compute individual category probability values, i.e.;

- $logit = \ln(odds)$;
- $Probability = odds/(1 + odds)$

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❖ $logits \rightarrow odds \rightarrow estimated\, probability$

Recall from equation 5.13 – 5.15

$$ln\left(\frac{\pi_1}{1-\pi_1}\right) = \alpha_1 - (\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}) \quad 5.54$$

$$ln\left(\frac{\pi_2}{1-\pi_2}\right) = \alpha_2 - (\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}) \quad 5.55$$

$$ln\left(\frac{\pi_3}{1-\pi_3}\right) = \alpha_3 - (\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}) \quad 5.56$$

$$ln\left(\frac{\pi_4}{1-\pi_4}\right) = \alpha_4 - (\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}) \quad 5.57$$

Note: to make the interpretation of the coefficients more intuitive, SPSS uses negative in place of the positive sign after the threshold. This is to establish the positive coefficient to indicate an association of increases in the explanatory variable with higher scores on the dependent variable and negative coefficients to indicate an association of increases in the explanatory variable with lower scores on the dependent variable, it is exactly the other way round if the positive sign is used.

Hence, substituting the value of the coefficients into the above equation (equation 5.54 to 5.57).

$$ln\left(\frac{\pi_1}{1-\pi_1}\right) = -18.042 - (0.228x_{i1} - 6.374x_{i2} - 0.649x_{i3} - 3.216x_{i4} - 1.741x_{i5} + 0.014x_{i6} + 0.254x_{i7}) = Q_1 \quad 5.58$$

$$ln\left(\frac{\pi_2}{1-\pi_2}\right) = -8.611 - (0.228x_{i1} - 6.374x_{i2} - 0.649x_{i3} - 3.216x_{i4} - 1.741x_{i5} + 0.014x_{i6} + 0.254x_{i7}) = Q_2 \quad 5.59$$

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$$ln\left(\frac{\pi_3}{1-\pi_3}\right) = -3.188 - (0.228x_{i1} - 6.374x_{i2} - 0.649x_{i3} - 3.216x_{i4} - 1.741x_{i5} + 0.014x_{i6} + 0.254x_{i7}) = Q_3 \quad 5.60$$

$$ln\left(\frac{\pi_4}{1-\pi_4}\right) = 4.841 - (0.228x_{i1} - 6.374x_{i2} - 0.649x_{i3} - 3.216x_{i4} - 1.741x_{i5} + 0.014x_{i6} + 0.254x_{i7}) = Q_4 \quad 5.61$$

Once the logit of Q_1, Q_2, Q_3 and Q_4 Are determined, the cumulative probabilities associated with each user's individual level of quality perception (i.e., QoE) level can then be determined using the expression below:

$$P(QoE = 1) = \frac{Exp(Q_1)}{1+ Exp(Q_1)} \quad 5.62$$

$$P(QoE = 2) = \frac{Exp\ (Q_2)}{1+Exp\ (Q_2)} - \frac{Exp(Q_1)}{1+ Exp(Q_1)} \quad 5.63$$

$$P(QoE = 3) = \frac{Exp\ (Q_3)}{1+Exp\ (Q_3)} - \frac{Exp\ (Q_2)}{1+Exp\ (Q_2)} \quad 5.64$$

$$P(QoE = 4) = \frac{Exp\ (Q_4)}{1+Exp\ (Q_4)} - \frac{Exp\ (Q_3)}{1+Exp\ (Q_3)} \quad 5.65$$

$$P(QoE = 5) = 1 - \frac{Exp\ (Q_4)}{1+Exp\ (Q_4)} \quad 5.66$$

The category with the highest probability of QoE value is then chosen as the predicted category. For example: assuming users vehicle environment is in the city, user expectation is high and the user terminal environment is a low definition. The QoE level can be predicted as follow:

$$ln\left(\frac{\pi_j}{1-\pi_j}\right) = \alpha_j - [\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \beta_6 x_{i6} + \beta_7 x_{i7}] \quad 5.67$$

Assuming we are considering the $108th$ row (i.e., $i = 108$). For when $i = 108$, throughput is 21.88Mbps, the delay is 0. 67s, loss is 16.7Npps, gender is female, social context is group, bite rate is 32kbps and frame rate is 15fps (see appendix A). Therefore, by substituting the value of the parameters in the above equation (i.e., Eq. 5.67):

$$ln\left(\frac{\pi_j}{1-\pi_j}\right) = \alpha_j - [\beta_1(21.88\ ) + \beta_2(0.67) + \beta_3(16.7) + \beta_4(1) + \beta_5(1) + \beta_6(32) + \beta_7(15)] \quad 5.69$$

Substituting the values of βs in table 44 into equation 5.69.

$$ln\left(\frac{\pi_j}{1-\pi_j}\right) = \alpha_j - [(0.228 \times 21.88) + (-6.374 \times 0.67) + (-0.649 \times 16.7) + (-3.216) + (-1.741) + (0.0140 \times 32) + (0.254 \times 15)] \quad 5.70$$

For QoE equal to five categories (i.e., $j = 1, 2, \dots, 5$), to derive the cumulative probabilities for each possible j outcome, the cumulative odds or the logit of the sequence of $j = 1, \dots, J - 1$ cumulative probabilities have to be determined.

And so,

$$ln\left(\frac{\pi_1}{1-\pi_1}\right) = -18.042 - [(0.228 \times 21.88) + (-6.374 \times 0.67) + (-0.649 \times 16.7) + (-3.216) + (-1.741) + (0.0140 \times 32) + (0.254 \times 15)] \quad 5.71$$

$$ln\left(\frac{\pi_2}{1-\pi_2}\right) = -8.611 - [(0.228 \times 21.88) + (-6.374 \times 0.67) + (-0.649 \times 16.7) + (-3.216) + (-1.741) + (0.0140 \times 32) + (0.254 \times 15)] \quad 5.72$$

$$ln\left(\frac{\pi_3}{1-\pi_3}\right) = -3.188[(0.228 \times 21.88) + (-6.374 \times 0.67) + (-0.649 \times 16.7) + (-3.216) + (-1.741) + (0.0140 \times 32) + (0.254 \times 15)] \quad 5.73$$

$$ln\left(\frac{\pi_4}{1-\pi_4}\right) = 4.841 - [(0.228 \times 21.88) + (-6.374 \times 0.67) + (-0.649 \times 16.7) + (-3.216) + (-1.741) + (0.0140 \times 32) + (0.254 \times 15)] \quad 5.74$$

The cumulative probabilities associated with each user's individual level of quality perception (i.e., QoE) levels can then be determined as:

$$P(QoE = 1) = \left(\frac{Exp(-7.22276)}{1 + Exp(-7.22276)}\right) = 7.2925323 \times 10^{-4}$$

$$P(QoE = 2) = \left(\frac{Exp(2.20824)}{1 + Exp(2.20824)}\right) - 7.2925323 \times 10^{-4} \quad = 9.0026 \times 10^{-1}$$

$$P(QoE = 3) = \left(\frac{Exp(7.63124)}{1 + Exp(7.63124)}\right) - 9.0098702 \times 10^{-1} \quad = 9.8528 \times 10^{-2}$$

$$P(QoE = 4) = \left(\frac{Exp(15.66024)}{1 + Exp(15.66024)}\right) - 9.9951517 \times 10^{-1} \quad = 4.8467 \times 10^{-4}$$

$$P(QoE = 5) = 1 - 9.9999984 \times 10^{-1} \quad = 1.6 \times 10^{-7}$$

The group with the highest membership value is chosen as the predicted category. In this example, the group class with the highest probability of QoE value is category 2. Which means that the predicted QoE for this instance is “poor”.

