QoE Prediction for Multimedia Services:
Comparing Fuzzy and Logic Network Approaches

Natalia Kushik, Department of Information Technologies, Tomsk State University, Tomsk, Russia and Department of Network Software, TELECOM SudParis, Evry, France

Jeevan Pokhrel, Department of Network Software, TELECOM SudParis, Evry, France and Montimage, Paris, France

Nina Yevtushenko, Department of Information Technologies, Tomsk State University, Tomsk, Russia

Ana Cavalli, Department of Network Software, TELECOM SudParis, Evry, France

Wissam Mallouli, Montimage, Paris, France

ABSTRACT

This paper is devoted to the problem of evaluating the quality of experience (QoE) for a given multimedia service based on the values of service parameters such as QoS indicators. This paper proposes to compare two self learning approaches for predicting the QoE index, namely the approach based on logic circuit learning and the approach based on fuzzy logic expert systems. Experimental results for comparing these two approaches with respect to the prediction ability and the performance are provided.

Keywords: *Fuzzy Logic Expert Systems, Logic Networks, Multimedia Services, Quality of Experience, Quality of Service*

1. INTRODUCTION

Nowadays, multimedia services are progressing very fast as multimedia information is usually transmitted using public or private networks. A multimedia traffic is considered to be any combination of audio, image, video or data traffic. One may notice that such multimedia traffic has become a principal traffic source in today Internet. The advancement of networking technologies as well as higher achievable bitrates has helped a lot in the growth and popularity of multimedia traffic. It is expected that video traffic will reach 66% of the global mobile traffic by the year 2015 with one million minutes of video content crossing the Internet every second (Cisco, 2011). On the other hand, multimedia traffic challenges the service providers and network operators, for instance, the former is

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required to have higher bandwidth or stringent QoS requirements (Kumar and et al., 2002). Moreover, it is essential for service providers and network operators to measure the quality of real-time multimedia applications, such as video streaming, mobile IPTV, and other kinds of audio and video applications (Serral-Gracià et al., 2010).

A service that is used to deliver a multimedia traffic to an end-user is considered to be a *multimedia service*, and the quality of such service plays a crucial role when an end-user chooses between two multimedia services. In other words, the service quality is an argument that allows attracting customers and thus, this parameter has to be estimated thoroughly. Usually, the *Quality of a (multimedia) Service (QoS)* is defined as a vector which components are values of given attributes (parameters), such as time delay, packet loss rate, etc. The QoS is a metrics that represents some objective service parameter values that can be, for example, effectively measured based on the traffic analysis (Khirman & Henriksen, 2002). The QoE metrics is more involved with services, since it measures the user satisfaction (Winckler et al., 2013; ITU-T Recommendation G.1080, 2008) and thus, the QoE becomes one of the challenging metrics to evaluate the quality. Moreover, when dealing with Clouds and/or Internet of Things, various multimedia/web service compositions are usually considered. Therefore, new methods and techniques for estimating quality of such compositions need to be provided.

The QoS parameters reflect the objective network and service level performance and they do not directly address the user satisfaction of the delivered service or application. However, it is well known that when the QoS parameters vary, the QoE is influenced as well. The relationship between QoS and QoE is hard to estimate, since this relationship is not linear. Moreover, the higher QoS level does not always yield the higher QoE value. Various QoS/QoE correlation algorithms can be found, for example, in (Rubino et al., 2006; Mushtaq et al., 2012; Wang et al., 2010). The relationship between the QoS and QoE metrics has a number of applications, including multimedia, web, etc., when assessing an end-user satisfaction with a given service (Wijnants et al., 2009; Mushtaq et al., 2012; Pokhrel et al., 2014).

An algorithm for the QoE evaluation has to be adapted to a human's brain in order to 'predict' what a user likes/dislikes. This is the reason why different self-adaptive models and algorithms are now used when evaluating/predicting the QoE of different services (Kushik et al., 2014; Pokhrel et al., 2014). The advantage of a self-adaptive model is that it can be learned or trained by a 'teacher' or by itself according to the feedback from people who use the service. As usual, an initial model/machine is derived based on some statistics that contain a number of user estimations of the service depending on measurable service parameters. Afterwards, the model can 'predict' a user satisfaction of the service for current values of service parameters. Usually the more statistics are gathered the better is the 'prediction'. Moreover, a model is self-adaptive, and thus, when new statistical data appear for which the model does not behave in an appropriate way, the model is adjusted to this new data. This process is called the model training.

