ANALYSIS OF THE MOST INFLUENTIAL FACTOR ON QUALITY OF EXPERIENCE IN MOBILE NETWORK

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Abstract

As the quality of service (QoS) on mobile networks constantly changes, the communication service providers always examine and improve the network performance to maintain the number of customers. In terms of network optimization, communication service providers just focus on adjusting the QoS parameters to the standards of the mobile service but that does not approach the customers' actual needs. The researchers recognize the importance of the QoS parameters along with the users' satisfaction or users' experience which are evaluated using the principles of quality of experience (QoE). In this paper, the relationships among the parameters using model creation based on a feed-forward backpropagation neural network are presented. The same evaluator for all evaluations is utilized because the locations are alien in different environments. The activities for the evaluation of the users' opinions consist of watching the YouTube service, using a web browser, and sending a message via the Line service. These relationships are analyzed to get the QoS parameters that have the most impact on changes of the QoE score using mean absolute deviation (MAD). This study can be used as a guideline for investigation and management of problematic parameters for communication service providers.

Keywords: **Quality of service (QoS), quality of experience (QoE), feed-forward backpropagation neural network, mean absolute deviation (MAD)**

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Introduction

The mobile telecommunications industry has been successful and has grown enormously in terms of business due to the vast demand of consumers for access to internet communication in their daily lives for social media for news and interpersonal communication, online entertainment, or multimedia applications (Cisco Systems, Inc., 2017). Therefore, there is competition among the communication service providers in order to get higher profits along with maintaining standards and quality of service (QoS) in responding to the users' requirements and the very rapid increase in the number of users. The service providers can do this by continuously monitoring the quality of the network with the help of QoS parameters. The QoS parameters are used to improve the network performance in mobile communication and define the quality level of the network which the service providers can guarantee. In spite of the fact that maintaining standards and the QoS can indicate the network performance experienced by the users, they do not reflect the requirements of the users because user requirements cannot be realized with the help of these standard parameters. Actually, a good quality of experience (QoE) allows users to effectively access the service because the QoE is a satisfaction indicator based on the users' perspectives about the overall QoS. The users' satisfaction can be recognized by a survey of the users, which is usually on a scale of 1 (not recommended) to 5 (very satisfied). Therefore, maintaining the QoS coupled with the QoE is the best and most effective method to increase the quality of the network.

As mentioned earlier, it is a challenge for the service providers to improve the quality of the network, keeping in mind that the QoS and QoE are important parameters. Therefore, it is necessary to study the concurrent relationship between the QoS and QoE for correct application to the network. So far, most researchers have used the feed-forward backpropagation neural network method (Rivera *et al*., 2013; Aroussi and Mellouk, 2014; Anchuen *et al*., 2016) for investigating the relationship, which is the creation of a QoE model based on the QoS. The reasons for choosing the artificial neural networks (ANNs) method are because of the high flexibility to analyze data and, even though the information is massive or very complicated, because it is always adjustable, as shown in the literature (Ghalut *et al*., 2015; Pierucci 2015; Danish *et al*., 2016). Furthermore, ANNs have the capability for forecast accuracy due to the learning process, which is the pattern recognition algorithm of data relationships. The learning process includes the adjustment of the network weight and the error value, which are important procedures. These procedures will be discussed in Section III. In model creation employing ANNs, we apply the QoS network parameters into the input and get the output results that represent the user' s satisfaction with a mobile network. The users' satisfaction score levels are divided into 5 levels according to the ITU E.800 standard (International Telecommunication Union, 2008a).

In fact, the QoS in a mobile network has always changed because of many factors, whether it is the environment, the type of terminal device and application, usage behavior, or the number of mobile network subscribers active at a particular moment. As a result, the QoS parameters have changed as well because these parameters are the description of the overall performance of a mobile network. Therefore, the research involving the relationship between the QoE and QoS cannot conclude which parameters might affect the users' satisfaction. However, we have studied the change of the parameters with a comparison of the QoE models, which create the relationship between the mean opinion score (MOS) and each QoS parameter for determining which parameters most affect the QoE.

This paper investigates the process of QoE modeling with the QoS parameters. Then, we compare each model to analyze the most important parameters which impact the change of the QoE model. In terms of the parameters collected for the modeling, we collected information which consisted of watching video on the YouTube service, visiting a website on the web browser service, and sending a message on the Line service in the various situations. This data collection is explained later. The rest of the paper includes 6 sections comprising: theories and related research; a description of the experimental approach on neural networks; a discussion on the results of the experiments; and the analysis of the results. Finally, we show the summary of which parameters affect the differences between the QoE models on the mobile networks.

