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QoE Models for Adaptive Streaming: A Comprehensive Evaluation

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Abstract: Adaptive streaming has become a key technology for various multimedia services, such as online learning, mobile streaming, Internet TV, etc. However, because of throughput fluctuations, video quality may be dramatically varying during a streaming session. In addition, stalling events may occur when segments do not reach the user device before their playback deadlines. It is well-known that quality variations and stalling events cause negative impacts on Quality of Experience (QoE). Therefore, a main challenge in adaptive streaming is how to evaluate the QoE of streaming sessions taking into account the influences of these factors. Thus far, many models have been proposed to tackle this issue. In addition, a lot of QoE databases have been publicly available. However, there have been no extensive evaluations of existing models using various databases. To fill this gap, in this study, we conduct an extensive evaluation of thirteen models on twelve databases with different characteristics of viewing devices, codecs, and session durations. Through experiment results, important findings are provided with regard to QoE prediction of streaming sessions. In addition, some suggestions on the effective employment of QoE models are presented. The findings and suggestions are expected to be useful for researchers and service providers to make QoE assessments and improvements of streaming solutions in adaptive streaming.

Keywords: quality of experience; quality model; adaptive streaming; multimedia services

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1. Introduction

Watching online videos has become one of the most popular user activities due to the fast development of multimedia services, such as online learning, mobile streaming, Internet TV, etc. According to [1], the average online video viewing hours have increased 68% globally in 2019. As of 2021, streaming video accounts for over 53% of all traffic on the Internet [2]. HTTP Adaptive Streaming (HAS) has become the standard solution for multimedia streaming over the Internet nowadays [3]. In HAS, a video is firstly encoded into multiple versions corresponding to different quality levels. Then, each version is divided into short chunks called *segments*. Every segment has the same playback duration commonly ranging from 2 s to 10 s. Segments with suitable versions are delivered to the user device according to the estimated throughput. Because of throughput fluctuations, the segments' versions are often changing, resulting in quality variations during a streaming session. In addition, stalling events may occur when segments do not reach the user device before their playback deadlines. To reduce dramatic quality variations and sudden stalling events, a special stalling event, which is called an initial delay, is inserted before starting the video playback [4]. However, all these factors are well-known to cause negative impacts on the Quality of Experience (QoE) perceived by users [5]. Therefore, to provide the highest possible quality to users, it is imperative to assess the QoE of streaming sessions taking into account the joint impacts of the factors.

In the literature, many models have been proposed for predicting the QoE of HAS streaming sessions [6–13]. These models are different in the number of considered factors, modeling approach, etc. Moreover, they are usually evaluated over a small number of databases (mostly one or two), making it difficult to realize the true effectiveness of existing QoE models [6–9,11]. Recently, many QoE databases have been made available to the public with different settings of the impact factors, viewing devices, codecs such as H.264 [14] and HEVC [15], session durations, and session generation methods [16–22].

To the best of our knowledge, there have been no extensive evaluations of QoE models in the literature. Thus, it is challenging for service providers and practitioners to choose appropriate QoE model in practice. In addition, it is worth emphasizing that the evaluation of any QoE model should be carried out over different databases to truly reveal the model's performance. In this paper, we present a comprehensive evaluation of thirteen existing QoE models (see Table 1) for HTTP Adaptive Streaming over up to twelve open databases. Through experiment results, various findings and suggestions are provided with regard to the performance of the models. In particular, we are able to obtain the following important observations.

- All considered models yield better performance on H.264-encoded streaming sessions than HEVC-encoded ones. Surprisingly, even the models taking into account HEVC characteristics such as *P.1203* and *KSQI* are not very effective for HEVC-encoded sessions.
- To obtain the high and stable performance for different devices, it is recommended to use Mean Opinion Score (MOS) and Video Multi-method Assessment Fusion (VMAF) to calculate segment quality values.
- Besides quality variations and stalling events, temporal relations between impairment events should be also considered in QoE models.
- The use of multiple statistics as model inputs is indispensable to fully represent quality variations and stalling events in a streaming session. However, it is also found that complex models that contain more statistics do not always lead to better performance.
- Among the considered models, the *LSTM* model [10] is the best one since it provides the highest and most stable performance across viewing devices and session durations. However, there is still room for improvements of the existing models, especially in the cases of various viewing devices and advanced video codecs.

The rest of this paper is organized as follows: an overview of existing QoE models is given in Section 2. The experiment settings of the evaluation are described in Section 3. The obtained results and discussions on the performances of individual models are presented in Section 4. Finally, Section 5 concludes the paper and gives an outlook on future work.

2. Overview of QoE Models

In the context of video streaming, the concept of Quality of Experience (QoE) is referred to as *the extent users are annoyed or delighted with videos provided by applications or services* [3,23,24]. In the literature, many QoE models have been proposed that use different inputs and modeling approaches to estimate the impacts of quality variations and stalling events. In this section, we present a brief overview of typical QoE models. For detailed classifications and discussions of QoE models, the readers are referred to other survey studies [3,25].

In general, a QoE model can be characterized by five aspects, namely (1) the key influence factors, (2) segment quality metrics, (3) model inputs, (4) modeling approaches, and (5) session durations. Table 1 presents a comparison of typical models according to these aspects. Here, the key influence factors are initial delay, quality variations, and stalling. In addition, the modeling approaches could be simple analytical functions or complex machine learning models like deep neural networks.

From Table 1, we can see that, with respect to the included influence factors, all these models take into account the impact of quality variations. The influence of initial delay and stalling events is also considered in most of the models, except *Rehman's*, *Guo's*, and *Vriendt's*. For memory-related effects, they are included in the seven models of *LSTM*, *ATLAS*, *P.1203*, *CQM*, *biQPS*, *SQI*, and *KSQI*.

Table 1. Summary of existing models

Models	Modeling Approaches	Segment Quality Parameters	Session Duration (Seconds)	Inputs Used to Represent the Impacts of Factors			
				Impact of Initial Delay	Impact of Quality Variations	Impact of Stalling Events	Memory-Related Effects
Rehman's [6]	Analytical functions	Subjective quality metric (i.e., MOS)	5–15	—	First segment quality Sum of the impacts of the previous quality switches which is modeled by a piece-wise linear function of the switching amplitudes	—	—
Guo's [7]	Analytical functions	Subjective quality metric (i.e., MOS)	10	—	Median segment quality value Minimum segment quality value	—	—
Vriendt's [11]	Analytical functions	Subjective quality metric (i.e., MOS)	120	—	Average and standard deviation of segment quality values Number of segment quality switches	—	—
Singh's [9]	Random neural network	Bitstream-level parameter (i.e., QP)	16	Initial delay is considered as a stalling event	Average of QP values over all macro-blocks in all frames of the whole session	Total number of stalling events Average of stalling durations Maximum of stalling durations	—
Liu's [8]	Analytical functions	Objective quality metric (i.e., VQM)	60	Linear function of initial delay duration	Weighted sum of segment quality values Average of the square of switching amplitudes	Total number of stalling events Sum of stalling durations	—
Yin's [12]	Analytical functions	Bitstream-level parameter (i.e., bitrate)	N/A	Linear function of initial delay duration	Average of segment quality values Average of switching amplitudes	Sum of stalling durations	—
LSTM [10]	Long-Short Term Memory (LSTM)	Subjective quality metric (i.e., MOS)	60–76	Initial delay is considered as a stalling event	Segment-basis parameters	LSTM network with stalling durations	Segment-basis parameters and stalling durations
ATLAS [26]	Support Vector Regression (SVR)	Objective quality metric (e.g., STRRED or VMAF)	10 and 72	Initial delay is considered as a stalling event	Average of frame quality values Time per video duration over which a segment quality decrease took place	Total number of stalling events Sum of stalling durations	Time since the last stalling event or segment quality decrease
P.1203 [13]	Analytical functions and Random forest	Subjective quality metric (i.e., MOS) or Bitstream-level parameters (i.e., frame types, sizes, and QPs of frames, bitrates, resolutions, and frame-rates of segments)	60–300	Initial delay is considered as a stalling event	Number of segment quality switches Number of segment quality direction changes Longest quality switching duration First and fifth percentile of segment quality values Difference between the maximum and minimum segment quality values Average of segment quality values in each interval)	Total number of stalling events Average interval between events Frequency of stalling events Ratio of stalling duration	Weighted sum of segment quality values Weighted sum of stalling durations Time since the last stalling event

