QoE Assessment Model for Addis Ababa LTE Video Streaming Service Using Machine Learning Techniques

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Abstract

In today's connected world, the availability of fast Internet access and penetration of smart-phones has created an opportunity for the emerging of new telecom services. Similarly, in Ethiopia, the improvement of technology brought a change from the traditional services to more advanced communication like video streaming service. To ensure whether the customers have satisfied for a given service or not, capturing user Quality of Experience (QoE) is important. Traditionally, Internet Service Providers (ISP)s monitor the network performance by collecting network key performance indicators without involving users' perception. However, user-perceived QoE estimation is multidimensional, which is affected by different influencing factors. So, estimating user-centric QoE based on Network-level QoS (NQoS) remains challenging tasks for ISPs. Yet, QoE assessment model for video streaming services that map Quality of Service (QoS) to QoE concerning users' perception has not been performed in Ethiopia.

This thesis proposes video streaming QoE assessment models using machine learning techniques to estimate user-perceived experience in the Long-Term Evolution (LTE) network. The model predicts perceived QoE in a Mean Opinion Score (MOS), by evaluating NQoS, Application-level QoS (AQoS) and contextually formulated survey questionnaire. The models take NQoS metrics such as upload bit rate and download bit rate in Megabits Per Second (Mb/s), latency and jitter in milliseconds (ms), and packet loss in percentage. Content-type and resolution also considered from the application level. Contrary to existing models for QoE prediction, the proposed model gives a good estimation of the perceived quality with a minimum Mean Squared Error (MSE) of 7.74%; and Pearson and Spearman correlations of 97.94% and 97.43%, corresponding to the measured QoE. The result obtained from the model shows that the average MOS value is 2.79, which is below the recommended one. Accordingly, the proposed model allows ISP to monitor the perceived QoE level accurately.

Keywords- LTE, QoE, QoS, Video streaming, Machine Learning, Multivariate Linear Regression, Support Vector Regression

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This is to certify that the thesis prepared by Addisu Shiferaw Fite, entitled: *QoE Assessment Model for Addis Ababa LTE Video Streaming Service using Machine Learning Techniques* and submitted in partial fulfillment of the requirements for the degree of Master of Science in Telecommunication Engineering complies with the regulations of the University and meets the accepted standards concerning originality and quality.

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Dean, School of Electrical and Computer Engineering

Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other University, and all sources of materials used for the thesis have been fully acknowledged.

Signature

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February 2020

This thesis has been submitted for examination with my approval as a University advisor.

Signature

Dr. Eng. Yihenew Wondie
February 2020

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Lists of Acronyms

AF	Application Function
AQoS	Application-level QoS
BBERF	Bearer Binding and Event Reporting Function
DPI	Deep Packet Inspection
EDGE	Enhanced Data rates for GSM Evolution
eNB	Evolved Node-B
EPC	Evolved Packet Core
EPS	Evolved Packet System
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
GPRS	General Packet Radio Service
GSM	Global System for Mobile communication
GBR	Guaranteed Bitrate
HSPA	High-Speed Packet Access
HSS	Home Subscriber Server
HAS	HTTP Adaptive Streaming
IFs	Influencing Factors
ITU	International Telecommunication Union
IP	Internet Protocol
ISP	Internet Service Providers
KPI	Key Performance Indicators
LTE	Long-Term Evolution
Mb/s	Megabits Per Second

ms	milliseconds
MOS	Mean Opinion Score
MSE	Mean Squared Error
MIMO	Multiple Input, Multiple Output
MLR	Multivariate Linear Regression
MME	Mobility Management Entity
NQoS	Network-level QoS
NMS	Network Management System
OFDMA	Orthogonal Frequency Division Multiple Access
PDN	Packet Data Network
P-GW	PDN Gateway
PCC	Policy & Charging Control
PCEF	Policy Control Enforcement Function
PCRF	Policy Control and Charging Rules Function
QoE	Quality of Experience
QoS	Quality of Service
QCI	QoS Class Identifier
RBF	Radial Basis Function
RF	Radio Frequency
RMSE	Root Mean Squared Error
RTT	Round-Trip Time
S-GW	Serving Gateway
SMS	Short Message Service
SPR	Subscription Profile Repository

SAE	System Architecture Evolution
SC-FDMA	Single-Carrier Frequency Division Multiple Access
SVR	Support Vector Regression
TSP	Telecom Service Provider
TDMA	Time Division Multiple Access
UICC	Universal Integrated Circuit Card
UMTS	Universal Mobile Telecommunications System
USIM	Universal Subscriber Identity Module
UE	User Equipment
4G	Fourth Generation
5G	Fifth Generation
3G	Third Generation
2G	Second Generation

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Chapter 1

Introduction

This chapter presents the motivation, statement of the problem, and the established objectives. Some contributions that resulted from the work are also presented in this chapter. The existing service-specific Quality of Experience (QoE) models are shown in the literature part. Finally, the thesis layout is described.

1.1 Motivations

We are currently experiencing a paradigm shift of Internet traffic from web traffic to multimedia traffic due to the proliferation of smart-phones, tablets, computer accessibility, etc [8]. As a seven weeks survey measurement of mobile Internet traffic from 25-10-2018 to 6-12-2018 shows in Figure 1.1, multimedia traffics is dominating web traffic by almost 70% at Addis Ababa, Ethiopia. According to a report in [9], from multimedia traffics, video traffic continues to grow, driven by increased viewing time, online embedded video and streaming services, plus the evolution toward higher resolutions. The report stated, video traffic in mobile networks is forecast to grow by around 35% annually through 2024 to account for 74% of all mobile data traffic.

Such a drastic upsurge in the use of the video streaming requires upgrading network infrastructures and investing in the deployment of new technologies (e.g., optical fibers, Fourth Generation (4G)/Fifth Generation (5G) mobile networks) at the Internet Service Providers (ISP) end to assure the required level of quality [10]. Likewise, ethio telecom is also working on its current technology and business approaches for providing the required quality perceived by users, which in turn ensure customer satisfaction.

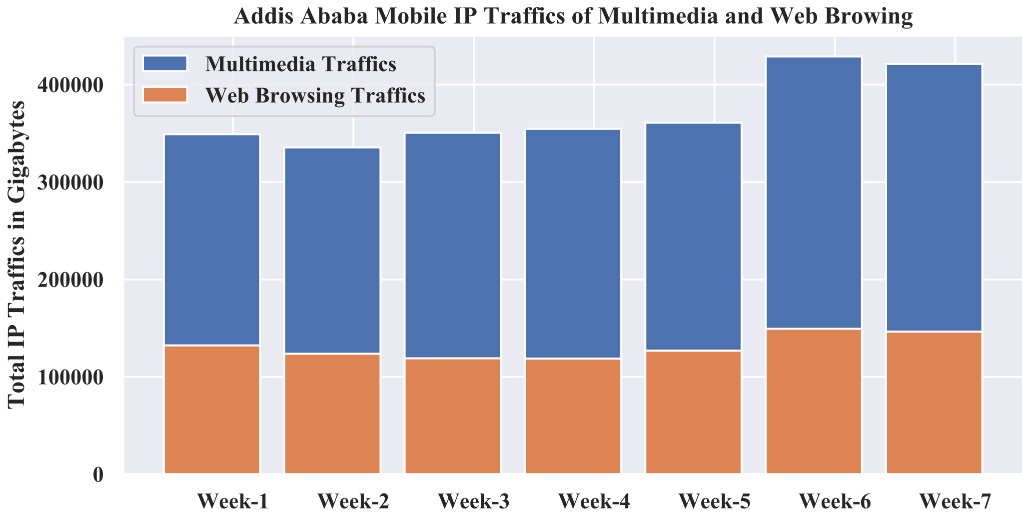


Fig. 1.1 Comparison of multimedia and web browsing IP traffics in Gigabytes [1]

On the provisioning of service quality to the users, Quality of Service (QoS) becoming inadequate since it only handles pure technical aspects regarding a service. QoS does not incorporate any kind of human-related quality-affecting factors and nor does it not reflect real perceived experience. So, the recent research has shifted from QoS to QoE, which reflects the user-perceived quality [11].

The International Telecommunication Union (ITU) defines QoE [12] as "The overall acceptability of an application or service, as perceived subjectively by the end-user which includes a complete end to end system effects (client, terminal, network, services infrastructure, etc.) that may be influenced by user expectations and context". Laghari and Connelly [13] have further explained QoE by introducing objective QoE concept "QoE is a blueprint of all human subjective and objective quality needs and experiences arising from the interaction of a person with technology and with business entities in a particular context."

There are different QoE assessment taxonomy [11, 14] for quantifying the QoE level of a provided services. The main classifications include subjective, objective, and hybrid QoE assessment models. Subjective tests bases on user studies, customer surveys, and interviews to translate user feedback into statistical metrics. A reliable QoE assessment is a subjective test. However, it is expensive, time-consuming, and usually not real-time hence cannot be used for in-service quality monitoring. In the second case, objective techniques use some prediction models and infer QoE from network traffic or QoS data obtained from the system as well as directly from the users. The third category of QoE modeling lies between subjective and objective ones and operates in a hybrid fashion. Machine learning tools are used in hybrid methods. These hybrid classifications use subjective test scores as input to train the QoE models then map network parameters to Mean Opinion Score (MOS) values for real-time quality prediction.

The MOS is the most extensively used measurement scale for observing the experience of users on the quality of the given services [12]. Table 1.1 depicts the predefined values of these MOS scales.

Table 1.1 Video MOS score

Value	**Evaluation**	**User perception**
5	Excellent	Extremely satisfied
4	Good	Very satisfied
3	Fair	Moderately satisfied
2	Poor	Slightly satisfied
1	Bad	Extremely Dissatisfied

1.2 Statement of the Problem

The evaluation of user-perceived QoE is essential for network engineering to design in line with customers' demands. However, measurement, modeling, and prediction of quality perceived by end-users remain a challenging task for ISPs. Traditionally, ISPs monitors the network performance by extracting network Key Performance Indicators (KPI) data without directly involving users' perception since measuring network KPI is very easy for the ISPs from the system and using drive tests. But, especially for video streaming, it could not express the real perceived quality the end-users until they asked for their opinion about the quality of the services. So it is essential to develop a mapping model to predict perceived QoE based on QoS parameters and user perception. But, as far as my knowledge goes, QoE assessment model has not been proposed yet, particularly in Ethiopia. Thus, it is quite challenging for the company to establish an accurate QoS to QoE mapping method for different services. It is also challenging to evaluate user experience, concerning QoS and context data as acquiring these different parameters is difficult in a cellular environment.

Though there are different existing QoE assessment model proposed by the researcher to quantify user-perceived quality, most of the techniques discovered in the literature depend only on a single point of view without involving human dimensions. They do not consider service dependent influential factors like video resolution and content type in the case of video streaming. Some of the proposed techniques were restricted to simulation and thus difficult to apply in the real world.

In contrast to the existing solutions, QoE prediction is multidimensional, and it is not only limited to the technical factors which ISPs can measure be it at the application level or the network level [5]. A good Network-level QoS (NQoS) does not necessarily mean that the end-user is satisfied with the provided service for their satisfaction depends on another quality affecting factors from now on called, Influencing Factors (IFs). So, QoE forecasted by analyzing only network traffic or application-level metrics does not represent the actual perceived quality by the users.

1.3 Objectives

1.3.1 General Objectives

The main goal of this thesis is to evaluate the performance of two machine learning algorithms; Multivariate Linear Regression (MLR) and Support Vector Regression (SVR) in predicting video streaming perceived quality by end-users through the already measured video IFs, in Long-Term Evolution (LTE) for Addis Ababa scenario.

1.3.2 Specific Objectives

The specific objectives of this thesis are:

- To identify and formulate relevant network, application, and context quality measuring metrics for video streaming services. Besides, this work interprets collected video quality affecting factors from standard perspectives.
- Explore different machine learning-based QoE prediction algorithms and select algorithms for implementation.
- To propose QoE estimation models using selected algorithms that take as input parameters the video IFs and returns as output a QoE in MOS scale.
- Analyze the performance of the proposed models and selecting the final QoE model.

- To show the spatial distribution of estimated QoE by applying the chosen QoE model.
- Deduce conclusion and recommendations based on performance analysis.

1.4 Scope and Limitation

This thesis focuses on proposing machine learning bassed QoE model and predicting user perceivedQoE for video streaming in the 4G LTE network. The work emphasizes on the technological details of how the proposed model works for predicting QoE.

The data used in the thesis was obtained directly from the users of ethio telecom using questionnaires and network performance measuring toll called nPerf [15]. The work is limited to using fundamental video IFs such as video resolution, content-type, upload throughput, download throughput, packet delay, jitter, and packet loss. The thesis did not examine the impacts of Radio Frequency (RF) metrics on user's perceptions. But, the author is confident that the collected parameter will predict actual user-perceived QoE on the ethio telecom network. Hence, these factors do not significantly limit the applicability of the study.