5.9 SUMMARY

This chapter reveals how ordinal regression and in particular the proportion odds model can successfully be applied to estimate the QoE of real-time multimedia services over an ever dynamic network such as VANETs. The stages and steps involved has

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been clearly defined and the outcome indicates that the seven considered explanatory variables were significant determinants in the estimation of the overall quality of experience. In the study, the user's quality perception (QoE) was found to rise with increase throughput, bite rate and frame rate, as the three parameters were found to have positive influence in the user's quality perception ratings. On the other hand, user's quality perception (QoE) was found to be on the decrease with the influence of the other remaining four explanatory variables. The remaining four parameters (i.e., loss, delay, gender and social context) were all found to sustain a negative influence on user's quality perception rating. The result obtained also indicate packet loss to be the end-to-end QoS parameter to hold the highest degree of negative influence on QoE. While social context on the other hand was found to be the human and contextual factors that sustain the highest level of negative influence on the QoE rating. To ascertain the feasibility and reliability of the proposed QoE prediction model, a lengthy evaluation and validation procedure was carried out. The statistical model formulated proved to be well adjusted and able to explain the conduct of the service users and could predict their conceivable QoE ratings with high degree of accuracy. The relatively low variability and minimal bias obtained from the validated result, clearly expresses the potential determination of the stability and generalizability of the fitted QoE prediction model.

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CHAPTER SIX: Conclusion and Future Work

6.1. CONCLUSION

In this thesis, a novel approach for modelling and predicting quality of experience (QoE) of real-time ITS based multimedia services in a vehicular network was presented. QoE is a complex multi-disciplinary concept, which is influenced by several technological and human and contextual factors such as; user device functionalities, gender, age, social context, etc.), QoS network parameters (end-to-end throughput, end-to-end packet delay and end-to-end packet loss rate) and QoS service parameters (frame rate, bite rate, etc.,). Therefore, in order to understand and measure QoE requirements for multimedia services, it is significant to recognize the interaction between the human and contextual factorss and the technological factorss that collectively defines the quality perception of users for any multimedia services. Nevertheless, studies in the area of QoE evaluation have shown to be rather complex due to the extreme ambiguity surrounding the human and contextual factors and the correlation between subjective measure scales and objective parameters. Different stakeholders have different ideas when it comes to the 'right' level of quality, making the concept even more difficult to process and to define appropriate metrics to quantify it. However, it was understood from related literatures that user's perception of multimedia quality can be influenced by; the complete end-to-end system effects (i.e., network infrastructure) and user subjective factors (such as: gender, age, social context, etc). While the component related to network infrastructure enable easy definition of quality metrics, issues related to end-users subjective factors are difficult to expose in the form of measurable parameters, due to their inherent subjectivity. Thus, The work described in this thesis is an attempt to address the inherent problem of the subjectivity of quality of experience.

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By developing a prediction model for QoE evaluation that characterize the user's perception of multimedia quality through a mapping between end-to-end network QoS parameters, and relevance influencing human and contextual subjective factors. Taking into account the goals, motivation and the context around this work, an extended review of related literature was conducted, with special focus on the concepts related to the estimation of real-time multimedia service QoE, the objective and subjective quality assessment methods, and the evolved quality assessment models that already taking into account human factor (see chapter two for details). By and large, this research was built up from a combination of the literature reviews on existing prediction techniques specifically used for QoE evaluation of multimedia services. Fortified with this complete survey on the state-of-art, a strategy and assessment architecture was defined. After defining the main functional requirements, it was followed by the design of the process that would culminate with the formulation of basic QoE metrics. The process considered two distinct areas: the technological factor (i.e., the QoS factors) and the human and contextual subjective factors. The first area (i.e., the QoS factors) was designed using five objective QoE parameters: the Bite rate, frame rate, end-to-end throughput, end-to-end delay and end-to-end packet loss rate. The second aspect was the definition of the subjective human factors that impact on the QoE, two metrics were also defined: gender and social context. After defining these metrics, a set of statistical procedures was used to encapsulate the different metrics into a single standardized QoE estimation expression. Observations for 200 scenarios each were selected as the dataset for the model development. The data for the analysis were collected part from the output files of the simulation experiment in chapter 4, section 4.6, and others from empirical subjective QoE assessment dataset made freely available on the Internet by group of researchers such as; the Multimedia Computing Reseach Group of Technical University of Delf and Video Communication Research Group of IRCCyN (see section

5.2). The evaluation was performed on these datasets (The variables included in the dataset are given in Appendix A), using ordinal logistic regression analysis, these data were then analysed, validated and some conclusions about the impact of the studied features on the perceived quality were drawn. Taking into account all the analysis and their corresponding results, a parameterized expression that predicted the perceived quality outcome for the multimedia services was formulated and defined. The final results attest to be very promising, as the proposed model exhibits good modelling and inferencing ability with high degree of accuracy (an overall accuracy of 98% was observed). The low variability and minimal bias shown by the validated results clearly expresses the potential determination of the stability and generalizability of the fitted QoE prediction model. It is therefore possible to conclude that the proposed model is appropriate and accurate non-reference metric that could be used to infer QoE of real-time multimedia services in a vehicular network.

6.2. FUTURE WORKS

As described in the previous segment (section 3.2.3.1), the coefficient or more appropriately called parameters in the ordered logit model are obtained through the maximum likelihood technique. But, these are only the mean of these parameters, in statistics, it's called a "point estimate" of the parameters. The point estimation always depends on the currently available data. The problem with the point estimation is that, the estimations are only valid for current network connectivity matrix. Considering the distinctive characteristic of VANETs, most especially the speed at which the vehicles travel on the road, which results in frequent link failures and broken connections. In order for communications continuity, finding a new path is required and the process of establishing a new path also causes delays and packet lost. Therefore, to update the

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model parameters to be consistent with the dynamic nature of VANETs links, new data have to be appended to the information set that is used to support the current parameters. Hence, to fulfil the QoE criterion over a certain time interval (Δt), an updating technique is required to build an updating process that will use the current model information to bring about a posterior QoE estimated. This updating technique can be achieved through Bayesian inference. However, in this dissertation, due to the limited resources and time constraint, the researcher was unable to pursue this theorem further at the moment. Nevertheless, this opening should be understood as an opportunity for future work.

