Perceived Video Quality Evaluation based on Interactive/Repulsive relation between the QoE IFs

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***Abstract*—The user satisfaction measurement has gained high attention from Network Operators (NOs) and Service Providers (SPs) because their businesses are highly dependent on the user's satisfaction. Generally, the traditional strategies to measure the user's perception are based on Quality of Service (QoS), which is not sufficient to reflect the real user's perceived quality. Therefore, NOs and SPs start to develop new strategies based on the Quality of Experience (QoE) metric to analyze the relationship between the user's satisfaction and influence factors (QoE IFs). In this paper, a new method to build a predictive model to estimate user's satisfaction in terms of Mean Opinion Score (MOS) is proposed. The proposed method uses the dataset collected using the controlled testbed based on the YouTube video service. In the proposed model, the correlation matrix is used to develop a new heuristic method that used back-jumping technique to select the most beneficial factors to predict the optimal user's satisfaction.**

Keywords : ***Quality of Experience (QoE), Pearson correlation, Crowdsourcing, Mean Opinion Score (MOS), YouTube video.***

I. Introduction

In the 21^{st} century, the use of multimedia services has increasingly spread in many countries around the world according to the annual CISCO reports[8]. In fact, using only the QoS mechanisms to evaluate the satisfaction of users (using multimedia services) is beneficial but not sufficient. That's why, to analyze the impact of the network performances on the user's satisfaction, NOs and SPs start to develop new strategies based on the Quality of Experience (QoE) metric to analyze the relationship between the user's satisfaction and influence factors commonly called : QoE Inference Factors (QoE IFs).

We can measure the user's satisfaction through two methods : First, by asking the user directly about his experience. Secondly, by building models to predict it. In this paper, we consider the second method and propose a new method to estimate the user's QoE using YouTube. Our proposal is a generic QoE predictive model that uses several stages to predict the QoE. Initially, experiments using an experimental platform presented in [3] is performed in order to build a dataset that contains the user's MOS under certain conditions (QoE IFs). Secondly, the Pearson $'r'$ correlation matrix is built for the dataset collected. This matrix is used to develop a new heuristic based on the interactive/repulsive relation between QoE IFs themselves to avoid the problem of interaction between factors explain in [5], [2]. In addition, our heuristic used back-jumping algorithm to select the large number of QoE IFs and the most beneficial factors to predict the optimal user's satisfaction.

The rest of this paper is structured as follows : In section II, we present the technical aspects of our proposed testbed. The Pearson ('r') correlation is explained in section III. In section IV, we present our proposed video QoE prediction model. In the next section V, we detail the prediction model process using our proposed heuristic. In section VI, we present the evaluation and we finish with a conclusion and some future works in the last section.

II. Technical aspects

In this section, we detail our choices for building the dataset emphasizing the positive aspects that are specific to mobile environments.

A. Why video ?

We choose to focus our work on video services. According to the annual CISCO reports[8], the video traffic will represent

	2014	2015	2016	2017	2018	2019	CAGR 2014–2019
By Application Category (TB per Month)							
Web/Data/VoIP	918,204	1,379,822	2,003,961	2,791,530	3,665,435	4,684,122	39%
Video	1,377,497	2,399,765	4,104,719	6,840,211	10,950,770	17,454,028	66%
Audio Streaming	193,756	323,915	521,071	801,106	1,157,536	1,623,894	53%
File Sharing	35,574	74,694	141,316	245,650	391,052	593,533	76%

Fig. 1. Global data traffic between 2014-2019 in the word.

nearly 80% of Internet traffic in France by 2018. Note that, until 2019, the video will remain the most dominant on the overall traffic of the Internet. Figure 1 shows the Global data traffic between 2014-2019 in the word.

B. Why Youtube ?

YouTube is a video-sharing website. This service uses progressive download technique, which enables the playback of the video before the content downloaded is completely finished[11]. Our choice of this service has been justified by the size of its users (more than 1 billion users) and the huge number of views every day (people watch hundreds of millions of hours on YouTube and generate billions of views every day). According to Citrix Mobile Analytics Report (September 2014)[9], figure 2 shows the comparison between YouTube and NetFix for relative demand in each one.

