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A Model for Mapping Combined Effects of Quality of Service Parameters and Device Features on Video Streaming Quality of Experience

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Abstract

Maintaining quality of streaming video is challenged by network faults resulting into freezes and rebufferings on the video. On top of the network effects, device features have impacts on the image of the video frames displayed during streaming. Despite the simultaneous impacts of video quality from network and device, previous studies considered individual impact of network parameters or devices as influencing factors to propose Quality of Experience (QoE) models. This study proposed QoE model by mapping combined effects from both network and device on video streamed QoE. An experiment to study the effects of video quality from combined effects of network and device over the wireless involved 35 subjects. Combination of packet loss, packet reordering, and delay were emulated using network emulator following Design of Experiment methodology. Through analysis of variance, the study found that packet loss had the highest impact, followed by device features, reordering, and delay on the video QoE. From the combined effects, two-way interactions and three-way interactions had significant effects on the video QoE. Through additive and linearity behavior of the input factors from network and device on video streaming QoE, a multi-factor model was derived.

Keywords: Design of Experiment (DOE), Mean Opinion Score (MOS), Quality of Experience (QoE), Quality of Service (QoS), Video Quality Assessment.

Introduction

The advancement of smartphones has increased demands for mobile data required for video streaming applications (Anshari et al. 2017). Video applications have been highly adopted for social, academic, and business purposes through video calls, video sharing, and video conferences (Hou and Wang 2017, Zhang et al. 2020b). According to Cisco, mobile video is expected to cover about 82% of the total customer mobile data traffic by 2021 (Barman and Martini 2019).

Despite the mobility of video streaming over end users' mobile devices, video streaming is challenged by the capability of the mobile device features and reliable network to support streaming technology (Sidaty et al. 2014). Varieties on hardware and software feature capabilities, such as RAM, CPU, Operating System version, screen size, and resolution have impacts on maintaining the video quality. Display size and resolution have impacts on the clarity of an image or video viewed by end users (Cubelos 2019). The number of pixels contained in an original video frame can be distorted when the display resolution of the device is low (Elmnsi 2017). Moreover, network conditions to support the transmission of video traffic are still a challenge to wireless environments due to unavoidable packet loss, packet reordering, and delay.

At the end user, video quality suffers from delays and rebuffering which annoy the user (Alreshoodi and Woods 2013). End users are sensitive to quality degradation such that they would prefer quality video streaming regardless of access device capability (Sani et al. 2018). Once the quality of the service is unsatisfactory, they do not seek customer complaints, instead, they may find alternative service providers. Service providers work hard to ensure the provision of service is at an acceptable quality to beat the competitive market demands (Bartolec et al. 2020) through the Quality of Service (QoS) measures.

QoS is measured by network performance through network parameters (packet loss, jitter, bandwidth, packet reordering, and delay) (Wahab et al. 2020). However, network parameter performance does not necessarily mean good end users' experience (Zhang et al. 2020a). Thus, service providers shift from relying on the QoS measurements to user perception measurements, commonly known as Quality of Experience (QoE) (Solera et al. 2018).

QoE is measured from how end users perceive the quality of the service subjectively through studying end users' opinion on the perceived quality or objectively using mathematical metrics, such as peak-signal-to-noise-ratio (PSNR) (Kalpana and Karthik 2020). Therefore, network parameters from QoS should be measured with respect to QoE to understand their impacts on user experience. It is also important to establish a relationship between them by mapping their dependencies (Vega et al. 2018). According to Hoßfeld et al. (2016) when combined factors are to be considered to identify and analyze their impacts on video streaming QoE, multidimensional analysis techniques like regression analysis should be applied.

