Mobile Network Quality of Experience using Big Data Analytics Approach

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Abstract- Traditionally, Quality of experience is mostly examined in a laboratory experiments to enable a fixed contextual factor. While the results present an estimated mean opinion score representing perceived QoE. It is imperative to estimate mean opinion score employing large data (big data) gathered from the mobile network comprising of different user's location and time for a specific service. Because time and location can have a huge influence on the user perceived quality of experience. Therefore, this paper proposed a framework for modelling perceived QoE through big data analytics. The proposed framework describes the process of estimating perceived quality of experience to assist the mobile network operators effectively manage the network performance and aid satisfactory provision of mobile internet services.

Keywords--Mean Opinion Score, Big data analytics, Mobile Network Operator, Telecoms.

I. INTRODUCTION

The wide usage of internet based services has been traced down to the emergence of high-speed mobile network situated on Universal Mobile Telecommunication Systems (UMTS), Long Term Evolution (LTE) and other telecommunications (Telecoms) standards. Equally, the availability of higher data transmission speed (throughput) enables mobile internet users to go beyond web surfing, by enabling services such as file transfer, file download, video streaming and voice over internet protocol (VOIP). However, the Mobile network operators (MNOs) tends to limit the existing data-rate achievable by the users because of the high cost involved in acquiring spectrum [1]. At the same time, the increase in the rate of subscribers have enhanced competitive advantage and provision of affordable services, thereby imposing additional challenge on the MNOs in providing a satisfactory level of service performance to the mobile internet users [2], [3], [1]. Specifically, mobile networks are vulnerable to channel availability (such as decreased channel availability) that dynamically changes overtime because of the local congestion, which often result into compromising the user session [4]. The stated instances, increase in limited data rate and local congestion can seriously have impact on the mobile internet user experience.

It is equally important to keep in mind that the expectation of the mobile internet users is based on realized experiences from the network performance (NP), which are traditionally expected to be stable and less congested. To enable a satisfactory level of user experience, the MNOs are required to be well informed about the traffic characteristics caused by the geographical and dynamic nature of the network traffic [1]. Understanding the network traffic characteristics would enable the MNOs to plan and optimized the NP to understand the geographical and temporal service-related Quality of Experience (QoE) from both the users' and network perspectives.

Generally, a service-related QoE is usually quantified using the value of the mean opinion score (MOS), which represents the subjective experience of a user for a specific service quality of the network. Several studies have used MOS to evaluate the QoE of difference services, the likes of video streaming [5], VOIP [6], Skype Voice calls [7], and web browsing [8], [9]. However, the use of large database gathered from the mobile network traffic comprising of all the QoE influence factors to serve as input for the QoE model is still limited in the literature [10], [11], [9], because most times the raw data is limited or not available for examination [1]. Furthermore, while these studies presented a precise estimated QoE, use of multiple possible metrics comprising of time and location within a mobile network is

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still limited in the literature. Because most QoE studies employed the use of participants in a laboratory experiments to aid the estimation of the QoE measurements [12], [9].

To estimate the user perceived service-related QoE quantified.by MOS, this paper proposed the use of big data analytic approach, which enables the analysis of the data obtained from the mobile network traffic. The use of big data approach, employs the objective measurement obtained from the network traffic to be used for the estimation of user perceived QoE, by considering different services along with the time and location of the users. Usage of big data approach can assist the MNOs in allocation of network resources in geographical areas that might need network optimization to enhance their service provisioning. The remainder of this article is organized as follows. Quality of experience, perceived QoE measurement and Perceived QoE modelling are discussed in Section II, followed by big data analytics and types of big data analytics in section III. Section IV presents proposed framework for modelling perceived QoE with big data analytics. Lastly, section V discusses conclusion and future works.