1.5 Contributions

The work in this thesis contributes two QoE models using machine learning algorithms for video streaming in LTE cellular network. The output of this research can be applied to optimize and enhance user-perceived quality in mobile communication networks.

The main contributions of this work are the following:

- Discuss relevant service-based quality affecting factors with their influences and showing the techniques to assess user-perceived QoE
- Proposes more preferable QoE model in LTE networks using machine learning algorithms for ISPs, specifically for ethio telecom.
- To compare the proposed approaches in terms of QoE prediction accuracy and select the best-performed model.

- To show spatial distribution and density of estimated QoE for further network engineering.

1.6 Literature Review

Accurate monitoring, evaluation, and reporting of a QoE are essential requirements for ISPs. Consequently, many researchers are contributing their role to the industry using machine learning and other techniques. The machine learning technology enables dynamic prediction of the QoE metrics depending on the input training data set. This section provides a review of some existing QoE estimation models implemented using machine learning and other techniques.

The work reported in [16] proposes a logistic function to predict video QoE based on NQoS parameters and examines the influence of each NQoS parameters on users MOS score independently. However, in reality, multiple parameters including video resolution, content and context could harm the perceived video quality at the same time. The results revealed that when a packet loss rate, jitter, and throughput limitations have a strong correlation with the perceived video quality, an initial delay does not have a significant impact on video streaming perceived quality. Similarly, Wang et al. [17] presented a simulation study carried out with NS-2. The study aims at finding a correlation between QoS and QoE for video streaming services over wireless networks. The result highlighted the impact of packet loss rate, bandwidth, and a Group of a Picture (GoP) on video streaming under the same conditions. The authors stated that the greater the packet loss rate, the poorer the video quality; the larger the bandwidth, the better the video quality; the shorter the GoP, the better the video quality.

Moreover, article [14] proposes a QoE prediction model for multidimensional MOS prediction by applying Artificial Neural Network. The proposed solution is verified through an experimental study based on video streaming emulation over LTE, which allows the measurement of subjective assessment and network-related IFs. The relationship between the scores of collected and predicted MOS rates are also evaluated in terms of mean prediction error and mean square error. The specific advantage of this solution lies in the real-time verification and optimization of the MOS prediction process.

The authors in [18] proposed a user-centric, context-aware solution using MLR for measuring video QoE on smartphones. The collection of QoS, contextual, and user ratings are done locally on user smart-phones. The proposed framework has the capability of collecting user-related, application-related, device-related, and network performance-related information. However, the relation between QoS parameters and QoE scores shown using only packet loss and packet reordering independently. The result of the article presented as obtained QoE scores is inversely related to disturbance of QoS parameters like packet loss and packet reordering.

The authors in [19] proposed an objective QoE model for Universal Mobile Telecommunications System (UMTS) voice calls and web browsing in LTE networks using machine learning techniques. Drive tests have been used to produce the QoE prediction models. The authors have used the SVR algorithm for developing the model. These models estimate the user-perceived quality by evaluating RF channel measurements and QoS metrics. The performance of proposed models was assessed using a Root Mean Squared Error (RMSE), Pearson correlation and Spearman correlation. The algorithm used performed with a lower RMSE and a higher correlation for both services. Though the authors contribute QoE assessment models for voice calls and web browsing in the cellular environment, however, a growing mobile video streaming service is not considered.

Another study in [20] focuses on the evaluation of QoE for UMTS enterprise data subscribers. The work evaluates objective QoE using Network Management System (NMS) and crowdsourcing tool from the network side. The author considered download and upload throughput with Latency for assessing the experience of UMTS data subscribers. In addition to the objective quality metrics, the perceptions of enterprise customers are also collected separately for validations using a survey questionnaire and expressed in the MOS scale.

Existing research activities are summarized in Table 1.2 with investigated quality affecting metrics and applied techniques for prediction of QoE over a cellular network. From the analysis of the state of art of QoE models, we can conclude that:

1. Available and widely discussed models limited to simulation environments that are difficult to apply in the real world and implements an ineffectual dataset size.
2. Most of the techniques found in the literature focus on metrics that can be collected from the network side and drops important IFs such as video resolution, content type, etc. However, video QoE is multidimensional, and focusing only on NQoS or Application-level QoS (AQoS) may not express perceived quality by the users.

3. Interactions between essential video IFs and their effects on QoE are not well defined.
4. Methodology of the proposed models are challenging and missing.

Table 1.2 Comparison of existing QoE Models with different parameters

QoE Model	Metrics	Services	Measurement Technique	Algorithms
[16]	Network delay packet loss, jitter and throughput	Video	Subjective and Objective	Logistic Function
[14]	Packet delay, packet jitter and loss	Video	Subjective and Objective	Artificial Neural Network
[18]	Packet loss packet reordering	Video	Subjective and Objective	MLR
[19]	RF Metrics	Voice and Web browsing	Subjective and Objective	SVR

1.7 Methodology

The methodology used in the thesis includes:

- Conduct literature reviews to identify and select predominant video streaming IFs, and explore machine learning algorithms capable of assessing QoE.
- For the subjective measurements, a video of 4:36 length is selected, and customers are asked to watch the video before rating their satisfaction. Then, questionnaires' are conducted related to the user's satisfaction on mobile network quality using the MOS scale according to the ITU P.800 recommendation [12, 21]. The questionnaire was directly given to the customers of ethio telecom's via Google Form (see Appendix B).
- For each subjective measurement, key QoS inputs parameters are identified and collected using a network performance measuring tool called nPerf [15], which is an active an end to end testing solution. An Internet package of 26 gigabytes per month provided by ethio telecom is used for watching the video and collecting selected in parameters.

- Data formatting, data cleaning, and dealing with missed values are tasks that included in data preprocessing. From preprocessed data, normalized features were selected accordingly.

- Anaconda Python software is applied to train the machine learning algorithms.

- A total of 1167 data set was collected. When 80% of these data set is used for training the model, and 20% is used to evaluate the performance of the hypothesis to be developed. The training set is the input of the learning algorithm. The test set is used to determine the final performance of the model.

- The best-performed model is used at the end to show the spatial distribution of estimated QoE.

- Performance of selected algorithms are analyzed and the best-performed algorithm is selected with an Mean Squared Error (MSE), Pearson and Spearman correlations, as evaluation metrics.

The Overall experimental process is given in Figure 1.2.

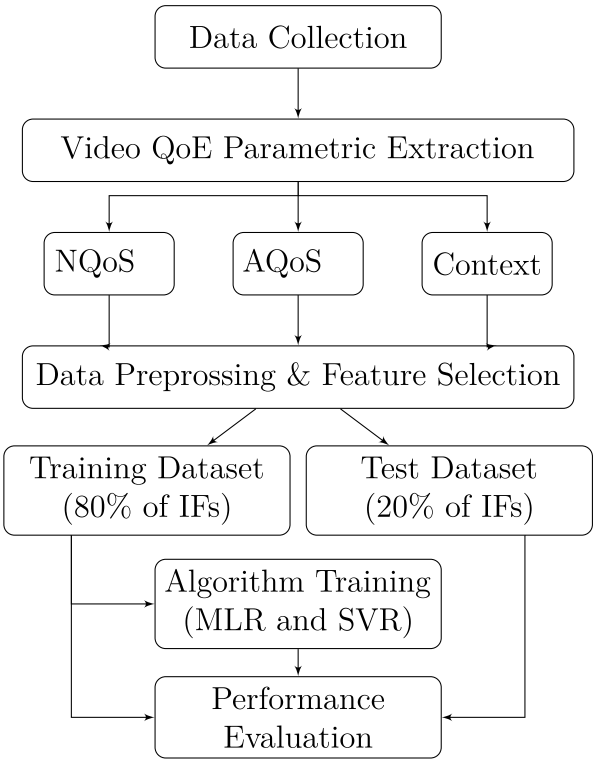


Fig. 1.2 Overall experimental process

1.8 Thesis Layout

This thesis consists of five chapters. In Chapter 1, an introduction statement of the problem objectives and the methodologies used in this thesis are given. The history of mobile communication in Ethiopia and an overview of the 4G LTE network are highlighted in Chapter 2.

Chapter 3 introduces the proposed machine-learning solution for multidimensional MOS prediction.

Furthermore, in Chapter 4, the procedure conducted for the development of the proposed model is presented.

Chapter 5 exhibits the evaluations of the collected parameters and the proposed model, showing the most relevant results. Chapter 5 also examines the obtained results in terms of the relationship between the real collected and predicted MOS values in detail. The application of the proposed model is given at the end of this chapter.

Finally, conclusions and future work are drawn corresponding to the proposed models in Chapter 6.

Chapter 2

Background on LTE Networks

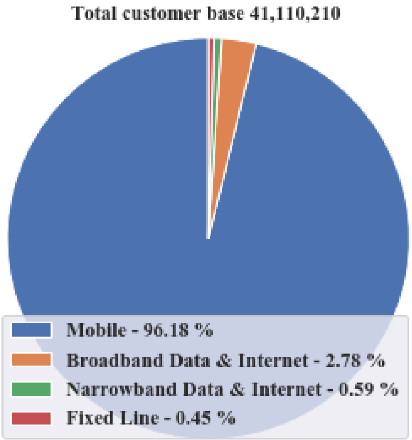
2.1 History of Mobile Communication in Ethiopia

In an emerging global economy, the ability of the telecommunications sector to provide an internationally competitive network for transferring information has significant implications for trade and economic growth in one country [22]. In Ethiopia, ethio telecom provides all telecom services including fixed, mobile, Internet, and data communications to the users.

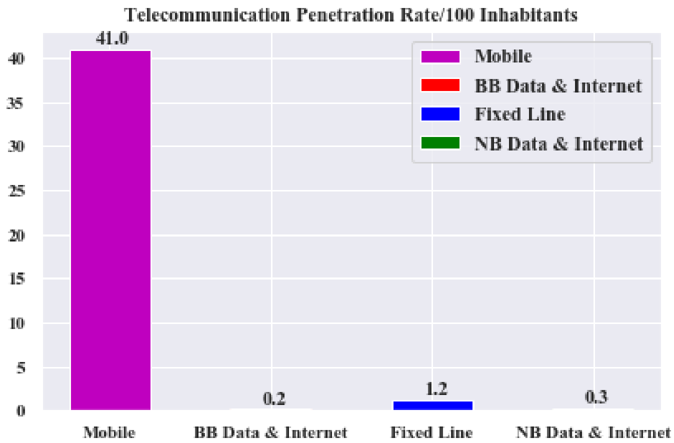
In ethio telecom, the Global System for Mobile communication (GSM) network was the first network used to offer voice and Short Message Service (SMS) services. GSM also evolved to handle Internet service General Packet Radio Service (GPRS) and Enhanced Data rates for GSM Evolution (EDGE) for improved data transfer rates.

Third Generation (3G) networks deployed after several years of release time of Second Generation (2G) to more improve data rate and it enables the end-users to use multimedia streaming services. However, the performance of 3G did not meet the demand for driving future high-performance data-hungry multimedia applications. Thus, the company has launched a 4G mobile service in the capital Addis Ababa, aiming to achieve higher throughput, lower delays and improved QoS in 2015.

As the recent forecast of the ethio telecom [2] on mobile subscriber shares and density given in Figure 2.1, 96% of total customers use mobile service. When we see mobile service geographical coverage, and capacity 85% of the country covered by a 2G network, 66% of the country was covered by the 3G network. The coverage of LTE is available only in Addis Ababa in 332 Sites with an offered capacity of 399,735.



(a) Total customer base



(b) Density by subscription/100 inhabitants

Fig. 2.1 Teledensity in Ethiopia as of December 31, 2018 ethio telecom [2]

2.2 LTE Network Architecture

LTE is a global standard for mobile broadband access that achieves high data rates primarily by improvements in radio technologies. High data rates are especially important for video streaming services. LTE has a theoretical net bit rate capacity of up to 100Megabits Per Second (Mb/s) in the downlink and 50Mb/s in the uplink if a 20 MHz channel is used and more if Multiple Input, Multiple Output (MIMO) antenna arrays are used. The information presented in section 2.2 was mainly based on [6, 23, 24].

The technology aims to provide seamless full Internet Protocol (IP) connectivity between User Equipment (UE)s and the Packet Data Network (PDN), without any disruption to the end-users applications during mobility. The core technologies have moved from circuit-switching to the all-IP Evolved Packet Core (EPC). Meanwhile, access has evolved from Time Division Multiple Access (TDMA) to Orthogonal Frequency Division Multiple Access (OFDMA) as the need for higher data speeds and volumes as increased [23]. This technology used OFDMA in the downlink and Single-Carrier Frequency Division Multiple Access (SC-FDMA) in the uplink respectively [24].

