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Modeling video streaming quality of experience using Taguchi and fuzzy logic methods

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Abstract

The popularity of mobile video streaming has increased significantly in recent years, and is expected to account for two-thirds of global internet traffic in the near future. However, determining accurately end-users' satisfaction based on network parameters remains a challenge. Existing research often uses network parameters, such as packet loss, delay, and jitter, to estimate users' Quality of Experience (QoE). However, most models present QoE estimates in Mean Opinion Scores (MoS), which are not easily understood by the customers. In this study, we used the Taguchi approach to conduct QoE experiments over a wireless tested. We investigated the simultaneous effects of packet loss, corruption, delay, and jitter on video streaming QoE, as well as their interaction effects. Furthermore, we developed a Fuzzy logic model in MatlabR2016a to establish the relationship between input variables and video streaming QoE. The model presents the results in an easily understandable linguistic terms such as excellent, good, average, bad, and poor. Additionally, the proposed model achieves a correlation of 0.875 between the predicted and user scores, with a Root Mean Square Error of 0.344.

1. Introduction

Over the past decade, the popularity of video streaming apps has increased due to the availability of affordable smart devices and broadband internet. According to the 2020 Cisco Annual Internet Report, there will be 29.3 billion internet-connected devices by 2023, and the number of internet users will reach 5.3 billion, which represents 66 percent of the global population [1]. It was reported that, in January 2023, the number of social media users worldwide was 4.76 billion, and social media platforms enable users to create various types of content, such as text, pictures, and video[1]. Audio and video streaming applications are the most preferred content on the internet and generate a significant amount of traffic over the internet [2-4] . Furthermore, these applications require a seamless transmission to deliver reliable and constant flow packets that depend on the condition of the network [5]. Normally, the network condition disrupts services resulting in a poor experience that may annoy customers. In a competitive business ecosystem, studies indicate that 90% of unsatisfied customers do not report to their service providers about their experiences. Instead, they just abandon the services and switch to a competitor [6]. To guarantee elevated levels of customer satisfaction, it is imperative that the network and service providers have a thorough understanding of customers' Quality of Experience (QoE). According to ITU-T, QoE is defined as the overall acceptability of an application or service, as perceived subjectively by the end user [7]. Being able to estimate QoE is crucial for network and service providers as it allows them to optimize their network resources to meet the ever-changing demands of their customers. To measure customers' QoE, numerous researchers have devoted significant effort to developing prediction models.

When it comes to predicting the performance of multimedia applications, many studies classify QoE prediction models into three distinct categories: full-reference (FR), reduced-reference (RR), and no-reference (NR) models. This categorization is based on whether or not reference information is present as a feedback mechanism to the prediction model [8, 9]. On one hand, FR model requires reference information to be available for comparison against the model output. Although FR models are believed to be capable of producing highly accurate results, they tend to require more resources to process the information [10]. In contrast, the reduced-reference (RR) models use only a portion of the available reference information to estimate the model output. As a result, the accuracy of the RR model is lower compared to the FR model, but it requires fewer computational resources to process the information [11].

Moreover, the most widely used type of QoE prediction model is the NR model, which aims to predict the model output without requiring reference information as a feedback mechanism to improve accuracy. This makes the NR model an ideal solution for predicting the QoE of video streaming accessed over a network and estimating customers' satisfaction with the service. Various research studies have put forth no-reference (NR) models for predicting QoE of video streaming [12-14]. They utilize numeric input variables to provide QoE scores in terms of Mean Opinion Score (MOS), which is a metric used to measure viewers' satisfaction [15-17] .

However, the use of MOS to present QoE is confusing because it essentially represents an ordinal variable. The numbers in the scale merely indicate QoE categories that may be experienced by customers. Therefore, presenting MOS as the average of an ordinal variable lacks numerical meaning [18]. Consequently, using the MOS scale to interpret viewers' satisfaction can be challenging [19, 20]. Scholars suggest that QoE predictions are easily understood when results are presented using an ordinal scale, such as bad, poor, average, good, or excellent, which relates to human language [21].

This study, therefore, proposes a fuzzy-based model to predict video streaming QoE on a scale that is easily understood by users. The paper is

[1] https://www.statista.com/statistics/617136/digital-population-worldwide/

divided into six sections: Section 2 reviews related research work; Section 3 describes the research methodology; Section 4 explains the Fuzzy based prediction model; and Section 5 presents the conclusion.