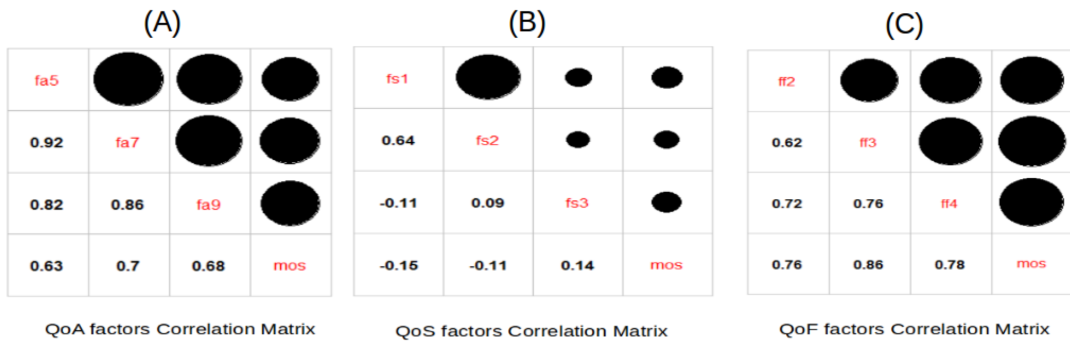

Fig. 2. Correlation matrix of the most correlated factor in QoA, QoS and QoF categories.

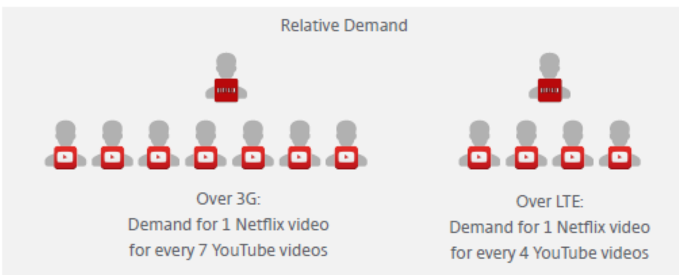

Fig. 3. Comparison between YouTube and NetFix of the relative demand.

C. *Why crowdsourcing ?*

Crowdsourcing is a model that assigns tasks traditionally undertaken by employees or contractors to an undefined crowd. In our case, it was presented by an unspecified Internet crowd rather than a specific group of people[14]. The goals of using a crowdsourcing approach is to quickly build a large dataset and to obtain a real quality measurement given by users in different contexts (laboratory, university...etc.).

III. Pearson correlation

To identify the relationship between the QoE IFs and the user's satisfaction on YouTube QoE, the intensity of the connection which may exist between these factors and the user's MOS (Mean Opinion Score) is studied. This connection is called : 'correlation'. It can be represented by different ways including the Pearson $'r'$ correlation defined by :

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (1)$$

where : $x \in$ first set of data , $y_i \in$ second set of data. And it presents how well sets of data are related [6].

In our case, this correlation is used to understand the impact of QoE IFs on the user's MOS. To attempt this end, the $rcorr$ method in $Hmisc$ Package R[10] is used to compute a matrix of Pearson's r correlation coefficients for all possible pairs (QoE IFs and MOS). Finally, based on this matrix, we will (i) study the interactive/repulsive relation between QoE IFs and user's MOS and (ii) we will use it to optimize the prediction model build.

A. *Pearson correlation and prediction performance*

This section describes how to use the Pearson's r correlation to improve our user's QoE prediction performance. In other words, it shows if the level of correlation using Pearson correlation (r) is significant.

To answer this question, our platform [3] is used to build the collected dataset. In this dataset, QoE IFs are categorized in 5 categories (application, network, device, user feedback and MOS) as explained in the last work [2]. In fact, the application (QoA), network (QoS) and user's feedback (QoF) are used in this experimentation.

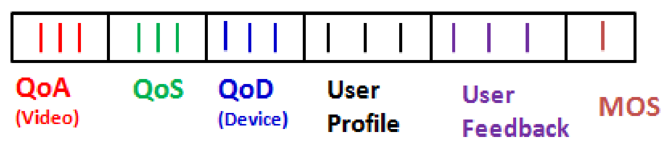

Fig. 4. QoE IFs categories.

Then, to answer the question about the signification of correlation level using Pearson correlation (r), we will proceed on two steps. In each step, a different number of categories is considered. Finally, we note that ANFIS [16] and SVM [12] estimation methods were used in this experience.

A/ Step 1

The first evaluation concerns the QoA and QoS categories considering 3 QoE IFs for each category (Figure 5 : (A,B)).

For explanation, these scenarios are taken because : (i) The scenarios have the same number of factors (3 factors), (ii) the factors were chosen because they are highly correlated with the user's MOS in each scenario according the Pearson r correlation. (iii) Each scenario is the best compared to the others scenarios (in the same category and with the same factors number)

Demonstration 1

Let :

$$\begin{cases} t_1 &= scenario\ 1 = \{a_5, a_7, a_9\} \\ t_2 &= scenario\ 2 = \{s_1, s_2, s_3\} \end{cases} \quad (2)$$

According the Figure 5, we have :

$$\begin{cases} |Mean\ r(t_1)| = (|r(a_5)| + |r(a_7)| + |r(a_9)|)/3 = 0.65 \\ |Mean\ r(t_2)| = (|r(s_1)| + |r(s_2)| + |r(s_3)|)/3 = 0.12 \end{cases} \quad (3)$$

Testing these two scenrios to predict the user's MOS, we have the results below :

$$\begin{cases} |Mean\ r(t_1)| = 0.65 \\ |Mean\ r(t_2)| = 0.12 \end{cases} \Longrightarrow \begin{cases} RMSE\ (t_1) = 0.91 \\ RMSE\ (t_2) = 1.40 \end{cases} \quad (4)$$

Result 1 : Using a high value of $|r|$, a better performance prediction will be achieved (The Pearson correlation (r) is significant) .