The evolution of the LTE's radio access represented through the Evolved UMTS Terrestrial Radio Access Network (E-UTRAN). It was accompanied by the evolution of non-radio aspects, designated by System Architecture Evolution (SAE), which includes the EPC. Together LTE and SAE comprise the Evolved Packet System (EPS). The main role of the EPS is to provide the user with IP connectivity to a PDN for accessing the Internet. This is achieved by establishing the concept of EPS bearer to route IP traffic from a gateway in the PDN to UEs. A bearer is an IP packet flow with a defined QoS between the gateway and the UE. Multiple bearers can be established for a user to provide different QoS streams or connectivity to different PDNs [23].

The LTE architecture, or EPS, is composed of the UE, the E-UTRAN, and the EPC. The access network of LTE (E-UTRAN) includes Evolved Node-B (eNB)s, which are interconnected with the EPC using the S1 interface and to each other through X2. The E-UTRAN oversees all radio-related functions, such as Radio Resource Management, header compression, security, and connectivity to the EPC [23, 24]. The overall network architecture including the network elements and the standardized interfaces are shown in Figure 2.2.

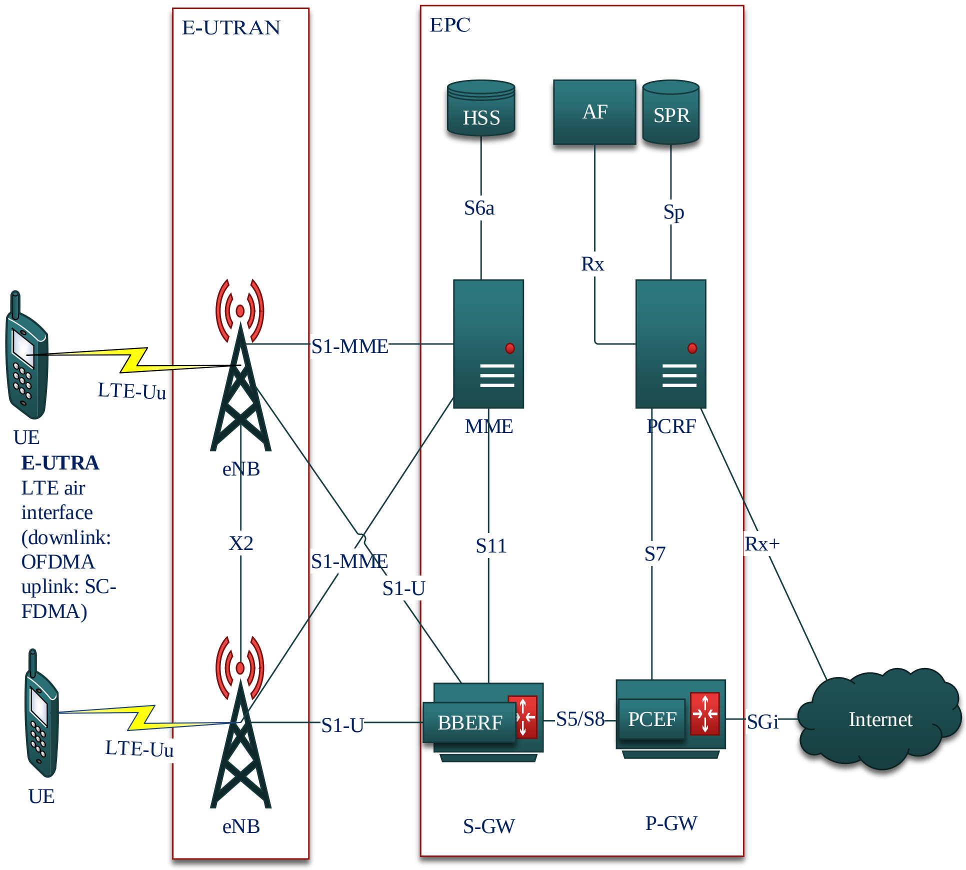


Fig. 2.2 LTE Network Architecture [24]

The EPC is responsible for the UE control and the establishment of bearers, which are the paths used by the user traffic to connect with PDN through the LTE transport network. The main logical nodes of the EPC are PDN Gateway (P-GW), Serving

Gateway (S-GW) and Mobility Management Entity (MME). In addition to these nodes, EPC also includes other logical nodes and functions such as the Home Subscriber Server (HSS), the Policy Control and Charging Rules Function (PCRF), Subscription Profile Repository (SPR) and Application Function (AF). Each logical nodes play their role in providing full services to the users[23, 24].

PCRF is the policy engine of Policy & Charging Control (PCC). It is responsible for policy control decision-making and for controlling the flow-based charging functionalities in the Policy Control Enforcement Function (PCEF). For building the PCC rule, PCRF receive information from PCEF, Bearer Binding and Event Reporting Function (BBERF), SPR, and AF.

PCEF is located at P-GW. This logical component provides information about the detected traffic at the user plane. The PCEF ensures if services billed according to the user's subscription profile. The policy enforcements (Gate and QoS) are also given by PCEF. To realize the policy enforcement, service data flow detection and flow-based charging functionalities, that are defined for the PCEF, a technology called Deep Packet Inspection (DPI) is used. DPI allows the ISP to examine network QoS metrics in real-time and to differentiate them according to their payload, service type, or predefined criteria.

3GPP/3GPP2 has defined the main QoS requirements called QoS Class Identifier (QCI)s for nine traffic classes mainly according to their priority, delay in milliseconds (ms), packet error loss, and resource type (e.g. Guaranteed Bitrate (GBR)) [6]. Table 2.1 shows the main QCIs requirements and example services.

The PCEF/BBERF provides information about the bearer characteristics. HSS is a repository of all subscriber and service-specific information, containing users' SAE subscription-related information. P-GW is responsible for IP address allocation to the UE, as well as QoS enforcement and flow-based charging according to the rules from the PCRF. P-GW also performs several IP functions such as address allocation, policy enforcement, packet filtering, and routing. S-GW is a local mobility anchor for data bearers when the user moves between eNBs. It manages and stores UE contexts and retains the information about the bearers when the UE is in the idle state. The S-GW prime responsibility is routing and forwarding of user IP-packets [23, 24].

The bearer management (establishment, maintenance, and release of the bearers) and connection management is the responsibility of MME. SPR is a database storing information related to network usage policies of a user such as charging related

Table 2.1 Standardized QCIs for LTE [6]

QCIs	Resource Type	Priority	Delay Budget	Error Rate	Example Services
1	GBR	2	100ms	10^{-2}	Conversational Voice
2		4	150ms	10^{-3}	Conversational video (Live Streaming)
3		3	50ms	10^{-3}	Real Time Gaming
4		5	300ms	10^{-6}	Non-Conversational Video (Buffered Streaming)
5	Non-GBR	1	100ms	10^{-6}	IMS Signalling
6		6	300ms	10^{-6}	Video(Buffered Streaming) TCP-based(e.g., www, e-mail, chat, ftp, p2p file sharing, progressive video, etc.)
7		7	100ms	10^{-3}	Voice, Video(Live Streaming) Interactive Gaming
8		8	300ms	10^{-6}	Video(Buffered Streaming) TCP-based(e.g., www, e-mail chat, ftp, p2p file sharing, progressive video, etc.)
9		9			

information, etc. AF provide information about the session characteristics such as media type, bandwidth, etc. to the PCRF.

The third component of LTE, UE, is used by an end-user to communicate with the network. It contains the Universal Subscriber Identity Module (USIM), which is an application placed into a removable smart card called the Universal Integrated Circuit Card (UICC). The USIM derives a security key for protecting, identifying, and authenticating the users in the radio interface transmission.

2.3 Advantages of LTE Technology

There are several reasons which are sufficient to answer a question- why do we need to adopt 4G technology? The technology offers several distinct advantages over other wireless technologies. These advantages include increased performance attributes, such as high peak data rates and low latency, and greater efficiencies in using the wireless spectrum. Improved performance and increased spectral efficiency will allow ISP using LTE to offer higher quality services and products for their customers [25].

As in [25], LTE support up to 200 active phone calls in every 5 MHz with low user plane latency $<$ 5ms for small IP packets. The 4G channel offers four times more bandwidth than current 3G systems and is scalable. So, while 20MHz channels may not be available everywhere, 4G systems will offer channel sizes down to 5MHz, in increments of 1.5MHz. The technology also allows more information to be transmitted in a given bandwidth while increasing the number of users and services the network can support. Two to four times more information can be transmitted versus the previous benchmark, High-Speed Packet Access (HSPA). In addition to spectral efficiency, it also improves at the coverage area or cell edge. Data rates improve two to three times at the cell edge over the previous benchmark, HSPA.

The LTE technology also reduces handover latency and packet loss which is key to delivering a quality service. This reduction is considerably more challenging with mobile broadband than with fixed-line broadband. The time variability and unpredictability of the channel become more acute. Additional complications arise from the need to hand over sessions from one cell to another as users cross-coverage boundaries. These handover sessions require seamless coordination of radio resources across multiple cells.

Chapter 3

Machine Learning Algorithms

3.1 Introduction

Machine learning is a branch of artificial intelligence that aims at enabling machines to perform a specific task without using explicit instructions, relying on patterns and inference instead. Machine learning algorithms build a mathematical model based on sample data, known as "training data" and provide some expertise in the form of a computer program that can perform some task as an output. The inputs are provided as concepts, instances, and attributes while the outputs are displayed using different knowledge representation styles such as decision tree, decision table, classification rule, association rule, clusters or regression. The incorporation of prior knowledge is inevitable for the success of machine learning algorithms [26].

Machine learning performs complex tasks that are performed by human beings and beyond the capabilities of human beings. Examples of tasks performed by human beings include driving, speech recognition, and image understanding. Another wide family tasks of machine learning techniques are related to the analysis of very large and complex data sets: Fraud detection and prediction, astronomical data, turning medical archives into medical knowledge, weather prediction, analysis of genomic data, Web search engines, and electronic commerce [27].

On the other hand, the adaptive nature of machine learning algorithms to environmental changes makes them preferable compared to other programming codes. Typical successful applications of machine learning to such problems include programs that decode handwritten text, where a fixed program can adapt to variations between the handwriting of different users; spam detection programs, adapting automatically to changes like spam e-mails; and speech recognition programs [27].

Machine learning comes in many different flavors, depending on the algorithm and its objectives. Many kinds of literature divide machine learning algorithms into three main groups based on their purpose or the way they learn: supervised, unsupervised, and reinforcement learning [28].

In supervised learning, we are given a data set and already know what our correct output should look like, having the idea that there is a relationship between the input and the output.

Supervised learning problems are categorized into regression and classification problems. In a regression problem, we are trying to predict results within a continuous output, meaning that we are trying to map input variables to some continuous function. In a classification problem, we are instead trying to predict results in a discrete output. In other words, we are trying to map input variables into discrete categories.

The majority of practical machine learning uses a supervised learning algorithm. In supervised learning, input parameter (typically a vector) and the desired output value exist with a description or labels, and the objective is to find a general rule that maps input to output. It means some data already tagged with the correct answer, and the learned rule is to label new data with an unknown output value. Supervised learning stops learning when the algorithm achieves an acceptable level of performance. Supervised learning problems can be further grouped into regression and classification problems [28].

- Classification: In a classification problem, we are trying to predict results in a discrete output. In other words, we are trying to map input variables into discrete categories. For instance, given a patient with a tumor, we have to predict whether the tumor is malignant or benign.

- Regression: In a regression problem, we are instead trying to predict results within a continuous output, meaning that we are trying to map input variables to some continuous function, for example predicting real state prices.

Unsupervised learning is used where only input data exists and no corresponding output variables. It aims to model the underlying structure or distribution in the data to learn more about the data. There no correct answers, and thus, algorithms are left to their devises to discover and present the interesting structure in the data.

Unsupervised learning problems can be further grouped into clustering and association problems.

- Clustering: Clustering is used in a problem where we want to discover the inherent groupings in the data, such as grouping customers by purchasing behavior.
- Association: An association rule learning problem is where we want to discover rules that describe large portions of our data, such as people that buy A also tend to buy B.

A problem that sits in between supervised and unsupervised learning called semi-supervised learning that is applied for a large amount of input data and only some of the data is labeled. For instance, a photo archive where only some of the images are labeled and the majority are unlabeled. We can use unsupervised learning techniques to discover and learn the structure in the input variables. We can also use supervised learning techniques to make best guess predictions for the unlabeled data. Feed that data back into the supervised learning algorithm as training data and use the model to make predictions on new unseen data.

Machine learning technology is applied in different telecommunication tasks such as user QoE prediction [16, 17, 14, 18, 19, 29], failure prediction [30], fraud detection [31], and designing customer churn prediction model [32, 33]. The customer churn prediction model helps to analyze the satisfaction level of users, and then potential customers who may leave for another Telecom Service Provider (TSP) are identified.