The study by Mongi and Anatory (2017) to suggest a mapping function of combined parameters from network, smart-device, and video characteristics on video QoE found that video content type had the highest impact followed by bit rate, network delay, jitter, and pixel density index. However, researchers did not consider the effects of packet loss, packet reordering, rebuffering events, and startup delay which may also affect video QoE. Evaluating the effects of QoS parameters on the QoE YouTube videos on 3G and 4G mobile networks subjectively by Vilaikruad et al. (2017) found that buffering duration and download throughput were found to have more influence on user experience. However, no network QoS parameters like packet loss and delay were considered to establish their impacts on video quality. Wang and Bin Hou (2018) proposed a model for mapping the effects of packet loss on video QoE using objective assessment through PSNR as a quality metric. However, the study did not consider other network parameters like delay and reordering, which may also affect video QoE. The study by Plakia et al. (2019) investigated whether there is a significant relationship between the impact of network and application QoS on user experience. The study suggested involvement of user devices, content type, and context to improve user engagement on QoE. Khokhar et al. (2019) proposed a QoS to QoE predictive model from internet video traffic on controlled experiments using machine learning. However, the model did not include the impact of device features, since variations of mobile device screen size and resolution may have an impact on user experience. Despite researchers reporting network and device being the influencing factors for video quality QoE, complexity of studying multiple parameter manipulations subjectively resulted into QoE models from single factors. However, in real life cases, the ultimate QoE is a result of combinations of network parameters (Pal and Vanijja 2017) and device features (Su et al. 2016). Unlike earlier studies, this research intended to propose a model that maps the combined effects from network parameters and device features on video streaming QoE. From the network, the study considered packet loss, delay, and reordering. From device features, the study considered screen size and resolution, which were presented in form of pixel density index (PDI) values. The main contribution of this study is to provide an understanding of the combined effects from network and device features on the quality of streamed video as judged by the end user. Furthermore, the study aimed at proposing a model that maps the combined interaction effects from network and device parameters on streamed video QoE.

Materials and Methods

The research followed a quantitative experimental approach to study the impact of the combined effects of network parameters and device features on streamed video QoE. From the resulting impact, a model that maps the combined effects of network parameters and device features on video streaming QoE was developed. The experimental phase aimed at collecting users' responses on the quality of the streamed video from manipulated combined factors of network and device features. Questionnaires were used to collect users' opinions after they watched sample videos in the experiments. Design of Experiment (DOE) as a mathematical methodology for planning, conducting experiments, analyzing, and interpreting experimental results used MINITAB 19 software. To study the impact of factorial combinations of the input factors (packet loss, delay, reorder, and PDI) on the response variable (QoE) in form of MOS, the full factorial design was applied (Şimşek et al. 2013). From full factorial design, a design matrix that guided all possible combinations of the input factors to be studied in the experiments was developed. ANOVA, a statistical analysis tool, was applied to identify significant factors and their effects of combined interactions using a P-value of 0.05. Based on results from ANOVA, a predictive regression model was obtained. Since DOE models are linear regression models, validation of the model performance was through the goodness of fit using R^2 and adjusted R^2 values. Graphically, the model performance was validated by figuring out the relationship between experimental MOS results against corresponding predicted MOS from the model.

QoE Assessment Methods

Subjective methods

In this study, video QoE assessment was done through subjective assessment approach. The subjective assessment approach applied Absolute Category Rating **(**ACR) method as per ITU-T recommendations (ITU-T 2008). In ACR, subjects are requested to rate video samples one at a time independently. The quality ranges were excellent, good, fair, poor, and bad, with values from 5 to 1, respectively. Following the guideline from ITU-T recommendations, thirty-five subjects were selected through a non-probability sampling technique. Since the subjects targeted were multimedia users in the video streaming aspect, the sample was obtained through the convenience technique.

The consent of each individual who participated in the study was considered. Also, the confidentiality of their information was observed. The subjects streamed video from the server through selected smartphones and requested to provide their video quality opinion on a questionnaire provided at the end of each video. From the collected video quality opinion, subjective QoE metric using mean opinion score (MOS) was calculated for each streamed video as per Equation (1) by (Laghari et al. 2018).

$$\mathrm{MOS} = \frac{\sum_{i=1}^{n} X_i}{N} \tag{1}$$

Where,
X_i is the individual score rate for a given video dataset by N subjects; n is the total number of scores.

Parameter selection

From several literature reviews (Nightingale et al. 2013, Frnda et al. 2016, Pal 2017, Mongi and Anatory 2017, Laghari et al. 2018), the QoS parameters selected were packet loss, packet reordering, and packet delay. From the device features, parameters selected were screen size and screen resolution presented in form of pixel density index (PDI). Value rates for each parameter considered are shown in Table 1.

Table 1: Parameter details used for subject quality of experience experiment

Parameter	**Details**
Packet Loss	0.1%, 1%
Delay	10 ms, 50 ms
Reordering	5% 10%, 25% 50%
Pixel Density Index	282 ppi, 233 ppi

Video selection

Three sample videos were randomly selected from YouTube by considering videos with fast, medium, and slow-motion content for the streaming experiment. The properties of the video selected are as shown in Table 2. Fast motion video considered was a football clip, medium motion content was a news clip and slow motion was an athletic man jumps high clip.