B/ Step 2

To confirm the first evaluation's result, a third category which is : user's feedback ((Figure 5 : (C))) is also considered .

For explanation, we add this scenario because it has the same number of factors (3 factors) and it is the best compared to the other scenarios in the QoF category.

Demonstration 2

Let :

$$\{ t_3 \ = \ scenario\ 3 = \{f_2, f_3, f_4\} \quad (5)$$

Then, according to the Figure $4(C)$, the result is :

$$\{ |Mean\ r(t_3)| = (|r(f_2)| + |r(f_3)| + |r(f_4)|)/3 = 0.82 \quad (6)$$

Finally, to confirm the result 1, the RMSE for each scenario is calculated and compared to the other scenarios. Equation 7 shwos the results :

$$\begin{cases} |Mean\ r(t_1)| = 0.65 \\ |Mean\ r(t_2)| = 0.12 \\ |Mean\ r(t_3)| = 0.82 \end{cases} \Longrightarrow \begin{cases} RMSE\ (t_1) = 0.91 \\ RMSE\ (t_2) = 1.40 \\ RMSE\ (t_3) = 0.69 \end{cases} \quad (7)$$

As we see, when we have a factor's $|r|$ higher, using this factor in the correlation model gives us better performance prediction.

IV. Proposed Video QoE prediction Model

There are many works in the literature that highlight the importance of the user's perception (QoE) [13], [14], [7], and its significance for NOs and SPs. These works try to help NOs and SPs to analyze their networks performance in the perspective of user's satisfaction for increasing their businesses. In the previous sections, the QoE concept is explained with the considered technical choices that used in our experimental platform.

Our proposed predictive model estimates the user's satisfaction in terms of MOS using YouTube service. Initially, a testbed setup based on experimental platform presented in [3] is performed. A dataset containing 600 samples (the real user's MOS and QoE IFs) are collected. To identify the relationship between these factors, the Pearson $'r'$ correlation is used. The matrix of Person $'r'$ correlation is used as an input for our proposed heuristic method which is based on the interactive/repulsive relation between QoE IFs. The objective of our proposed heuristic approach is to avoid the problem of interaction between the factors explained in [5], [2]. In addition, our proposed prediction heuristic method used back-jumping algorithm to select the most beneficial factors to optimize the user's satisfaction. Furthermore, a Broker is implemented to compare a set of estimation methods (e.g : Support Vector Machine, Random Forest, ...etc.) in order to get the best one for the given dataset and the considered context.

In summary, we have :

A) Input : With our $CLLF$ platform[3] a subjective dataset was built.

QoE IF	S	Description
Video id	$a1$	Integer between 1 and 8 presenting the video type (news, sports, ...etc.).
Movement	$a2$	Integer between 1 and 3 presenting the mouvement level.
Resolution	$a3$	Codec used ($144p$, $240p$,..., $1080p$).
Vlc_caching	$a4$	Vlc caching value expressed in ms.
Video size	$a5$	Total read packets.
Mean_bitrate	$a6$	Bits number conveyed per second.
Frame rate	$a7$	Frames number displayed per second.
Frame lost	$a8$	Frames number that are lost per second.
Audio rate	$a9$	Audio bytes number received per second.
Audio lost	$a10$	Number of audio bytes that are lost.
Buffer_time	$a11$	First frame time of display.
MOS	mos	Mean Opinion Score (between 1 and 5).

TABLE I
CLLF QoE IFs description.

Table 1 presents a description from a part of the collected factors (QoA factors).

B) Tool (Broker) : In order to select the best prediction model with our Broker according to our gathered dataset, the R[1] programming language and software environment for statistical computing (R software) is used. Using this software, a set of machine learning estimation methods are implemented (Linear regression (LM), Random Neural Networks (RNN)[4], Random Forest (RF)[4], Support Vector Machines (SVM) [16] and Adaptive Neuro Fuzzy Inference System (ANFIS)[12]). So, different configurations to minimize the error rate (RMSE) are defined (after intern tests) for each method. For example, in the case of RNN method, we have :

$hidden$: Number of (vertices) hidden neurons in each layer.
$threshold$: the partial derivatives value of the error function as stopping criteria.

TABLE II
Configurations selected-.