Background Overview

Quality of Service (QoS)

The QoS represents the cumulative effect of the service performance and determines the level of customer satisfaction (International Telecommunication Union, 2008a). Mobile network operators have focused on monitoring the QoS parameters to improve a network's overall performance. This monitoring can be explored from either the drive test or walk test approach. The drive test is a method of measuring and assessing the coverage, capacity, and QoS parameters on a mobile network while driving, which is suitable for testing in open outdoor locations. On the other hand, the walk test is suitable for narrow areas or inside buildings (Rahnema, 2008). In our experiments, we applied the walk test to collect data. Usually, the QoS parameters are divided into 2 types as follows:

(a) Radio parameters, which are parameters that indicate the quality of receiving and transmitting a signal in the provider's perspective. In addition, the network engineers use these parameters to improve the quality of a network, i.e., the reference signal received power (RSRP), reference signal received quality (RSRQ), received signal strength indicator (RSSI), signal to interference and noise ratio (SINR), and transmission (Tx) power in long term evolution (LTE) parameters.

(b) End parameters, which are parameters that terminal users can recognize while utilizing the mobile service, i.e., throughput download (Kbps), duration to first play (s), buffering count (n) and buffering duration (s) on the YouTube service, send time

Table 1. Description of QoS parameters

QoS parameters	Description
Radio parameters	
- RSRP	Reference Signal Received Power is the received power level in a network.
- RSRQ	Reference Signal Received Quality is the quality of the received reference signal.
- RSSI	Received Signal Strength Indicator is the average total of the received power.
- SINR	Signal to Interference and Noise Ratio is all the quantities of signal quality and receiver noise.
- Transmission (Tx) power	Tx power indicates the power of the equipment transmission.
End parameters	
- Throughput download	Throughput download is the data that can be transferred in a given amount of time.
- Duration time (Web browse service)	Duration time is all the time used to download a page.
Sending time (Line service)	Duration time is all the time used to send messages.
- Duration of first play (YouTube service)	Duration of first play is all the time used to download a video before it starts.
- Buffering duration (YouTube service)	Buffering duration is all the time when a video is paused.

(ms) and send duration (s) on the Line service, and duration time (s) and throughput download (Kbps) on a web browser service. The description of the QoS parameters is shown in Table 1.

Quality of Experience (QoE)

The QoE is a parameter that indicates the overall quality of the system from the users' perspective. Moreover, the QoE can also help operators to understand the customers' requirements and measure the success of business communication competition (International Telecommunication Union, 2008b). The QoE evaluations are divided into 2 methods as follows (International Telecommunication Union, 2016):

(a) The subjective evaluation method which estimates from the users' perspective of the service overview and is the best method for the QoE evaluation because it directly accesses the users' opinion. However, direct access to the users' opinion may not be practical because it is a complicated experiment that requires many people and is time-consuming and costly. The users' satisfaction score levels in the subjective evaluation method are divided into 5 levels. These score levels are called mean opinion scores (MOS), which are commonly used for the QoE evaluation according to the International Telecommunication Union's E.800.1 standard (International Telecommunication Union, 2008c) as shown in Table 2.

(b) The objective evaluation method, which has the principle of predicting the quality of a network by mathematical methods and statistical methods from measurement using a subjective, user-centred evaluation method.

Table 2. MOS rating scale

MOS	Quality	Impairment
5	Excellent	Imperceptible
4	Good	Perceptible but not annoying
3	Fair	Slightly annoying
2	Poor	Annoying
1	Bad	Very annoying

Artificial Neural Networks

Artificial Neural Networks (ANNs) are a branch of artificial intelligence that can emulate the behavior of the human brain using information processing and recognizing the information from the experience of learning. In addition, ANNs can link various facts for concluding the relationships among the information (De Veaux and Ungar, 1997). The function of a hidden layer is to act as a processor that receives data from the input layer and passes it to the output layer. Details regarding the characteristics, structure, and algorithm of ANNs are provided in the following subsections.

(a) Characteristics of Artificial Neural Networks

The characteristics of ANNs are divided into 2 types, which are the single-layer (SL) neural network and multi-layer (ML) neural network (Psaltis *et al*., 1988). The characteristics of ANNs are presented in Figure 1. The SL neural network consists of the input layer and output layer but the ML neural network has a hidden, additional layer. The function of the input layer is input data processing, which will be analyzed with the data appropriate to the ANNs. Next, the function of the hidden layer is as a processor that receives data from the input layer and passes it to the output layer. The hidden layer has advantages that we can use to manage complicated data. Finally, the function of the output layer is as a processor to get the final result from a neural network.