Regression techniques have been widely applied for predicting the perceived quality of video streaming since the output is expressed in terms of MOS, which is a continuous value ranging from 1 to 5. This thesis employed two regression techniques for estimating video QoE scores: the MLR [3, 19, 28] and the SVR [4, 19]. MLR was used to aggregate linearly video quality affecting factors to predict user-perceived QoE. Conversely, SVR allows capturing the non-linear relationship between the quality affecting factors and output. As in [29], SVR techniques deliver a unique optimal solution since it is based on a convex optimization problem and can learn very complex non-linear Kernel functions, which can handle highly overlapped and non-linearly separable data. So, the SVR technique already showed good results in different studies used.

3.2 Multivariate Linear Regression Algorithm

Linear regression is a popular statistical tool for modeling the relationship between some "explanatory" variables and some real-valued outcome [27]. Simple linear regression use only one input feature to predict the output. But, to predict user-perceived QoE for video streaming, there are more than one quality affecting factors, and thus MLR is used. MLR is a linear regression technique that uses more than one input feature to estimates a single regression model with one or more than one outcome variable. Graphical model representation is depicted in Figure 3.1.

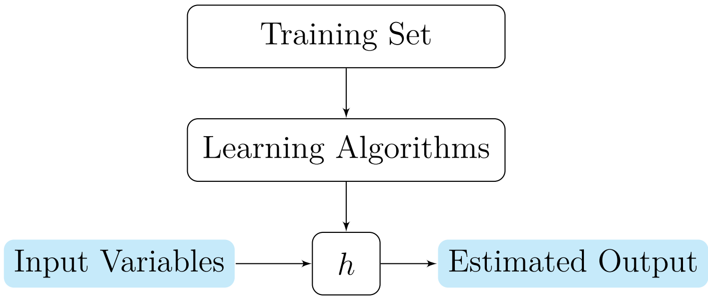


Fig. 3.1 Linear Regression Model Representation [3]

MLR [3] aims to obtain hypothesis $h(x)$ that represent the model to be learned for predicting future values of video QoE for a giving sample vector (x). The model takes n input features $x_j; j = 1, ..., n$, and $y^{(i)}$ to denote the "output" or target variable that we are trying to predict (QoE). To obtain this expression, a learning algorithm is used which considers a training set $x_1^{(i)}, x_2^{(i)}, ..., x_n^{(i)}, y^{(i)}; i = 1, ..., m$ containing m training examples of $x_j; j = 1; ..., n$ and y. We use the training set to train each hypothesis. Note that the superscript "(i)" in the notation is simply an index into the training set, and has nothing to do with exponentiation. Notation for equations where we can have any number of input variables shown here.

$h(x)$ = hypothesis to be learned for a giving sample vector (x)

$x_j^{(i)}$ = value of feature j in the i^{th} training example

$x^{(i)}$ = the input (features) of the i^{th} training example

$y^{(i)}$ = the output of the i^{th} training example

m = the number of training examples

n = the number of features

Mathematically [3, 28], hypothesis $h(x)$ is given by Equation (3.1), where $\theta_j; j = 0, ..., n$ are the weights of corresponding input parameters or parameters of the model.

$$h_\theta(x_1, ..., x_n) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + ... + \theta_n x_n \tag{3.1}$$

The learning algorithm tries to predict the best values of the hypothesis parameters (vector of θ values) by minimizing the difference between the target value and real collected value. The evaluation of how close a fit the model estimates a target value can be calculated in several ways. One of this method is a cost function given in [3, 18]. The cost function involves evaluating the coefficients in the learning model by calculating a prediction for each training set in the input features and measures the average difference between the predicted values by the hypothesis h and the original values y for the same input features. Equation (3.2) defines mathematical expressions of the cost function J. The higher this value, the worse the model is.

$$J(\theta_1, ..., \theta_n) = \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2 \tag{3.2}$$

3.2.1 Parameter Learning

To calculate the θ values that minimize the cost some models have been developed. One of them is the Normal Equation model, that takes $J(\cdot)$ derivatives regards to the θ_j's and sets them to zero. This way, it is possible to determine the θ_j's that minimize the cost for a hypothesis h [3]. And these expression is given in Equation (3.3) where X is an $(m) \times (n+1)$ matrix with all the training examples corresponding to $x_j; j = 1, ..., n$ features. y is an m-dimensional array with all training examples corresponding to y; θ is an m-dimensional array with the calculated $\theta_j; j = 0, ..., n$, as shown in Equation (3.4).

$$\theta = (X^T X)^{-1} X^T y \tag{3.3}$$

$$X = \begin{bmatrix} 1 & x_1(1) & x_2(1) & x_3(1) & \dots & x_n(1) \\ 1 & x_1(2) & x_2(2) & x_3(2) & \dots & x_n(3) \\ 1 & x_1(3) & x_2(3) & x_3(3) & \dots & x_n(3) \\ \vdots & \vdots & \vdots & \vdots & \ddots & \dots \\ 1 & x_1(m) & x_2(m) & x_3(m) & \dots & x_n(m) \end{bmatrix}; \quad y = \begin{bmatrix} y^{(1)} \\ y^{(1)} \\ y^{(1)} \\ \vdots \\ y^{(m)} \end{bmatrix}; \quad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix} \tag{3.4}$$

This algorithm may suffer from an overfitting problem since it aims to minimize the cost. An overfitting, or high variance, is caused by hypothesis function that fits the training set very well ($J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 \approx 0$), but fail to generalize well to predict new data when too many features exist. To avoid overfitting problem in advance, reducing the number of features can be seen as a solution. But, removing single features may be similar to removing the information, and thus we use regularization methods. Regularization techniques keep all the features but reduce the values of parameters θ_j. So, in Subsection (3.2.2), a regularized linear regression is introduced.

3.2.2 Regularized Linear Regression

Regularized Linear Regression is an extension of linear regression model aims to prevent overfitting problem [28]. Regularization parameter λ is introduced and applied when there exist a lot of features and each contributes a bit to the prediction. Mathematically, the regularized linear equation is given in Equation (3.5) by modifying the cost function [3].

$$J_{reg}(\theta_1, ..., \theta_n) = \frac{1}{2m}\left[\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2 + \lambda\sum_{j=1}^{n}\theta_j^2\right] \tag{3.5}$$

Where, $\lambda\sum_{i=1}^{n}\theta_j^2$ is the regularization term and λ is called the regularization parameter.

The regularization parameter is included in the Normal Equation model as expressed in Equation (3.6). L is a $(n+1)\times(n+1)$ matrix similar to the identity matrix. But, 0 is assigned for the first value of diagonal as shown in Equation (3.7).

$$\theta = (X^TX + \lambda \cdot L)^{-1}X^Ty \tag{3.6}$$

$$L = \begin{bmatrix} 0 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix} \tag{3.7}$$

Notice that λ has to be chosen carefully. If we introduce too much λ, we can underfit the training set and have worse performance on the training set. A too-small value of λ does not guarantee any improvement for overfitting problem and there is no difference to the hypothesis without regularization and it can suffer from an overfitting problem.

3.3 Support Vector Regression Algorithm

In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. As the name implies, the SVR is a regression algorithm that works with continuous values instead of classification analysis, which is the support vector machine.

SVR aims to find a function $f(x)$ that has at most ϵ deviation from the obtained targets y for a given set of n features $x_j; j = 1; ..., n$ and at the same time is as flat as possible [4]. In other terms, we do not care about errors as long as they are less than ϵ, but will not accept any deviation larger than this. The learning algorithm minimizes the ϵ-insensitive loss function is shown in Figure 3.2. To obtain this expression, a learning algorithm (SVR) considers a training set $x_1^{(i)}, x_2^{(i)}, x_n^{(i)}, y^{(i)}; i = 1, ..., m$ containing m training examples of $x_j; j = 1; ..., n$ and y.

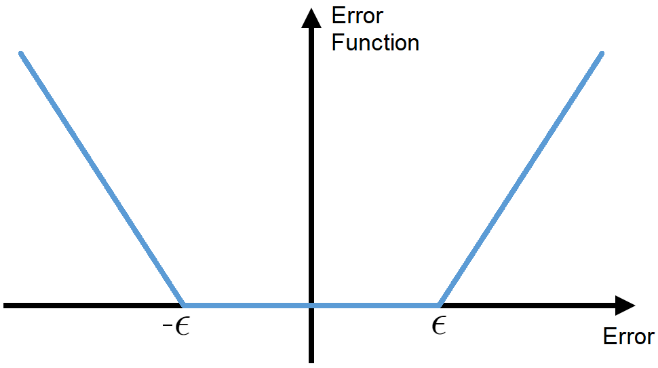


Fig. 3.2 ϵ-insensitive Loss Function [4]

One of the main characteristics of SVR is the capability of solving linear and non-linear problems, and it can make more complex predictions than the MLR model. The underneath subsections highlight the algorithm for these two regression problems.

3.3.1 Linear SVR

The linear functions f of SVR taking the form given by Equation (3.8) [4].

$$y = f(x) = \langle w, x \rangle + b \tag{3.8}$$

Where $w \in \mathbb{R}^n$ identifies the weight vector having a unit length laid at a right angle with the hyper-plane, and $b \in \mathbb{R}$ corresponds to the threshold coefficient and are the parameters to be optimized. $x \in \mathbb{R}^n$ is an array with the features. The $\langle \cdot, \cdot \rangle$ denotes dot products of the x and w.

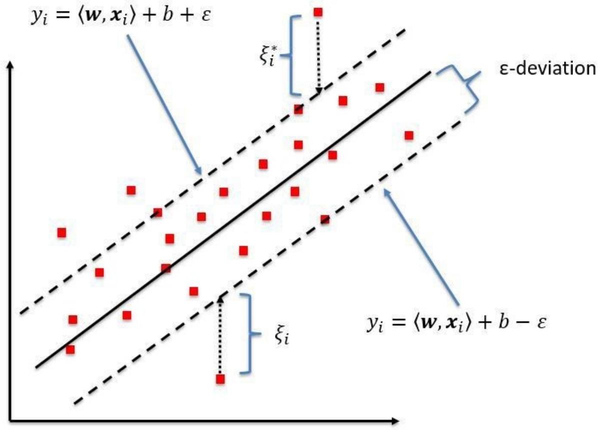


Fig. 3.3 The soft margin loss setting for a linear SVR [4]

To make a function f in Equation (3.8) as flat as possible, or to avoids overfitting problem, the norm of w has to be minimized, i.e. $\|w^2\| = \langle w, w \rangle$. Additionally, we have stated that the deviation of predictions has to be less than ϵ. However, in practice, the ϵ margin is difficult to ensure, and we also may want to allow for some errors. Therefore, as in [4], we write this problem by introducing slack variables ξ_i and ξ_i^*, as a convex optimization problem as shown in Equation (3.9).

$$\begin{aligned} &\text{minimize} && \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \\ &\text{subject to} && \begin{cases} y^{(i)} - \langle w, x^{(i)} \rangle - b \leq \epsilon + \xi_i \\ \langle w, x^{(i)} \rangle + b - y^{(i)} \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \qquad\qquad\qquad \geq 0 \end{cases} \end{aligned} \tag{3.9}$$

Where C is the constant > 0 that determines the trade-off between the flatness of function f and the amount up to which deviations larger than ϵ are tolerated. ξ_i, ξ_i^* are the amount by which the predictions may exceed the margin ϵ. $x^{(i)}$ and $y^{(i)}$ are corresponding to each training set. $i = 1, \ldots, n$ to identify input features that deviate from the ϵ-insensitive zone. Figure 3.3 depicts the situation graphically.

3.3.2 Non-Linear SVR

In the case of non-linear SVR [4], the kernel functions are introduced for transforming the data into a higher dimensional feature space to make it possible to perform the linear separation. This algorithm uses k support vectors by applying them in a kernel function. The functions to be optimized is given by [4, 19]:

$$f(x) = \langle w, K(x, SV) \rangle + b \tag{3.10}$$

Where $b \in \mathbb{R}, w \in \mathbb{R}^k, x \in \mathbb{R}^n$, and $SV \in \mathbb{R}^n \times \mathbb{R}^k$. The SV is a matrix with k support vectors $(k \geq n)$that are used to transform the data. $K(\cdot)$ is the kernel function that can be expressed in a different form. Since x and each individual SV line is applied to the function, the result is an array of dimension k.