Furthermore, it is far from the end to come up with a full understanding of the factors that impacts on QoE of VANETs real-time multimedia services. As previously mentioned, QoE is a very complex concept; equally it is influenced by numerous factors such as the technological features of the application, user personality and expectations, user demographics, device usability, usage context, etc. Especially when assessing networking-based applications, the influence of the underlying network itself as its interplay with the specific application have to be connected to the users' opinion. However, in this thesis, only seven of these factors were studied. In this context, it is regarded as an important future research field to include more QoE factors in the model plan. By incorporating more factors, apparently, the difficulty to arrive at a hypothetical formulated solution will increase, but if successful, a much more potent QoE prediction model could be attained.

Lastly, a brief description of some QoE parameters that are not included in this thesis due to resource limitation is given as a suggestion for future research in the field of VANETs QoE modeling and estimation.

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- Context based on the user's vehicle environmental (it should be noted that user's vehicle environment refers to city and highway/rural VANETs communication environment). Study in (Han, et al., 2012), show that users tend to have higher expectation for service quality when they are in a relatively comfortable and undisturbed environment. And that their expectation decreases as the environmental interference increases, even when they are presented with high quality signals the QoE may still not be satisfied. Consequently, in VANETs city environment, where there are lots of environmental interference, user(s) watching any multimedia content may not expect much from the service content quality, as he/she already understood that such crowded environment with lots of vehicle traffic could be noisy. In this state of affairs, even if the user is supplied with low sound quality multimedia signal, the user may experience an acceptable QoE. Yet, if the same user is in an undisturbed or less crowded environment such as in rural or highway, his/her expectation for high content quality will be eminent. As such, if confronted with video of same sound quality as the one given in the city environment, the user may perceive an unacceptable QoE. The cause is attributed to the fact that, in the city environment, the existence of of environmental interference lowered the user's expectation, therefore, causing the user to worry more about the significance of the picture rather than bothering about the audio quality. Whereas, in the case of the rural/highway environment, where the environmental intervention is relatively low, the user is more comfortable and hence can easily acknowledge the defects in the sound character.
- Context based on users’ device capability (user device refers to the vehicle on-board display unit, i.e., Visual Display Unit (VDU)). Vehicle VDU comes in different sizes, processing power and functionalities. End users' terminal characteristics such as screen resolution, device screen size, etc., have a substantial influence on users'

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quality perception while watching video (Skorin-Kapov & Varela, 2012; Stankiewicz & Jajszczyk, 2011). For example User watching a high definition quality motion picture on a terminal which does not support the high resolution quality of the video, may perceive a low QoE, even when the service delivery quality is high.

- User cultural background: Cultural background is another user demographic factor that has been shown to influence users' QoE. For example, it has been show in (Zhu, et al., 2015) that Asian users rates video QoE higher than their Western counterparts. This they supposed might be ascribed to the different rating habits across culture and then conclude that QoE rating might be "area-specific" and that the user country of origin place a significant role on how the quality of multimedia content is being comprehended. They emphasized though, that further research is needed to further ascertain such conclusion.
- Age: there is evidence in the literatures that shows that the age of users plays a substantial role in how the quality of multimedia content is being perceived. Study in (Song, Tjondronegoro, & Docherty, 2010), indicated that younger people of age 30 years and below, have higher expectation for higher quality video than the elder people of age above 30 years. This implies that younger people may tend to rate video quality more negative than older people.

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SUPPLEMENTARY

List of Publications and work under review that relate to this research

<u>Published Articles</u>

Michael Oche, Rafidah Md Noor, Ali Jalooli, "Quality of Service Management for IPTV services support in VANETs: A Performance Evaluation Study", Wireless Networks, Springer ((IF = 1.055, Accepted Aug 2014). DOI: 10.1007/s11276-014-0787-x. (*ISI-Cited Publication*)

Michael Oche, Rafidah Md Noor, Johnson Ihyeh Aghinya, "Network Centric QoS Performance Evaluation of IPTV Transmission Quality over VANETs", Computer Communications, Elsevier (IF = 1.695, Accepted Dec 2014) Doi:10.1016/j.comcom.2014.12.001 (*ISI-Cited Publication*)

<u>Article Under review</u>

Michael Oche, Rafidah Md Noor, Christopher Chembe, " A Multivariate Statistical Approach for Estimating QoE of Real-Time ITS Multimedia Services ", Computer Communication, Elsevier (IF = 1.695, *ISI-Cited Publication*)

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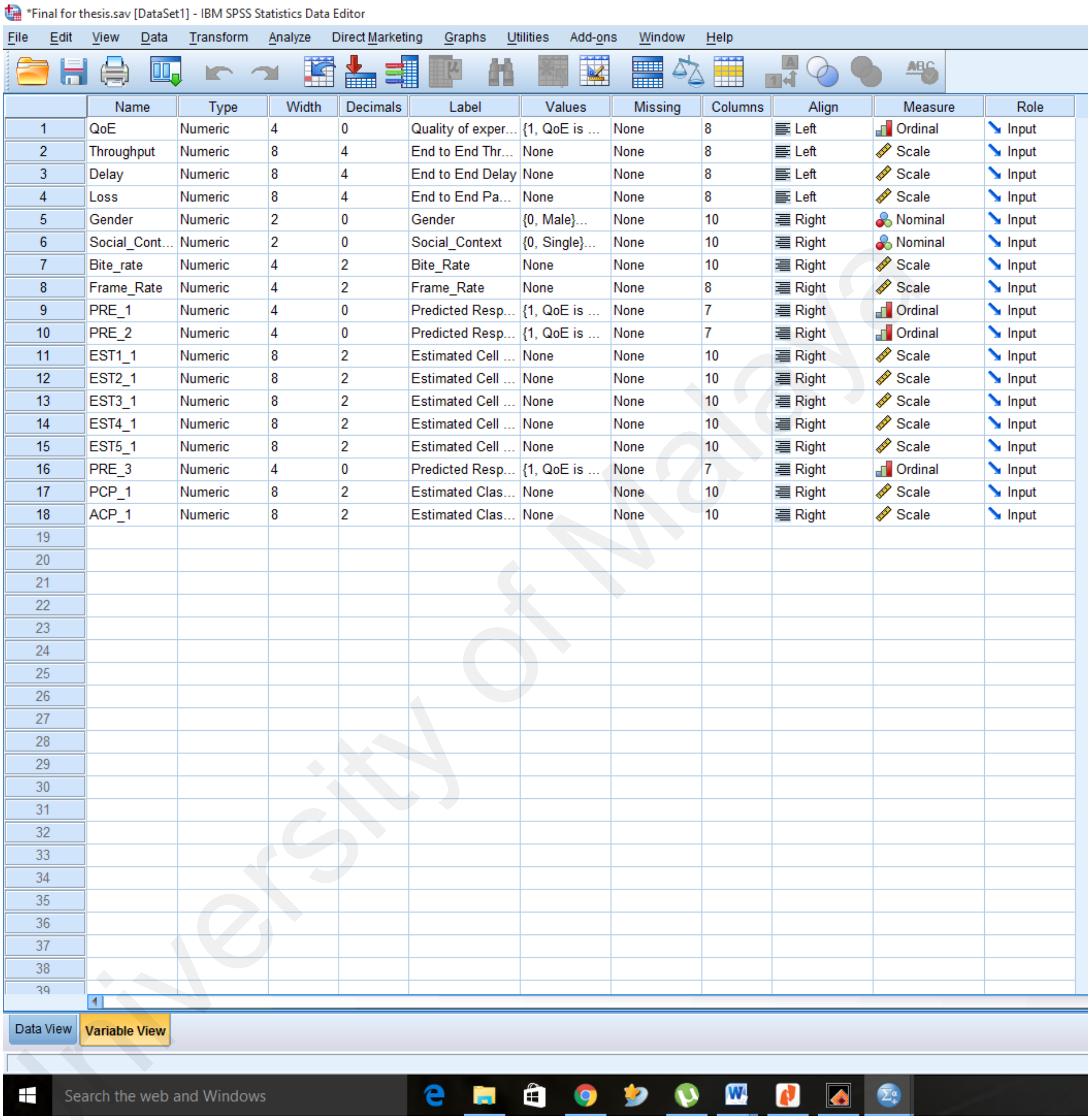
APPENDIX A