(b) Structures of Artificial Neural Networks

The structures of ANNs include 2 types, which are the feed-forward neural network and feedback neural network (Belavkin, 2014). The structures of ANNs are presented in Figure 2. Both have different types of data entering them. The feed- forward neural network is used to get the desired result using only a forward data process between the layers. However, the feedback neural network is different from the feed-forward neural network because we can use this structure to get a suitable result for ANNs using the feedback loops between layers. In addition, the feedback neural network is suitable for investigating the non-obvious relationships between data.

(c) Algorithms of Artificial Neural Networks

In this section, we will discuss the detail of the main algorithms in ANNs including the learning neural network, the testing neural network, and the activation function.

(i) Learning Neural Network

The learning neural network uses a pattern recognition algorithm to predict the final outcome of ANNs and is classified into 2 types. They consist of supervised learning and unsupervised learning. The supervised learning is a learning function that maps data from the input layer to the output layer and repeatedly predicts the outcome from the training dataset until the correct answer is obtained (Fritzke, 1994). If the answer is not correct, the backpropagation (BP) approach is used to find the error caused by the difference between the outcomes from ANNs and the expected results. The unsupervised learning is a process that has no error detection and learning of the expected results.

(ii) Testing Neural Network

The testing neural network has a function to receive parameters from the learning neural network to investigate the relationship between the data and to create a model from the relationship. In addition, the model's efficiency can be calculated to reduce error in creation of the model. The error values are called the sum of squared errors (SSE).

(iii) Activation Function

The activation function is a function to judge the results in the ANNs (Specht, 1991). It is divided into continuous and discrete functions. The function selection depends on the characteristics of the data for the input and output layers as shown in Table 3. From the literature, there are many popular functions such as the sigmoid function, linear function, and tan-sigmoid function.

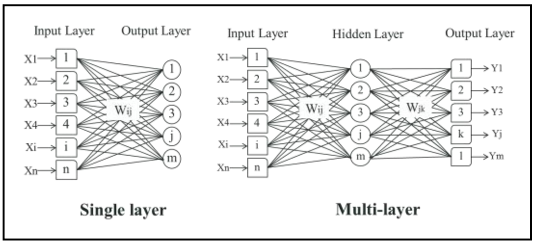


Figure 1. Characteristics of ANNs

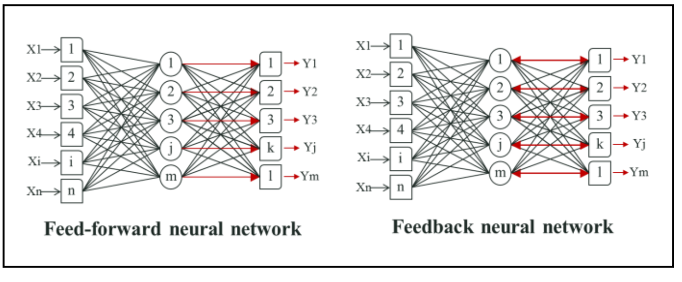


Figure 2. Structures of ANNs

Experimental Design

In this section, we discuss details of the experiment which consists of 3 major steps. The first step is information preparation for applying the data to the modeling process. Subsequently, we present the modeling process. Finally, we compare and analyze the models to conclude the factors that affect the differences between the scores of the users' satisfaction.

Information Preparation

Information preparation is an important step in optimizing our models because there is selection and conversion of the QoS parameters before we apply these parameters to establish the models as shown in Figure 3. The information preparation procedures include 3 steps as follows: (a) information collection from the walk test approach, (b) calculation of the correlation coefficients' values, and (c) data conversion into the modeling process.

(a) Information Collection

We collected information with the walk test approach. After that, we divided the information into 2 sets, which are the QoS parameters and the opinion scores of the users (MOS). In terms of the walk test approach, we utilized 3 popular services which were YouTube, Line, and the web browser application in a department store in Nakhon Ratchasima province. The information obtained from the walk test approach is as follows:

(i) The QoS parameters which are values that can be used to monitor the performance of a mobile network according to the communication standards. In the collection of the QoS parameters, we obtained these parameters from the Azenqos application for each service on a smartphone. The Azenqos application is the program used to test the connection or speed of a network, for which our work utilized the services on the 4G network due to it having many mobile subscribers. Moreover, the application displays the real time of the QoS parameters and the route with the signal strength on a map.