2. Related Work

Despite significant efforts by researchers to develop no-reference (NR) QoE prediction models, there remains a challenge in accurately predicting QoE. The QoE prediction models utilize exponential and logarithmic functions, respectively, to predict QoE based on individual input variables, such as packet loss, delay, and jitter [22, 23]. However, wireless channels experience simultaneous changes, such as packet corruption, packet loss, delay, and jitter occurring at the same time [22].

Song and Yang proposed a prediction model that utilizes packet losses to predict QoE on a numeric scale [25]. Other studies present models that use input variables from both content and network Quality of Service (QoS) [26, 27]. However, some researchers suggest that input variables should also be collected from three key domains: content, network, and device [23] and [24]. It is worth noting that the interaction effects among input variables may also have a significant impact on QoE, beyond their direct impact on video streaming. On the contrary, several studies focus on the main effects of input variables on QoE [30, 31].

To improve the accuracy of QoE prediction, researchers proposed machine learning techniques to classify video quality based on various extracted features [32, 33]. These models are designed to enhance the user's QoE. Additionally, the work presented by Alreshoodi et al. [26] introduces a fuzzy-based model that predicts QoE in MoS, using input variables obtained from the application and physical layer. However, the model presents QoE in MoS using a 1 to 5 point scale. Similarly, Rahman et al. [27] suggest a fuzzy-based algorithm to select the appropriate packet size, which can efficiently use the network bandwidth to ensure high QoE at the viewer's end. Based on the reviewed cases, fuzzy logic has a strong potential for output prediction and decision-making. This is because fuzzy logic can accept input variables in various states and provide results in fuzzy values that can be interpreted in categorical scales, such as good, average, or poor. With the continuous advancement of technology and the increasing usage of video content on the internet, the estimation of QoE is becoming a fundamental protocol in network management. However, it is suggested that effective QoE models should consider the appropriate distribution of QoE [36, 37]. Furthermore, research indicates that presenting QoE in a categorical scale, rather than a numerical variable, is more meaningful [30]. Additionally, studies suggest that network links are frequently affected by variables, such as packet loss, jitter, and delay at the same time and less affected by other variables, such as content, context, and device features [39, 40].

This study, therefore, aimed to investigate the impact of network variables on video streaming QoE and propose a fuzzy logic prediction model that can provide video streaming QoE on a scale that is easily understood by users.

3. Methodology

The research employed a quantitative approach, in which numerical network variables were applied to the simulated testbed to induce changes in the video streaming QoE, which was then rated by viewers. The network experiments were conducted according to the Taguchi method, and the QoE experiments adhered to the ITU-T 910 procedures.

3.1 Taguchi Approach

The Taguchi approach is a design of experiments method that aims to achieve an optimum output using a limited number of input variable combinations compared to the factorial design [33]. It employs mathematical orthogonal arrays to determine the possible combinations of rows and columns that require a minimum number of experiments. To determine the appropriate orthogonal array, the following information is necessary:

i. The number of variables investigated, m;
ii. The levels through which the variables are fixed, s;
iii. The number of experiments, N; and
iv. The strength of orthogonal arrays, t.

The generic orthogonal array is presented as $L_N(s^m)$ (Table 1).

Table 1: Taguchi orthogonal arrays.

Two-levels series	Three-levels series	Four-levels series	Mixed-levels series
$L_4(2^3)$	$L_9(3^4)$	$L_{15}(4^5)$	$L_{18}(2^1, 2^7)$
$L_8(2^7)$	$L_{27}(3^{13})$	$L_{64}(4^{21})$	$L_{36}(2^{11}, 3^{12})$
$L_{16}(2^{15})$	$L_{81}(3^{40})$		
$L_{32}(2^{31})$			
$L_{12}(2^{11})$			

(a) Selection of input variables

To manipulate the emulator during experiments, packet corruption, loss, delay, and jitter were utilized, with the range of control variables determined derived from literature. Specifically, the range of packet loss (PL) and delay (DL) was selected from 0.1% to 2.0% and 50 ms to 300 ms, respectively, [34]. The impact of jitter (JT) and packet corruption (PC) was also set over a range from 10 ms to 50 ms and 1% to 16%, respectively [35]. Before commencing the experiments, trials were conducted to observe the response of input variations on video streaming on both mobile devices and computers. The variables were categorized into three levels, labeled as level 1, level 2, and level 3 (Table 2).

Table 2. Input variables for network emulation.