Finally, with this Broker, the training and validation phase are explained as follows :

- In each fold, $2/3$ is used for learning (training) and $1/3$ for evaluation. In addition, a cross validation method with

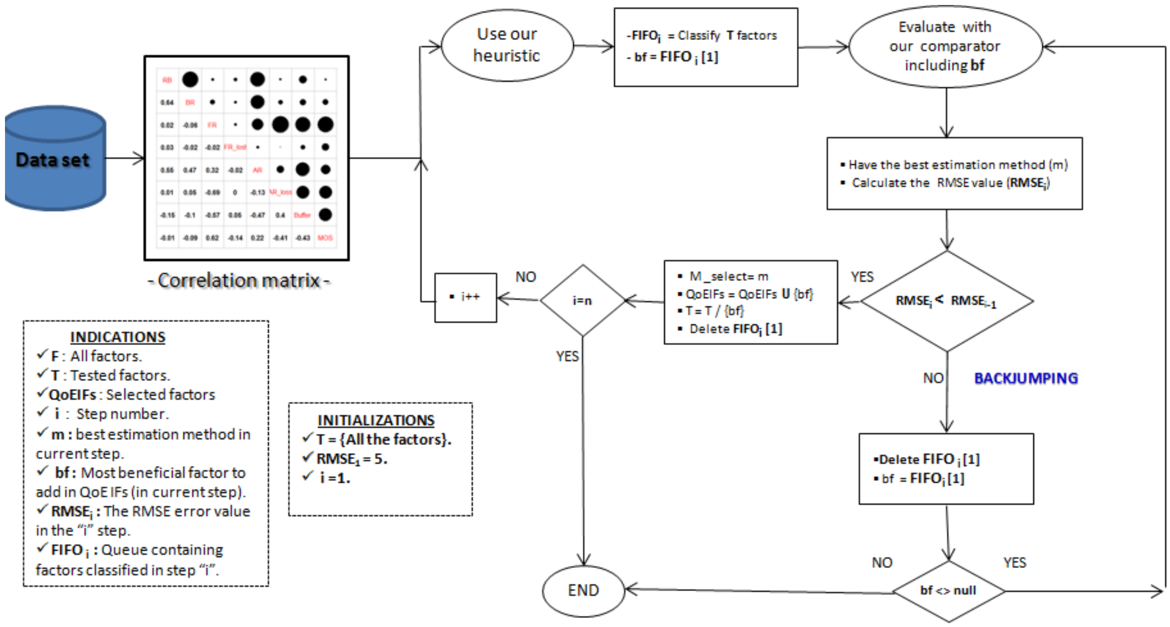

Fig. 5. Correlation Model built process.

$k = 10$ fold is used.

- The best estimation (configuration) method is generated for the given input (QoE IFs) based on the $RMSE$ calculated.

C) Heuristic (QoE IFs interactive/repulsive relation) : The proposed heuristic approach avoids the interaction of QoE IFs (presented in [5], [2]) by taking into account only those QoE IFs that have the more influence on user's QoE. It is based on the interactive/repulsive relation between the QoE IFs that we find in the Pearson "r" correlation matrix. In other words, heuristic approach is proposed for calculating the added value including or not a factor in the QoE IFs input set. In the proposed heuristic, an utility function is used to calculate this added value. This utility function is defined in equation (8) and given in (9) :

$$f\_benefit{:}[-1{,}1]\times[-1{,}1]\longrightarrow[0{,}2] \tag{8}$$

where $f\_benefit$ represented factor's added value. Thereby, the function formula is :

$$f\_benefit{=}(1{-}AV(r(f\_candi{,}f\_used))){+}r(AV(f\_candi){,}MOS) \tag{9}$$

where f_candi is an input, **r(x,y)** presents the Pearson $'r'$ correlation value between (**x**,**y**) and **AV(x)** presents the absolute value of **x**.

Justification

- Use 1, according to the AV value of the Pearson $"r"$ correlation($AV(r)$ is in $[0, 1]$).
- Take $(1{-}AV(r(f\_candi{,}f\_used)))$ to presents repulsion between QoE IFs.
- Use $r(AV(f\_candi){,}MOS)$ to presents interaction between the factor and MOS.

D) Back-jumping technique : It is an algorithm proposed by Gaschnig in 1979. It can go back on decisions (several levels) to avoid deadlock in the case of no improvement in the result. According [15], it allows to step back on sub trees resolved without having to find all distinct solutions normally required to validate the universal variables.

In our case, this algorithm aims to select the large number of factors that will be as input for the Broker. In fact, this algorithm is used to verify the untested factors that can improve the prediction performance to build an optimized predictive model.

E) Output : The final estimation model that predicts the user's QoE for any input in real time.