Table 2: Sample video properties

Video	Resolution (pixels)	Frame rate (fps)	Video length (s)
Football clip	1280 * 720	30	10
News clip	1280 * 720	30	10
Athletic man jumps high clip	854 * 480	30	10

Experimental setup

An experimental testbed involving video streaming over a wireless network was set. Network traffic characteristics (packet loss, packet reordering, and delay) were emulated using a network emulator (NetEm) as they transfer video traffic from the server (Ubuntu 18.04) to user's device through wireless. The number of experiments run to study the effects of the response (QoE) from combined factors (from network and device) was proposed through full factorial design. The full factorial design considers all possible combinations of the input factors. A full factorial design is a convenient approach to study the effects of all possible combinations of the input factors when resources are available and a low number of factors are to be studied (Durakovic 2017). A 2^k full factorial requires studying two levels (maximum as +1 and minimum as -1) of each input factor. This study required a combination of four factors (packet loss, delay, reorder, and PDI) which at two levels, required 16 experiment runs. For the experiment to control variability and validity, randomization of the experiment run and four replications were considered to make a total of 64 runs (Casler et al. 2015). Randomization balances extraneous conditions that can affect the result by randomizing the order by which experiment runs. Randomization also allows an estimate of the inherent variation in materials and conditions so that one can make valid statistical inferences based on the data from the experiment (Roudbari et al. 2017). The **NetEm** command uses **tc (traffic command) utility** to manipulate loss, delay, and reordering of network traffic from the sender to the receiver. The command to manipulate the network traffic was ***# sudo tc qdisc <OP_TYPE> dev <INTF_NAME> root netem <PROPERTY><DELAY> <REORDER><LOSS>.*** Manipulation of network parameters followed a combination order as proposed by full factorial design matrix in Table 3. Example of emulation command for the first row in the Table 3 where delay, loss and reorder are at low level was ***$ sudo tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 0.1%.*** After emulation of network traffic, videos from the server to user's device were streamed through VLC media player.

Data Analysis and Results

To establish a relationship between the individual and the combined effects of network and device on video QoE, ANOVA was applied. From factorial analysis, ANOVA table was used to identify parameters that were significant to video QoE through the P-value of the factors. Both the main effect and interaction effects of the input factors on the response variable were identified. The main effect considered is the effect that an individual input factor has on the measured response factor whereas the interaction effect is the combined effect from two or more input factors have on the measured response.

Table 3: Full factorial design matrix to study the impact of combined parameters from network and device on MOS

SN	Input factors (independent variables)				Response variable (dependent)
	Loss (%)	Delay (ms)	Reorder (%)	PDI (ppi)	MOS
1	0.1	10	5 10	233	
2	1	10	5 10	233	
3	0.1	50	5 10	233	
4	1	50	5 10	233	
5	0.1	10	25 50	233	
6	1	10	25 50	233	
7	0.1	50	25 50	233	
8	1	50	25 50	233	
9	0.1	10	5 10	282	
10	1	10	5 10	282	
11	0.1	50	5 10	282	
12	1	50	5 10	282	
13	0.1	10	25 50	282	
14	1	10	25 50	282	
15	0.1	50	25 50	282	
16	1	50	25 50	282	

Factorial analysis was run by MINITAB 19 software where identification of combined interaction effects of the parameters (2-way interaction, 3-way interaction, and 4-way interaction) are provided in Table 4. 2-way interaction considered interaction effect when two input factors combined, 3-way interaction considered interaction effect when three input factors are combined and 4-way interaction is the interaction effect when all four input factors considered. MOS from 2240 video datasets (35 subjects x 64 videos) were analyzed through ANOVA and results are provided in Table 4 and Table 5. The study found that all four parameters (packet loss, delay, reorder, and PDI) were statistically significant on QoE. From the combined interaction effects, 2-way interactions (loss and delay, delay and device, and reorder and device) were significant and at 3-way interactions (loss, delay, device), (loss, delay, reorder) and (loss, reorder, device) were also found to be significant.