II. QUALITY OF EXPERIENCE

QoE is defined by [13] "*as the degree of delight or annoyance of the user of an application or service. It results from the fulfilment of his or her expectations with respect to the utility and / or enjoyment of the application or service in the light of the user's personality and current state*." QoE definition connects user perception, expectations, experience of the service application and NP. User perceived QoE is often affected by varieties of influence factors. QoE influence factors are the characteristics of the service provided by the MNOs such as system (throughput, delay, jitter, loss, and security), human (gender, age, background, and education) and context (location, movement, time of the day costs and subscription type) influence factors [13]. Quantified QoE influence factors allows the estimations of QoE as perceived by the users [14]. The most studied QoE influence factor is the system factors constituting the Quality of service (QoS) parameters (throughput, loss, bandwidth, delay, and jitter). Because some parameters like bandwidth can be adjusted to increase the end user's satisfaction [10]. While there exist many studies that examined throughput measurement for wireless applications for web traffic [9], [15], few studies used user experience measurements obtained from the mobile network traffic, as most studies focus on collecting basic network information and performance data in a laboratory experiments through the desktop applications [15], [9]. Measurement obtained from the desktop in a laboratory experiment are less useful because of the fixed contextual factor [1]. Therefore, it is imperative to examine specific service-related throughput in mobile networks traffic in relation to expectations, mobility (location and time), and different services like file transfer protocol (FTP) and Hypertext Transfer Protocol (HTTP). It is as such imperative to take QoE measurement from the mobile network traffic to understand the user's experience from both the network and user's perspectives.

A. PERCEIVED QOE MEASUREMENT

There are two types of perceived QoE measurements, namely subjective and objective measurements. The subjective measurements are based on customer perception of the services delivered to the customers, while objective measurement is the means of estimating subjective quality solely from the measurement obtained from the network traffic [14]. The subjective measurement is the standard and most reliable way of assessing the perceived QoE. Subjective measurement has been used in several studies to analyse the MOS in the form of numeric value ranging from 1 to 5 (i.e. poor to excellent) [10]. The limitation of subjective measurement is time consuming, expensive, lacks repeatability and not effective in real-time [10], [14]. In contrast to the subjective measurement like a survey measurement, mostly conducted in a laboratory experiments [15], [3], objective measurement aims at predicting the subjective assessment methods based on the estimated MOS [3]. Objective measurement requires a meaningful mapping function into the predicted subjective measurement [10]. Objective measurement is preferred because of its ability to be implemented and be embedded into the network using software applications [16] and the capability to allow researchers model the relationship between the expectation and perceived influence factors to determine the MOS (i.e. Perceived QoE) [17].

B. PERCEIVED QOE MODELLING

Modelling of perceived QoE is used to quantify the QoE influence factors by defining a correlation or prediction model that estimates the MOS. Machine learning algorithms is the most common technique used in modelling perceived QoE [7], [5], [18]. Machine learning algorithms is a technique that design and develop algorithms capable of building a reality model from the data, either by improving the existing model or building a new model [18]. Machine learning algorithms aimed at correlating QoE influence factors through prediction, which focused on some known properties or acquired from an observation that reflect both the network and customer's perception [18]. Decision Tree, Random forest, Support vector machine, K-nearest and artificial neural network are the most commonly used machine learning algorithm for the modelling of perceived QoE [7], [5], [18], [19]. Several studies have used machine learning to model perceived QoE of different internet applications as depicted in Table 1.

TABLE 1 MODELLING PERCEIVED QOE WITH MACHINE LEARNING ALGORITHM

Authors	**Dataset/Scenerio**	**Application/ Service Type**	**Machine Learning Algorithms**
[20]	Network tool/Experiment	Smartphone	Neural Network
[21]	Participant data/Experiment	Over-the-top Video	Decision Tree
[6]	Test-bed Experiment	VOIP	Decision Tree, Gaussian naïve bayes, Artficial neural network and support vector machine
[19]	Testbed Experiment	Video on Demand (VoD)	Artficial neural network, K-nearest, Support vector machine, Decision Tree, Naïve bayes and Random forest
[5]	Participant data/ Laboratory Experiment	Video	Naïve bayes, Decision Tree, Random forest, Support vector machine and Neural network
[7]	Testbed Experiment	Skype Voice calls	Decision Tree, Rule Induction, Logistic Regression, Support vector machine, Neural network, Lazy learners and Ensemble method.
[8]	Mobile websites data / Cellular Network	Mobile web Browsing	Text Classification (Decision Tree and Linear Regression)
[9]	Participant data/ Laboratory Experiment	Web browsing	Exponential Regression and Hidden Markov Model.
[22]	Participant data/ Testbed experiment	Video	Naïve bayes, Decision Tree, Random forest, Support vector machine, K-nearest and Neural network
[23]	Testbed Experiment	IPTV	Neural network
[24]	Participant data/ Laboratory Experiment	Web browsing	Exponential Regression, Support vector machine and Hidden memory markov models
[25]	Testbed Experiment	Multimedia Streaming	Artficial neural network
[26]	Simulation Test Experiment	Video	Neural Network
[27]	Testbed Experiment	Video	Support vector machine and Decision Tree