Table 1. *Cont.*

Models	Modeling Approaches	Segment Quality Parameters	Session Duration (Seconds)	Inputs Used to Represent the Impacts of Factors			
				Impact of Initial Delay	Impact of Quality Variations	Impact of Stalling Events	Memory-Related Effects
CQM [22]	Analytical functions	Subjective quality metric (i.e., MOS)	60–360	Logarithm function of initial delay duration	Histogram of segment quality values Histogram of switching amplitudes Average window quality value	Histogram of stalling durations	Last window quality value Minimum window quality value Maximum window quality value
biQPS [27]	Long-Short Term Memory (LSTM) and Analytical functions	Bitstream-level parameters (i.e., QPs, bitrates, resolutions, frame-rates of segments)	60–360	Initial delay is considered as a stalling event	LSTM network with segment-basis parameters Average window quality value	LSTM network with stalling durations	LSTM network with segment-basis parameters and stalling durations Last window quality value Minimum window quality value Maximum window quality value
SQI [16]	Analytical functions	Objective quality metric (i.e., VMAF)	10	Initial delay is considered as a stalling event	Sum of segment quality values per session duration	A piece-wise function inputted by stalling durations	Using the Hermann Ebbinghaus forgetting curve to estimate the impact of each stalling event A moving average fashion of the previous cumulative quality and the instantaneous quality
KSQI [28]	Operator Splitting Quadratic Program solver	Objective quality metric (i.e., VMAF)	8, 10, 13, and 28	Initial delay is considered as a stalling event	Impact of each quality switch depends on the instantaneous segment quality and the switching amplitude	Impact of each stalling event depends on the previous segment quality and the stalling duration	A moving average fashion of the previous cumulative quality and the instantaneous quality

To represent segment quality, *Rehman's*, *Guo's*, *Vriendt's*, *LSTM*, and *CQM* models employ the subjective quality metric of MOS while *Liu's*, *ATLAS*, *SQI*, and *KSQI* models use objective quality metrics such as VQM, STRRED, and VMAF. On the other hand, for *Singh's*, *Yin's*, and *biQPS* models, each segment is attributed by one or several bitstream-level parameters such as quantization parameter (QP), resolution, and bitrate. It should be noted that the *P.1203* model can be optionally fed by either MOS values or bitstream-level parameters.

Regarding model inputs, the *LSTM* and *biQPS* models are inputted by segment-basis parameters while the others employ various statistics on a session basis, i.e., calculated over the whole session such as the median and the minimum segment quality values. With regard to modeling approaches, simple analytical functions (e.g., a weighted sum, exponential and natural logarithm functions) are applied in seven models, namely *Rehman's*, *Guo's*, *Vriendt's*, *Liu's*, *Yin's*, *CQM*, and *SQI*. Meanwhile, *Singh's*, *LSTM*, *ATLAS*, and *KSQI* models utilize advanced machine learning methods (e.g., random neural network, LSTM, and regression models). Interestingly, the *P.1203* and *biQPS* models employ both analytical functions and advanced machine learning in different modules of the models.

Finally, regarding session durations, five of the models (*Rehman's*, *Guo's*, *Singh's*, *SQI*, and *KSQI*) are built using only short sessions (i.e., $\leq$30 s) while four models (*Vriendt's*, *Liu's*, *LSTM*, *ATLAS*) employ medium sessions (i.e., 1–2 min). Meanwhile, long sessions (i.e., $>$2 min) are considered in only three models, namely *P.1203*, *CQM*, and *biQPS*.

3. Evaluation Settings

3.1. Selected QoE Models

Our evaluation aims to investigate existing QoE models for HTTP Adaptive Streaming by focusing on the following objectives. First, we want to study how existing QoE models perform across databases with different characteristics of video codec and session duration. Second, we would like to examine the impact of various factors such as user viewing devices on performance of QoE models. Our third objective is to investigate the influence of different design choices (factors, inputs, modeling approaches) to the performance of a QoE model. To cover a wide variety of existing models, we select thirteen state-of-the-art models with various characteristics, namely *Rehman's* [6], *Guo's* [7], *Vriendt's* [11], *Singh's* [9], *Liu's* [8], *Yin's* [12], *LSTM* [10], *ATLAS* [26], *P.1203* [13,29,30], *CQM* [22], *biQPS* [27], *SQI* [16], and *KSQI* [28]. These models are summarized in the above Table 1.

3.2. Databases

To evaluate the performances of QoE models, we will consider a large number of open databases proposed by different research groups. In this study, we will employ the following twelve databases: *W-SQoE-I* [16], *W-SQoE-II* [17], *W-SQoE-III* [18], *W-SQoE-IV (full)* [19], *TRDB* [31], *VLDB* [31], *TR04 (full)* [21], *VL04* [21], *TR06 (full)* [21], *VL13* [21], *TRCQ* [22] and *VLCQ* [22]. Among these databases, only *W-SQoE-IV (full)* has both H.264 and HEVC video formats while all the other databases have just H.264 video format. Most databases are tested by PC monitors, except that *W-SQoE-IV (full)*, *TR06 (full)*, and *TR06 (full)* are tested on both PC monitors and smartphones. In addition, *TR06 (full)*, *VL13*, *TRCQ*, and *VLCQ* are the only databases that contain long sessions of 3 to 6 min. There are some other databases like *LIVE-NFLX-II* [20], *LIVE-NFLX* [32], *LIVE-Stall* [24], and *LIVE-TVSQ* [33]. However, they are not considered in our study because (1) they are quite simple in terms of influence factors and/or (2) the segment parameters such as bitstream-level parameters or MOS values are not fully provided.

In order to have a better understanding the performances of the models, the *W-SQoE-IV (full)*, *TR04 (full)*, and *TR06 (full)* databases are divided into sub-databases; each corresponds to a pair of a viewing device and a codec as shown in Table 2. In addition because subjective segment quality values are not available for some databases (i.e., *W-SQoE-III*, *W-SQoE-IV (full)*, *TR04 (full)*, *VL04*, *TR06 (full)*, and *VL13*), we use the *P.1203*

model to estimate these values from the corresponding bitstream-level parameters. This helps to evaluate the models using as many databases as possible.

Table 2. Settings of sub-databases.

Original Database	Sub-Database	Viewing Device	Codec
W-SQoE-IV (full)	*W-SQoE-IV_pH264*	Smartphone	H.264
	W-SQoE-IV_pHEVC	Smartphone	HEVC
	W-SQoE-IV_fH264	FHD	H.264
	W-SQoE-IV_fHEVC	FHD	HEVC
	W-SQoE-IV_uH264	UHD	H.264
	W-SQoE-IV_uHEVC	UHD	HEVC
TR04 (full)	*TR04p*	Smartphone	H.264
	TR04f	FHD	H.264
TR06 (full)	*TR06p*	Smartphone	H.264
	TR04f	FHD	H.264

3.3. Evaluation Procedure and Performance Metrics

With respect to the model implementation, similar to [18,34], we re-implement *Rehman's*, *Guo's*, *Vriendt's*, *Singh's*, *Liu's*, and *Yin's* models based on the corresponding publications since their implementations are not publicly available [6–9,11,12]. For the *LSTM*, *ATLAS*, *CQM*, *biQPS*, *SQI*, and *KSQI* models, we employ the implementations publicized by the respective authors. Regarding the *P.1203* model, an implementation of the standard that is free to use for research purposes is used [30,35]. Note that, although the *P.1203* model has four input modes, of which mode#3 provides the highest performance, it is not applicable to some databases (namely *W-SQoE-I*, *W-SQoE-II*, *W-SQoE-III*, and *W-SQoE-IV (full)*) due to the lack of input data. Therefore, for these databases, the *P.1203* model is tested with mode#0 while mode#3 is employed for the others.

The impact of initial delay could be separately modeled by a function of its duration which is then simply integrated into QoE models as an additive component [36,37]. Hence, in the same way, the models of *Rehman's*, *Guo's*, and *Vriendt's* that do not originally consider the impact of initial delay are tested in two cases of (1) original (denoted *ori*) and (2) modified (denoted *mod*) by adding the impact of initial delay. It is expected that this addition will help obtain more understanding of the performance of the models and the impact of factors as well. Particularly, since most existing models use logarithm functions to model the impact of initial delay [4,36], such a function that is proposed in [4] with a very high prediction performance is added into *Rehman's*, *Guo's*, and *Vriendt's* models as follows:

$$QoE_{pred} = Q + I_{ID}, \tag{1}$$

and

$$I_{ID} = -0.862log(d + 6.718), \tag{2}$$

where Q and QoE_{pred} are respectively the predicted QoE values before and after modifying, and I_{ID} denotes the impact of the initial delay with the duration of d seconds.

Because each model was developed using one or several specific training databases, these databases will be excluded from the performance evaluation of that model. In other words, the performances are calculated on only test databases. In particular, Table 3 describes the training and test databases for each model. In addition, it should be noted that, because of the lack of input data (e.g., objective quality values of segments), *Liu's*, *ATLAS*, *SQI*, and *KSQI* models are not evaluated over some databases such as *TR04f*, *TR04p*, and *VL04* databases as indicated by NA (i.e., not applicable) in Table 3.

Table 3. Evaluation setting of the databases corresponding to each model. NA: Not applicable.