Table 4: ANOVA table of four factors and their interactions

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	68.41	4.56	572.34	0.00
Linear	4	66.28	16.57	2079.55	0.00
Loss	1	53.10	53.10	6664.49	0.00
Delay	1	1.78	1.78	224.49	0.00
Reorder	1	1.85	1.85	232.96	0.00
Device	1	1.53	9.53	1196.25	0.00
2-Way Interactions	6	1.55	0.25	32.57	0.00
Loss*Delay	1	1.07	1.07	135.08	0.00
Loss*Reorder	1	0.00	0.00	0.18	0.67
Loss*Device	1	0.00	0.00	0.02	0.88
Delay*Reorder	1	0.00	0.00	0.49	0.48
Delay*Device	1	0.40	0.40	51.00	0.00
Reorder*Device	1	0.06	0.06	8.65	0.00
3-Way Interactions	4	0.55	0.13	17.27	0.00
Loss*Delay*Reorder	1	0.06	0.06	8.65	0.00
Loss*Delay*Device	1	0.40	0.40	51.00	0.00
Loss*Reorder*Device	1	0.05	0.05	7.08	0.01
Delay*Reorder*Device	1	0.01	0.01	2.37	0.13
4-Way Interactions	1	0.01	0.01	2.37	0.13
Loss*Delay*Reorder*Device	1	0.01	0.01	2.37	0.13
Error	48	0.00			
Total	63				

Table 5: Table for coded coefficients of the model

Term	Effect	Coefficient	T-value	P-value	VIF
Constant		2.82	253.03	0.00	1.00
Loss	-1.82	-0.91	-81.64	0.00	1.00
Delay	-0.33	-0.16	-14.98	0.00	1.00
Reorder	-0.34	-0.17	-15.26	0.00	1.00
Device	0.77	0.38	34.59	0.00	1.00
Loss*Delay	0.25	0.12	11.62	0.00	1.00
Loss*Reorder	-0.00	-0.00	-0.42	0.67	1.00
Loss*Device	0.00	0.00	0.14	0.88	1.00
Delay*Reorder	0.01	0.00	0.70	0.48	1.00
Delay*Device	-0.15	-0.07	-7.14	0.00	1.00
Reorder*Device	-0.06	-0.03	-2.94	0.01	1.00
Loss*Delay*Reorder	-0.06	-0.03	-2.94	0.01	1.00
Loss*Delay*Device	0.15	0.07	7.14	0.00	1.00
Loss*Reorder*Device	-0.05	-0.02	-2.66	0.01	1.00
Delay*Reorder*Device	-0.03	-0.01	-1.54	0.13	1.00
Loss*Delay*Reorder*Device	0.03	0.01	1.54	0.13	1.00

From the Pareto chart in Figure 1, the demarcation line (red line) shows the highest impact factor to the lowest impact factor on QoE, which indicates that packet loss had the highest impact on video QoE, followed by device, reorder, and delay. The demarcation line is the reference line separating significant and insignificant combined factors from network and device on video streaming QoE. The effects are standardized from the values in Table 5 for clear plotting of the Pareto chart.