As seen in table 1, most of the studies focused on a specific application/ service, because the authors tend to make the contextual factors as fixed as possible. However, evidence has shown experimentally that there is need to quantify QoE of different mobile internet applications in relation to time and location within a mobile network [1], [28], [29]. To quantify perceived QoE of mobile applications, [1] used an android application to gather the QoE representation in MOS values, because the android application was already designed to evaluate multiple performance measures. The study only focused on gathering data from an android application by instructing the clients/users to create traffic that contains a GET request for a web page from Wikipedia [1]. In this case, the data gathered could be restricted to a certain set of clients in a certain location, because the clients must be given instruction on a specific website that the measurement test data needs to be collected. Considering the increase in the volume of broadband data traffic of the mobile network caused by the diverse and large amount of mobile internet users, recent literature suggests the need for an advanced QoE management scheme and optimization algorithms for both wireless and mobile system [19], [9]. The advanced QoE management scheme may involve a process of gathering large user experience in relation to user behaviour from the mobile network traffic [29]. Such large user experience data is fundamentally a big data problem, and requires some big data analytics for such data to be effective and analysed [30].

III. BIG DATA ANALYTICS

Big data constitutes the collection and analysis of large amount of data [30], which has the ability of changing rapidly within a specific period. Due to the large and diverse data set generated within the network traffic, telecoms industries are much more interested in data-driven decisions to deal with disruptions as observed in the NP and provide an optimal solution based on the insights (information and knowledge) derived from the data [30]. Big data comprises of five characteristics such as volume, velocity, variety, value, and veracity. Volume describes the mass or quantity of data. Velocity is concerned with the speed of data creation, which is how quick to generate and process data to meet the present network demand and prepare for future challenges. Variety comprises of different types of data, especially the categories of data generated in the same network traffic. Veracity describes the accuracy, correctness, quality of data sources and the uncertainty that may exist in the data. Value describes the type of insight that can be extracted from the supposed big data. Information Telecommunication Union (ITU), [31] asserts that the data generated in the mobile network traffic comprises of all these five characteristics. Hence, big data gathered from the mobile network traffic can be used for QoE modelling, estimations, and monitoring in a diverse heterogeneous environment, which is vital for network optimization [32]. Equally, the usage of big data can assist the MNOs to prevent future occurrence of network problems, proper allocation of infrastructural resources in different geographical area and allow the selections of accurate key indicators to measure and improve perceived user experience [32].

Big data analytics is the techniques used for analysing the large data gathered from the mobile network traffic. Big data analytics is classified into three different types (descriptive, predictive, and prescriptive) [30], [32]. Descriptive analytics entails the process of understanding the occurrence of NP trends in the mobile network traffic. Descriptive analytics employs the use of exploratory data analysis consisting of statistical techniques such as central tendency (mean, media, and mode), measures of dispersion (standard deviation), charts, graphs, and frequency distribution to aid the understanding and visualization of the big datasets. Predictive analytics takes a further step of descriptive analytics when data is used to seek for the future state of business performance. The origin of predictive analytics can be traced back to artificial intelligence, statistics, machine learning, and data mining. Predictive analytics focuses on predicting future probability of occurrence of patterns or trends in data, and sometimes referred to as one-click data mining, because it simplifies and automate data mining process to discover the factors leading to certain outcomes, as well as predicting the likely outcomes with the degrees of confidence in the predictions [33]. An advantage of predictive analytics is that, it can predict network outages analysing customer complaints and network data. It predicts valuable customer segments to be used for customer retention campaigns. This would enable the MNOs to identify the root causes of network failures and to direct retention campaigns to a focused group to generate average revenue per user (ARPU) and increase the spending of loyal customers [30]. Prescriptive analytics is the last stage of big data analytics techniques. It is sometimes referred to as optimisation analytics, since organisations can use it to optimise their scheduling, production inventory and supply chain design. Prescriptive analytics suggest decision options with their implications. An example in mobile telecoms industry is the allocation of infrastructural resources to locations which would enable the MNOs to operate their networks more efficiently [32]. Prescriptive analytics adopts the use of mathematical programming, heuristic search, and simulation modelling to identify the optimum actions to be taken by MNOs to improve their NP. Collectively, the use of big data analytics to manage the user experience in the mobile network can assist the MNOs to have an adequate insight on the most important user experience measurements (such as total throughput, download transfer time and connection duration) that can impact the perceived users experience.