Model	Database													
	W-SQoE-I	*W-SQoE-II*	*W-SQoE-III*	*W-SQoE-IV (full)*	*TRDB*	*VLDB*	*TR04f*	*TR04p*	*VL04*	*TR06f*	*TR06p*	*VL13*	*TRCQ*	*VLCQ*
Rehman's [6]	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test
Guo's [7]	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test
Vriendt's [11]	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test
Singh's [9]	Test	Test	Test	Test	**Train**	Test	Test	Test	Test	Test	Test	Test	Test	Test
Liu's [8]	Test	Test	Test	Test	Test	Test	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**
Yin's [12]	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test	Test
LSTM [10]	Test	Test	Test	Test	**Train**	Test	**Train**	Test	Test	Test	Test	Test	Test	Test
ATLAS [26]	Test	Test	Test	Test	Test	Test	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**	Test	Test
P.1203 [13]	Test	Test	Test	Test	Test	Test	**Train**	**Train**	Test	**Train**	**Train**	Test	Test	Test
CQM [22]	Test	Test	Test	Test	**Train**	**Train**	Test	Test	Test	Test	Test	Test	**Train**	Test
biQPS [27]	Test	Test	Test	Test	**Train**	Test	**Train**	Test	Test	Test	Test	Test	**Train**	Test
SQI [16]	**Train**	**Train**	Test	Test	Test	Test	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**	Test	Test
KSQI [28]	**Train**	**Train**	Test	Test	Test	Test	**NA**	**NA**	**NA**	**NA**	**NA**	**NA**	Test	Test

In addition, given a combination of a model and a database, a first order linear regression is applied for subjective and predicted quality values following Recommendation ITU-T P.1401 [38]. The aim is to compensate for possible variances of different databases related to subjective experiments.

Regarding the rating scale, besides the 5-point scale from 1 to 5, some models (i.e., *Liu's*, *ATLAS*, *SQI*, and *KSQI*) and databases (i.e., *W-SQoE-I*, *W-SQoE-II*, *W-SQoE-III*, and *W-SQoE-IV (full)*) use the 100-point scale from 0 to 100. To obtain the consistency in our evaluation, all the quality values in the 100-point scale are converted to the 5-point scale by (3) following Recommendations ITU-T P.1203.1 and ITU-T G.1071 [29,39]:

$$Q_5 = \min(Q_{max}, \max(Q_{min}, Q_{min} + (Q_{max} - Q_{min}) \times Q_{100}/100 + Q_{100} \times (Q_{100} - 60) \times (100 - Q_{100}) \times 0.000007)) \quad (3)$$

where $Q_{max} = 4.9$, $Q_{min} = 1.05$, Q_5 and Q_{100} respectively denote the quality values in the 5-point scale and the 100-point scale.

To measure the performances of the models, we employ three metrics of Pearson Correlation Coefficient (PCC), Spearman rank-order correlation coefficient (SROCC), and Root-Mean-Squared Error (RMSE). In particular, the PCC, the SROCC, and the RMSE are respectively used to measure the linear relationship, the rank correlation, and the difference between the predicted quality values of a model and the corresponding subjective quality values in a database. Note that a higher PCC value, a higher SROCC value, and a lower RMSE value mean better prediction performance.

4. Evaluation Results and Discussion

In this section, we will first analyze the performance of the models across all the selected databases. Then, the performance comparisons are conducted for individual database settings of codecs, viewing devices, and session durations. Based on the obtained results, some suggestions on how to effectively use the models in different scenarios will be provided.

4.1. Performance Variation across Databases

Figure 1 shows the performance of all the models corresponding to different databases, where the red line indicates the average performance of each model. With respect to the performance variations, it is clear that, for most of the models, their performances vary significantly across databases. For *Rehman's (ori)* model, the PCC value can be as high as

0.93 in case of the *W-SQoE-I* database but can also be as low as 0.29 in case of the *VL13* database. More drastically, variations in PCC can be observed with *Singh's*, *Yin's*, and *biQPS* models. On the other hand, the performances of the *LSTM*, *SQI*, and *KSQI* models are relatively stable with PCC values in [0.63, 0.96]. From Figure 1b,c, the performances in terms of RMSE and SROCC also show the similar trend to that of PCC.

In terms of the average performance, the models of *Rehman's* (both *ori* and *mod*), *Singh's*, and *Yin's* have the lowest average performance (i.e., PCC $\leq$ 0.57, SROCC $\leq$ 0.56, and RMSE $\geq$ 0.67). Meanwhile, the highest average performance is obtained by the *LSTM* model (i.e., PCC = 0.88, SROCC = 0.87, and RMSE = 0.38). For more details, Table 4 shows the performances of all models per database in terms of PCC. It can be seen that the highest performances are achieved by one of the eight models *LSTM*, *Guo's*, *Vriendt's*, *P.1203*, *SQI*, *KSQI*, *biQPS*, and *CQM*. In particular, the *LSTM* model is very effective, offering the highest performance on six databases. In contrast, none of the *Rehman's* (both *ori* and *mod*), *Singh's*, *Liu's*, *Yin's*, or *ATLAS* models deliver the highest PCC value on any database.

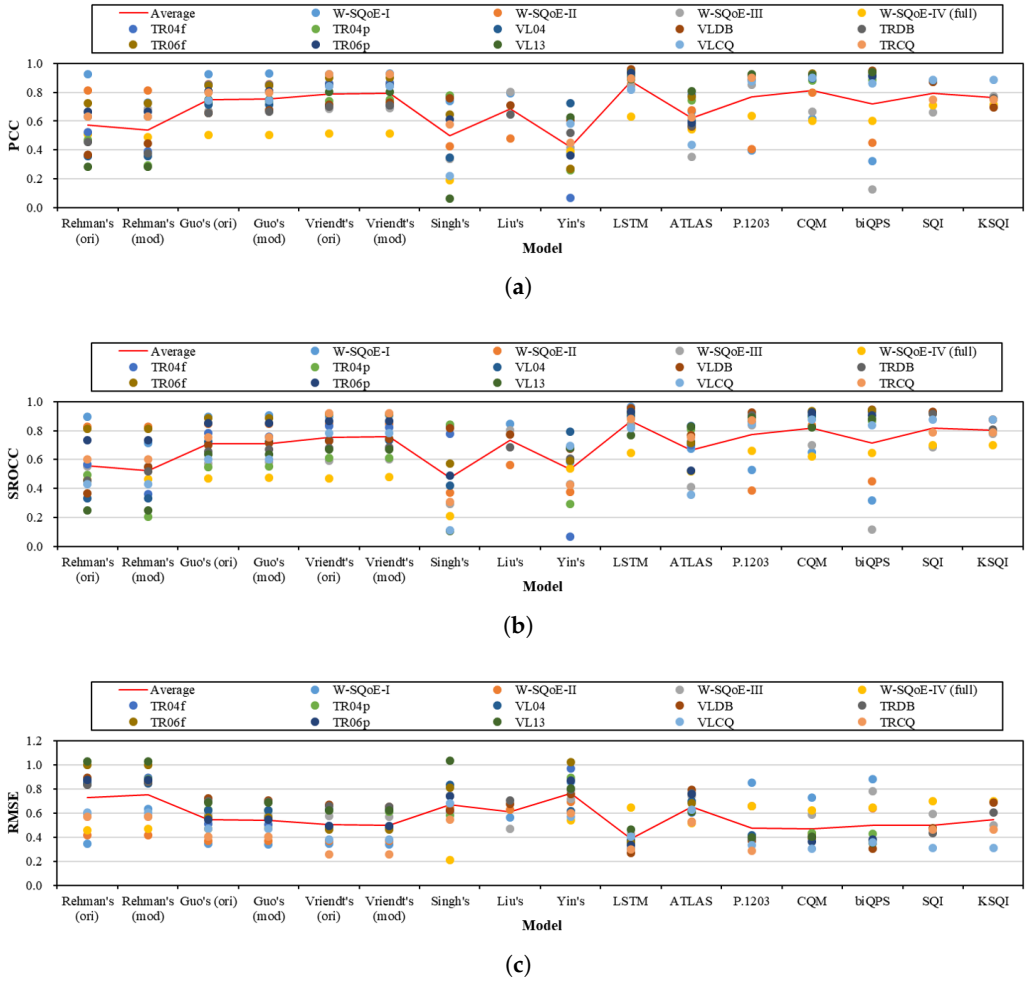


Figure 1. Performances of individual QoE models across different databases. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

Table 4. Performance in terms of PCC of all models per database. The bold-underlined numbers show the model having the highest performance.