Variable print screen view of the QoE Prediction model data



	Name	Type	Width	Decimals	Label	Values	Missing	Columns	Align	Measure	Role
1	QoE	Numeric	4	0	Quality of exper...	{1, QoE is ...	None	8	Left	Ordinal	Input
2	Throughput	Numeric	8	4	End to End Thr...	None	None	8	Left	Scale	Input
3	Delay	Numeric	8	4	End to End Delay	None	None	8	Left	Scale	Input
4	Loss	Numeric	8	4	End to End Pa...	None	None	8	Left	Scale	Input
5	Gender	Numeric	2	0	Gender	{0, Male}...	None	10	Right	Nominal	Input
6	Social_Cont...	Numeric	2	0	Social_Context	{0, Single}...	None	10	Right	Nominal	Input
7	Bite_rate	Numeric	4	2	Bite_Rate	None	None	10	Right	Scale	Input
8	Frame_Rate	Numeric	4	2	Frame_Rate	None	None	8	Right	Scale	Input
9	PRE_1	Numeric	4	0	Predicted Resp...	{1, QoE is ...	None	7	Right	Ordinal	Input
10	PRE_2	Numeric	4	0	Predicted Resp...	{1, QoE is ...	None	7	Right	Ordinal	Input
11	EST1_1	Numeric	8	2	Estimated Cell ...	None	None	10	Right	Scale	Input
12	EST2_1	Numeric	8	2	Estimated Cell ...	None	None	10	Right	Scale	Input
13	EST3_1	Numeric	8	2	Estimated Cell ...	None	None	10	Right	Scale	Input
14	EST4_1	Numeric	8	2	Estimated Cell ...	None	None	10	Right	Scale	Input
15	EST5_1	Numeric	8	2	Estimated Cell ...	None	None	10	Right	Scale	Input
16	PRE_3	Numeric	4	0	Predicted Resp...	{1, QoE is ...	None	7	Right	Ordinal	Input
17	PCP_1	Numeric	8	2	Estimated Clas...	None	None	10	Right	Scale	Input
18	ACP_1	Numeric	8	2	Estimated Clas...	None	None	10	Right	Scale	Input

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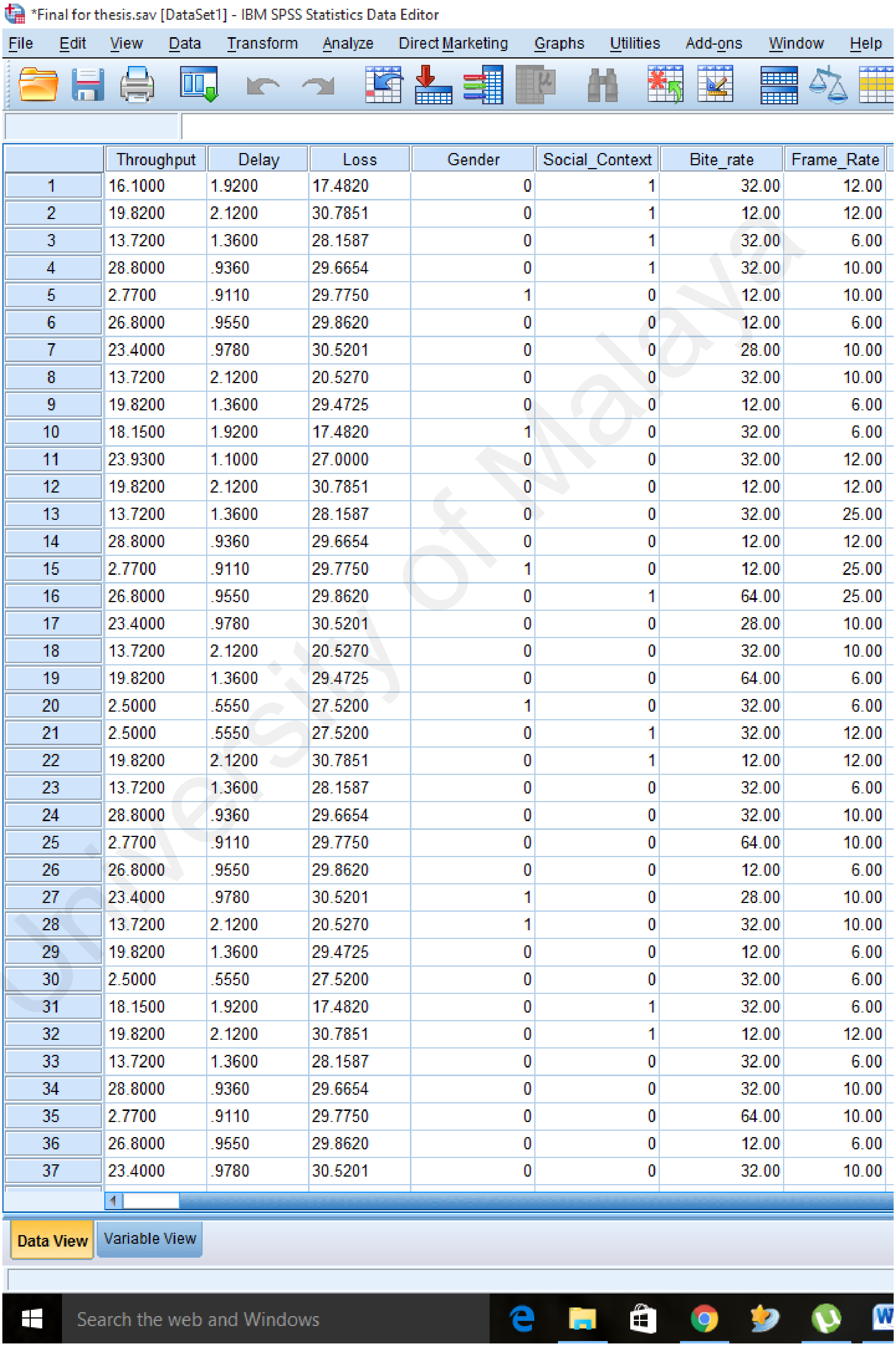
APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset



	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
1	16.1000	1.9200	17.4820	0	1	32.00	12.00
2	19.8200	2.1200	30.7851	0	1	12.00	12.00
3	13.7200	1.3600	28.1587	0	1	32.00	6.00
4	28.8000	.9360	29.6654	0	1	32.00	10.00
5	2.7700	.9110	29.7750	1	0	12.00	10.00
6	26.8000	.9550	29.8620	0	0	12.00	6.00
7	23.4000	.9780	30.5201	0	0	28.00	10.00
8	13.7200	2.1200	20.5270	0	0	32.00	10.00
9	19.8200	1.3600	29.4725	0	0	12.00	6.00
10	18.1500	1.9200	17.4820	1	0	32.00	6.00
11	23.9300	1.1000	27.0000	0	0	32.00	12.00
12	19.8200	2.1200	30.7851	0	0	12.00	12.00
13	13.7200	1.3600	28.1587	0	0	32.00	25.00
14	28.8000	.9360	29.6654	0	0	12.00	12.00
15	2.7700	.9110	29.7750	1	0	12.00	25.00
16	26.8000	.9550	29.8620	0	1	64.00	25.00
17	23.4000	.9780	30.5201	0	0	28.00	10.00
18	13.7200	2.1200	20.5270	0	0	32.00	10.00
19	19.8200	1.3600	29.4725	0	0	64.00	6.00
20	2.5000	.5550	27.5200	1	0	32.00	6.00
21	2.5000	.5550	27.5200	0	1	32.00	12.00
22	19.8200	2.1200	30.7851	0	1	12.00	12.00
23	13.7200	1.3600	28.1587	0	0	32.00	6.00
24	28.8000	.9360	29.6654	0	0	32.00	10.00
25	2.7700	.9110	29.7750	0	0	64.00	10.00
26	26.8000	.9550	29.8620	0	0	12.00	6.00
27	23.4000	.9780	30.5201	1	0	28.00	10.00
28	13.7200	2.1200	20.5270	1	0	32.00	10.00
29	19.8200	1.3600	29.4725	0	0	12.00	6.00
30	2.5000	.5550	27.5200	0	0	32.00	6.00
31	18.1500	1.9200	17.4820	0	1	32.00	6.00
32	19.8200	2.1200	30.7851	0	1	12.00	12.00
33	13.7200	1.3600	28.1587	0	0	32.00	6.00
34	28.8000	.9360	29.6654	0	0	32.00	10.00
35	2.7700	.9110	29.7750	0	0	64.00	10.00
36	26.8000	.9550	29.8620	0	0	12.00	6.00
37	23.4000	.9780	30.5201	0	0	32.00	10.00

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APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset

*Final for thesis.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Add-ons Window Help

1 :

	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
38	13.7200	2.1200	20.5270	0	0	32.00	10.00
39	19.8200	1.3600	29.4725	0	0	64.00	6.00
40	18.1500	1.9200	17.4820	0	0	32.00	12.00
41	12.1800	.6100	13.8000	0	0	64.00	20.00
42	23.9300	1.1000	15.7900	0	0	64.00	25.00
43	12.7200	.5700	16.5557	0	0	32.00	25.00
44	27.1000	1.2500	9.6600	0	0	64.00	12.50
45	2.7000	.3190	14.5400	1	0	32.00	10.00
46	23.9300	1.1000	27.0000	1	1	28.00	15.00
47	23.0000	.5760	29.5000	0	1	64.00	12.00
48	12.7200	1.9200	11.2500	0	1	12.00	10.00
49	18.1500	.5700	19.3000	1	1	28.00	12.00
50	17.1300	.4600	16.7100	1	0	92.00	6.00
51	24.8000	.4600	14.6200	0	0	96.00	10.00
52	23.9300	1.1000	15.7900	0	0	112.00	6.00
53	12.7200	.5700	16.5557	0	0	32.00	10.00
54	27.1000	1.2500	9.6600	0	0	64.00	12.50
55	2.7000	.3190	14.5400	1	0	32.00	10.00
56	23.9300	1.1000	27.0000	1	1	28.00	15.00
57	23.0000	.5760	29.5000	0	1	192.00	12.00
58	12.7200	1.9200	11.2500	0	1	12.00	10.00
59	18.1500	.5700	19.3000	0	1	28.00	12.00
60	17.1300	.4600	16.7100	0	0	92.00	15.00
61	24.8000	.4600	14.6200	0	1	96.00	6.00
62	23.9300	1.1000	27.0000	1	0	64.00	10.00
63	12.7200	.5700	16.5557	0	0	32.00	10.00
64	27.1000	1.2500	9.6600	0	0	64.00	12.50
65	2.7000	.3190	14.5400	0	0	32.00	10.00
66	23.9300	1.1000	15.7900	0	0	28.00	15.00
67	23.0000	.5760	29.5000	0	1	64.00	12.00
68	12.7200	1.9200	11.2500	0	1	12.00	10.00
69	18.1500	.5700	19.3000	0	1	28.00	12.00
70	17.1300	.4600	16.7100	0	0	92.00	16.00
71	2.5000	.5550	27.5200	1	1	96.00	10.00
72	23.9300	1.1000	15.7900	0	0	64.00	6.00
73	12.7200	.5700	16.5557	0	0	32.00	10.00
74	27.1000	1.2500	9.6600	0	0	64.00	12.50

Data View Variable View

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APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset

*Final for thesis.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Add-ons Window Help

1 :