(ii) The opinion scores which are a parameter used to measure the actual usage of the customers' experience while they utilize multimedia services. We assessed the opinion scores for each service as follows:

In the assessment method for the YouTube service, we began by assessing the satisfaction from the start of downloading a video until the video ended. We employed 1 video content, in which the video length was approximately 2 min and the quality of the video was 1080p resolution.

In the assessment method for the Line service, we assessed the users' satisfaction from the duration time of sending an image (the image size was 1250×1250 pixels) from a mobile phone to another mobile phone. Then, we began by assessing the satisfaction from the start of uploading a picture and successfully sending it to the terminal equipment.

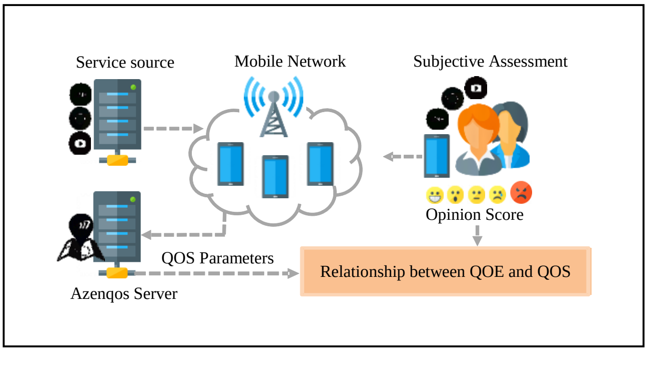


Figure 3. Preparing data for the modeling process

In the assessment method for the web browser service, we assessed the users' satisfaction during the time a webpage was downloading (www.facebook.com) until the download was complete.

(b) Calculation of Correlation Coefficients

The correlation coefficients are used to measure the degree of correlation between variables in the datasets (Zaid, 2015). In our work, these variables are the QoS parameters and opinion scores. The correlation coefficients have values between -1 to 1. If the values of the correlation coefficients are less than 0.8, we do not use these parameters for the ANNs because there is a weak linear relationship which means that the datasets have no correlation. The correlation coefficients are divided into 3 relationships as follows:

The correlation coefficients that are approximately -1 indicate a negative linear relationship and have a relationship between variables in the inverse direction. For example, if 1 variable decreases, another increases.

The correlation coefficients that are approximately 1 indicate a positive linear relationship and have a relationship between variables in the same direction.

The correlation coefficients that are close to 0 indicate no relationship at all. From the literature, the most commonly used equation for correlation coefficients (r) is Pearson's correlation, which is defined as:

$$r_i = \frac{\sum_{P=1}^{p}(x_{i,P}-\bar{x})(y_{i,P}-\bar{y})}{\sqrt{\sum_{P=1}^{p}(x_{i,P}-\bar{x})^2\sum_{P=1}^{p}(y_{i,P}-\bar{y})^2}} \quad (1)$$

where

r_i is the correlation coefficients' values (between the opinion scores and ith QoS parameters),

P is the total amount of information,

x_i is the information from variable 1 (QoS parameters),

y_i is the information from variable 2 (opinion scores),

$\bar{x}$ is the mean of x_i, and

$\bar{y}$ is the mean of y_i.

(c) Data Conversion

We converted the data into the learning neural network for decreasing the complicated data and improving data to the same standard as shown in Equation (2).

$$c_i = \frac{\left|\sum_{i=1}^{p} y_{i,p}x_{i,p}\right|}{\sum_{i=1}^{p} x_{i,p}^{\ 2}} \quad (2)$$

where

c_i is the input data converted,

P is the total amount of information,

x_i is the data from variable 1 (QoS parameters), and

y_i is the data from variable 2 (opinion scores).

Then, we used the data which is calculated from the above Equation to pass on to the learning neural network.

Model Creation

In model creation, we established models from the relationship between the QoS and QoE parameters using ANNs because ANNs are based on flexible algorithms for learning the complicated relationships between variables. Moreover, ANNs are not restricted regarding the characteristics of the input variables. Additionally, we obtained the information from the previous step to create the models which have the following steps:

(a) ANNs Configuration

In our research, the characteristic of the ANNs which we used was the multi-layer neural network which consists of 1 input layer, 1 hidden layer, and 1 output layer. In terms of node numbers, the input layer has 1 node but the hidden node and output nodes have 5 nodes as shown in Table 4. The ANNs' structure is the feed-forward neural network without reverse data in the ANNs' process.