Variable	**Level**		
	1	**2**	**3**
Packet loss (PL)	0.1%	1.0%	2.0%
Packet Corruption (PC)	1.0%	8.0%	16.0%
Jitter (JT)	5 ms	20 ms	50 ms
Delay (DL)	10 ms	150 ms	300 ms

(b) Subjective experiments procedure

The experiments were conducted in the computer laboratory, and participants were given an introduction to the procedure, tools, and environment before beginning the experiments. To design the experiment sequence, the Taguchi orthogonal array $L_9(3^4)$ was chosen because we had four input variables, each with three different levels of variation. Each session lasted for 1 minute, and, at the end of each session, participants rated their viewing experience on a scale of bad, poor, average, good, and excellent. Variables combination in each experimental session presented to viewers is depicted in Table 3.

Table 3: Input variables combination

S/N	**PC**	**PL**	**DL**	**JT**
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

(c) Emulation test-bed set-up

The emulation process utilized Linux Ubuntu 10.4, 64-bit operating system installed on a Dell desktop featuring an Intel® Core™ i7-3770 CPU @ 3.40 GHz and 16 GB of RAM. The emulator was connected to a network-attached storage device (NAS325v2) via the eth0 Ethernet port, and to a wireless access point through the eth1 Ethernet port. The Cisco Linksys x1000 access point was used, which operates on 2.4 GHz and is compatible with IEEE 802.11b, 802.11g, and 802.11n. To enable emulated traffic from the video server to pass from one point to another, the eth0 and eth1 ports were bridged. Figure 1 displays the commands used to bind the ports.

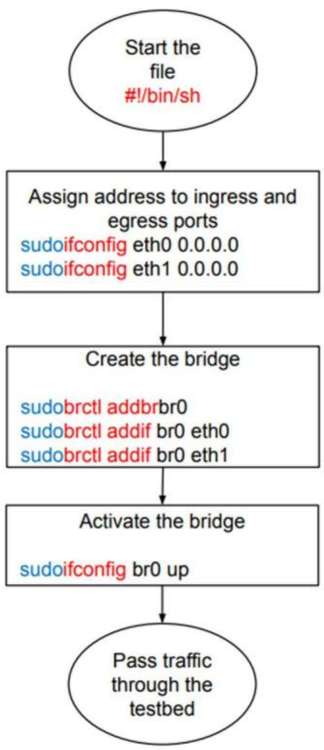

Figure 1: Ethernet ports binding.

The video streaming traffic was transmitted from the server through the eth0 port to the emulator, which received the traffic through the eth1 port. The experimental conditions were set up to reflect the variations in network variables, as designed using the Taguchi method and coded using the program described in Figure 2.