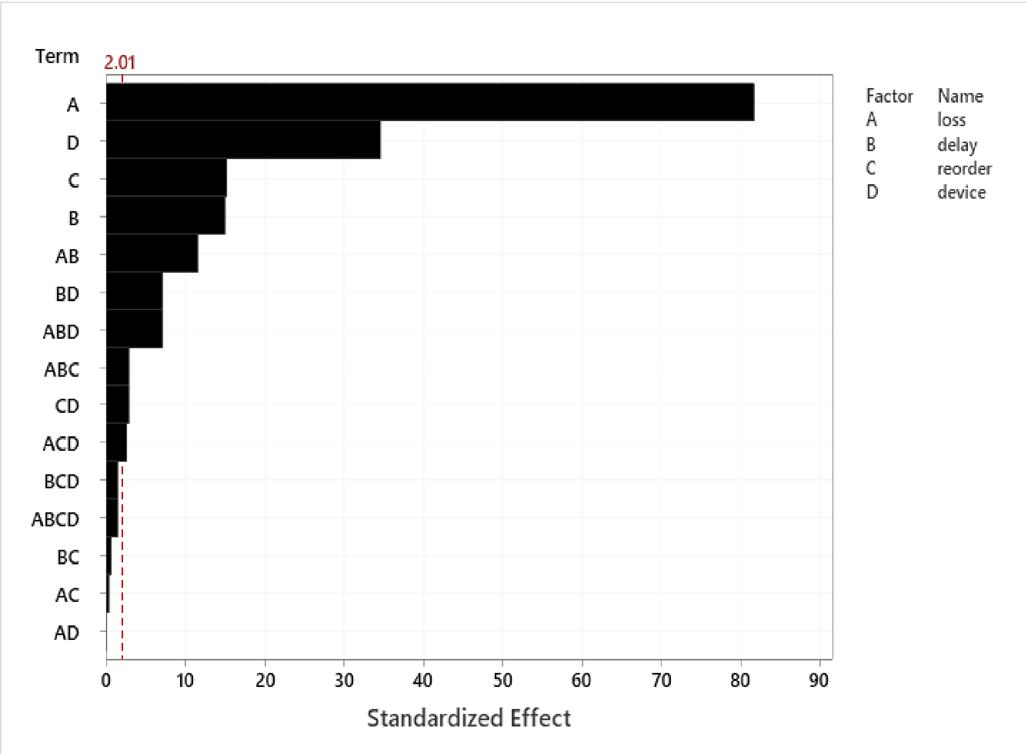

Figure 1: Significant effect level of the parameters.

Model derivation

When several influencing factors together influence a single response factor, then the influencing factors should be combined in a regression model. Therefore, model derivation followed an assumption that the effect of the combined factors (loss (ℓ), delay (d), reorder (r) and device (s)) on the studied response ($\mathcal{MOS}$) follows linearity behavior and they are additive to get the general model in Equation 2. The resulting ANOVA table guided the derivation of the final mathematical model by considering only factors that were significant to the QoE and their combined interaction effect.

$$\mathcal{MOS} = \beta_0 + \beta_1\ell + \beta_2 d + \beta_3 r + \beta_4 s + \beta_{12}\ell d + \beta_{13}\ell r + \beta_{14}\ell s + \beta_{23} dr + \beta_{24} ds + \beta_{34} rs + \beta_{123}\ell dr + \beta_{124}\ell ds + \beta_{134}\ell rs + \beta_{234} drs + \beta_{1234}\ell drs \quad (2)$$

Where:

β_0 is the global mean of the response;

β_1,β_2,β_3,β_4 are the main effect of factors ℓ, d,r, s respectively;

β_{12}, β_{13}, β_{14}, β_{23}, β_{24}, β_{34} is the 2-way interaction effect of factors ℓd, ℓr, ℓs, dr, ds, rs respectively;

β_{123}, β_{124}, β_{134}, β_{234} is the 3-way interaction effect of factors ℓdr, ℓds, ℓrs, drs respectively.

β_{1234} is the 4-way interaction effect of factors ℓdrs.

From the coefficient of factors in Table 5, the final model dropped a combined effect from loss and reorder (ℓr), loss and device (ℓs), delay and reorder (dr), delay, reorder and device (drs) and loss, delay, reorder and device (ℓdrs). The dropped factors were found to have no significant effect on video streaming QoE because their P-values were higher than 0.05. Thus, the final model was reduced from the default model (3) to be (4). The final model was then used to predict QoE and a line graph was plotted against user's QoE score, which had high predictive accuracy that the trending line of predicted MOS values is close to user MOS value (Figure 2).

$$\mathcal{MOS} = 2.8234 - 0.9109\ell - 0.1672d - 0.1703r + 0.3859s + 0.1297\ell d - 0.0047\ell r + 0.0016\ell s + 0.0078dr - 0.0797ds - 0.0328rs - 0.0328\ell dr + 0.0797\ell ds - 0.0297\ell rs - 0.0172drs + 0.0172\ell drs \quad (3)$$

$$\mathcal{MOS} = 2.8234 - 0.9109\ell - 0.1672d - 0.1703r + 0.3859s + 0.1297\ell d - 0.0797ds - 0.0328rs - 0.0328\ell dr + 0.0797\ell ds - 0.0297\ell rs \quad (4)$$