The kernel function may be represented as a modified dot product of two functions, as in Equation (3.11). As shown in Figure 3.4, by applying Equation (3.11) to the input data set, a non-linear problem can be transformed into a linear one.

$$K(u; v) = \langle \varphi(u), \varphi(u) \rangle = \varphi(u) \cdot \varphi(u) \tag{3.11}$$

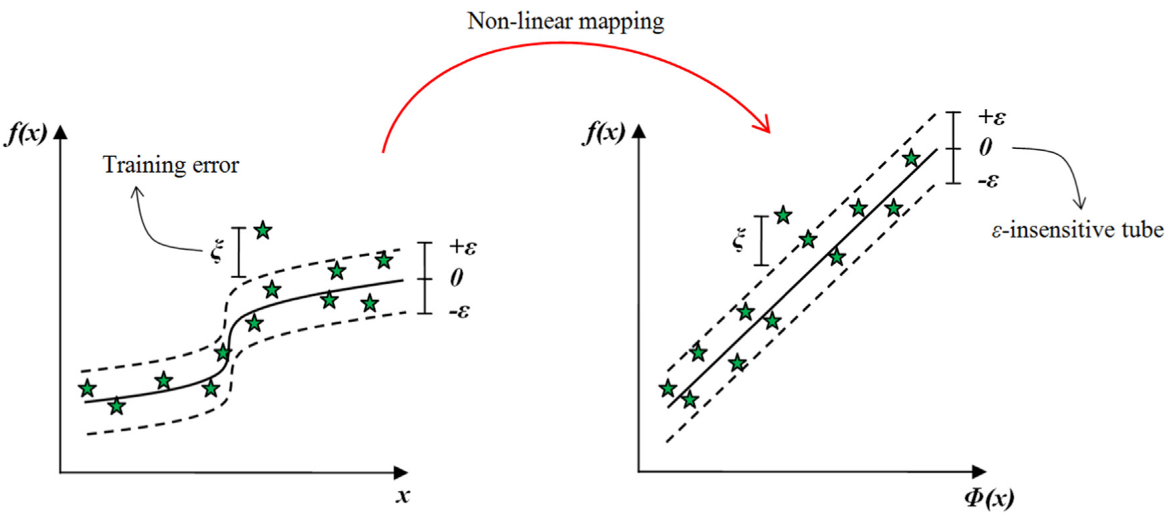


Fig. 3.4 Mapping a non-linear SVR into feature space and its ϵ-insensitive loss setting[4]

There are different forms of Kernel function. Due to this, selecting specific kernel types and kernel function parameters requires application-domain knowledge and should reflect the distribution of training data inputs. The most common kernel types corresponding to their equations are given below in Equation (3.12) [4, 19, 28].

$$
\begin{array}{ll}
\text{Linear Kernel} & K(u;v) = u \cdot u \\
\text{Polynomial of degree d} & K(u;v) = (\gamma u \cdot u + c_0)^d \\
\text{Radial Basis Function} & K(u;v) = e^{-\gamma \|u-v\|^2} \\
\text{Sigmoid} & K(u;v) = \tanh\left(\gamma u \cdot u + c_0\right)
\end{array}
\tag{3.12}
$$

In the case of a linear kernel, the kernel defines the similarity or a distance measure between new data and the support vectors. For the case of the polynomial kernel, the degree d must be specified to the learning algorithm. When $d = 1$ this is the same as the linear kernel. Gamma γ of Radial Basis Function (RBF) kernel is a parameter that must be specified to the learning algorithm. A good default value for γ is 0.1, where it is often $0 < \gamma < 1$. The RBF kernel is very local and can create complex regions within the feature space, like closed polygons in a two-dimensional space [28].

3.4 Model Evaluation Metrics

To evaluate the performance of the developed hypothesis by MLR and SVR, we use MSE, the Pearson correlation, and the Spearman correlation performance evaluation metrics [3, 19, 28].

MSE measures the average squared error of predictions. For each data point, it calculates the square difference between the predictions and the target and then averages those values. Mathematically, the MSE metric is defined by Equation (3.13), where $y^{(i)}$ and $\hat{y}^{(i)}$ are the original and predicted values of the i^{th} set of parameters, respectively. The higher the value of MSE, the worse the model is.

$$
\text{MSE} = \frac{1}{m} \sum_{i=1}^{m} \left(y^{(i)} - \hat{y}^{(i)}\right)^2 \tag{3.13}
$$

The Pearson correlation evaluates the linear relationship between the original values $y^{(i)}$ and predicted ones $\hat{y}^{(i)}$. In another term, it examines if measured and predicted one is similar. A relationship is linear when a change in one variable is associated with a proportional change in the other variable. The mathematical expression is given in Equation (3.14).

$$
R_{Pearson} = \frac{\sum_{i=1}^{m} (\hat{y}^{(i)} - \overline{\hat{y}})(y^{(i)} - \overline{y})}{\sqrt{\sum_{i=1}^{m} (\hat{y}^{(i)} - \overline{\hat{y}})^2} \sqrt{\sum_{i=1}^{m} (y^{(i)} - \overline{y})^2}} \tag{3.14}
$$

Where $\overline{y}$ represent the mean of the original values, the $\overline{\hat{y}}$ represents the mean of predicted values.

Spearman correlation is often used to evaluate the strength and direction of association involving ordinal variables. The Spearman correlation coefficient is based on the ranked values for each inputs parameters rather than raw data. Then after being ranked, the same Equation (3.14) is applied to those rankings.

Chapter 4

LTE Video Streaming QoE Model

This chapter presents LTE video streaming QoE models. First, potential video streaming QoE IFs are identified, followed by selected input metrics/parameters. The QoE model development process is shown using two different approaches. A first approach is a linear approach that used MLR to capture linear properties of selected metrics, whereas the second approach used SVR to show nonlinear properties. The performances of the proposed models are also presented using evaluation metrics described in Section 3.4.

4.1 Video Streaming QoE Influencing Factors and Metrics

To estimate video QoE perceived by end-users, we have to consider different video IFs, according to their type and map them to the QoE using a mapping function or machine learning algorithm. This IFs can be any characteristic of a user, system, service, application, or context whose actual state or setting may influence the user's QoE. As in [5], these factors falling into one of the four following multidimensional spaces, and it is illustrated in Figure 4.1 additionally.

- *Application space:* composed of dimensions representing application/service configuration factors. An instance of such factors includes encoding, resolution, sample rate, frame rate, buffer size, signal to noise ratio, etc. Content-type is also a key factor to be considered in this space.

- *Resource space:* composed of dimensions representing the characteristics and performance of the technical systems, and network resources used to deliver the service. Examples of such factors include NQoS in terms of delay, jitter, loss, error rate, and throughput. Furthermore, system resources such as server processing capabilities and end-user device capabilities (e.g. computational power, memory, screen resolution, user interface, battery lifetime, etc.) are included.
- *Context space:* composed of dimensions indicating the situation in which a service or application is being used. A wide variety of dimensions may be considered in this space, include ambient conditions (e.g., lighting conditions, noise), user location, time of day, and social context. Additionally, the purpose of watching a video is considered at this level. Dimensions representing economic context may also be considered, such as service costs.
- *User space:* composed of dimensions related to the specific user of a given service or application. An example of such factors includes demographic data, user preferences, requirements, expectations, prior knowledge, mood, motivation, the particular role taken on by a user, etc.

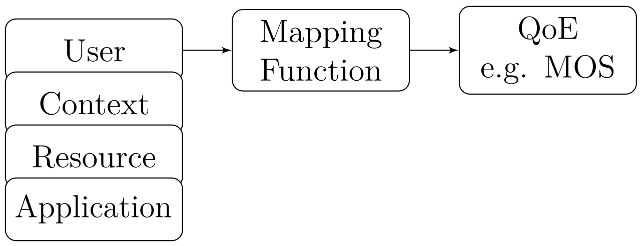


Fig. 4.1 The dimensions of Video IFs[5]

4.2 Video Streaming QoE Model Development

In the following, feature extraction and their impact on video streaming services are described briefly. Then, the QoE development process will be presented. The model development process is done using MLR and SVR algorithms to predict the MOS value with the measured parameters. Both MLR and SVR are applied to collections of the parameter to obtain different hypotheses and to choose the best one. The MLR is used to show if the influence of the parameters on the MOS value is a linear and the SVR to show if impact is a nonlinear one. We see the detail of development process in the following subsection.

4.2.1 Data Collection Procedures

After defining the dimension of video IFs in Section 4.1, let us dive into the most predominant parameters collected for video streaming QoE model generation.

A sum of 1167 user satisfaction/MOS ratings, video resolution, and content type were collected directly from ethio telecom users after watching preferred video streaming. From a content type perspective, 358 of 1167 users watch the video on politics frequently. When we see from a video resolution point of view, 778 of them watch in available quality without changing their resolution. NQoS metrics were measured corresponding to each MOS ratings at 376 different areas using the nPerf tool [15]. The impact of time of the day on QoE is captured by repeating the data collection areas.

These collected parameters are mapped to user-perceived QoE using considered machine learning algorithms or mapping functions, which are MLR and SVR in our case. Figure 4.2 shows the collected parameters for the QoE model development process.

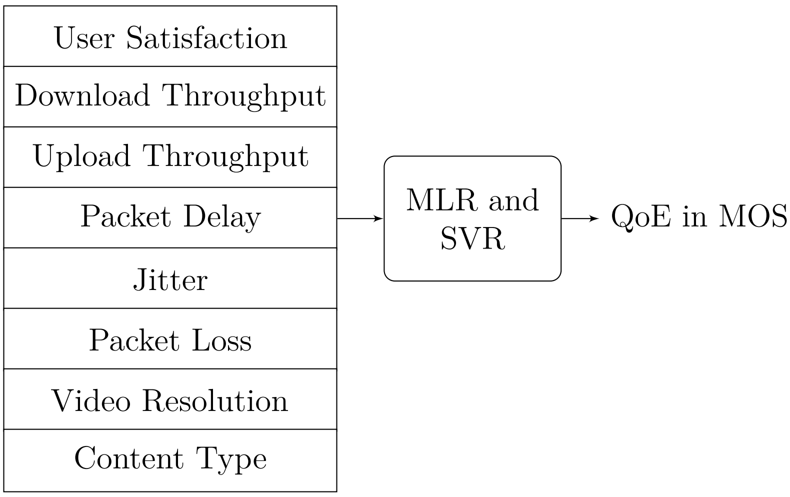


Fig. 4.2 Collected parameters for video streaming QoE model development

As noted, user's satisfaction can be affected on different layers. On each separate layer, different quality affecting factors play different impacts on video streaming services. So, exploring the consequence of chosen parameters on video streaming is significant. Network layer quality affecting QoS parameters and corresponding influences are highlighted in [17] without examining other factors on a different layer. Table 4.1 shows us impacts and the details of each selected metric for QoE model development.

Table 4.1 Considered parameters and their influence on video streaming quality

Metrics	**Values**	**Description**
Satisfaction	$[1, 5]$	Satisfaction is an input collected from the user to determine how the customers are happy with an ethio telecom's LTE service qualities. The customer is asked to watch the video in [34]. After watching a video, their happiness with LTE service is received through MOS ratings. It is the output $y^{(i)}$ of the model to be developed.
Content	Sport, educational, politics, religious	Content may differ in genre and enjoyability. An individual likes watching religious videos may be dissatisfied with the video produced on politics, films, sport, etc. That means users give his rating on the type of videos rather than the quality provided by the ISP.
Resolution	1080p HD, 720p HD, 480p, Auto	Video streaming quality is usually defined based on resolution. The video contents were encoded based on the available bandwidth at multiple resolutions by using the de-facto standard called HTTP Adaptive Streaming (HAS). The problem with this standard is that the user suffers video freezes as high Round-Trip Time (RTT) is introduced to it when the available bandwidth suddenly switches.
Download (Mb/s)	$[0, \infty)$	Shows the amount of data LTE connection can receive in one second from the video server. When available download throughput is less than the video streaming bit rate, the quality of the image degrades.
Upload (Mb/s)	$[0, \infty)$	Indicates the amount of data LTE connection can send in one second to the video server. The video is uploaded with the most insignificant quality if upload throughput is less than the video bitrate.
Delay (ms)	$[0, \infty)$	It is the amount of instant time between capturing and displaying a frame. Due to the buffer size limitation of the user, if the latency is too large, the packet dropped and results in a degradation in image quality.
Jitter (ms)	$[0, \infty)$	It is a delay variation due to the inherent variability in arrival times of individual packets. When it is too long, packets are dropped and induces decreasing in quality.
Loss (ms)	$[0, 100]$	Packet loss is the average number of packets lost relative to sent to the video server in a second. It is the main reason that causes the deterioration of video image quality, especially if it is a keyframe.

4.2.2 Video Streaming QoE Model using MLR

The MLR algorithm introduced, in Section 3.2, was first applied to a set of hypotheses of the selected features. Table 4.2 reveals the description and values of the measured data set for both MLR and SVR algorithms.