Database	*Rehman's (ori)*	*Rehman's (mod)*	*Guo's (ori)*	*Guo's (mod)*	*Vriendt's (ori)*	*Vriendt's (mod)*	*Singh's*	*Liu's*	*Yin's*	*LSTM*	*ATLAS*	*P.1203*	*CQM*	*biQPS*	*SQI*	*KSQI*
W-SQoE-I	0.93	0.73	0.93	0.93	0.93	0.93	0.74	0.79	0.38	**0.95**	0.67	0.39	0.62	0.32	N/A	N/A
W-SQoE-II	0.81	0.81	**0.86**	**0.86**	**0.86**	**0.86**	0.43	0.48	0.27	**0.86**	0.68	0.40	0.80	0.45	N/A	N/A
W-SQoE-III	0.66	0.69	0.67	0.68	0.68	0.69	0.34	0.80	0.42	0.84	0.35	**0.85**	0.67	0.13	0.66	0.77
W-SQoE-IV (full)	0.51	0.49	0.50	0.51	0.51	0.52	0.19	N/A	0.39	0.63	0.54	0.64	0.60	0.60	**0.71**	**0.71**
TR04f	0.52	0.39	0.85	0.85	0.86	**0.87**	0.77	N/A	0.07	N/A	0.79	N/A	N/A	N/A	N/A	N/A
TR04p	0.47	0.29	0.73	0.74	0.74	0.75	0.78	N/A	0.26	**0.92**	0.74	N/A	0.88	0.88	N/A	N/A
VL04	0.36	0.36	0.72	0.72	0.71	0.71	0.35	N/A	0.72	**0.91**	0.60	0.88	0.90	**0.91**	N/A	N/A
VLDB	0.37	0.44	0.65	0.68	0.71	0.73	0.76	0.71	0.61	**0.96**	0.56	0.92	N/A	0.95	0.87	0.70
TRDB	0.46	0.38	0.66	0.67	0.70	0.71	N/A	0.65	0.52	N/A	0.57	0.91	N/A	N/A	**0.88**	0.76
TR06f	0.73	0.73	0.85	0.85	0.90	0.90	0.65	N/A	0.27	0.94	0.77	N/A	0.93	**0.94**	N/A	N/A
TR06p	0.66	0.66	0.81	0.81	0.85	0.85	0.61	N/A	0.36	**0.93**	0.59	N/A	0.92	0.91	N/A	N/A
VL13	0.29	0.29	0.75	0.75	0.80	0.80	0.06	N/A	0.63	0.89	0.81	0.92	0.92	**0.94**	N/A	N/A
VLCQ	0.63	0.63	0.74	0.74	0.84	0.84	0.22	N/A	0.58	0.82	0.44	0.88	**0.90**	0.86	0.89	0.89
TRCQ	0.63	0.63	0.80	0.80	**0.92**	**0.92**	0.58	N/A	0.45	0.89	0.63	0.90	N/A	N/A	0.75	0.75

4.2. Performance across Video Codecs

In this subsection, a performance evaluation of the models is done separately for H.264 and HEVC. For this, we divide the *W-SQoE-IV (full)* database into two sets. The first set (denoted *H.264-encoded*) consists of three H.264-encoded sub-databases of *W-SQoE-IV_pH264*, *W-SQoE-IV_fH264*, and *W-SQoE-IV_uH264*. The second set (denoted *HEVC-encoded*) is comprised of three HEVC-encoded sub-databases of *W-SQoE-IV_pHEVC*, *W-SQoE-IV_fHEVC*, and *W-SQoE-IV_uHEVC*. As the two sets are from the same database of *W-SQoE-IV (full)*, they share the same settings except the codec. This helps eliminate the possible bias in the evaluation process.

Figure 2 illustrates the average performance of individual models on the two database sets. The error bars show the standard deviation values. The trend is that the models generally yield better performance on the *H.264-encoded* set. In particular, the *KSQI* model, which achieves the highest performance for both of the sets, has quite high performance for the *H.264-encoded* set (i.e., PCC = 0.87, SROCC = 0.87, and RMSE = 0.36) but much lower performance for the *HEVC-encoded* set (i.e., PCC = 0.70, SROCC = 0.73, and RMSE = 0.59). This result shows that all the considered models, even the ones taking into account HEVC characteristics such as *P.1203* and *KSQI*, are not very effective for HEVC-encoded sessions. This could be because these models are trained first with H.264-encoded videos and then additionally extended to support HEVC-encoded videos. As the performances on HEVC-encoded sessions are low, hereafter only the databases using H.264 will be discussed in the rest of the paper. This helps maintain a reliable analysis as well as reduce the complexity of the evaluation.

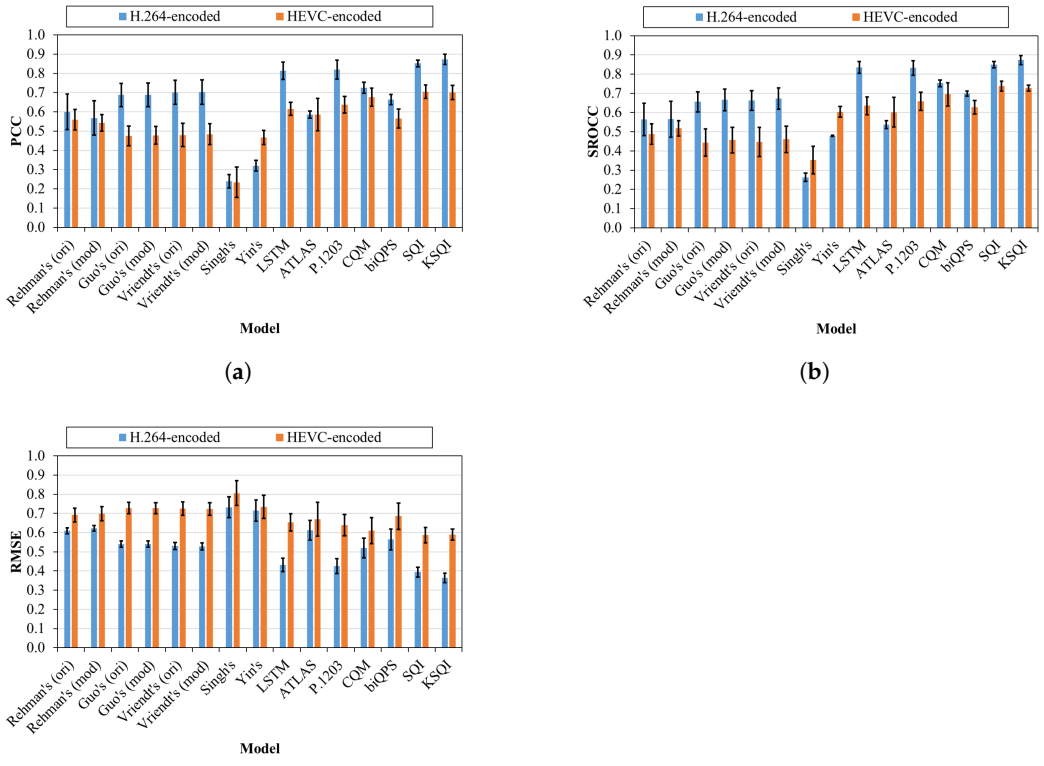


Figure 2. Average performances of individual QoE models over *H.264-encoded* set and *HEVC-encoded* set. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

4.3. Performance across Viewing Devices

To investigate the performance of the QoE models across different viewing devices, we consider three separate device combinations corresponding to three database sets. Particularly, the first set (denoted *DBS1*) includes three sub-databases of *W-SQoE-IV_pH264*, *W-SQoE-IV_fH264*, and *W-SQoE-IV_uH264*, which corresponds to three devices of smart phones, full high definition (FHD) monitor, and ultra high definition (UHD) TV, respectively. With the focus on smart phone and PC, the second set (denoted *DBS2*) contains two databases of *TR04p* and *TR04f*. Similarly, the third set (denoted *DBS3*) is composed of *TR06p* and *TR06f* databases. It is worth noting that the difference between the databases in a given set is the viewing device only. This allows us to reliably compare the performance of the same model across different devices.

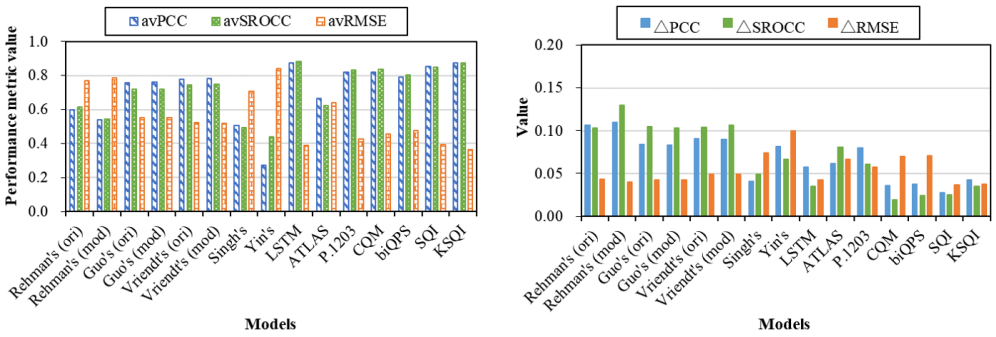
To analyze the impact of viewing devices on the performances of the models, we use two metrics of average performance (denoted *av*) and mean difference (denoted Δ). The use of *av* and Δ is to respectively measure the main tendency and the variation of performances across viewing devices. The formulas of these metrics are given by (4) and (5). In particular, given a model, the first metric is measured as the average performance computed over all the seven databases in the three sets. For the second metric, the performance differences are firstly calculated between all the database pairs in the same set. Then, the mean of all the differences is considered as the mean difference value:

$$av = \frac{\sum_{i=1}^{N} \sum_{j=1}^{K_i} M_{i,j}}{\sum_{i=1}^{N} K_i}, \tag{4}$$

$$\Delta = \frac{\sum_{i=1}^{N} \sum_{j=1}^{K_i - 1} \sum_{l=j+1}^{K_i} \mid M_{i,j} - M_{i,l} \mid}{\sum_{i=1}^{N} \binom{K_i}{2}}, \tag{5}$$

where $N = 3$ is the number of sets, K_i is the number of databases in set i, and $M_{i,j}$ is the performance metric value corresponding to database j in set i.