IV. FRAMEWORK FOR MODELLING OF PERCEIVED QOE WITH BIG DATA ANALYTICS

Modelling of perceived QoE involves the process of predicting the QoE perceived by the users through an abstract representation of data and its relationship within the big dataset gathered from the mobile network. Framework proposed in this study was developed from the drawbacks highlighted and methods suggested in previous literatures. One of the limitations highlighted in previous studies is that there is limited use of large and diverse database for the modelling of perceived QoE [10], [25], [9]. It was observed that despite the vast amount of data constituted in the mobile network, MNOs are faced with the challenges of dealing with the large and diverse datasets generated in the mobile network traffic [34], [30]. Hence, it was suggested that big data could be employed to have a clear and current understanding of the user experience, which can be used to measure and model perceived QoE of the mobile internet subscribers [34].

Another observation from the previous literatures is that, the voluminous nature of the big data could result in huge amount of inconsistencies or dirty dataset [35], [36]. In addition, big data are commonly available in an unstructured form that may not be suitable for modelling perceived QoE. Thus, it is necessary to employ the use of data preparation. Data preparation will ensure the reliability, completeness, randomness, and consistency of the dataset [35]. The reliability of the dataset is to ensure that the represented dataset is accurate enough to suit the analytical modelling stage. The randomness of the datasets represents the statistical characteristics of the complete datasets, which is useful for exploratory data analysis and visualization of the dataset. Then the consistency of the data is to ensure that the dataset produce the same result within an acceptable error margin when a different random sample analysis is conducted [36], [35]. Overall, the use of the exploratory data analysis, traditional data pre-processing methods (such as data cleaning, data integration, data reduction and data transformation) commonly used in data mining technique, feature selection and extraction can be employed to efficiently operate with the big data analytics methodology [37], [36].

In addition, use of expectation comprising of service level agreement (SLA) is not commonly used in the literature [11]. Most studies usually use the subjective method to gather user expectation during the laboratory experiment to model the perceived QoE, because the studies assumed user expectation grows as network and applications continually developed [9]. Considering the time-consuming and expensive nature of the subjective method used in gathering individual subscribers expectation [3], [15], [16], subjective method of gathering user expectation may not be suitable in a large- scale settings. Equally, the subjective method lacks repeatability and not effective in real-time scenarios [10], [14]. Therefore, [11], [1], proposed the use of SLA for the modelling of perceived QoE for large-scale and real-time scenarios. SLA is an agreement between the MNOs and the customers on service characteristics [11]. The use of SLA in modelling perceived QoE would aid the MNOs to determine when one or more variables do not meet the agreed level of the SLA and how exactly the variables involved impact the user experience [11]. Collectively, the use of SLA as user expectation in modelling perceived QoE, would aid the process of determining the expected MOS, based on the maximum and minimum values stated in the SLA.

Lastly, descriptive, predictive, and prescriptive analytics incorporated in the framework was from previous studies [30], [32]. The studies suggested descriptive analytics can identify root cause of problems by investigating the status and history of the mobile network traffic [30]. Equally, predictive analytics can be used to seek the future occurrences in the mobile network traffic by using the network event data [30]. Similarly, prescriptive analytics can be used for optimization purposes, such as network planning and allocation of network resources [32]. Considering all the benefits of the three types of big data analytics, MNOs can use the proposed framework for proactive purposes in the network traffic, to anticipate network problem and to improve the overall mobile internet customer experience in the telecoms industry. Figure 1 presents the framework for modelling perceived QoE with big data analytics.