V. Prediction Model process

The main goal of the prediction process is to obtain a large number of factors (QoE IFs) that (i) participate in the prediction model and (ii) optimize the user's MOS in real time. In fact, after collecting the dataset (section 3.1) and following the correlation matrix build (section 3.2), the process is repeated in order to get the most beneficial QoE IFs. The prediction process can summary as follows :

- At the beginning of each step, performance of the prediction model by adding the most correlated factor is verified, i.e : verifying if the current $RMSE_i$ is lower than the RMSE value in the previous step($RMSE_{i-1}$).
- At each step, if we don't improve the prediction ($RMSE_i > RMSE_{i-1}$), our proposed approach tests (using the back-jumping technique if necessary) all the remaining factors ($T = C(F/(T \cup QoEIFs))$) to observe if one of them will contribute improving the prediction performance.

- The prediction process will stop when (i) all the QoE IFs (F) are tested , or (ii) none of the untested factors (T in part 2) improve the prediction ($RMSE_i$) compared to previous step $RMSE_{i-1}$.

A. Prediction Model process parts

In this section, the prediction model process is explained in two parts : Initialization and Build process. To conduct well the explanation, the following notations are introduced.

- f_used : Considered factor in before step.| **f_used** $\in$ **QoEIFs**.

- f_candi : Candidat factor.| **f_candi** $\in$ **F**.

Part 1 : Initialization

First, the following initializations are identified :

$-QoEIFs{=}\{a_i\}$ //factor having the highest $'r'$ value with MOS

$-f\_used{=}a_i$

$-T{=}\{a_k\text{: } all\ the\ factors\ considered,\ a_k{\neq}a_i\}$ // Factors to test

$-RMSEi{=}5$ // In the worst case $RMSE = 5$ ($MOS \in [1, 5]$)

$-i{=}2$

Part 2 : Build process

// (1) Calculate the added value for each $factor$.
while $(f\_candi{\in}T)$ **do**
- $f\_benefit{=}(1{-}r(f\_candi,f\_used)){+}r(f\_candi,MOS)$;
- $FIFO\_i{=}Classify(f\_candi)$;

end
// (2) Selected the tested factor (bf).
- $bf{=}FIFO_i[1]$

// (3) Process prediction : Broker call
- $RMSE_i{=}Min(RMSE(QoEIFs{\cup}\{bf\}))$

// (04) Evaluation process with our comparator.
if $(RMSE_i{<}RMSE_{i-1})$ **then**
- $M\_select{=}$ "Best estimation method for this step"
- Add f to $QoEIFs$;
- $T\ =\ T\ /\ \{bf\}$;
- Delete $FIFO_i[1]$;

if $(i{=}n)$ **then**
// Test all the factors that we had
- The prediction process ends with : M_select prediction method and **QoEIFs** as input.

else
// The preiction was not improved in this step
- Go to the next step ($i{+}{+}$) ;

end
else
// Don't improve prediction with our heuristic (do back-jumping)
- Delete $FIFO_i[1]$;
- $bf{=}FIFO_i[1]$

ANFIS [16] and SVM [12]
if $(bf{<>}null)$ **then**
// Test the next element in the Queue
- Go to (04)

else
// Queue empty
- The prediction process ends with : M_select prediction method and **QoEIFs** as input.

end
end

VI. Evaluation

The proposed heuristic method is evaluated using the collected dataset based on an experimental platform [3]. In our experience, 11 variables (all QoE IFs in QoA) are used as inputs for testing. Using the R software [1], the correlation matrix is built for each category in (Figure 6).

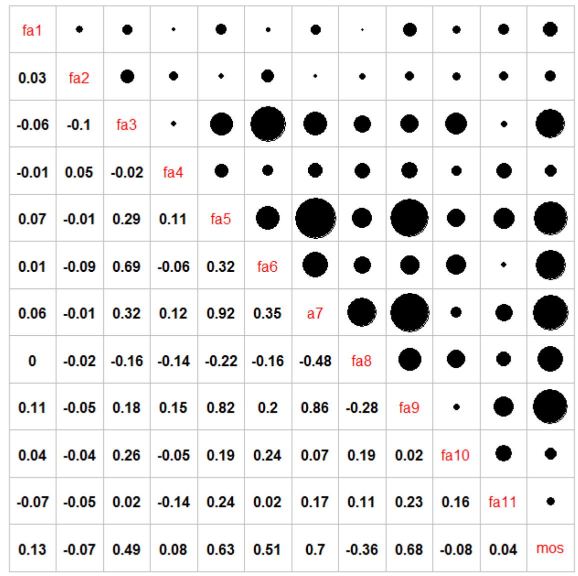

Fig. 6. Correlation matrix of QoA category.

Step 1 **:** To test the proposed prediction model (with the back-jumping technique), the correlation matrix (Figure 6) is used to initialize the variable used as follows :

$-f\_used{=}f_{a7}$ // The largest correlation value.