Table 4.2 Overall description of collected data

	Satisfaction	**Download**	**Upload**	**Delay**	**Jitter**	**Loss**
Count	1167	1167	1167	1167	1167	1167
Mean	2.79	30.02	6.2	288.27	34.41	0.04
Std	1.27	21.68	5.58	87.87	21.81	0.28
Min	1	0.61	0.06	60.1	2	0
25%	2	12.5	1.19	242	18	0.0
50%	3	23.7	3.57	251	31	0.0
75%	4	43.19	11.1	279	46	0.0
Max	5	92.05	27.89	761	207	3

The methodology introduced in Section 1.7 was applied to train and assess the developed hypothesis. The data set is divided into a training set and a test set. When 80% of the data set is used for training the predictive model, and 20% is used to evaluate the performance of the developed hypothesis. Equation (3.1) applied to the measured dataset to compute the best intercept and coefficients of each feature and to learn the most fitting hypothesis. The final obtained intercepts and coefficients of each data set used by MLR are shown in Equation (4.1) below.

$$\begin{aligned} h_\theta(x) = 1.654 + 4.795(DL) + 5.25(UL) - 1.2(PD) + 2.481(PJ) \\ - 2.793(PL) - 6.392(480p) - 2.914(720p) - 1.694(Auto) \\ - 4.839(Plt) + 4.862(Rel) - 1.878(Spt) \end{aligned} \tag{4.1}$$

The proposed QoE model in this section relies on a MLR. Thus proving the following assumptions is significant to show whether quantifying user-perceived video streaming QoE by MLR is possible or not. These assumptions are:

- There must be a linear relationship between each feature and the predicted satisfaction when the other remained constant.
- The errors should be independent and normally distributed.
- Homoscedasticity: the errors have a constant variance relative to the predicted values and any feature.

Analysis of the proposed model was conducted to ensure whether the above linear regression assumption is achieved or not. The linear dependence of each feature on the expected value was examined by plotting real user satisfaction in the MOS scale and predicted MOS values. The scatter diagrams are depicted in Figure 4.3, where horizontal coordinate describes the real user satisfaction in the MOS scale, and the vertical coordinate describes the estimated MOS.

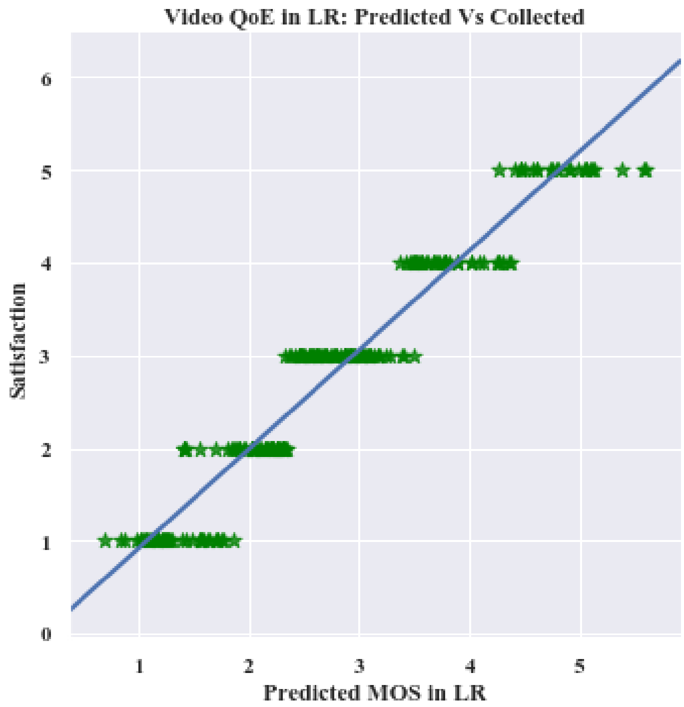


Fig. 4.3 The correlation between the collected satisfaction and predicted MOS value by using MLR

The plot, in Figure 4.3, should be symmetrically scattered around a regression line. The difference between each data point and the regression line is the residue or prediction error of each MOS estimation. If each data point exactly fits the regression line, the prediction error becomes 0, and the correlation between predicted and collected MOS becomes 100%.

Though, as noticed from Figure 4.3, the residual or distance between data points and the regression line indicates that it does not fit well the linear properties. We can also observe the same thing from the properties of each NQoS feature with each other and concerning the estimated MOS value from the distribution of the data depicted by the grid plot in Figure 4.4. For instance, we cannot express the properties between jitter and upload using MLR since there are no linear properties between those parameters.

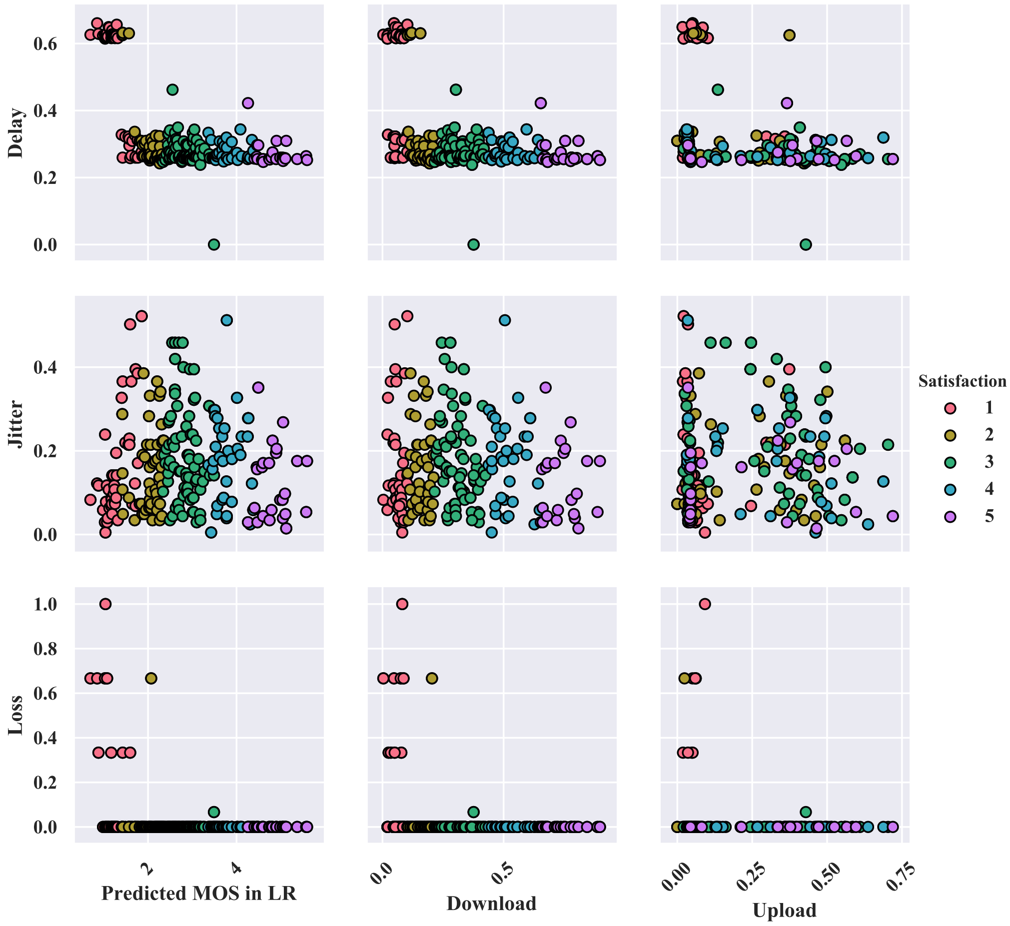


Fig. 4.4 The distribution of NQoS and predicted MOS value by using MLR

To minimize these residuals and to examine if the performance is enhanced comparative to the model done using MLR, we consider the second nonlinear algorithm presented in Section 3.3 to map the collected IFs into the video QoE.

4.2.3 Video Streaming QoE Model using SVR

QoE provides an evaluation of human perceptions, feelings, emotions, and intentions concerning a particular product or application. User-perceived experience can be affected by several technological, business, and contextual factors. Hence, a reliable network quality may not confirm that the users have surpassing level satisfaction. In such conditions, we can not express end-user perception using a linear model.

As stated, there are multiple causes of nonlinear properties for measured parameters with each other and with predicted QoE. For instance, as plotted in Figure 4.4, jitter has nonlinear characteristics with the upload and forecasted QoE. The reason behind these properties can be the time of the day, location of the users, service cost, etc.

Let's dive into one step. The user had been experiencing a reliable network quality and seeing the video in high video resolution. High video resolution requires high data rates and is the best choice to see a video in high-grade quality. However, these requirements of a high data-rate require expensive service costs that abuse the level of end-user satisfaction.

To overcome the shortcomings of the linear QoE calculation model and solve the nonlinear problem of multi-parameter, we use the SVR algorithm rather than MLR. The SVR algorithm introduced in Section 3.3 is used to train the same training set used in MLR. The methodology used in SVR is also the same as the methodology used for MLR algorithms presented in Section 1.7. The RBF hyperparameters of SVR γ, C and ϵ showed in Equation (3.12), were optimized carefully. After careful selection of the hyperparameters and train each hypothesis, the performance was evaluated using the performance evaluation metrics.

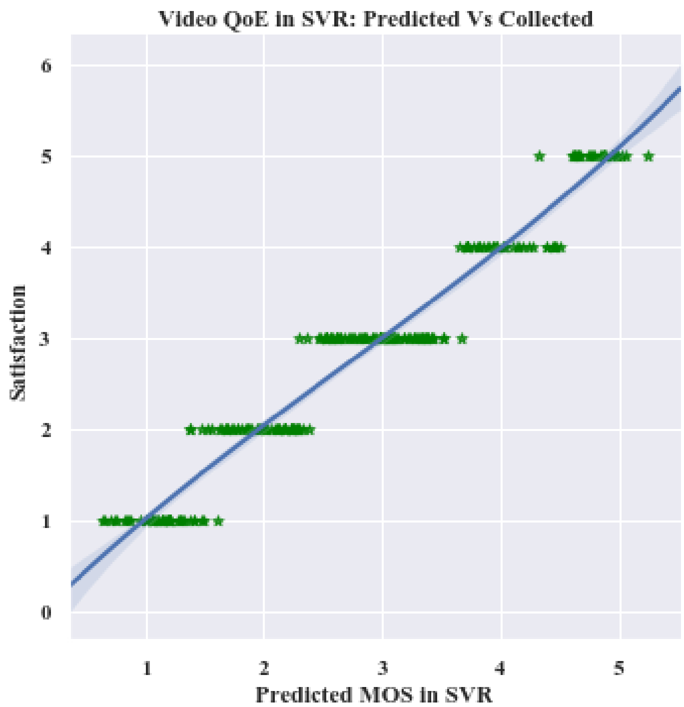


Fig. 4.5 The correlation between the collected satisfaction and predicted MOS value by using SVR

As done in MLR, the comparison of the collected and predicted satisfaction for the SVR model was shown in Figure 4.5. From the diagram, we can easily recognize enhancements in the SVR algorithm. SVR captured nonlinear properties of the obtained parameters accordingly. The data points are scattered symmetrically near the regression line than the MLR. The distance between each data point and the regression line is residual of the prediction. MSE was applied to evaluate the residuals of both the QoE prediction model as an accuracy measuring metric.

The learning curves for both MLR and SVR were depicted in Figure 4.6 to evaluate if the developed models overfit or not. When the training set increases in sizes, the MSE decreases, and the model generalizes more reliably. Hence, adding data sets will improve the performance of the model by decreasing the difference between measured and predicted MOS values. SVR algorithms need too much data set than MLR to learn hypotheses and generalizes the data. But, later having sufficient data, SVR generalizes more reliable than that of MLR. On the other hand, someone can observe that MSE approaches to more comparable values as the training set increases. Therefore, adding too many data set improves the performance of the model, and couldn't be the case for the overfitting problem.

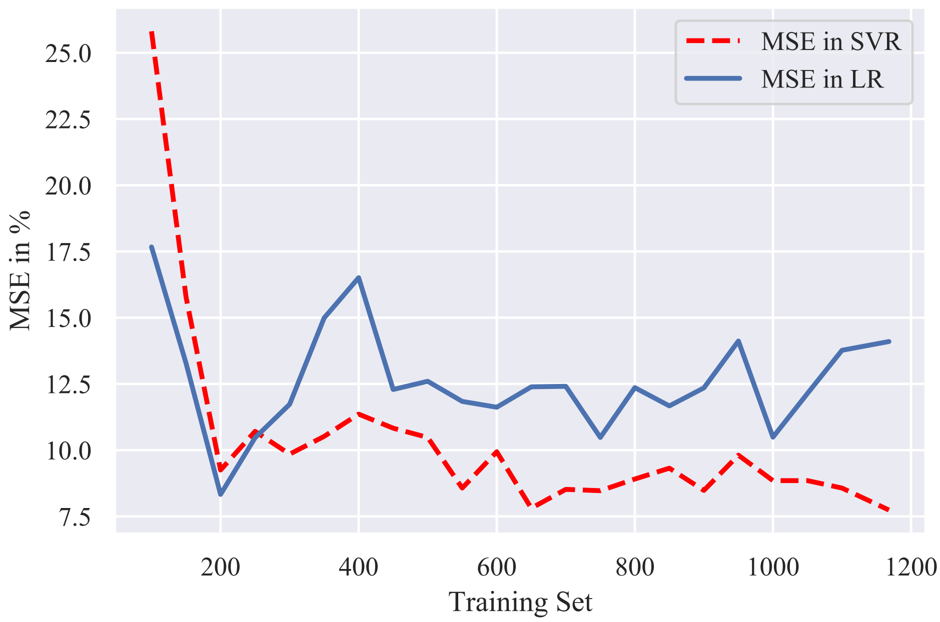


Fig. 4.6 Learning curves of each algorithm for video streaming QoE model

After examining the obtained results in both case, in the following chapter, the performance of the proposed model and different interpretation is given from the standard perspective briefly.