Figure 3 shows the results of individual QoE models. It can be seen that, among the models, the *Yin's* model has the lowest average performance with avPCC = 0.27, avSROCC = 0.44, and avRMSE = 0.84. Meanwhile, the *Rehman's* model is found to have the strongest performance variation. Specifically, its mean differences of ΔPCC, ΔSROCC, and ΔRMSE are respectively 0.11, 0.10, and 0.04 in the *ori* case, and 0.11, 0.13, and 0.04 in the *mod* case. By contrast, the performance of the *LSTM*, *SQI*, and *KSQI* models is not only high (i.e., high *av*) but also quite consistent (i.e., low Δ). Particularly, the avPCC, avSROCC, and avRMSE values are 0.87, 0.88, and 0.39 for the *LSTM* model, 0.85, 0.85, and 0.39 for the *SQI* model, and 0.87, 0.87, and 0.36 for the *KSQI* model. In addition, the ΔPCC, ΔSROCC, and ΔRMSE values are respectively 0.06, 0.03, and 0.04 for the *LSTM* model, 0.03, 0.03, and 0.04 for the *SQI* model, and 0.04, 0.03, and 0.04 for the *KSQI* model. The reason might be that these models use either MOS or VMAF as a segment quality metric. Both of the metrics inherently take into account the impact of a viewing device on the user perceived quality. Thus, the *LSTM*, *SQI*, and *KSQI* models still perform quite well across viewing devices. This implies that, to obtain the high and stable performance for different devices, segment quality metrics should be ones that consider the effect of viewing devices such as MOS and VMAF. In addition, it is suggested that the *LSTM*, *SQI*, and *KSQI* models can be employed in the QoE prediction for different viewing devices.



(**a**) (**b**)

Figure 3. Average performance and mean difference of the models using the *DBS1*, *DBS2*, and *DBS3* sets. (**a**) average performance; (**b**) mean difference.

4.4. Performance across Session Durations

To study the impact of session durations on the performances of the models, the obtained results over all the databases with respect to different session durations are plotted in Figure 4. Note that the first six databases in the horizontal axis (i.e., *W-SQoE-I*, *W-SQoE-II*, *W-SQoE-III*, *W-SQoE-IV_fH264*, *W-SQoE-IV_pH264*, and *W-SQoE-IV_uH264*) contain only short sessions with the lengths of from 8 to 28 s. For the next five databases (i.e., *TR04f*, *TR04p*, *VL04*, *VLDB*, and *TRDB*), they consist of medium sessions of about 1-minute in length. With the last five databases (i.e., *TR06f*, *TR06p*, *VL13*, *TRCQ*, and *VLCQ*), long sessions (i.e., ≥3 min) are included. To facilitate the performance comparison between the models, Figure 5 shows the average and standard deviation (stdev) of the performances of each model over all the databases.

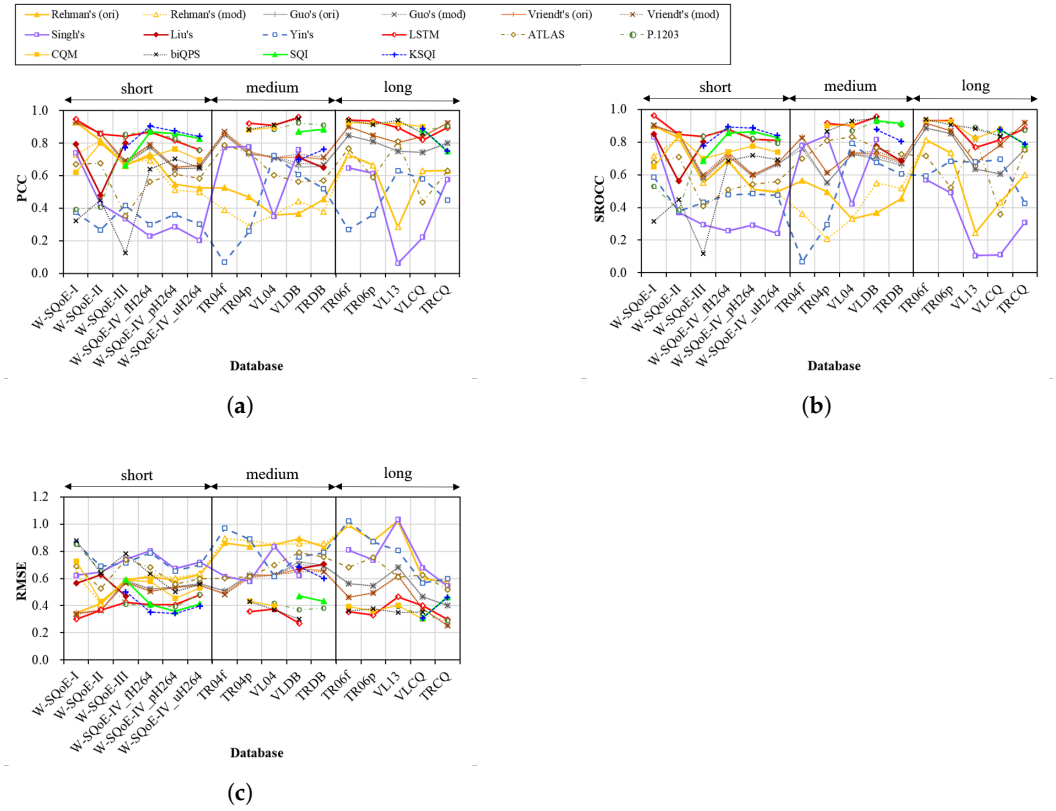


Figure 4. Performance of all the models with respect to different session durations. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

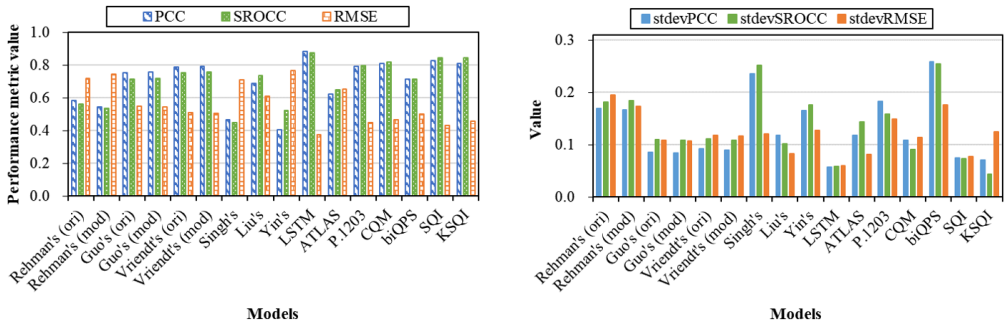


Figure 5. Average and standard deviation performance of the models over all the databases. (**a**) average performance; (**b**) standard deviation performance.

From these figures, we divide the models into four groups. The first group consists of *Rehman's* (both *ori* and *mod*), *Singh's*, and *Yin's* models that have rather low average performances (i.e., PCC $\leq$ 0.58, SROCC $\leq$ 0.56, and RMSE $\geq$ 0.71). For the models in the second and third groups, their average performances are acceptable (i.e., 0.62 $\leq$ PCC $\leq$ 0.81, 0.65 $\leq$ SROCC $\leq$ 0.82, and 0.45 $\geq$ RMSE $\geq$ 0.65). In the second group, the included models are *Liu's*, *ATLAS*, *P.1203*, *CQM*, and *biQPS* that have drastically variable performances (i.e., stdevPCC $\geq$ 0.11, stdevSROCC $\geq$ 0.09, and stdevRMSE $\geq$ 0.08). The third group is composed of *Guo's* and *Vriendt's* models with both the *ori* and *mod* cases. In general, their performances are stable with stdevPCC $\leq$ 0.09, stdevSROCC $\leq$ 0.11, and stdevRMSE $\leq$ 0.12. For the fourth group, it contains three models of *LSTM*, *SQI*, and *KSQI* that have quite high average performances (i.e., PCC $\geq$ 0.81, SROCC $\geq$ 0.84, and RMSE $\leq$ 0.46). In the following, the models in each group will be discussed in detail.

4.4.1. First Model Group

Figure 6 compares the QoE models in the first group. It can be seen that the performances of these models are generally low and considerably variable. In particular, the ranges of the PCC, SROCC, and RMSE values are respectively [0.29, 0.93], [0.25, 0.90], and [0.35, 1.02] for *Rehman's* (*ori*) model, [0.29, 0.81], [0.21, 0.83], and [0.42, 1.02] for *Rehman's* (*mod*) model, [0.06, 0.78], [0.11, 0.84], and [0.55, 1.03] for *Singh's* model, and [0.07, 0.72], [0.07, 0.79], and [0.57, 1.02] for the *Yin's* model.