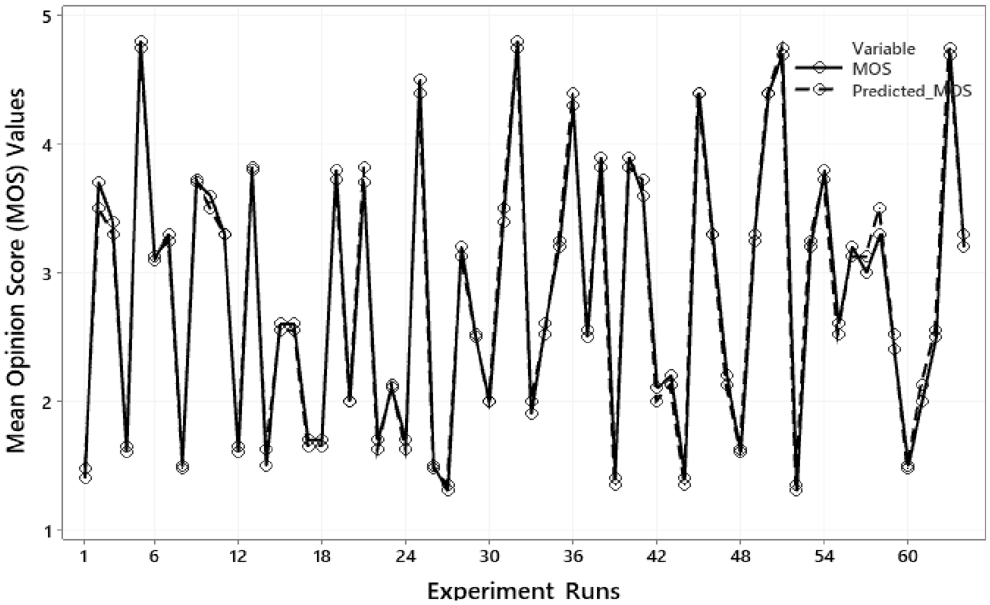

Figure 2: User Mean Opinion Score (MOS) vs predicted MOS.

Model validation

The performance of the model was validated by measuring the goodness of fit through quantitative metrics of R^2 and adjusted R^2. The R-squared value presents the proportion of the variance in the dependent variable (MOS) explained by independent variables (loss, delay, reorder, and device). Adjusted R-square measures the percentage of the variation in the response explained by the model adjusted for the number of predictors. The model summary of the performance metric provided by the suggested regression model for QoE shows that the model attained a high value of 99.44% and 99.27% for R^2 and adjusted R^2, respectively as Table 6 shows. Therefore, the model successfully maps the combined effects of network and device on video streaming QoE by 99.44%. Moreover, the model performance was qualitatively validated graphically (Figure 3), whereby linearity was observed between the predicted values of MOS from the models versus experiment results of MOS.

Table 6: Model summary

Std error of the estimate	R-square	Adjusted R-square	Predicted R-square
0.0892679	99.44%	99.27%	99.01%

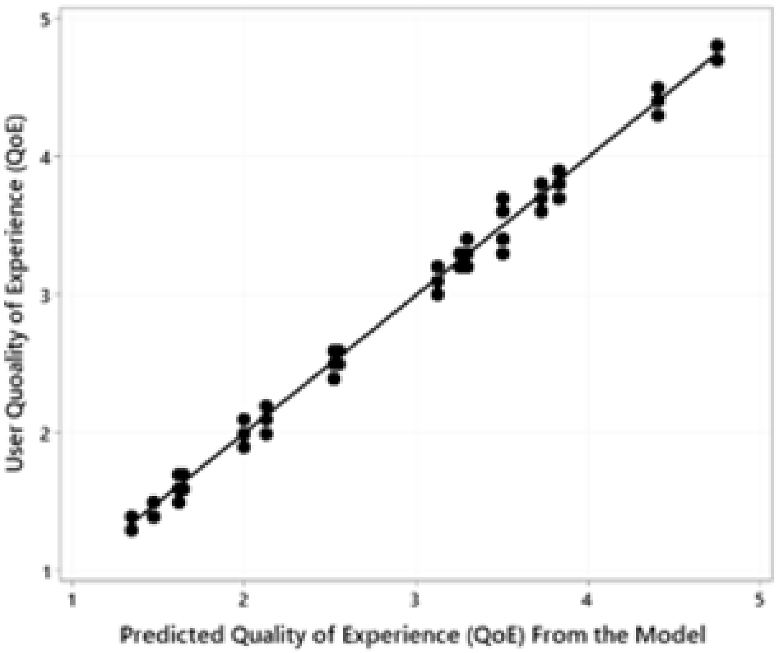

Figure 3: User Quality of Experience (QoE) versus predicted QoE.

Discussion and future work

From the study findings, the proposed QoS parameters and device features had significant effects on the video QoE. By using the proposed model to optimize the response factor (MOS), the QoS parameters should be maintained at their lowest levels while the PDI values should be maintained at their highest levels. In the future, other parameters that were not included in this study should be considered to establish a model that maps all parameters with significant effects. Also, the researchers consider a study of improving video quality by considering improving these parameters which have shown to have significant effects on video streaming QoE. Moreover, since this study has used subjective method as an approach for obtaining video QoE, future studies may consider adopting objective video quality assessment approach for QoE assessment.