Chapter 5

Results and Discussion

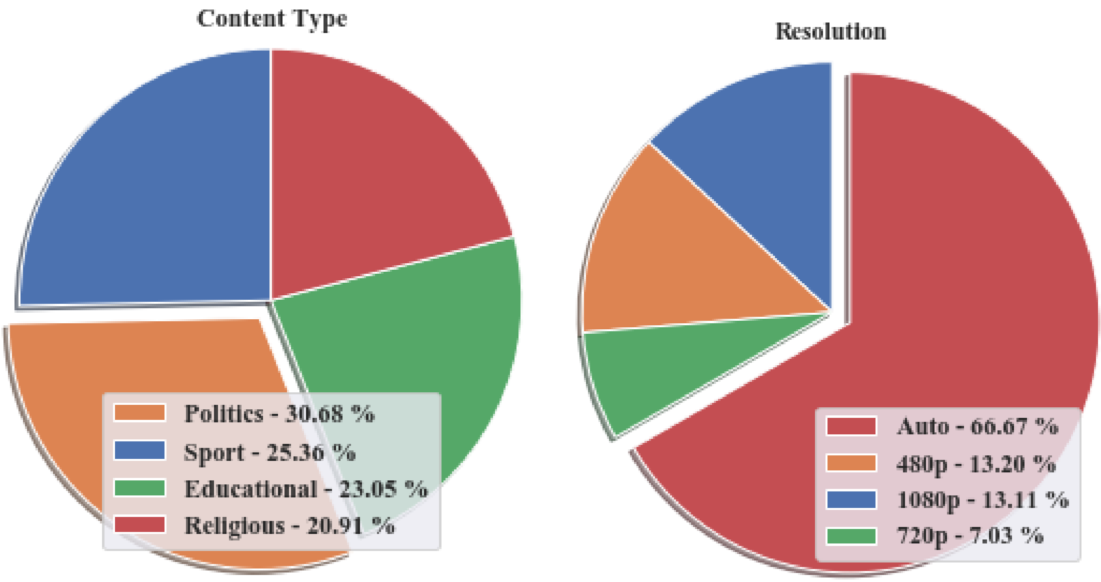
In this chapter, first, the collected features were interpreted from the standard perspective. Then, the proposed model is evaluated using performance evaluation metrics. Subsequently, the final video streaming QoE model is chosen based on achieved performance in both cases with its application.

5.1 Interpretation on measured video streaming QoE IFs

The evaluation of each collected IFs is done from the standard perspective and organized as follows.

Content-type is a critical video IFs to be considered for the user's perception. Content-type can express the user's motivation when watching a video. For instance, the image and audio quality of the video are very crucial for those who need to attend e-learning. In contrast, the audio quality might be enough for those who need watching entertainment. To show this situation, content-type that the users see frequently is collected and represented in Figure 5.1a. 358 of 1167 users watch politics related videos frequently. From this, we can conclude that users may provide their ratings based on their motivation without considering the quality provided by the ISP, ethio telecom.

One the other side, the video resolution is also one major factor in the determination of video streaming quality. The higher the resolution, the sharper the image of the video. The high-resolution selection is only as high as the resolution at which it was uploaded & transcoded. The resolution selections can be done using an adaptive and manual



(a) Content (b) Resolution

Fig. 5.1 Regular video resolution and content type chosen by ethio telecom users

selection method. For the case of manual selection, the video resolution no longer changes according to available network resources. As in [7], resource requirements recommended for different video resolutions were given in Table 5.1 and apply to mobile networks. The recommended code rates in this table are average values.

Table 5.1 Video resolution and recommended required mean bit-rates [7]

Video Definition	**Resolution**	**Bitrate (H.264)**	**Bitrate (H.265)**	**Description**
240p	427 × 240	250kbps	N/A	xP means the number of pixels in vertical direction
360p	640 × 360	450kbps	N/A	
480p	854 × 480	700kbps	N/A	
720p	1280 × 720	1.5Mb/s	0.9Mb/s	
1080p	1920 × 1080	3Mb/s	1.5Mb/s	xK means the number of pixels in horizontal direction
2.5/2K	2560 × 1440	6Mb/s	4Mb/s	
4K	3840 × 2160	13.5Mb/s	9.5Mb/s	

As shown in Figure 5.1b, 778 of 1167 users watch the video in the available resolution that is a more desirable choice to watch the video in the highest uploaded quality. But, the problem with selecting available resolution comes here. The HAS detects a user's bandwidth and CPU capacity in real-time and encodes video at multiple quality levels based on available resources seen in Table 5.1. Although results are promising smoother playback and a better QoE, current solutions often suffer from high RTT [35]. Due to the introduction of RTT, the users faced with video freezing that influences their MOS [36]. Besides, when HAS adapts dynamic network changes, the quality level changed another quality level, and this causes a resolution switch that degrades their user satisfaction [37].

From the NQoS perspective, Table 2.1 depicts the main QoS requirements for different services. The respective recommended average value of delay and packet error rate is to be less than 300ms and 10^{-6} for buffered streaming services. The delay should not be more than 150ms with an error rate of up to 10^{-3} for live streaming. Jitter should be no more than 50ms. The net bit rate capacity of the deployed LTE network is up to 100Mb/s in the downlink and 50Mb/s in the uplink. Though, the LTE network of ethio telecom achieved the mean of 30.02Mb/s in downloads and 6.2Mb/s for uploads (see Table 4.2). It also achieved a mean of 288.27ms in delay and 34.41ms of jitter with a Loss of 0.4%.

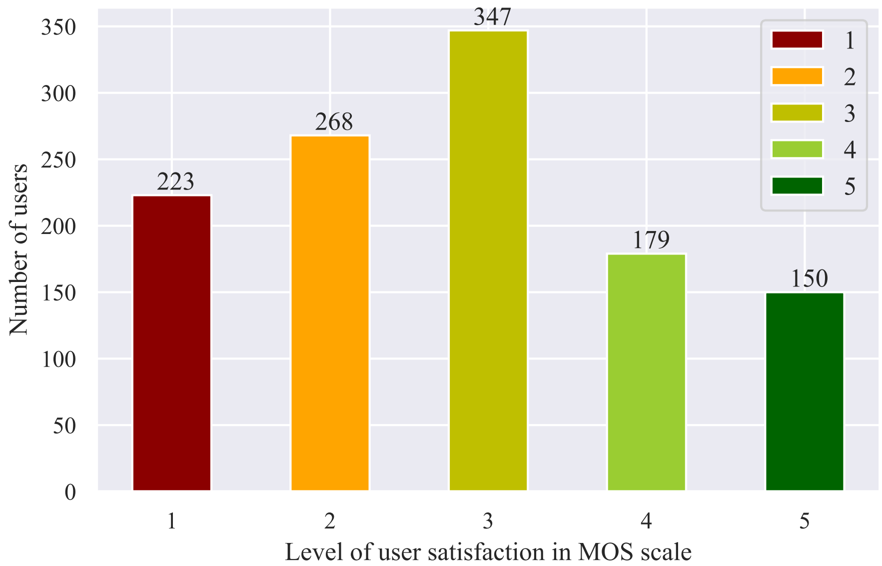


Fig. 5.2 User-rated satisfaction level concerning quality of ethio telecom LTE network for selected video streaming

As in [38], the average MOS value is recommended to be more than 3.5 for better end-user satisfaction. The users considered to have a good perception of the provided service if the average MOS value is more than 3.5. However, the results in Table 4.2 show that the MOS value is less than 3.5, degraded to a mean of 2.79 from a total of

1167 responses. The details of subjective assessment collected from the user were given from low satisfaction values to the highest using the MOS scale in Figure 5.2.

After examining the collected in IFs, the final video streaming QoE model is selected and recommended based on the performance of applied algorithms in the following subsection.

5.2 Performance evaluation and model selection

A powerful video streaming QoE model was determined using MLR and SVR algorithms to correlates collected video IFs to the MOS score. When MLR was applied to capture the linear properties of the measured parameters, SVR was used to capture the non-linearity. The model proposed using the MLR approach showed a higher MSE than the SVR approach.

As clearly revealed in Table 5.2, the SVR model performed better than the MLR in terms of learning hypotheses in a better way. The least MSE was obtained using the SVR algorithm for the test set, which is 7.74%. The relationships between measured and predicted MOS scores obtained from SVR are also better that of MLR.

Table 5.2 Correlations and MSE of applied algorithms for video streaming QoE models

Evaluation Metrics	**MLR**	**SVR**
MSE	14.1%	7.74%
Pearson Correlation	96.38%	97.94%
Spearman Correlation	97.31%	97.43%

As we can also notice from Figure 4.5, the data points are distributed symmetrically relative to the regression line than the data points scattered in Figure 4.3.

Therefore, the final model for the evaluation of user-perceived QoE in Addis Ababa LTE video streaming is the model achieved by the SVR algorithm.

5.3 Application of the proposed QoE model

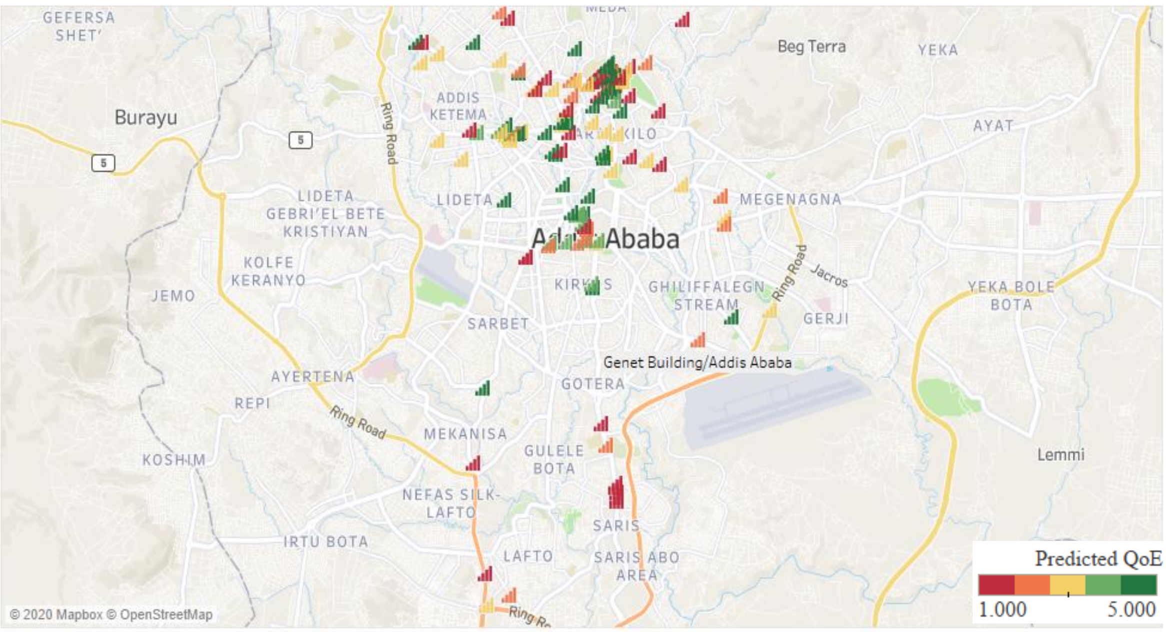
The proposed model is used to evaluates ethio telecom user's QoE when they see video streaming services. The video IFs described in Section 4.2.1 was used to predict the user-perceived quality.

First, the user is asked to watch video steaming and then rates her/his satisfaction on the quality of the LTE network through contextually formulated survey questionnaires. The questionnaire is given to the ethio telecom customers in Addis Ababa via Google Form, as included in Appendix B.

Then, for each collected satisfaction, NQoS metrics such as upload, download, delay and loss are measured from different locations using nPerf with corresponding coordinates.

Later, the selected model, the model proposed by SVR, is then applied to the collected video IFs for prediction of user-perceived QoE.

Finally, the spatial distribution and density of estimated QoE are analyzed to evaluate network performance metrics capable of influencing video streaming in cellular networks. The spatial distribution depicts the locations of the users with their corresponding perceived quality. The spatial density explains how tightly or loosely packed end-users are within a given space. The predicted MOS values were depicted on a map in Figure 5.3 as per the coordinates of NQoS metrics. These predicted MOS values were shown in the map using continuous scale colors from minimum scores to maximum ones. Using spatial and density distribution results if optimization or additional resources are required can be decided by ISP for better end-user satisfaction.



Map based on average of Longitude and average of Latitude. Color shows sum of Satisfaction. The marks are labeled by Location Name.

Fig. 5.3 Predicted video QoE in MOS score using SVR

The obtained achievement of the proposed model allows the ISP to estimates the user-perceived experience regarding video streaming services easily. Hence, the ISP can monitor perceived quality based on the spatial distribution and density by using this provided model. Accordingly, from now on, the ethio telecom can apply the recommended model to optimize or to controls the user-perceived quality for cellular networks.