(b) Learning Neural Networks Process

The learning neural networks are an important process for predicting the data used to create the models. In our research, we adopted the supervised learning method into the learning neural networks process because it has validation of the results between the target and output values from the ANNs. The supervised learning steps are as follows:

(i) Activation Function

In terms of the activation function, we adopted the sigmoid function in the learning neural network because we needed an outcome that is consistent with the results shown in Table 3. The output range of the sigmoid function is between 0 and 1. We proposed the following activation function procedure (Figure 4). The first step was to choose the input data which are the QoS parameters. Next, we adjusted the weighting networks and threshold values between the input layer with the hidden layer and the hidden layer with the output layer to learn the pattern recognition and data correlation. In weighting the networks and threshold values, we randomly set these values between 0 to 1 and investigated the relationships of the input data, weighting network, and threshold value in Equation (3). Finally, we calculated the outcome using the sigmoid function, which is shown as the transfer formula in Equation (4).

$$x_{net}(p) = \sum_{i=1}^{p} x_i(p) \times w_i(p) - \theta_j \qquad (3)$$

$$y_{out}(p) = \text{sigmoid}(x_{net}) \qquad (4)$$

where

x_{net} is the sum value of the input,

x_i is the input value (QoS parameters),

w_i is the weight network,

θ_i is the threshold value,

P is the total amount of the information, and

y_{out} is the output value.

The y_{out} value from Equation (4) will be adjusted to get the best value for the ANNs in the next step.

Table 3. Activation functions

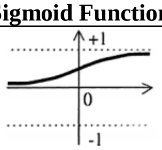
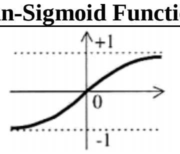
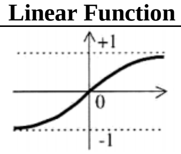
Function	Sigmoid Function	Tan-Sigmoid Function	Linear Function
Plot			
Equation	$f(x) = \frac{1}{1+e^{-x}}$	$f(x) = \frac{1-e^{-x}}{1+e^{-x}}$	$f(x) = x$
Range	[0,1]	[-1,1]	[-∞,∞]

Table 4. The target value of the output node

Quality	Opinion Score	Goal (Output layer = 5 nodes)				
		Node 5	Node 4	Node 3	Node 2	Node 1
Bad	1	0	0	0	0	1
Poor	2	0	0	0	1	0
Fair	3	0	0	1	0	0
Good	4	0	1	0	0	0
Excellent	5	1	0	0	0	0

(ii) Error Detection

We randomly set the weighting coefficients and threshold value until the outcome (y_k) from the output layers and the desired results ($y_{d,k}$) were equal. This is called error detection (e_k), which is calculated from Equation (5).

$$e_k(p) = y_{d,k}(p) - y_k(p) \quad (5)$$

If the outcome differs from the desired results, the outcome will be imported into the backpropagation algorithm (Rojas, 1996) to correct the discrepancies as much as possible and learn the new weighting coefficients from the error gradient formula.

(iii) Recurrent Adjustment

The recurrent adjustment of weighting the network and threshold value is repeated until the SSE is acceptable. We defined the SSE value as 0.001 because we needed the minimal error.

$$SSE = \sum_{i=1}^{p}\sum_{k=1}^{5}(e_k(p))^2 \quad (6)$$

where, the SSE is the sum of the square difference between the estimation outcome and the desired results. If the SSE is close to 0, it indicates that the random weighting coefficients are perfect.

(c) Testing Neural Network Process

In testing the neural network process, we applied the complete parameters from the learning neural networks, both the weighting coefficient and threshold values. Next, we examined the accuracy and precision of the parameters with new datasets of the QoS parameters using Equations (3) and (4). The outcome of these equations is between 0 to 1. However, the users' satisfaction has many levels in practice. Therefore, we calculated Equation (7) to get a consistent outcome with the MOS which is called the QoE score.

$$QoE = \frac{\sum_{k=1}^{5} k y_k}{\sum_{k=1}^{5} y_k} \quad (7)$$

where

y_k is the final outcome of the ANNs and

k is the number of nodes in the output layer.

Finally, we measured the performance of the model creation using the correlation of the model Equation (8):

$$\text{Correlation of model} = \frac{\sum_{p=1}^{P}(OS_p - \overline{OS})(QoE_p - \overline{QoE})}{\sqrt{\sum_{p=1}^{P}(OS_p - \overline{OS})^2}\sqrt{\sum_{p=1}^{P}(QoE_p - \overline{QoE})^2}} \quad (8)$$

where

OS_p is the datasets of the opinion score (from the actual users' satisfaction),

QoE_P is the datasets of the QoE score (from the ANNs),

$\overline{OS}$ is the mean of opinion score, and

$\overline{QoE}$ is the mean of the QoE score.