$-QoEIFs{=}\{f_{a7}\}$

$-T{=}\{f_{a1},f_{a2},f_{a3},f_{a4},f_{a5},f_{a6},f_{a8},f_{a9},f_{a10},f_{a11}\}$

Step 2 **:** Then, the prediction process begins with running the second part of the prediction model process presented in section 4.1 and explain in Figure 5. In fact, $FIFO_i$ is ordered as follow : $FIFO_2{=}\{f_{a3},f_{a6},f_{a1},...etc.\}$. Thus, $bf{=}f_{a3}$.

At the end of the comparator running, the result is $RMSE_2{=}0.7248$, which is better than the initial $RMSE_1{=}5$.

S	QoE IFs	Heuristic	RMSE
2	f_{a7} f_{a3}	$(1 - 0.32) + 0.49 = 1.17$	**0.7248**

Step 3 **:** With the same process as the second step, the second part of the prediction model process presented in section 4.1 is runned to have : $FIFO_3{=}\{f_{a9},f_{a5},f_{a8},...etc.\}$. Thus, $bf{=}f_{a9}$.

Using the compartor, we have $RMSE_3{=}0.7234$, which is better than the last one ($RMSE_2{=}0.7248$).

S	QoE IFs	Heuristic	RMSE
3	f_{a7} f_{a3} f_{a9}	$(1 - 0.18) + 0.68 = 1.53$	**0.7234**

Step 4 **:** With the same process (in the previous step), the result in this step is : $FIFO_4 = \{f_{a6}, f_{a8}, f_{a10}, ...etc.\}$. Thus, $bf = f_{a6}$.
Using the comparator, the result is $RMSE_4 = 0.7290$, which is worst than the last one ($RMSE_3 = 0.7234$).
In this case, another QoE IF is explored using the back-jumping technique. In fact, the head of the queue is deleted because it does not improve the prediction. $FIFO_4 = \{f_{a8}, f_{a10}, f_{a5}, ...etc.\}$. Next, another fb is defined as follow : $bf = f_{a6}$. Furthermore, the comparator is used to calculate $RMSE_4 = 0.7116$. As showing, the $RMSE_4$ is better than the last one ($RMSE_3 = 0.7248$) That's why, it will be choose to be in the QoE IFs selected.

S	QoE IFs	Heuristic	RMSE
4	f_{a7} f_{a3} f_{a9} f_{a6}	$(1-0.2)+0.51 = 1.31$	0.7290
	f_{a7} f_{a3} f_{a9} f_{a8}	$(1-0.28)+0.36 = 1.08$	0.7116

So : $QoEIFs = \{f_{a7}, f_{a3}, f_{a9}, f_{a8}\}$

Step 5 **:** With the same proceeding as the last step (4), the result in this step is : $FIFO_5 = \{f_{a5}, f_{a6}, f_{a1}, ...etc.\}$, and the table below :

S	QoE IFs	Heuristic	RMSE
5	f_{a7} f_{a3} f_{a9} f_{a8} f_{a5}	$(1-0.22)+0.63 = 1.41$	**0.7198**
	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6}	$(1-0.16)+0.51 = 1.35$	0.6964

So : $QoEIFs = \{f_{a7}, f_{a3}, f_{a9}, f_{a8}, f_{a6}\}$

Step 6 **:** At the step 6, the result is :
$FIFO_6 = \{f_{a5}, f_{a1}, f_{a11}, f_{a4}, f_{a2}, f_{a10}\}$.
Using the same proceeding as the two last steps (4 and 5), the below result are shown (after different back-jumping) :

S	QoE IFs	Heuristic	RMSE
6	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6} f_{a5}	1.31	0.7052
	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6} f_{a1}	1.12	0.7006
	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6} f_{a11}	1.06	0.6999
	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6} f_{a4}	1.02	0.7089
	f_{a7} f_{a3} f_{a9} f_{a8} f_{a6} f_{a10}	0.98	0.7093

A. Execution

As shown in different steps, at the beginning just the first part of our model proposal (without back-jumping) is used with our proposal heuristic (to select the most benefit candidate factor).

Starting from the 4^{th} step, back-jumping technique is used to explore other QoE IFs. This exploration is justified by the worst result given by the head of the $FIFO_4$. That's why, the second factor in the queue will be tested to have a better prediction.