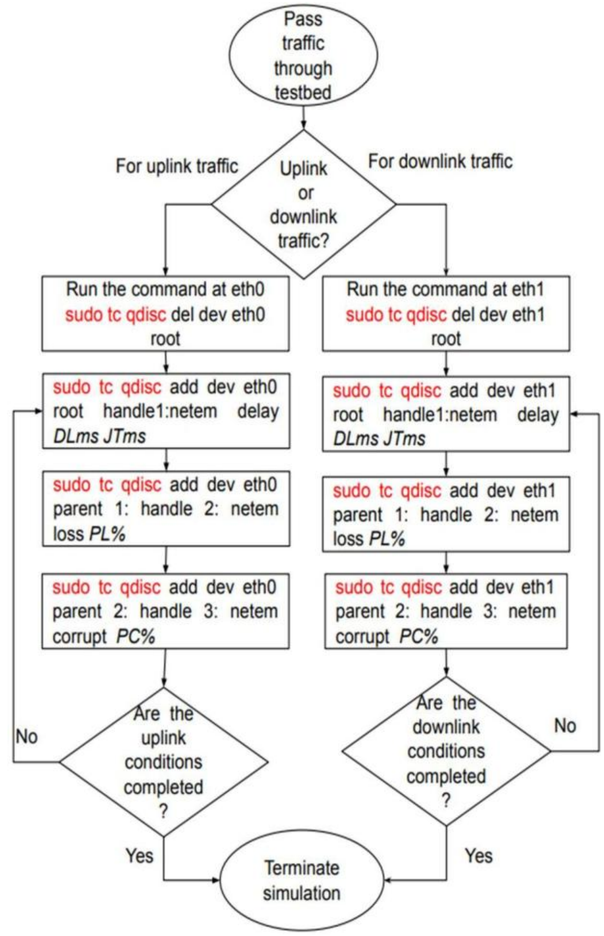

Figure 2: Wireless link simulation process

(d) Video content

To capture the distinct behaviors displayed by streamed video content, the video content was divided into three categories based on their spatial and temporal characteristics. These categories were fast, slow, and moderate-moving contents. In this study, soccer (football), news, and movie clips were selected to represent these categories, respectively. All clips were extracted from HD video content and were encoded into H.265 format with a resolution of 1280 x 720 pixels, a frame rate of 30 fps, and a bitrate of 2048 kbps. The Adobe Media Encoder was utilized to trim the videos into 10 seconds clips, ensuring that the participant's attention was maximized during the experiments. Figure 3 illustrates the traffic flow between the streaming server, emulator, and devices used to view video contents under different experimental conditions.

(e) Data collection

A group of 24 participants, comprising 14 males and 10 females, with ages ranging from 19 to 34 years (mean age of 26.45 years and a standard deviation of 4.68 years) were invited to attend the experiments. Before starting experiments, participants were given a brief introduction about the study and were oriented to the score sheets, selecting video contents and QoE rating based on the presented experience. Each participant was exposed to nine (9) experiments for three different content types. At the end of viewing, each video content, participants were asked to rate their viewing experiences on a scale that ranged from bad, poor, average, good, and excellent. The dataset generated in experiments was analyzed using ANOVA.

3.2 Data Analysis

A four-way repeated measure ANOVA was utilized to evaluate the impact of input variables and their interaction effects on video streaming QoE. The stepwise method was chosen with a threshold value (α) set at 0.25, and Minitab 17.0.1 was used for analysis. The *p*-value was used to measure the statistical significance of network impairments on QoE, with a value less than 0.05 indicating a significant effect. Results reveal that the main effects of PC, PL, JT, and DL significantly affected QoE. Moreover, the four-way interaction analysis revealed significant interaction effects between a pair of variables, specifically PC with DL, and JT with DL, both significantly impacting video streaming QoE at $p<0.05$. Further analysis showed that PC had the highest influence on video streaming QoE, followed by DL, then PL, and finally JT. PC caused severe loss of video received on viewing devices, while DL caused packets to drop in the network when the time to live (TTL) expired. PL was the third most influential variable, while JT ranked fourth as it caused video stalling during playback. However, the buffer size of devices could reduce the effect of JT, thus improving QoE. In general, the analysis reveals that the variables affect the output significantly, and are suitable for developing a QoE prediction model. A detailed overview of the impact of each variable on QoE can be found in Table 4

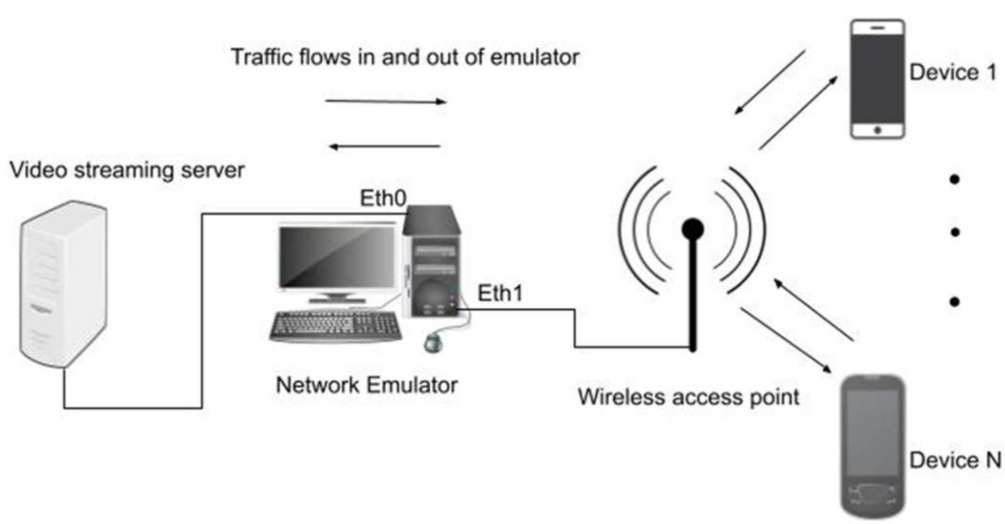

Figure 3. Wireless test-bed network.

Table 4: ANOVA analysis.