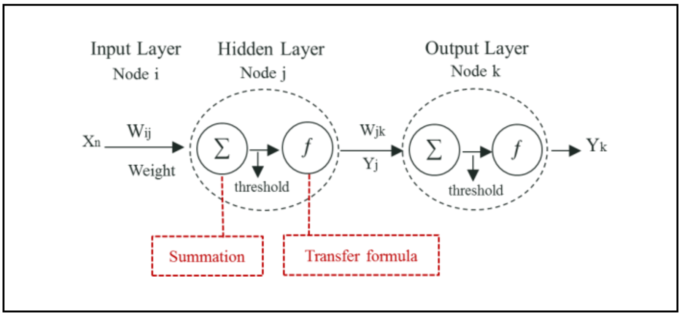


Figure 4. Functions of the activation function

Relationship Comparison

After we finished the model creation, we created graphs of the relationship between the opinion score and the QoS parameters as shown in Figure 5. Then, we compared these relationships between the models with the information from the walk test for 5 days.

Experimental Results

In this section, we present the comparison of the relationship between the QoS parameters and the QoE scores to determine the QoS parameters that impact the maximum change of the QoE score for each service used in our research. We will describe only the models which have high correlation coefficients because we can clearly observe the differences between the models.

The comparison between the QoS parameters in the QoE model for the web browser service is shown in Figures 6 and 7. The QoS parameters include the duration time, throughput download, RSRP, and RSRQ. The comparison between the QoS parameters in the QoE model for the Line service is in Figure 8, which consists of only the sending time parameters. From Figures 9 and 10, the QoS parameters for the YouTube service comprise throughput download, duration of first play, buffering duration, RSRP, RSRQ, and RSSI.

When we finished establishing the QoE models and the comparison, we took the result into the experiment analysis to conclude the important QoS parameters that affect the change of the QoE models in our research.

Experimental Analysis

In this section, we propose the analysis of the QoS parameters that affect the change of the QoE models using the MAD as shown in Equation (9). The MAD of the dataset is the average of the difference between 2 variables.

$$\mathrm{MAD} = \frac{\sum_{i=1}^{p} |X1_i - X2_i|}{p} \qquad (9)$$

where

$X1_i$ is the QoE scores from the first model,

$X2_i$ is the QoE scores from the next model, and

P is the total amount of data.

If the MAD value equals 0, this means that the dispersion of the datasets between 2 variables is not different. Next, we present the MAD values between the QoE models for each service in the form of column graphs in which Figures 11 and 12 show the MAD values for the web browser service. Figure 13 shows the MAD values for the Line service and Figures 14 and 15 show the MAD values for the YouTube service.

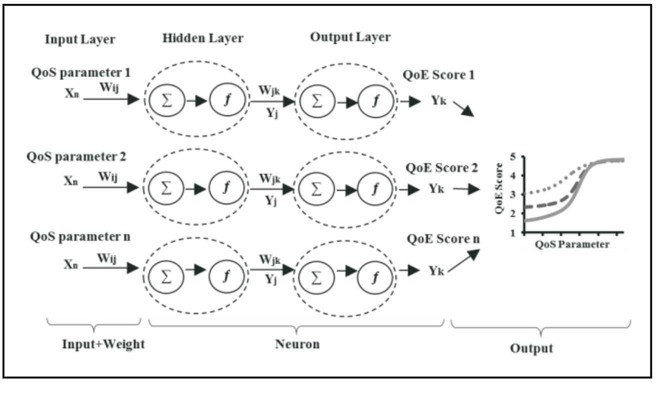


Figure 5. Comparison of the relationship between the QoS parameters and QoE scores

In Figures 11-15, the descriptions of the symbols are as follows: the QoE score I is the QoE model as established from the first collection of the QoS parameters and MOS; then, the QoE scores II, III, IV, and V are the QoE model as established from the next collection of the QoS parameters and MOS.

Figure 11 shows the MAD value which is a comparison of the dataset dispersion between the first QoE score with next QoE score. The difference between the MAD in the end parameter of the web browser service can be seen. The MAD value of the duration time is more valuable than the throughput download and has a value more than 0.38 but the MAD value between the radio parameters is not much different, as shown in Figure 12.

The Line service has only end parameters because the radio parameters are not dispersed between the dataset of the QoE score. For this reason, the authors do not show the MAD value of the radio parameters. In Figure 13, the parameter that affects the differentiation of the QoE model is the "Line Sent Time".