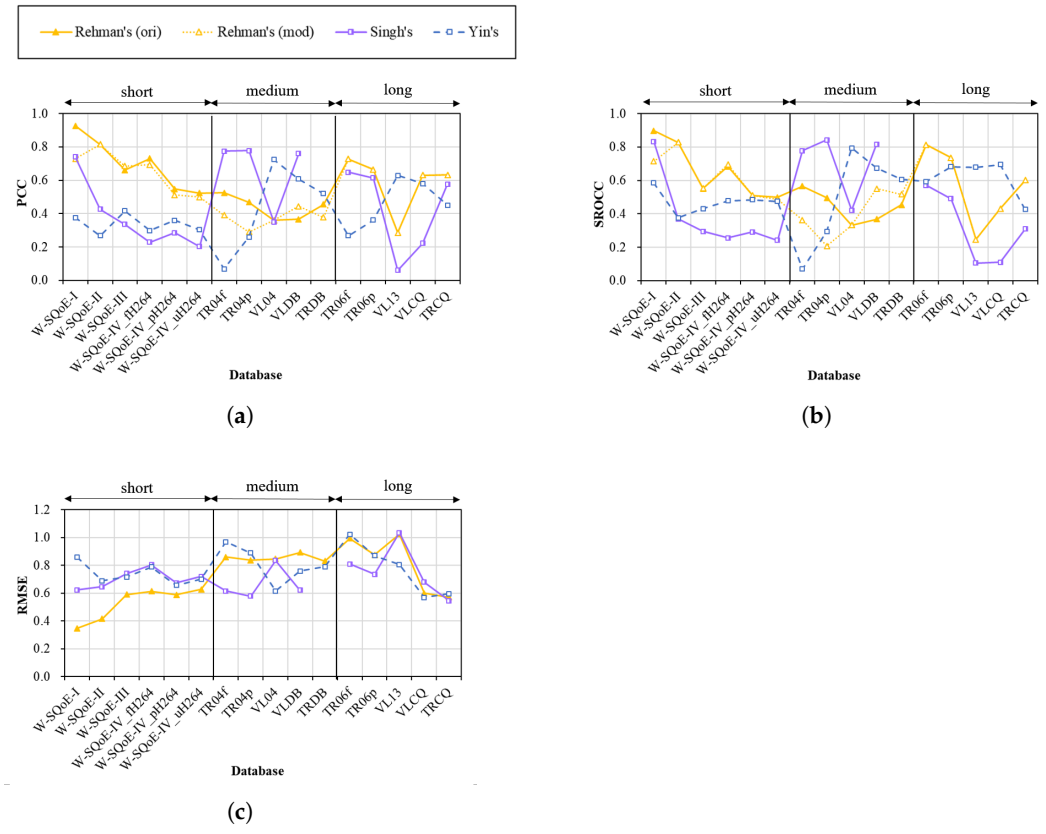


Figure 6. Performance of *Rehman's*, *Singh's*, and *Yin's* models in the first group over the test databases. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

With respect to the *Rehman's* (*ori*) model, this model yields high performance on the *W-SQoE-I* (PCC = 0.93) and *W-SQoE-II* (PCC = 0.81) databases, which contain short sessions (8-s and 10-s). By contrast, its performance is generally low on the other databases with longer session durations (PCC $\leq$ 0.73, SROCC $\leq$ 0.81, RMSE $\geq$ 0.57). It can be explained that this model is originally developed using short sessions (i.e., 5–15 s), and so not effective for longer sessions. In particular, it performs poorly on the databases including stalling events such as *VL04*, *VLDB*, and *VL13* (i.e., PCC $\leq$ 0.44, SROCC $\leq$ 0.55, RMSE $\geq$ 0.85). This is due to the fact that the model does consider the impact of stalling events. This result suggests that the model built based on short sessions such as *Rehman's* may not be effective for medium and long sessions. In addition, the impact of stalling events is crucial to be considered in QoE models.

From Figure 6, it can be seen that the performance of *Singh's* model on the *W-SQoE-I*, *TR04f*, *TR04p*, and *VLDB* databases is acceptable and significantly higher than those of the other databases. In particular, its PCC and SROCC values are in the range from 0.74 to 0.84 while its RMSE values are from 0.58 to 0.62. This result can be explained as follows. The *Singh's* model mainly focuses on quantifying the impact of stalling events by means of various inputs such as the total number of stalling vents and the maximum of stalling durations. Meanwhile, only one input of QP average is used to model the impact

of quality variations. However, this input is obviously not able to distinguish quality switches with different amplitudes [40]. Meanwhile, it is well-known that abrupt switches commonly cause more negative influence than smooth ones [40]. Thus, as a consequence, this model performs well on the four above databases that contain a major number of sessions with stalling events. Meanwhile, for the *W-SQoE-II*, *VLCQ*, and *TRCQ* databases that contain only quality variations, the *Singh's* model results in very low performance (i.e., PCC $\leq$ 0.65, SROCC $\leq$ 0.57, and RMSE $\geq$ 0.55). This shows that the use of only QP average is not sufficient to model the impact of quality variations.

In comparison to the *Singh's* model, the *Yin's* model is noticeably the worst on databases containing sessions with frequent stalling events such as *W-SQoE-I*, *TR04f*, *TR04p*, and *VLDB*. This is probably because the *Yin's* model simply uses the total stalling durations to quantify the impact of stalling events. Meanwhile, for the *VL04*, *VL13*, and *VLCQ* databases, the performance of the *Yin's* model is substantially higher. Note that, in the three databases, most or all of the sessions do not include stalling events. This implies that the use of the bitrate average and the average of switching amplitudes as in the *Yin's* model is more effective than the QP average in representing the quality variations. Still, the performance of the *Yin's* model is not very high. In particular, the PCC and SROCC values are less than 0.80 and the RMSE values are higher than 0.57. These results suggest that the use of the sum of stalling durations only is not able to fully represent stalling events appearing in streaming sessions. In addition, although the bitrate average and the average of switching amplitudes are generally better than the QP average, they are still not effective enough to model the impact of quality variations.

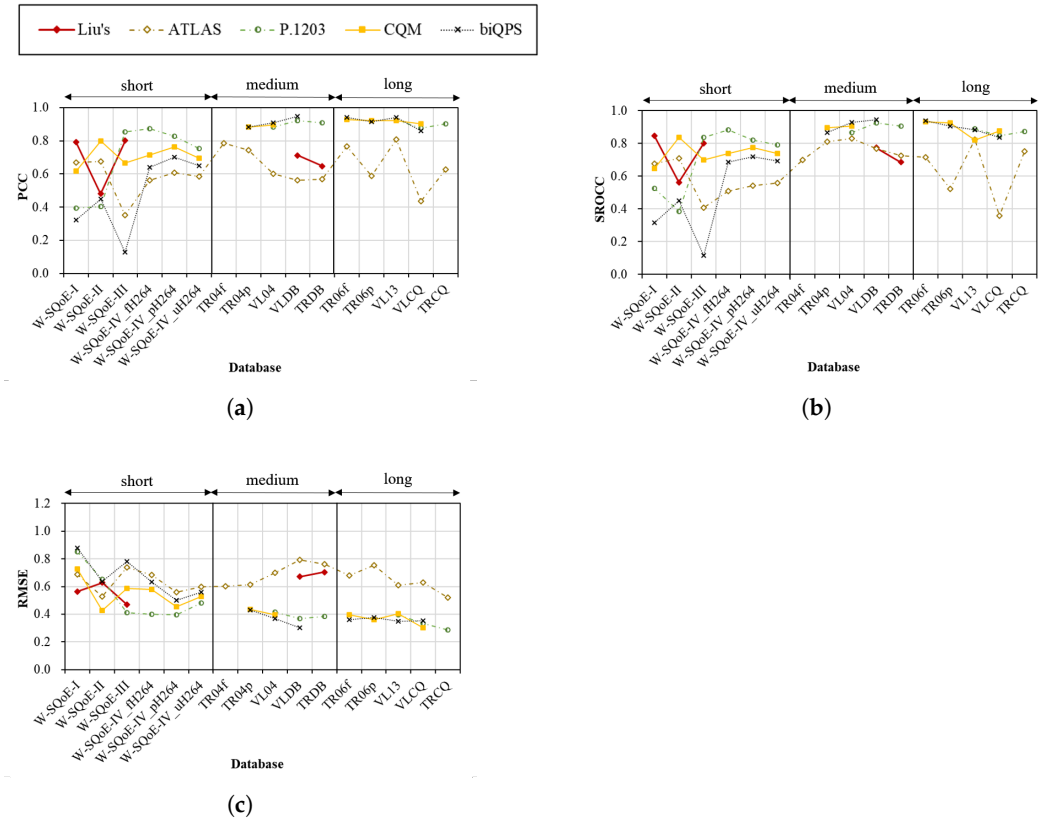
4.4.2. Second Model Group

Figure 7 shows the results of the models in the second group. Along with the sum of stalling durations, the total number of stalling events are additionally fed in *Liu's* and *ATLAS* models. Hence, from Figures 6 and 7, it can be seen that their performance is significantly higher than or similar to that of *Yin's* model for the *W-SQoE-I*, *TR04f*, *TR04p*, and *VLDB* databases. Compared to the *Liu's* model, the *ATLAS* model produces better results but is still not very high for the *W-SQoE-II* database that comprises sessions with only quality variations (i.e., PCC = 0.68, SROCC = 0.71, and RMSE = 0.53). This can be because this model relies on the frequency of quality switches to characterize the quality variations, which cannot account for the degrees of the quality switches (i.e., switching amplitude).