Source	Sum of squares	Degree of freedom	F-statistic	*p*-value
PC	410.99	1	600.39	0
PL	50.30	1	73.48	0
JT	31.34	1	45.79	0
DL	89.17	1	130.27	0
PC x JT	2.06	1	3.01	0.083
PC x DL	5.85	1	8.54	0.004
JT x DL	24.70	1	36.09	0

4. Modeling Fuzzy-Based QoE Prediction Model

4.1 An Overview of Fuzzy Inference System

Fuzzy logic is an expanded version of traditional set theory, and it enables the representation of linguistic constructs, such as "low," "many," and "few." This methodology is an effective way to model human reasoning since most decisions made by humans are not binary, but rather exist on a spectrum between absolute truth and absolute falsity. For instance, when evaluating the QoE, which ranges from bad to excellent, it can be difficult to assign a numerical value to how bad or good a particular service is since such assessments are subjective.

The Fuzzy Inference System (FIS) involves four key stages: fuzzification of inputs, rule formulation, decision-making, and defuzzification. In the fuzzification step, crisp values are transformed into fuzzy values, which typically involves mapping input variables to corresponding linguistic values and functions. To provide FIS with the ability to make decisions, membership functions and a set of fuzzy inferences are trained. Based on the established rules, FIS processes the inputs and maps the outputs. This study utilized PC, PL, JT, and DL as input variables for FIS, and QoE as the output variable (Figure 4).

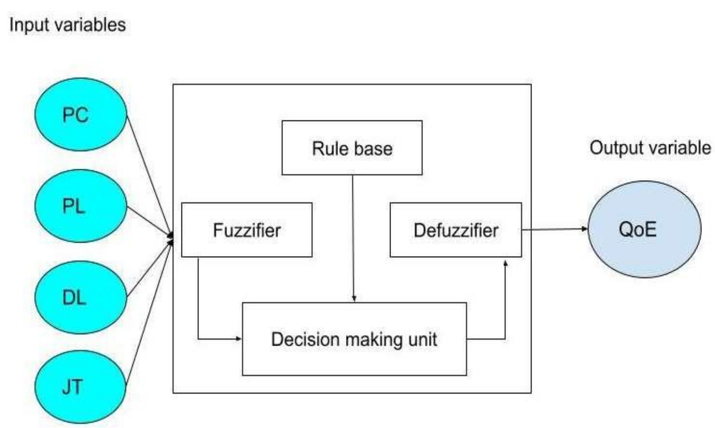

Figure 4. Block diagram for Fuzzy Inference System.

4.2 Assigning membership functions

The membership functions are graphical representations to characterize variable fuzziness. Usually, the membership functions are selected based on the proper presentation of the intended input and output information. Different shapes, such as triangles, trapezoids, bell curves, or gauss, can be used as long as the information distribution is accurately presented. In this study, the Gauss function was selected to represent the variables PC, PL, DL, JT, and QoE. The membership functions used fuzzy linguistic expressions to indicate the strength of variables at different levels. The three fuzzy sets assigned to input variables were defined as low, average, and high. Moreover, the output variable, QoE, was assigned five fuzzy sets described as bad, poor, average, good, and excellent.

4.3 QoE prediction

The FIS QoE prediction model proposed in this study utilizes a series of fuzzy rules that were created to forecast the output variable based on the membership functions of the input variables. Typically, these rules are implemented in the FIS to process the linguistic values of the inputs and assign them to a set of fuzzy elements. Additionally, rules are formulated based on previous experiences, observations, and the knowledge of an expert [36]. Generally, these rules are written using if-then statements and associated linguistic variables. The rules formulated in this study followed Mamdani's method [37], in which inference rules calculated the output based on the weight of each input variable. As an example, a set of three rules used by the fuzzy model to make decisions are presented in Table 5.

After processing the inputs and applying the fuzzy rules, the FIS produces a fuzzy value that is then transformed into a final crisp output. This conversion process is referred to as the defuzzification of output membership functions.