Figures 14 and 15 show the differences of the MAD values for the YouTube service. In terms of the end parameters, the parameter that most affects the difference of the QoE scores is the buffering duration. In terms of the radio parameters, the parameter that most affects the difference of the QoE scores is the RSRQ. As mentioned above, this means that it is the MAD value that indicates the change of the QoE model.

Conclusions

The purpose of our research was to investigate the QoS parameters that affect the change in users' satisfaction for the mobile network (4G) using the creation of a QoE model using ANNs. The datasets in our experiment were obtained from the exploration of the users' satisfaction and opinions on actual usage in a department store. For the data collection, we used 5 days to collect both the QoS and QoE parameters. Then, we compared the relationship between the QoS parameters and QoE score for each day with that on the next day to determine the QoS parameters of the 3 services that have an impact on the differences between each model. The results are summarized as follows.

In terms of the end parameters for the web browser, Line, and YouTube services, the

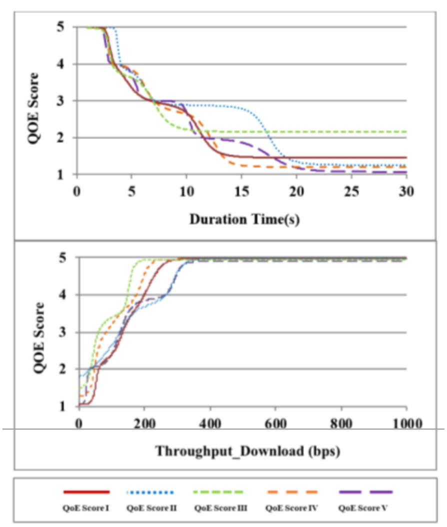


Figure 6. QoE scores' comparison with end parameters on the web browser service

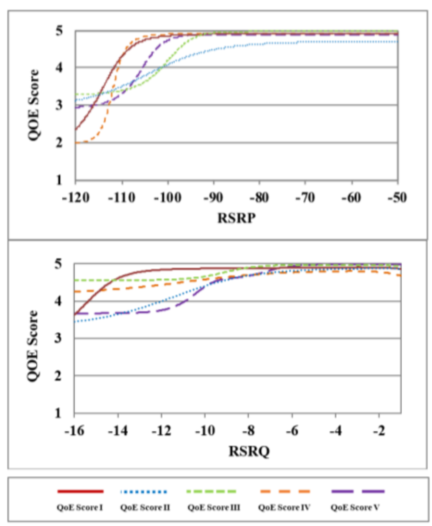


Figure 7. QoE scores' comparison with radio parameters on the web browser service

QoS parameters that affect the change of the QoE models for each of these services are: the duration time for the web browser, the sent time for the Line service, and the buffering time for the YouTube service. In terms of the radio parameters on the web browser and YouTube services, the QoS parameters that affect the change of the QoE models are the RSRP, RSRQ (for the web browser service), and the RSRQ (for the YouTube service). From all above-mentioned parameters, we have concluded these parameters using the MAD formula.

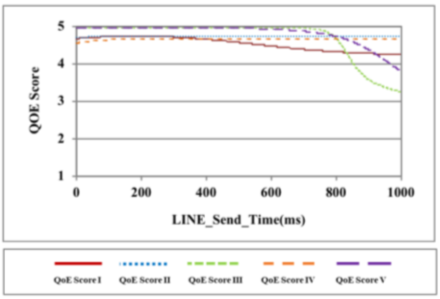


Figure 8. QoE scores' comparison with end parameters on the Line service

From the conclusion of the parameters that indicate the change of the QoE models, we can use these processes as a guideline to manage the problematic parameters for network operators. These parameters can be adjusted to meet the criteria so that users are satisfied with their usage of the mobile network. However, although the exploration and analysis of the QoS parameters and QoE score in our research can be used as a guideline for network improvement, we cannot use the results to judge users' satisfaction with their