	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
75	2.7000	.3190	14.5400	0	0	32.00	10.00
76	12.1800	.6100	13.8000	0	0	128.00	15.00
77	23.0000	.5760	29.5000	0	1	64.00	12.00
78	12.7200	1.9200	11.2500	0	1	12.00	10.00
79	18.1500	.5700	19.3000	0	1	28.00	12.00
80	17.1300	.4600	16.7100	1	0	92.00	16.00
81	17.3600	.4700	9.5000	0	0	64.00	6.00
82	24.6600	.6700	15.1476	1	0	128.00	12.50
83	24.8000	.4600	14.6200	0	0	128.00	10.00
84	34.7000	1.5100	8.7500	0	0	285.00	20.00
85	34.0000	1.8700	10.7500	0	1	192.00	16.00
86	24.0000	.3660	17.5000	0	0	96.00	12.20
87	21.8800	.3060	19.2300	0	0	194.00	12.20
88	21.8800	.6700	16.7000	0	1	128.00	15.00
89	24.6600	.4400	11.8100	0	1	64.00	15.00
90	12.1800	.4700	11.7204	0	0	32.00	10.00
91	24.3000	.3600	11.6616	0	0	32.00	6.00
92	20.9000	.3700	10.5361	1	0	12.00	12.50
93	24.8000	.4600	14.6200	0	0	32.00	10.00
94	34.7000	1.5100	8.7500	0	1	32.00	20.00
95	34.0000	1.8700	10.7500	0	1	192.00	16.00
96	24.0000	.3660	17.5000	0	1	96.00	12.20
97	21.8800	.3060	19.2300	0	0	194.00	12.20
98	21.8800	.6700	16.7000	0	0	128.00	15.00
99	24.6600	.4400	11.8100	0	1	194.00	15.00
100	12.1800	.4700	11.7204	0	1	112.00	10.00
101	17.3600	.4700	9.5000	0	0	64.00	6.00
102	12.1800	.4700	11.7204	0	1	128.00	12.50
103	17.3600	.4700	9.5000	0	1	128.00	10.00
104	34.7000	1.5100	8.7500	0	1	285.00	20.00
105	34.0000	1.8700	10.7500	0	1	192.00	16.00
106	24.0000	.3660	17.5000	0	1	64.00	12.20
107	21.8800	.3060	19.2300	1	1	32.00	12.20
108	21.8800	.6700	16.7000	1	1	32.00	15.00
109	24.6600	.4400	11.8100	0	1	12.00	15.00
110	12.1800	.4700	11.7204	1	1	32.00	10.00
111	17.3600	.4700	9.5000	1	1	32.00	6.00

Data View Variable View

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APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset

*Final for thesis.sav [DataSet1] - IBM SPSS Statistics Data Editor

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1 :

	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
112	20.9000	.3700	10.5361	1	1	128.00	12.50
113	20.9000	.3700	10.5361	0	1	128.00	10.00
114	34.7000	1.5100	8.7500	0	1	285.00	20.00
115	34.0000	1.8700	10.7500	0	1	192.00	16.00
116	24.0000	.3660	17.5000	0	1	96.00	12.20
117	21.8800	.3060	19.2300	0	1	194.00	12.20
118	21.8800	.6700	16.7000	0	1	128.00	15.00
119	24.6600	.4400	11.8100	0	1	194.00	15.00
120	20.9000	.3700	10.5361	0	1	112.00	10.00
121	29.9600	.3600	10.6700	0	1	256.00	16.00
122	17.3600	.6100	12.7300	1	1	224.00	20.00
123	29.9600	.3600	10.6700	1	0	192.00	16.00
124	26.0000	.8800	8.8100	1	0	32.00	20.00
125	37.9700	1.5300	10.0100	1	0	64.00	15.00
126	28.7000	.2010	15.5100	1	0	32.00	25.00
127	23.0000	.2440	17.5000	1	1	28.00	20.00
128	12.1800	.6100	13.8000	1	0	194.00	15.00
129	24.3000	.3600	11.6616	0	1	128.00	12.50
130	20.9000	.3700	7.3600	0	1	64.00	15.00
131	29.9600	.3600	10.6700	0	1	32.00	25.00
132	17.3600	.6100	12.7300	1	1	32.00	20.00
133	24.3000	.3600	11.6616	1	0	12.00	16.00
134	26.0000	.8800	8.8100	1	0	32.00	20.00
135	37.9700	1.5300	10.0100	1	0	32.00	15.00
136	28.7000	.2010	15.5100	1	0	303.00	15.00
137	23.0000	.2440	17.5000	1	1	243.00	20.00
138	17.1300	.4400	12.6587	0	1	194.00	15.00
139	17.1300	.4400	12.6587	1	1	128.00	12.50
140	20.9000	.3700	7.3600	0	1	224.00	15.00
141	24.6600	.6700	15.1476	1	1	256.00	15.00
142	17.3600	.6100	12.7300	1	1	224.00	16.00
143	24.3000	.3600	11.6616	1	0	192.00	20.00
144	26.0000	.8800	8.8100	1	0	285.00	15.00
145	37.9700	1.5300	10.0100	1	0	384.00	16.00
146	28.7000	.2010	15.5100	1	0	303.00	16.00
147	23.0000	.2440	17.5000	1	1	243.00	20.00
148	12.1800	.6100	13.8000	1	1	194.00	15.00

Data View Variable View

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APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset

	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
149	29.9600	.3600	10.6700	0	1	128.00	12.50
150	20.9000	.3700	7.3600	1	1	224.00	15.00
151	17.1300	.4400	12.6587	0	1	256.00	16.00
152	17.3600	.6100	12.7300	1	1	224.00	20.00
153	24.6600	.6700	15.1476	1	0	192.00	16.00
154	26.0000	.8800	8.8100	1	0	285.00	20.00
155	37.9700	1.5300	10.0100	1	0	384.00	20.00
156	28.7000	.2010	15.5100	1	1	303.00	16.00
157	23.0000	.2440	17.5000	1	1	243.00	20.00
158	24.6600	.6700	15.1476	0	1	194.00	20.00
159	17.1300	.4400	12.6587	0	1	128.00	12.50
160	20.9000	.3700	7.3600	0	1	224.00	15.00
161	71.3400	.3100	10.1500	1	0	384.00	25.00
162	57.9400	.0580	13.5461	1	1	285.00	20.00
163	37.9700	.0380	11.5092	0	1	448.00	25.00
164	49.1000	.0820	8.5600	0	1	349.00	25.00
165	48.5000	.1350	9.5100	0	1	224.00	15.00
166	45.6000	.2370	12.5000	1	1	32.00	25.00
167	49.0000	.2120	14.1300	1	1	64.00	29.00
168	29.9600	.0580	10.5500	0	1	32.00	25.00
169	57.9400	.0380	8.5100	1	1	28.00	20.00
170	71.3400	.0310	6.1500	1	1	224.00	15.00
171	71.3400	.3100	10.1500	1	0	384.00	16.00
172	57.9400	.0580	13.5461	1	1	285.00	20.00
173	37.9700	.0380	11.5092	0	1	448.00	25.00
174	49.1000	.0820	8.5600	0	1	349.00	25.00
175	48.5000	.1350	9.5100	0	1	224.00	15.00
176	45.6000	.2370	12.5000	0	1	363.00	25.00
177	49.0000	.2120	14.1300	1	1	512.00	29.00
178	29.9600	.0580	10.5500	0	1	420.00	29.00
179	57.9400	.0380	8.5100	1	1	363.00	25.00
180	71.3400	.0310	6.1500	1	1	224.00	25.00
181	71.3400	.3100	10.1500	1	0	384.00	25.00
182	57.9400	.0580	13.5461	1	1	285.00	20.00
183	37.9700	.0380	11.5092	0	1	448.00	25.00
184	49.1000	.0820	8.5600	0	1	349.00	25.00
185	48.5000	.1350	9.5100	0	1	224.00	15.00