Table 5. Fuzzy rules

Rule1: Sample condition for excellent QoE If (PC = Low) Λ (PL= Low) Λ (JT= Low) Λ (DL=Low) → (QoE= Excellent)
Rule2: Sample condition for average QoE If (PC= Low) Λ (PL= High) Λ (JT=High) Λ (DL=High) → (QoE= Average)
Rule3: Sample condition for poor QoE If (PC=Average) Λ (PL= Low) Λ (JT= Low) Λ (DL= High) → (QoE =Poor)

Different methods, such as the center of gravity, indexed (or threshold), mean of maxima, or center of the area, can be used to defuzzify fuzzy outputs. Among these methods, the center of gravity is the most efficient [38]. Mathematically, the center of gravity is expressed by (1).

$$Y = \frac{\sum_{i=1}^{M} S_i K_i}{\sum_{i=1}^{M} K_i} \quad \ldots\ldots\ldots\ldots\ldots\ldots.. (1)$$

whereby, Y is the defuzzified output, M is the number of rules, S_i is the value of output for a rule, K_i is the inferred weight of i^{th} output membership function.

4.4 Model testing

To validate the model, we compared its predictions against real users' QoE. We implemented the model in the fuzzy logic toolbox of Matlab R2016a and simulated it by putting various combinations of packet corruption, packet loss, delay, and jitter. In each session, we recorded the model-predicted scores and compared them against the user's QoE scores in Minitab 17. The model showed a correlation coefficient of 0.875 between the predicted and users' QoE, and a small root mean square error (RMSE) of 0.344. These results suggest that the proposed model can be utilized for subjective evaluation of video streaming QoE in-network settings, replacing user surveys that can be costly and time-consuming. Figure 5 depicts the scatter plot between the model's predicted QoE and subjective user QoE.

5. Conclusion

We have introduced a fuzzy-logic model as an alternative method for predicting the QoE in human language, which facilitates the interpretation of results. An accurate understanding of customer QoE is crucial for network operators to dimension networks appropriately to meet the demand of subscribers. Our approach takes into account the influence of input variables to replicate scenarios that may affect the communication network. To investigate the impact of input variables on video streaming QoE, we created a network emulator that mimics the network environment in a computer laboratory. By using Taguchi orthogonal arrays, we reduced the number of experiments from 81 to 9 sessions for input variables combination. We analyzed variations in video streaming QoE against different combinations of input variables at three distinct levels, which showed no significant impact on video streaming QoE at $p>0.05$. We also developed a Fuzzy Inference System (FIS) using a set of fuzzy rules to establish the relationship between input variables and video streaming QoE. The proposed model presented input and output variables in the linguistic form such as good, poor, or bad, which are more easily understood by humans than MoS scores such as 1, 2, or 2.5 that lack a meaningful interpretation. Our model achieved RMSE of 0.344 and 87.5% correlation between model output and actual QoE scores. However, the study was limited to four input variables (PC, PL, DL, and JT), which were reproduced in a laboratory environment. Future studies should include the impact of other parameters from data link and network layers of the next generation networks, such as 5G networks.

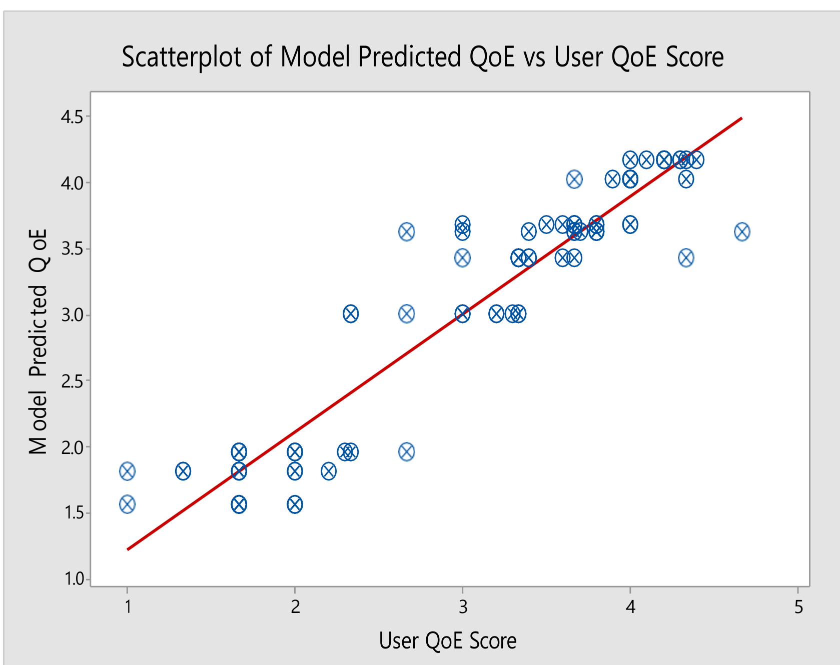

Figure 5. Scatter plot of Model predicted and Subjective User QoE Score.

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