In spite of using the same inputs to represent the impacts of stalling events, the *Liu's* model brings out significantly higher performances than the *ATLAS* model for the databases including sessions with stalling events (i.e., *W-SQoE-I*, *W-SQoE-III*, *VLDB*, and *TRDB*). This may be caused by the difference between the modeling approaches used in the two models. Interestingly, the *Liu's* model that has higher performance utilizes the simple linear function, whereas the *ATLAS* model uses the more sophisticated one of Support Vector Regression. However, in general, both the approaches are not very effective in quantifying the impact of stalling events (i.e., PCC $\leq$ 0.81, SROCC $\leq$ 0.85, and RMSE $\geq$ 0.47). Hence, both *Liu's* and *ATLAS* models are not very effective to predict the QoE of streaming sessions. In addition, the use of more complicated modeling approaches does not always result in higher performance.

For the *P.1203*, *CQM*, and *biQPS* models, their performances are very high for the databases with medium and long sessions, namely *TR04p*, *VL04*, *VLDB*, *TRDB*, *TR06f*, *TR06p*, *VL13*, *VLCQ*, and *TRCQ*. In particular, their PCC and SROCC values are in the range from 0.82 to 0.95, and their RMSE values are between 0.29 and 0.43. The plausible explanation is that they are originally devoted to such session durations (i.e., 60 s–300 s for the *P.1203* model and 60 s–360 s for the *CQM* and *biQPS* models). For short sessions of 13 and 28 s (i.e., in *W-SQoE-III*, *W-SQoE-IV_fH264*, *W-SQoE-IV_pH264*, and *W-SQoE-IV_uH264*), the *P.1203* model generally performs quite well (i.e., PCC $\geq$ 0.76, SROCC $\geq$ 0.79, and RMSE $\leq$ 0.48). However, for shorter sessions of 8 and 10 s (i.e., in the *W-SQoE-I* and *W-SQoE-II* databases), its performance is drastically reduced (i.e., PCC $\leq$ 0.40, SROCC $\leq$ 0.53, and

RMSE $\geq$ 0.65). In a similar behavior, the performance of the *biQPS* model is acceptable for 28-second long sessions in *W-SQoE-IV_fH264*, *W-SQoE-IV_pH264*, and *W-SQoE-IV_uH264* (i.e., PCC $\geq$ 0.64, SROCC $\geq$ 0.69, and RMSE $\leq$ 0.63). However, its performance is unsatisfactory for shorter sessions (i.e., PCC $\leq$ 0.45, SROCC $\leq$ 0.45, and RMSE $\geq$ 0.64). Meanwhile, the performance of the *CQM* model is acceptable for all the databases including short sessions. However, these results are still not very high. Specifically, its PCC, SROCC, and RMSE values range respectively in [0.62, 0.80], [0.65, 0.84], and [0.73, 0.43]. This result implies that the *P.1203*, *CQM*, and *biQPS* models should be employed for only medium and long sessions with the lengths from 60 to 360 s.



(**a**) (**b**)

(**c**)

Figure 7. Performance of *Liu's*, *ATLAS*, *P.1203*, *CQM*, and *biQPS* models in the second group over the test databases. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

4.4.3. Third Model Group

Figure 8 shows the performance of the QoE models in the third group. Although *Guo's* and *Vriendt's* models are very simple, considering only the impact of quality variations, their performances in both the *ori* and *mod* cases are generally stable and acceptable for all the databases including those containing sessions with stalling events (i.e., PCC $\geq$ 0.64, SROCC $\geq$ 0.55, and RMSE $\leq$ 0.72). They even provide quite high performances for many databases such as the *W-SQoE-I*, *W-SQoE-II*, *TR04f*, *TR06f*, and *TR06p* databases (i.e., PCC $\geq$ 0.81, SROCC $\geq$ 0.76, and RMSE $\leq$ 0.56).

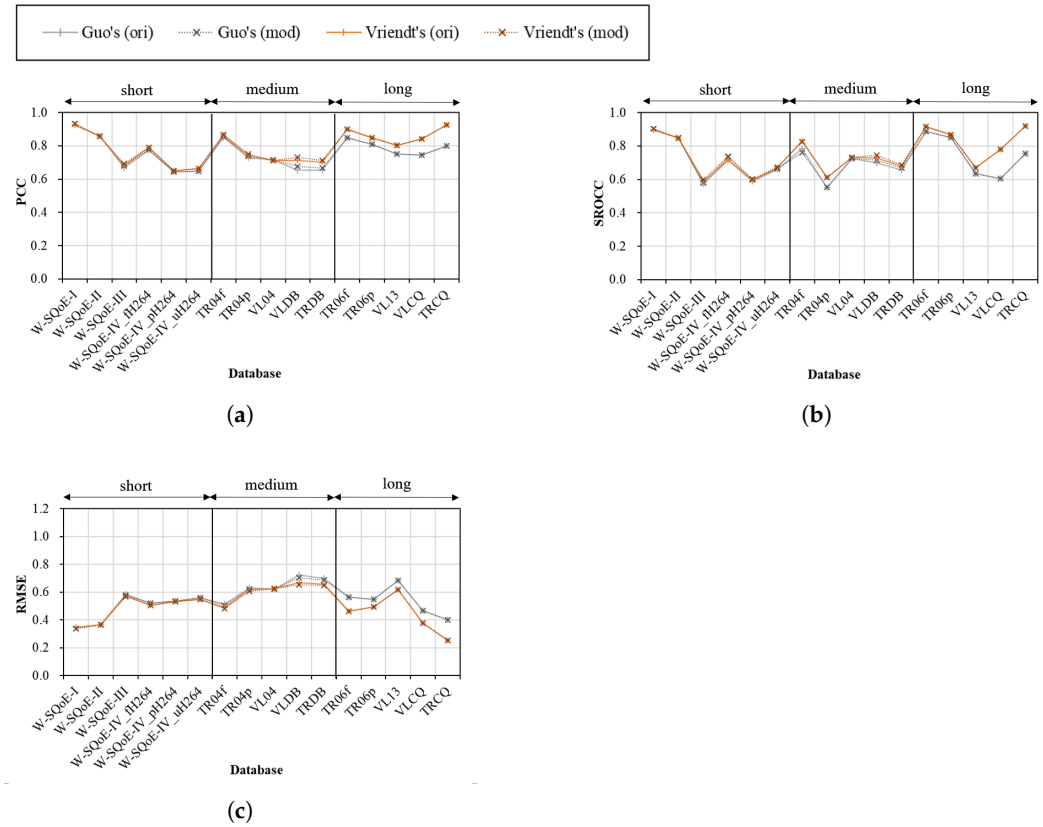


Figure 8. Performance of *Guo's* and *Vriendt's* models in the third group over the test databases. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

Although *Liu's* and *ATLAS* models additionally take into account the impacts of stalling events, their performances are not significantly higher and even, in some cases, lower than the simple models of *Guo's* and *Vriendt's*. This can be explained by the fact that stalling events commonly appear after segment quality decreases. Therefore, to a certain extent, modeling the impact of quality variations can somewhat reflect the impact of stalling events. In addition, it is suggested that the impact of quality variations is a key component in QoE models. In addition, it is once again confirmed that complex models that contain more inputs and take into account more influence factors do not always have better performances.

Within the same case of *ori* or *mod*, it can be seen that difference in performance of these two models depends on session durations. In particular, the difference is small for short and medium sessions. In such cases, the maximum difference is 0.06 for PCC, 0.07 for SROCC, and 0.05 for RMSE. Meanwhile, in case of long sessions, the longer the duration is, the bigger the difference becomes. For the *TRCQ* database, the difference is up to 0.13 for PCC, 0.16 for SROCC, and 0.15 for RMSE. In addition, the *Vriendt's* model tends to perform better than the *Guo's* model. This result implies that, to represent the impact of quality variations, the statistics used in the *Vriendt's* model (i.e., average and stdev of segment quality values, number of quality switches) are more effective than the ones employed in the *Guo's* model (i.e., median and minimum segment quality values), especially for long sessions.

From Figure 8, it can also be seen that the addition of the impact of initial delay to *Guo's* and *Vriendt's* models does not bring significant improvements as the difference between the two cases *ori* and *mod* is trivial for all the databases. In particular, the maximum gains of the *mod* case in terms of PCC, SROCC, and RMSE are respectively 0.02, 0.02, and 0.02 for both *Guo's* and *Vriendt's* models. A possible reason is that the initial delay in these databases is

commonly short (e.g.,1 s, 2 s, or 5 s) and could be tolerant [3]. Therefore, for short initial delay, its impact is marginal.