Chapter 6

Conclusions

This chapter gives a summary of all the work described in the thesis by inducing the conclusions. Future work is also in the last section.

6.1 Summary

This thesis aimed to propose a model capable of predicting the user-perceived quality through the already collected video IFs in LTE networks. MLR and SVR of machine learning techniques used to recommend the model. The better-performed model proposed by SVR is chosen as the final QoE model to determine video streaming quality perceived by the ethio telecom users.

Video IFs were identified and analyzed for the development of the model. The level of end-user happiness is captured by providing video and asking them to see it. And then, a subjective assessment was conducted through questionnaires regarding the quality of the LTE network. Satisfaction, resolution, and content type chosen by the user were collected using this approach.

A network performance measuring tool called nPerf developed by nPerf SAS company applied to collect the rest of NQoS parameters. The data set used in the thesis was collected by considering various locations. Additionally, there are repeated areas to investigate the impact of the time of the day. Measured data were analyzed using Anaconda Python.

First, MLR applied to the collected video IFs to identify if there is a linear relationship between each of the collected video IFs and QoE. Later, the SVR algorithm is applied to capture nonlinear properties of features with QoE. The least MSE is registered using the SVR algorithm. The correlations between collected and predicted MOS values were also better than that of the MLR.

The video streaming QoE model proposed by SVR achieved the least MSE of 7.74%, Pearson of 97.94%, and Spearman correlation of 97.43%. The higher the MSE value, the worse the proposed model is. MLR showed a higher MSE of 14.1% with a Pearson correlation of 96.38% and Spearman correlation of 97.31%. Accordingly, based on achieved performance, SVR is recommended for quantifying the user's perceived quality.

From the results, the proposed video streaming QoE model shows a high correlation and low MSE between the measured and the predicted QoE. The spatial distribution and density of the estimated QoE presented with the help of the preferred model.

So, this work advances the developed quality prediction models for ethio telecom to optimize mobile communication networks when the users watch video streaming services.

The limitation of the development of this work was related to the use of the nPerf tool since it requires a premium version to access additional enhanced services such as unlimited access to collected data in CSV format. Though the nPerf has such limitations, we can also monitor the quality of web browsing besides video streaming. It is compatible with all broadband and mobile connections.

6.2 Future Work

The future works planned from this research include:

- This model does not consider RF metrics such as received signal strength indicator, signal-to-noise ratio, etc. as video streaming IFs. Thus, someone can evaluate the impact of RF metrics on video streaming services by following the same approaches.

- The SVR is an essential regression algorithm that works well on regression problems, even problems that are not linearly separable. It is also relatively memory efficient. However, choosing the values of hyper-parameters and the best kernel function needs domain knowledge. Again, SVR does not perform very well when the data set has more noise. In cases where several features for each data point exceeds the number of the training data set, the SVR prone to overfitting problems and will underperform. Hence, someone can plan to study the possibility of using more advanced machine learning algorithms like neural networks to generate a QoE model with better accuracy.

- Increasing the size of the data set increases the performance of the proposed model. To address this data collection problem, developing an automated QoE Framework using the proposed model for monitoring QoE is the next planned task of the thesis. The privacy assessment result collected from the users also confirmed a good opportunity to work on the QoE Framework.

- Developing general models that can be applied to other ethio telecom services to optimize and enhance the wireless network quality without limiting to only video streaming services.

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Appendix A

nPerf Sample Result

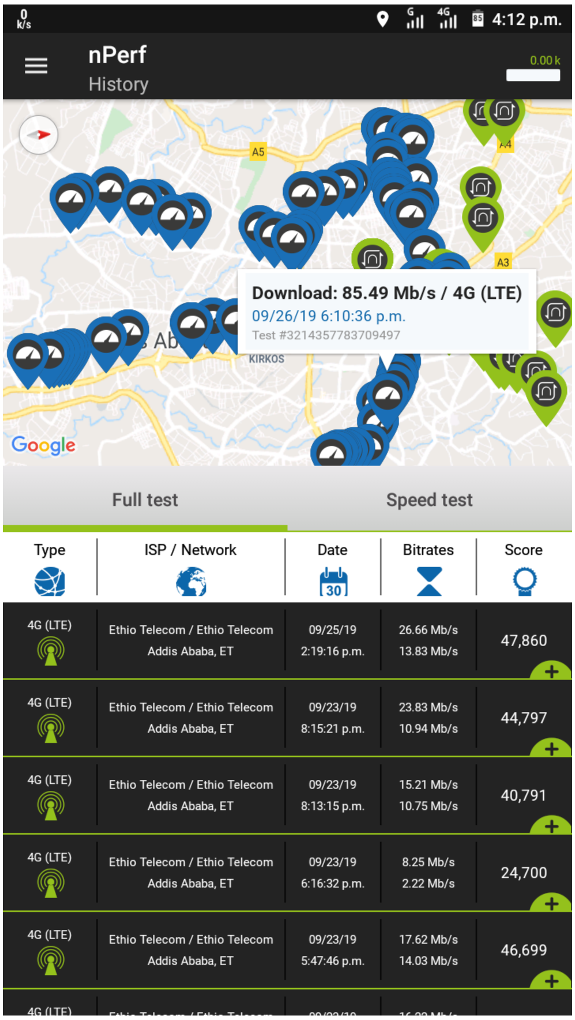

Fig. A.1 nPerf sample result

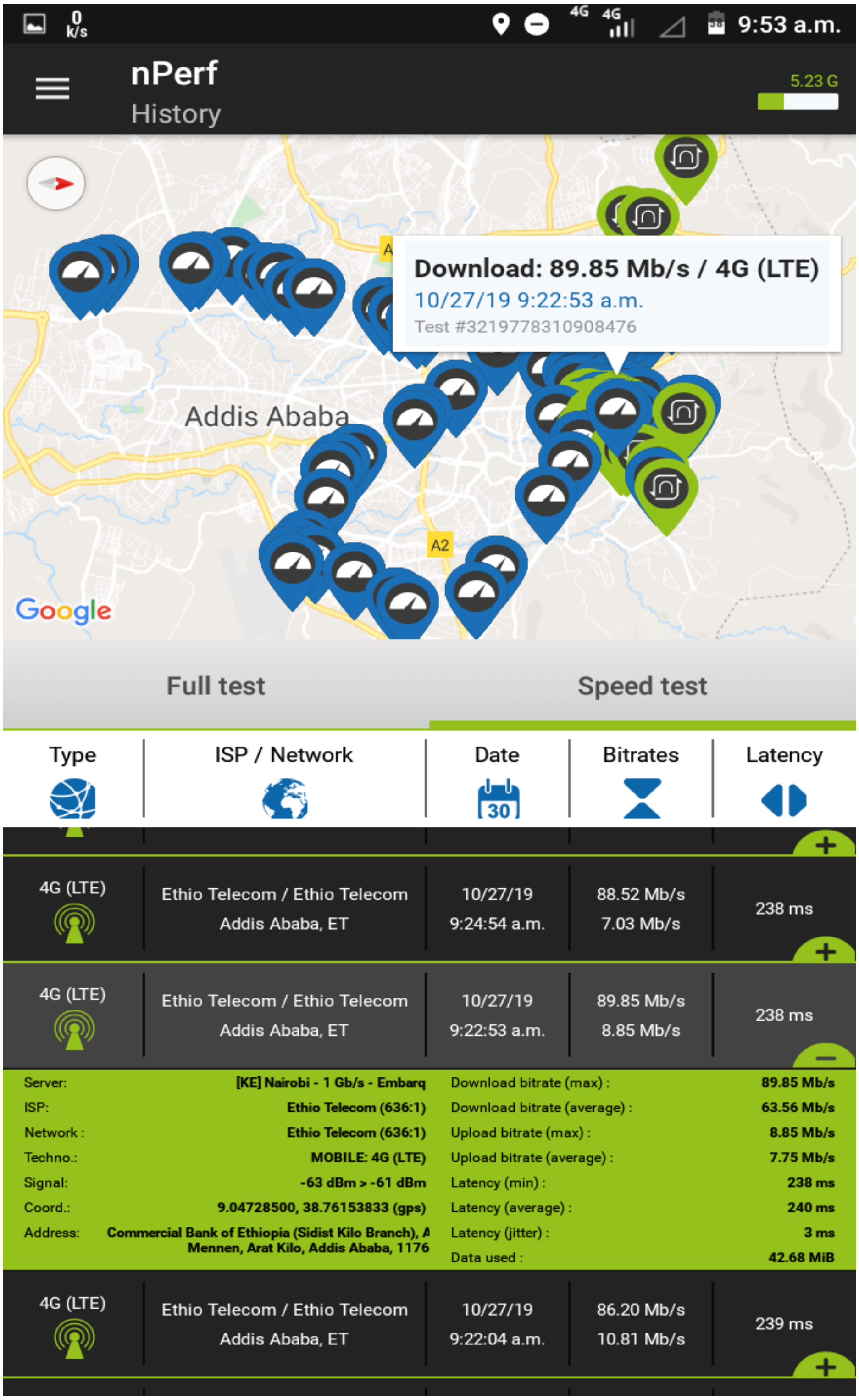

Fig. A.2 nPerf sample result

Appendix B

Survey Questionnaires

Survey on "QoE Assessment Model for Addis Ababa LTE Video Streaming Service using Machine Learning Techniques"

* Required

Satisfaction Assessment

1. Overall, how much are you satisfied with your Mobile Internet connection when you watch the selected Video Streaming? *

   Mark only one

	1	2	3	4	5	
Extremely Dissatisfied	○	○	○	○	○	Extremely Satisfied

2. Choose a time in which you get the best speed *

   Mark only one

   ○ Early Morning (5:00 AM to 8.30 AM)

   ○ Morning (8.30 AM to 12:00 PM)

   ○ Lunch time (12:00 PM to 1:30 PM)

- ○ Afternoon (1:30 PM to 6:00 PM)
- ○ Evening (6:00 PM to 9:00 PM)
- ○ Night (9:00 PM to 10:00 PM)

3. Choose a time in which you get the worst speed *

   Mark only one

   - ○ Early Morning (5:00 AM to 8.30 AM)
   - ○ Morning (8.30 AM to 12:00 PM)
   - ○ Lunch time (12:00 PM to 1:30 PM)
   - ○ Afternoon (1:30 PM to 6:00 PM)
   - ○ Evening (6:00 PM to 9:00 PM)
   - ○ Night (9:00 PM to 10:00 PM)

4. What is your default video quality resolution when you watch, upload or download a video? *

   Mark only one

   - ○ 1080p HD: 1920 pixels width * 1080 pixels height
   - ○ 720p HD: 1280 pixels width * 720 pixels height
   - ○ 480p: 640 pixels width * 480 pixels height
   - ○ Automatic: Plays Videos in the best quality available

5. What is your regular device to watch Video streaming (YouTube, Facebook, etc.) under cellular environment? *

   Mark only one

   - ○ Mobile
   - ○ Tablet
   - ○ Computer
   - ○ Other: ________________________

6. Which type of content do you watch regularly? *

   Mark only one

- ○ Sport
- ○ Educational
- ○ Politics
- ○ Religious
- ○ Other: ________________________

7. Do you use 4G (LTE) Services?

   Mark only one

   - ○ Yes Skip to question 9.
   - ○ No Skip to question 8.

8. What should I put a reason for not to level up to 4G? *

   Check all that apply

   - ☐ SIM upgrade is not free
   - ☐ My device doesn't support 4G (LTE)
   - ☐ LTE network is not available in our area
   - ☐ I don't see that much benefit than 3G
   - ☐ 4G will consume more data than 3G
   - ☐ Other:________________________

Privacy Assessments

9. How much privacy matters to you? *

   Mark only one

	1	2	3	4	5	
Low	○	○	○	○	○	High

10. In exchange for some benefits, will you allow Ethio Telecom to install an application on your device to monitor the quality of the network? *

    Mark only one

- ○ Yes
- ○ No

11. In which condition will you allow the Ethio Telecom to monitor the quality of the applications you are using in your device by installing QoE probes? *

    Check all that apply

    - ☐ In exchange for better quality
    - ☐ Discounts on the services
    - ☐ Extra bandwidth/data usage
    - ☐ Do not want to install any probe under any condition

12. Your gender: *

    Mark only one

    - ○ Female
    - ○ Male

13. Your age: *

    Mark only one

    - ○ Under 18
    - ○ 18-24
    - ○ 25-34
    - ○ 35-54
    - ○ Above 55

14. What is the highest educational qualification that you have completed? *

    Mark only one

    - ○ Master's Degree & above
    - ○ Bachelor's Degree
    - ○ University or Collage Student
    - ○ Diploma or Certificate
    - ○ Grade 11-12

- ○ Grade 10 & below

15. If you would like to share any additional comments or experience about 4G LTE Network when you watch Video Streaming