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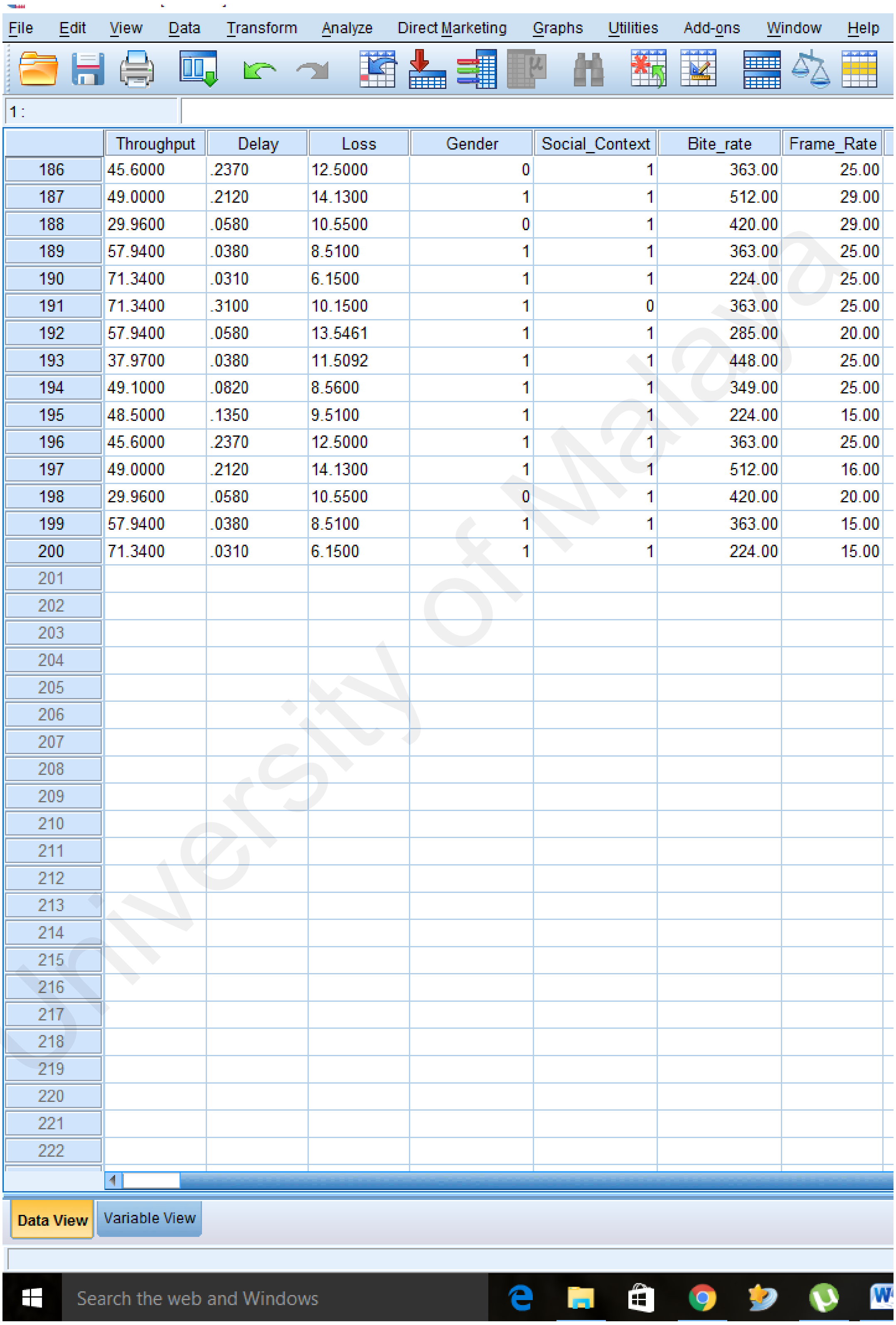
APPENDIX A (continuous)

Print screen view of the QoE Prediction model dataset



	Throughput	Delay	Loss	Gender	Social_Context	Bite_rate	Frame_Rate
186	45.6000	.2370	12.5000	0	1	363.00	25.00
187	49.0000	.2120	14.1300	1	1	512.00	29.00
188	29.9600	.0580	10.5500	0	1	420.00	29.00
189	57.9400	.0380	8.5100	1	1	363.00	25.00
190	71.3400	.0310	6.1500	1	1	224.00	25.00
191	71.3400	.3100	10.1500	1	0	363.00	25.00
192	57.9400	.0580	13.5461	1	1	285.00	20.00
193	37.9700	.0380	11.5092	1	1	448.00	25.00
194	49.1000	.0820	8.5600	1	1	349.00	25.00
195	48.5000	.1350	9.5100	1	1	224.00	15.00
196	45.6000	.2370	12.5000	1	1	363.00	25.00
197	49.0000	.2120	14.1300	1	1	512.00	16.00
198	29.9600	.0580	10.5500	0	1	420.00	20.00
199	57.9400	.0380	8.5100	1	1	363.00	15.00
200	71.3400	.0310	6.1500	1	1	224.00	15.00
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APPENDIX B

```
GET
  FILE='C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Final for thesis.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
PLUM QoE BY Gender Social_Context WITH Throughput Delay Loss Bite_rate Frame_Rate
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=LOGIT
  /PRINT=FIT PARAMETER SUMMARY TPARALLEL
  /SAVE=ESTPROB PREDCAT PCPROB ACPROB.
```

PLUM - Ordinal Regression

Notes

Output Created		02-DEC-2015 21:40:26
Comments		
Input	Data	C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Final for thesis.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	200

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Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the model.
Syntax		PLUM QoE BY Gender Social_Context WITH Throughput Delay Loss Bite_rate Frame_Rate /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8) /LINK=LOGIT /PRINT=FIT PARAMETER SUMMARY TPARALLEL /SAVE=ESTPROB PREDCAT PCPROB ACPROB.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.17
Variables Created	EST1_1	Estimated Cell Probability for Response Category: 1
	EST2_1	Estimated Cell Probability for Response Category: 2
	EST3_1	Estimated Cell Probability for Response Category: 3
	EST4_1	Estimated Cell Probability for Response Category: 4
	EST5_1	Estimated Cell Probability for Response Category: 5
	PRE_3	Predicted Response Category
	PCP_1	Estimated Classification Probability for the Predicted Category
	ACP_1	Estimated Classification Probability for the Actual Category

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[DataSet1] C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Final for thesis.sav

Warnings

There are 572 (80.0%) cells (i.e., dependent variable levels by observed combinations of predictor variable values) with zero frequencies.