Conclusion

In this paper, a mathematical model that maps the combined effects from QoS parameters (loss, reordering, and delay) and device features (screen size and resolution) was derived. The model was derived through an assumption of linearity and additive behavior of the input factors on video QoE using full factorial DOE models. Through ANOVA analysis, the model was derived from the identified significant parameters on video QoE. An experiment during subjective assessment adopted a five-way ACR method to collect end users' opinion rates on video quality. Following factorial analysis from MINITAB 19, ANOVA was used to identify parameters that were statistically significant on video QoE and their combined interaction effects. The derived model attained a value of 99.27% for adjusted-R^2 and 99.44% for R^2.

References

Alreshoodi M and Woods J 2013 Survey on QoE\QoS correlation models for multimedia services. *Int. J. Distribut. Parallel Syst.* 4(3): 53–72.

Anshari M, Almunawar MN, Shahrill M, Wicaksono DK and Huda M 2017 Smartphones usage in the classrooms: learning aid or interference? *Educ. Inf. Technol.* 22(6): 3063–3079.

Barman N and Martini MG 2019 QoE modeling for HTTP adaptive video streaming-a survey and open challenges. *IEEE Access* 7: 30831–30859.

Bartolec I, Orsolic I and Skorin-Kapov L 2020 Inclusion of end user playback-related interactions in youtube video data collection and ml-based performance model training. *2020 12th International Conference on Quality of Multimedia Experience, QoMEX 2020*, 1–6.

Casler MD, Vermerris W and Dixon RA 2015 Replication concepts for bioenergy research experiments. *Bioenergy Res.* 8(1): 1–16.

Cubelos J, Carballeira P, Gutierrez J and Garcia N 2019 QoE analysis of dense multiview video with head-mounted devices. *IEEE Trans. Multimed.* 22(1): 69–81.

Durakovic B 2017 Design of experiments application, concepts, examples: State of the art. *Perid. Engine. Nat. Sci.* 5(3): 421–439.

Elmnsi A, Osman N and Mkwawa IH 2017 Mobile devices pixel density and video quality. *2017 4th NAFOSTED Conference on Information and Computer Science, NICS 2017 - Proceedings, 2017-Janua*, 325–330.

Frnda J, Voznak M and Sevcik L 2016 Impact of packet loss and delay variation on the quality of real-time video streaming. *Telecom. Syst.* 62(2): 265–275.

Hoßfeld T, Skorin-Kapov L, Heegaard PE, Varela M and Chen KT 2016 On Additive and multiplicative QoS-QoE models for multiple QoS parameters. *Proceedings of the 5th ISCA/DEGA Workshop on Perceptual Quality of Systems PQS 2016*, 44–48.

Hou Y and Wang J 2017 Investigation on the QoE and packet loss rate of the IOT network. *Am. J. Data Min. Knowl. Discov.* 2(1): 15–29.

ITU-T 2008 Itu-T Recommendation P 800. *ITU-T P.910, Subjective Video Quality Assessment Methods for Multimedia Applications.*

Kalpana V and Karthik S 2020 Route availability with QoE and QoS metrics for data analysis of video stream over a mobile ad hoc networks. *Wireless Pers. Commun.* (0123456789), 1–22.

Khokhar M, Ehlinger T and Barakat C 2019 From network traffic measurements to QoE for internet video. *IFIP Networking Conference*, 1–10.

Laghari AA, He H and Channa MI 2018 Measuring effect of packet reordering on quality of experience (QoE) in video streaming. *3D Research* 9(3): 30.

Mongi AF and Anatory J 2017 *Mapping Smart-device , Network and Video Quality of Service Parameters to Quality of Experience*. 1–5.

Nightingale J, Wang Q, Grecos C and Goma S 2013 Modeling QoE for streamed H.265/HEVC content under adverse network conditions. *IET Conference Publications 2013*(641 CP), 249–253.

Pal D and Vanijja V 2017 Effect of Network QoS on User QoE for a mobile video streaming service using H.265/VP9 codec. *Proc. Comput. Sci.* 111: 214–222.

Plakia M, Tzamousis E, Asvestopoulou T, Pantermakis G, Filippakis N, Schulzrinne H, … Papadopouli M 2019 *Should I stay or should I go: Analysis of the impact of application QoS on user engagement in YouTube*. 1–23. Retrieved from http://arxiv.org/abs/1901.01603

Roudbari MN, Ojani R and Raoof JB 2017 Investigation of hot pressing parameters for manufacture of catalyst-coated membrane electrode (CCME) for polymer electrolyte membrane fuel cells by response surface method. *Energy* 140: 794–803.