Then, in the 4^{th} and 5^{th} step respectively, the estimation is improved with adding f_{a8} instead of f_{a6} and f_{a8} instead of f_{a6} respectively. Into have the follow QoE IFs containing : $QoEIFs = \{f_{a7}, f_{a3}, f_{a9}, f_{a8}, f_{a6}\}$.
But, in the 6^{th} step, no factor selected in the $FIFO_6$ queue improves the prediction performance. That's why, the final

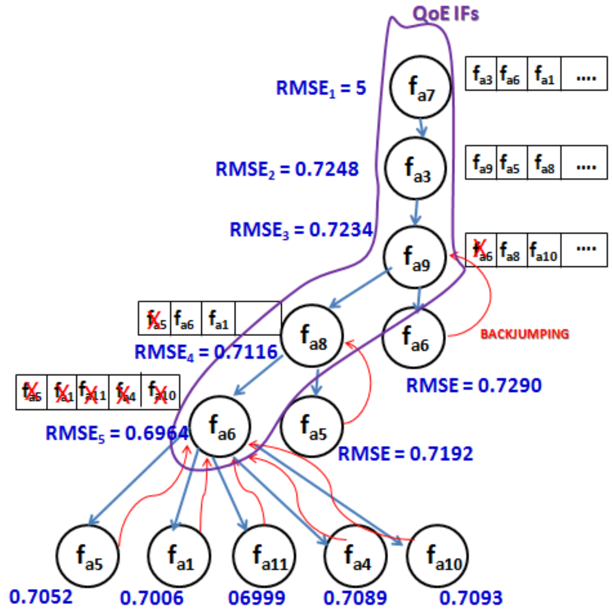

Fig. 8. Execution.

estimation model that predicts the user's QoE for our database is summarized as follow :

- **Input** : $QoEIFs = f_{a7}, f_{a3}, f_{a9}, f_{a8}, f_{a6}$
- **Method** : The best estimation method (configuration) which gives $RMSE_5 = 0.6925$ is : the Random Forest with $n = 20$.

B. Results

To compare the performances of estimation methods (LM, RNN, RF, SVM, ANFIS) in terms of Root Mean Squared Error (RMSE), we used a 600 samples database and a cross validation method with $k = 10$ folds. The mean RMSE and the standard deviation (sd) is calculated directly by our Broker in order to provide the best prediction model with less different values between real and predicted values.

Each estimation method is evaluated using three configurations which are based on a given number of QoE IFs. In the first configuration (called all in $fig7$), all QoE IFs are considered and their impact on the user perceived quality is analyzed. In the second configuration (called cor in $fig7$), the impact of the 5 most correlated (Pearson r correlation) QoE IFs with the users MOS are evaluated. The use of 5 factors was justified under the number of QoE IFs that we have with our heuristic. Finally, in the last configuration (called rand in $fig7$), 5 factors are selected randomly.

As shown in figure 7, the worst result is given by LM(rand) with RMSE = 0.98 ($sd = 0.09$) and the best one except our heuristic is given by RF(all) with RMSE = 0.72 (sd = 0.045). Our proposed heuristic gives the best prediction performance (RMSE = 0.6925 with $sd = 0.04$) compared to all other tests (15 tests), where the best predictions RMSE (RF(all)) is

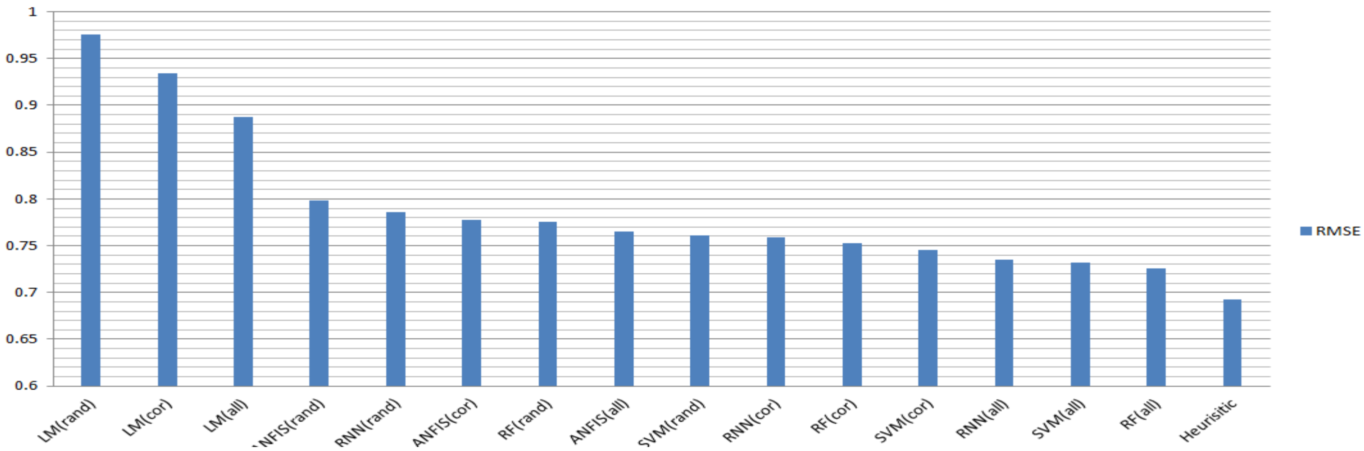

Fig. 7. RMSE error rate for the 3 defined scenarios with the selected estimation methods (LM, RNN, RF, SVM and ANFIS) .

improved by 7%, and the worst predictions RMSE (LM(rand)) is improved by 29%.