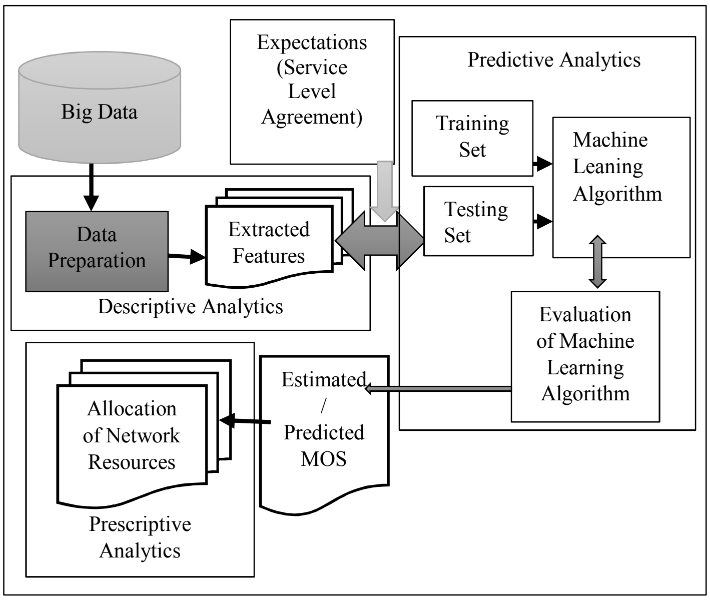

Figure 1: Framework for modelling Perceived QoE with Big Data Analytics

The first phase of modelling perceived QoE with big data analytics required gathering big datasets from the mobile network traffic. The dataset comprises of different mobile internet users for different location for different time of the day. An example of the datasets collected from the mobile network is depicted in tables 2 and 3 for both HTTP and FTP respectively.

Table 2: HTTP DATASETS

Features gathered from Mobile Network
Time
Date
Latitude and Longitude
Throughput Total
Carrier 1 channel quality indicator (CQI) – Mean
Categorized Received signal code power (RSCP): A1

Table 3: FTP DATASETS

Features gathered from Mobile Network
Time of the day
Date
Latitude and Longitude
Throughput Total (kbps)
Attachment set up time (secs)
Application layer throughput downlink (kbps)
FTP download transfer time (seconds)
Connection duration (seconds)
FTP download throughput mean (kbps)

The second phase requires the data preparation, this stage comprises of data pre-processing, data exploratory analysis, feature selection and extraction from the big dataset. The data pre-processing involves the cleaning, integration, and transformation of the data to suit the predictive analytics stage of the perceived QoE. Exploratory data analysis employs statistical techniques to aid and understanding of the dataset to be used for predictive analytic stage. Feature selection aimed at selecting most relevant attributes, while extraction combines the attributes into a reduced set of features. Hence, the feature selection and extraction enable the selection of subsets of features that are useful to build a good predictor, especially when some of the attributes are redundant.

The third phase which is predictive analytics involves the process of modelling perceived QoE (MOS). This phase comprises the observation of data instances. Observation of the data instances in this case represents the independent variable (that is, the extracted features from the big datasets and expectations) while the categories predicted is the possible values of dependent variables (perceived QoE) which is the classes or outcome. The categorical outcome is usually represented as Excellent =5, Good =4, Fair =3, Poor =2, and Bad =1 [38]. The modelling of perceived QoE using machine learning algorithms would map the combination of input parameters to a class value to build an efficient model that classify extracted features with the maximum precision through the perceived QoE function described as QoE≔f (User, Service, Variable) [11]. Expectation in relation to SLA is very important for modelling the perceived QoE. It allows maximum, minimum and expected values to be defined for the QoE influence factors selected and extracted from the big datasets [1]. This will estimate the MOS based on expected quality of a specific service.

The fourth phase which is the prescriptive analytics takes advantage of the results obtained from both descriptive and predictive analytics to decide the best decision or action that can be taken to improve the NP of the mobile network. As indicated in figure1, this articles suggests the predicted MOS can be used for proper allocation network resources in location where the MOS is below expectations. Conclusively, the use of big data analytics to manage the perceived QoE can enable the MNOs to provide proactive measures ahead before the users would perceive any network distortion while using the internet services provided by the MNOs. In addition, it can aid the MNOs to take optimal decisions for effective management of their NP to enable a better provision of the internet services.

V. CONCLUSION AND FUTURE WORK

This paper presented a framework for managing perceived QoE of various services internet services in mobile network using big data analytics. Since most measurement of the perceived QoE is restricted to specific context and service. The presented framework through the data gathered from the mobile network supports the use of multiple context and services. In addition, the implementation of the discussed framework can assist the MNOs to effectively manage the network performance to aid satisfactory provision of mobile internet services. Future works tends to implement the proposed framework using data gathered from the mobile network. In addition, the future work would validate the framework to determine its applicability in real-life environment.

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