Sani Y, Mauthe A and Edwards C 2018 On the trajectory of video quality transition in HTTP adaptive video streaming. *Multimedia Systems* 24(3): 327–340.

Sidaty NO, Larabi M and Saadane A 2014 Influence Of video resolution , viewing device and audio quality on perceived multimedia quality for streaming applications. *2014 5th European Workshop on Visual Information Processing (EUVIP), Paris*, 1–6.

Şimşek B, Tansel İç Y and H Şimşek E 2013 A full factorial design based desirability function approach for optimization of properties of C 40/50 concrete class. *Math. Comput. Appl.* 18(3): 330–339.

Solera M, Toril M, Palomo I, Gomez G and Poncela J 2018 A testbed for evaluating video streaming services in LTE. *Wireless Personal Communications* 98(3): 2753–2773.

Su GM, Su X, Bai Y, Wang M, Vasilakos AV and Wang H 2016 QoE in video streaming over wireless networks: perspectives and research challenges. *Wireless Networks, 22*(5): 1571–1593.

Vega MT, Perra C and Liotta A 2018 Resilience of video streaming services to network impairments. *IEEE Trans. Broadcast.* 64(2): 220–234.

Vilaikruad A, Anchuen P, Uthansakul P and Uthansakul M 2017 Effect of quality of service parameters on quality of experience for YouTube service in mobile networks. *ECTI-CON 2017-2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, 568–571.

Wahab A, Ahmad N and Schormans J 2020 Direct propagation of network QoS distribution to subjective QoE for Video on demand applications using VP9 Codec. *2020 International Wireless Communications and Mobile Computing, IWCMC 2020*, 929–933.

Wang J and Bin Hou Y 2018 Packet loss rate mapped to the quality of experience. *Multimed. Tools Appl.* 77(1): 387–422.

Zhang H, Dong L, Gao G, Hu H, Wen Y and Guan K 2020a DeepQoE: A multimodal learning framework for video quality of experience (QoE) prediction. *IEEE Trans. Multimed.* 9210(c): 1–1.

Zhang M, Qin F, Wang GA and Luo C 2020b The impact of live video streaming on online purchase intention. *Serv. Indust. J.* 40(9–10): 656–681.

Appendix: Network traffic alteration experiment

A wireless network from the server (Linux Computer) was set through a hotspot by which end users' smartphones to stream video was connected. Linux contains an open-source network emulator (NetEm), which manipulates packet loss, delay, and reordering during video streaming experiment using (Traffic Control) TC command **# $ tc qdisc add dev eth2 root netem delay 10ms reorder 25% 50% loss 0.1%.** Table 7 gives details of all cases emulated and their corresponding commands used to simulate.

Table 7: Experiment cases with corresponding simulation commands

SN	Combined input factors	Command
1	Loss=0.1% delay=10ms reorder= 5% 10% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 0.1%
2	Loss=1% delay=10ms reorder= 5% 10% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 1%
3	Loss=0.1% delay=50ms reorder= 5% 10% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 5% 10% loss 0.1%
4	Loss=1% delay=50ms reorder= 5% 10% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 5% 10% loss 1%
5	Loss=0.1% delay=10ms reorder= 25% 50% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 25% 50% loss 0.1%
6	Loss=1% delay=10ms reorder= 25% 50% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 25% 50% loss 1%
7	Loss=0.1% delay=50ms reorder= 25% 50% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 25% 50% loss 0.1%
8	Loss=1% delay=50ms reorder= 25% 50% device= 233ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 25% 50% loss 1%
9	Loss=0.1% delay=10ms reorder= 5% 10% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 0.1%
10	Loss=1% delay=10ms reorder= 5% 10% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 1%
11	Loss=0.1% delay=50ms reorder= 5% 10% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 5% 10% loss 0.1%
12	Loss=1% delay=50ms reorder= 5% 10% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 5% 10% loss 1%
13	Loss=0.1% delay=10ms reorder= 25% 50% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 25% 50% loss 0.1%
14	Loss=1% delay=10ms reorder= 25% 50% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 10ms reorder 25% 50% loss 1%
15	Loss=0.1% delay=50ms reorder= 25% 50% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 25% 50% loss 0.1%
16	Loss=1% delay=50ms reorder= 25% 50% device= 282ppi	$ tc qdisc add dev eth2 root netem delay 50ms reorder 25% 50% loss 1%