Case Processing Summary

		N	Marginal Percentage
Quality of experience	QoE is Bad	40	20.0%
	QoE is Poor	40	20.0%
	QoE is Fair	40	20.0%
	QoE is Good	40	20.0%
	QoE is Very Good	40	20.0%
Gender	Male	124	62.0%
	Femal	76	38.0%
Social_Context	Single	88	44.0%
	Group	112	56.0%
Valid		200	100.0%
Missing		0	
Total		200	

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Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	643.775			
Final	130.412	513.363	7	.000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	177.032	561	1.000
Deviance	130.412	561	1.000

Link function: Logit.

Pseudo R-Square

Cox and Snell	.923
Nagelkerke	.962
McFadden	.797

Link function: Logit.

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Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[QoE = 1]	-18.042	2.916	38.276	1	.000	-23.757	-12.326
	[QoE = 2]	-8.611	1.698	25.707	1	.000	-11.939	-5.282
	[QoE = 3]	-3.188	1.343	5.634	1	.018	-5.820	-.555
	[QoE = 4]	4.841	1.661	8.492	1	.004	1.585	8.097
Location	Throughput	.228	.042	30.173	1	.000	.147	.309
	Delay	-6.374	.992	41.272	1	.000	-8.319	-4.430
	Loss	-.649	.099	42.671	1	.000	-.844	-.454
	Bite_rate	.014	.004	15.366	1	.000	.007	.021
	Frame_Rate	.254	.065	15.128	1	.000	.126	.382
	[Gender=0]	-3.216	.653	24.242	1	.000	-4.496	-1.936
	[Gender=1]	0[a]	.	.	0	.	.	.
	[Social_Context=0]	-1.741	.515	11.427	1	.001	-2.751	-.732
	[Social_Context=1]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

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Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	130.412			
General	129.974[b]	.438[c]	21	1.000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

```
BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=QoE INPUT=Throughput Delay Loss Bite_rate Frame_Rate Gender Social_Context
  /CRITERIA CILEVEL=95 CITYPE=BCA  NSAMPLES=1000
  /MISSING USERMISSING=EXCLUDE.
```

Bootstrap

Notes

Output Created		07-JAN-2016 21:42:22
Comments		
Input	Data	C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Final for thesis.sav
	Active Dataset	DataSet1

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	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	200
Syntax		BOOTSTRAP /SAMPLING METHOD=SIMPLE /VARIABLES TARGET=QoE INPUT=Throughput Delay Loss Bite_rate Frame_Rate Gender Social_Context /CRITERIA CILEVEL=95 CITYPE=BCA NSAMPLES=1000 /MISSING USERMISSING=EXCLUDE.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.07

Bootstrap Specifications

Sampling Method	Simple
Number of Samples	1000
Confidence Interval Level	95.0%
Confidence Interval Type	Bias-corrected and accelerated (BCa)

```
PLUM QoE BY Gender Social_Context WITH Throughput Delay Loss Bite_rate Frame_Rate
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=LOGIT
  /PRINT=FIT PARAMETER SUMMARY.
```

PLUM - Ordinal Regression

Notes

Output Created		07-JAN-2016 21:42:22
Comments		
Input	Data	C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Final for thesis.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	166416
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the model.
Syntax		PLUM QoE BY Gender Social_Context WITH Throughput Delay Loss Bite_rate Frame_Rate /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8) /LINK=LOGIT /PRINT=FIT PARAMETER SUMMARY.

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Resources	Processor Time	00:00:07.44
	Elapsed Time	00:00:12.35

Bootstrap for Parameter Estimates

		Estimate	Bootstrap[a]			
			Bias	Std. Error	BCa 95% Confidence Interval	
					Lower	Upper
Threshold	[QoE = 1]	-18.042	-1.250	2.470	-21.571	-16.986
		-8.611	-.584	1.822	-11.696	-6.844
		-3.188	-.162	1.630	-6.675	-.329
		4.841	.484	2.076	.655	11.039
	Throughput	.228	.019	.043	.116	.399
		-6.374	-.505	.834	-7.534	-6.194
		-.649	-.043	.074	-.747	-.638
		.014	.002	.004	.006	.028
		.254	.016	.076	.110	.468
		-3.216	-.268	.762	-4.489	-2.527
		0	0	0	.	.
		-1.741	-.168	.537	-2.770	-1.173
		0	0	0	.	.

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

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Crosstabs

Notes

Output Created		07-JAN-2016 21:45:19
Comments		
Input	Data	C:\Users\um\Desktop\PHD JOURNAL COMPLETED 2\PhD Fnal QoE thesis\After ViVa SPSS\SUMO\Dataset\Thesis Datasets\N datasets\Final 4 thesis\Cross tab. Excelent.sav
	Active Dataset	DataSet2
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	200
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each table are based on all the cases with valid data in the specified range(s) for all variables in each table.
Syntax		CROSSTABS /TABLES=QoE BY PRE_4 /FORMAT=AVALUE TABLES /CELLS=COUNT ROW /COUNT ROUND CELL.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.04
	Dimensions Requested	2
	Cells Available	131029

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Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Quality of experience * Predicted Response Category	200	100.0%	0	0.0%	200	100.0%

Quality of experience * Predicted Response Category Crosstabulation

			Predicted Response Category					
			QoE is Bad	QoE is Poor	QoE is Fair	QoE is Good	QoE is Very Good	Total
Quality of experience	QoE is Bad	Count	40	0	0	0	0	40
		% within Quality of experience	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	QoE is Poor	Count	1	38	1	0	0	40
		% within Quality of experience	2.5%	95.0%	2.5%	0.0%	0.0%	100.0%
	QoE is Fair	Count	0	1	39	0	0	40
		% within Quality of experience	0.0%	2.5%	97.5%	0.0%	0.0%	100.0%
	QoE is Good	Count	0	0	1	39	0	40
		% within Quality of experience	0.0%	0.0%	2.5%	97.5%	0.0%	100.0%
	QoE is Very Good	Count	0	0	0	0	40	40
		% within Quality of experience	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%

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Total	Count	41	39	41	39	40	200
	% within Quality of experience	20.5%	19.5%	20.5%	19.5%	20.0%	100.0%

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