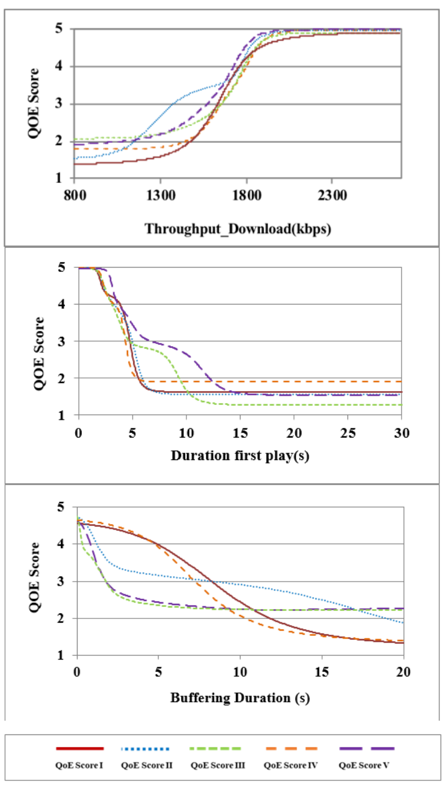


Figure 9. QoE scores' comparison with end parameters on the YouTube servic

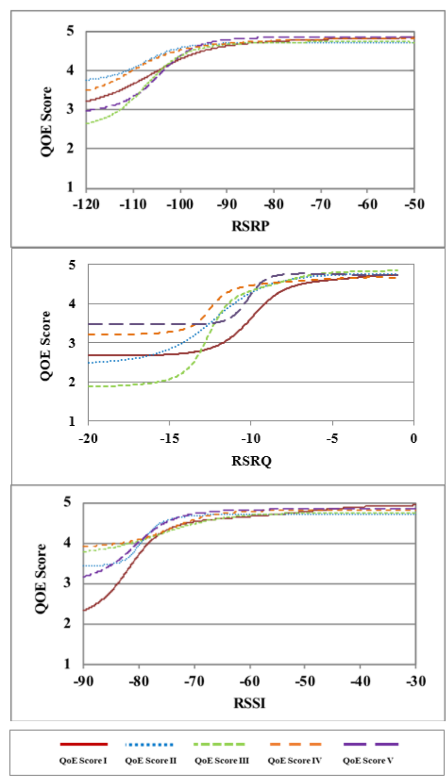


Figure 10. QoE scores' comparison with radio parameters on the YouTube service

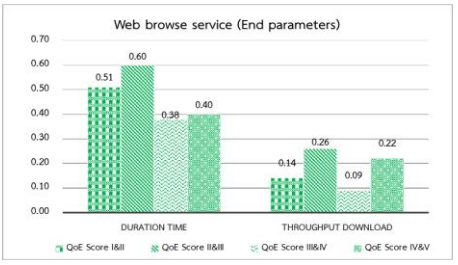


Figure 11. MAD between QoE models with end parameterson the web browser service

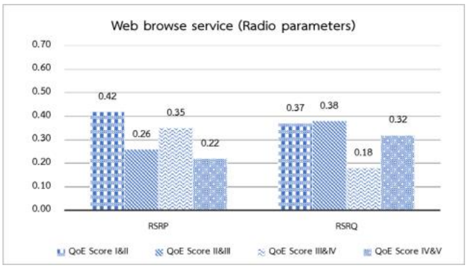


Figure 12. MAD between QoE models with radio parameterson the web browser service

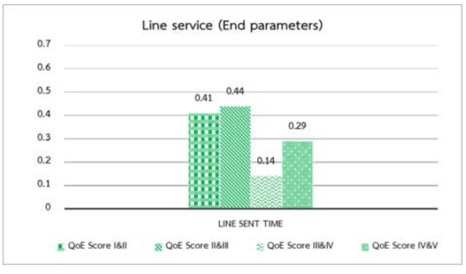


Figure 13. MAD between QoE models with end parameters on the Line service

usage of services on mobile networks in different environments.

Acknowledgment

The purpose of our research was to investigate the QoS parameters that affect the change in users' satisfaction for the mobile network (4G) using the creation

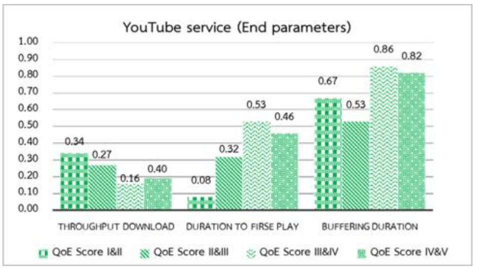


Figure 14. MAD between QoE models with end parameters on the YouTube service

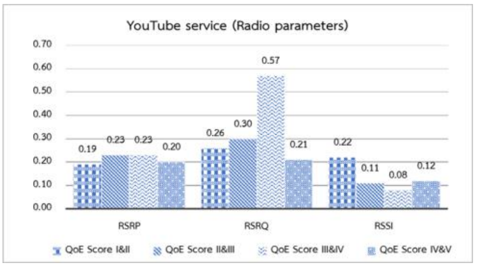


Figure 15. MAD between QoE models with radio parameters on the YouTube service

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