4.4.4. Fourth Model Group

Figure 9 compares the performance of the QoE models in the fourth group. We can see that these models perform generally well across the databases. In particular, the average PCC, SROCC, and RMSE values are respectively 0.88, 0.88, and 0.37 for the *LSTM* model, 0.83, 0.84, and 0.43 for the *SQI* model, and 0.81, 0.84, and 0.46 for the *KSQI* model. In particular, the performance of the *LSTM* model is generally the highest and most stable. In particular, the PCC, SROCC, and RMSE range respectively in [0.76, 0.96], [0.77, 0.96], and [0.27, 0.48] for the *LSTM* model, in [0.66, 0.88], [0.69, 0.93], and [0.31, 0.59] for the *SQI* model, in [0.70, 0.90], [0.78, 0.89], and [0.31, 0.69] for the *KSQI* model.

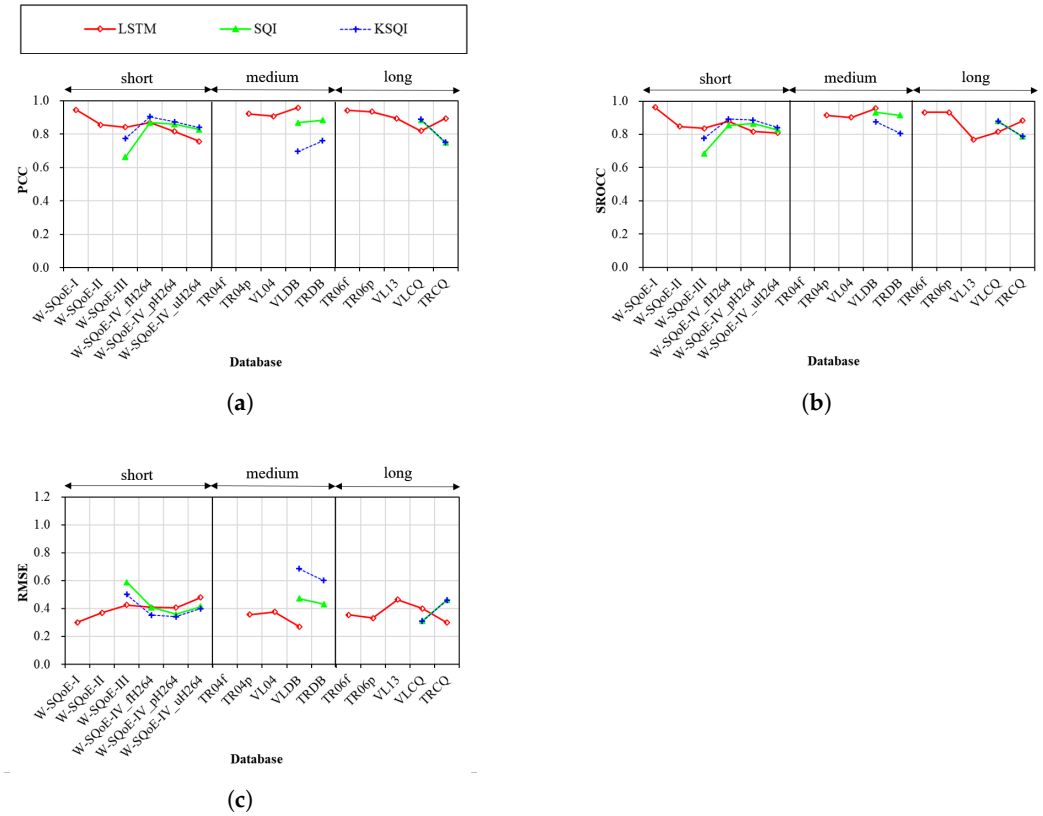


Figure 9. Performance of the *LSTM*, *SQI*, and *KSQI* models in the fourth group over the test databases. (**a**) PCC; (**b**) SROCC; (**c**) RMSE.

Except for the *W-SQoE-IV_uH264* database, the lowest PCC and SROCC values are 0.82 and 0.77 while the highest RMSE value is 0.46. For the *W-SQoE-IV_uH264* database using UHD TV, the obtained results are not very high but still acceptable (i.e., PCC = 0.76, SROCC = 0.81, and RMSE = 0.48). This result implies that, among the considered models, the *LSTM* model is the best one to predict the QoE of streaming sessions with various viewing devices and different session durations. In addition, it is suggested that the use of segment-basis parameters and an *LSTM* network is quite effective for reflecting the impacts of quality variations, stalling events, and memory-related effects. In addition, it is essential to consider temporal relations between impairment events in QoE models. However, there is still room for improvements of the *LSTM* model and the others as well, especially in the case of UHD TV.

For the *SQI* and *KSQI* models, their performances are acceptable, but not very high for most of the databases. In particular, the lowest performance in terms of PCC, SROCC, and RMSE is 0.66, 0.69, and 0.59 for the *SQI* model, and 0.70, 0.78, and 0.69 for the *KSQI*

model. This can be because these models are built based on some assumptions that are not completely valid for diverse session durations and for various patterns of quality variations and stalling events in the databases. For example, it is assumed that the influence of each impairment event is independent and additive. This means that temporal relations between events are not taken into account. In both the models, the impact of each stalling event only depends on its duration and the previous segment quality. While the *SQI* model does not consider the impact of quality switches, the *KSQI* model assumes that the impact of each quality switch is dependent on its switching amplitude and the current segment quality.

4.5. Concluding Remarks

In the above, our evaluation is divided into different cases, where models are evaluated in terms of codecs, viewing devices, and session durations. Based on different characteristics of models, a service provider may select an appropriate model. For example, for e-learning, a QoE model that supports PC screens and long sessions should be used, whereas a model that is good for smartphone screens and short sessions can be used for mobile streaming of short-form videos.

Based on the above results and discussions, the following important remarks regarding the considered QoE models can be made.

- In general, the performances of the models vary significantly across databases. Among them, the three models of *LSTM*, *SQI*, and *KSQI* are found to be the most stable ones.
- Regarding encoding codecs, all the considered models result in better performance on H.264-encoded streaming sessions than HEVC-encoded ones. Surprisingly, even the models taking into account HEVC characteristics such as *P.1203* and *KSQI* have the similar behavior.
- With respect to viewing devices, the use of MOS and VMAF as segment quality metrics is quite effective to help the model perform more consistently. It is suggested that the *LSTM*, *SQI*, and *KSQI* models can be employed for QoE prediction with different viewing devices.
- The models that are developed using short sessions such as the *Rehman's* model may result in low and drastically variable performances for medium and long sessions.
- The ability to effectively quantify the impacts of (1) quality variations and (2) stalling events significantly affects the performance of QoE models. Hence, these two factors should be equally considered in order to build an effective model. In addition, it is found that the impact of stalling events can be partially covered by the impact of quality variations as seen in the case of the *Vriendt's* model. In addition, it is essential to consider temporal relations between impairment events in QoE models.
- Only one single statistic such as the QP average is insufficient to fully represent quality variations in a streaming session. Combination of several statistics such as the average of segment quality values, the switch frequency, and especially the degrees of quality switches (i.e., switch amplitudes) is found to be indispensable to effectively quantify the impact of quality variations.
- Similarly, the total stalling duration alone, which is employed in most models, is not able to characterize the factor of stalling. Other statistics such as the number of stalling events and the maximum stalling duration should be additionally considered.
- Developing complex models (i.e., more inputs and complicated modeling approaches) does not always result in better performance as found in the case of *Yin's* and *ATLAS* models.
- Among the considered models, the *LSTM* model is the best one to predict the QoE of streaming sessions with different viewing devices and session durations. To evaluate the QoE of medium and long sessions (i.e., $\geq$1 min), the three models of *P.1203*, *CQM*, and *biQPS* are also comparable.
- There is still room for improvements of the existing models, especially in the cases of various viewing devices (e.g., ultra high definition TV) and advanced video codecs (e.g., HEVC).

5. Conclusions

In this paper, we have investigated the performances of thirteen existing QoE models over twelve open databases for QoE prediction in HTTP Adaptive Streaming. Based on the results of the evaluations, various findings were provided with important insights into the behavior/performance of the considered QoE models. In particular, it was found that the *LSTM* model is most efficient, followed by the *SQI* and *KSQI* models. Interestingly, simple models such as *Guo's* and *Vriendt's* are also found to be stable and acceptable for most databases. For the three models of *P.1203*, *CQM*, and *biQPS*, they are quite effective for long sessions. It is expected that the findings presented in this paper are useful for researchers and service providers to assess the QoE of streaming services and evaluate delivery solutions in HAS. However, there are some open issues to be tackled in the future. First, the support for the popular HEVC coding format should be very much improved. Second, investigations with more databases of various viewing devices and session durations will be conducted to better understand and enhance the existing models. The impact of quality scores (e.g., different MOS scales) on database developments and QoE model performances should also be studied in more detail. In addition, emerging content types such as 360-degree videos and volumetric videos will be a new and hot direction to be considered.

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