We can also notice that considering the Pearson r correlation helps improve the user estimation perception. This confirms what we have concluded in section 3.1: the estimation model can give better results by finely selecting the factors. For example, using the 5 most correlated factors in configuration 2 (the best method : RMSE(SVM)) improves by 5% the configuration 3, where the same number of factors are selected randomly to predict the users QoE. Our experience has shown that our heuristic approach, in addition to choosing 5 factors, has selected the best ones.

VII. Conclusion

In this paper, a generic prediction model is proposed to estimate the satisfaction of the YouTube user in terms of MOS. However, the proposed model can be easily extended to be used for others multimedia services. This model is developed based on collected dataset using our experimentation platform presented in [3]. In fact, the dataset contains the user's MOS under certain conditions (QoE IFs). In the proposed model, the correlation matrix is built to be used in the development of our proposal heuristic method based on a back-jumping algorithm (i) to select the most beneficial factors and (ii) to predict the optimal user's satisfaction. In the future, we shall improve our model by collecting a larger dataset of the real environment. In addition, we will establish our model in a real environment with more QoE IFs including the device, application and network ones.

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References

[1] R software, institute for statistics and mathematics of wu, (wirtschafts universität wien). http://www.r-project.org/.

[2] L. Amour, S. Souihi, S. Hoceini, and A. Mellouk. A hierarchical classification model of qoe influence factors. *13th International Conference on Wired and Wireless Internet Communications*, May 25-27, 2015.

[3] L. Amour, S. Souihi, S. Hoceini, and A. Mellouk. An open source platform for perceived video quality evaluation. *The* 18^{TH} *ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, November 2-6, 2015.

[4] O. O. O. B. T. Abe and T. Marwala. Hyperspectral image classification using random forests and neural networks. *Proceedings of the World Congress on Engineering and Computer Science 2012 Vol I, WCECS 2012, San Francisco, USA*, October 24-26, 2012.

[5] A. Balachandran, V. Sekar, A. Akella, S. Seshan, I. Stoica, and H. Zhang. Developing a predictive model of quality of experience for internet video. *SIGCOMM Comput. Commun. Rev.*, 43(4):339–350, August, 2013.

[6] J. Benesty, J. Chen, and Y. Huang. On the importance of the pearson correlation coefficient in noise reduction. *Audio, Speech, and Language Processing, IEEE Transactions on*, 16(4):757–765, May 2008.

[7] K.-T. Chen, C.-C. Wu, Y.-C. Chang, and C.-L. Lei. A crowdsourceable qoe evaluation framework for multimedia content. pages 491–500, 2009.

[8] CISCO. Cisco visual networking index: Global mobile data traffic forecast update, 2014-2019. pages 1–42, February 3, 2015.

[9] CITRIX. Citrix mobile analytics report september 2014, mobile subscriber data usage trends. September 3, 2014.

[10] H. F.E. and C. Dupont. Package 'hmisc'. available at:. http://cran.r-project.org/web/packages/Hmisc/Hmisc.pdf", April, 2015.

[11] G. Gómez, L. Hortiguela, Q. Pérez, J. Lorca, R. García, and M. C. A. Torres. Youtube qoe evaluation tool for android wireless terminals. *CoRR journal*, 1405-4709, 02 Jun, 2014.

[12] S. Gupta, R. Kambli, S. Wagh, and F. Kazi. Support-vector-machine-based on proactive cascade prediction in smart grid using probabilistic framework. *Industrial Electronics, IEEE Transactions on*, 62(4):2478–2486, April 2015.

[13] T. Hossfeld, M. Seufert, M. Hirth, T. Zinner, P. Tran-Gia, and R. Schatz. Quantification of youtube qoe via crowdsourcing. In *Multimedia (ISM), 2011 IEEE International Symposium on*, pages 494–499, December 2011.

[14] M. Mushtaq, B. Augustin, and A. Mellouk. Crowd-sourcing framework to assess qoe. In *Communications (ICC), 2014 IEEE International Conference on*, pages 1705–1710, June 2014.

[15] P. Prosser. Hybrid algorithms for the constraint satisfaction problem. *Computational Intelligence*, 9(3):268–299, 1993.

[16] L. S. Riza, C. Bergmeir, F. Herrera, and J. M. Benitez. Learning from data using the r package" frbs". *Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on*, pages 2149–2155, 2014.