Given a self-adaptive model, different service parameters might be considered. Usually QoS parameters are considered, as their values can be automatically measured. In this paper, we are focusing on predicting the user satisfaction with a multimedia service, i.e., on evaluating the QoE of the multimedia service when a number of objective multimedia parameter values have been already estimated. The parameters considered in this paper are the jitter and the packet loss of the video traffic. Considering self-adaptive models, in this paper, we focus on two approaches for predicting the QoE value: logic circuit based approach and fuzzy logic expert systems. The main objective of the paper is to compare these approaches w.r.t. the QoE prediction ability and the performance.

The comparison between two approaches that are used to estimate the QoE value for multimedia services has been performed based on the experimental evaluation. The end-user participants have been chosen in order to collect a dataset of 'real' QoE values of the videos that have been artificially deteriorated by increasing the jitter and the packet loss of the traffic. Furthermore, a distance between the 'real' QoE value and the value provided by each of self-adaptive algorithms has been evaluated.

Preliminary results of this paper have been partially published in (Kushik et al., 2014; Pokhrel et al., 2014; Pokhrel et al., 2013). Corresponding papers contain the theoretical descriptions of the proposed approaches for the QoE estimation, while in this paper, we make a step towards the comparison of these approaches. In other words, the main contributions of the paper are experimental results as well as metrics to compare the fuzzy logic expert system and the logic circuit approach for evaluating/predicting the QoE value.

The structure of the paper is as follows. Section 2 contains the preliminaries. This section introduces the basic concepts for both approaches presented in the paper. Section 3 provides a brief description of the use of logic circuits and fuzzy expert systems for estimating the service quality. Section 4 presents the experimental results and the discussion on comparing two approaches to estimate the QoE of multimedia services. Section 5 concludes the paper.

2. PRELIMINARIES

Nowadays, in computer sciences various logics are used for different purposes and in this paper, we discuss how the logic over Boolean vectors and corresponding relations over them (Boolean logic) can be used for evaluating/predicting the user satisfaction with a multimedia service. On the other hand, we also focus on the modification of the multi-valued logic, namely a fuzzy logic (Zadeh, 1965). Differently from the classical Boolean algebra, a fuzzy logic variable may have a truth value that ranges between 0 and 1. In this section, we provide basic definitions that are used along the paper, i.e., the definitions related to the Boolean and fuzzy formulae effectively represented by a logic circuit or by a corresponding fuzzy expert system.

2.1. Logic Circuits and Their Synthesis

A *logic network* (circuit) consists of logic gates. Each logic gate has input (-s) and a single output. Outputs of some gates are connected to inputs of the others. The inputs of some gates that are not connected to any other gate output are claimed to be primary inputs while the outputs of some gates are claimed as primary outputs. In this paper, we consider combinational circuits, i.e., feedback-free circuits which have no latches.

Each gate implements a Boolean function. Most common 2-input gates are AND/OR/XOR/NAND/NOR/XNOR that implement conjunction/disjunction/xor and their inversions. There are also 1-input gates such as NOT/BUFF that implement the inversion and the equality function, correspondingly.

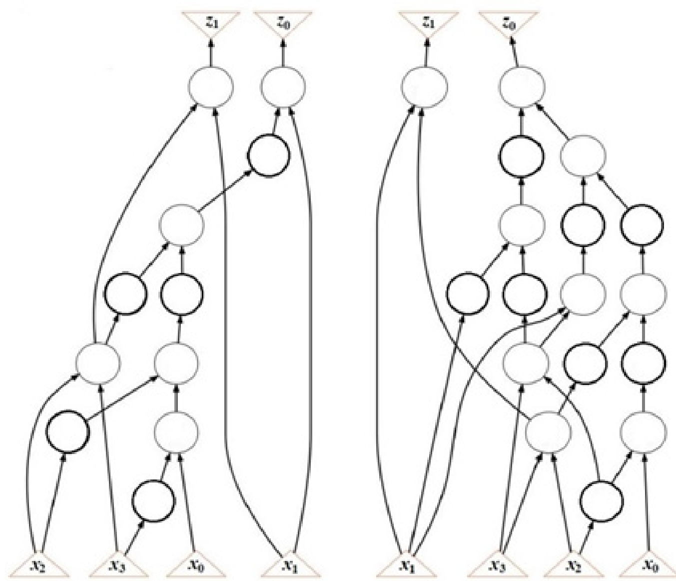
As an example, consider a combinational circuit in Figure 1a with a set $X = \{x_0, x_1, x_2, x_3\}$ of inputs, a set $Z = \{z_0, z_1\}$ of outputs, and 11 AND and NOT gates shown as nodes. Hereafter, we assume that NOT nodes are taken in bold; all other nodes correspond to AND-gates.

By definition, a logic circuit *implements* or *represents* a system of Boolean functions. A circuit accepts a Boolean vector as an input and produces the Boolean vector as an output according to the corresponding system of Boolean functions. Each logic circuit can be described by a Look-up-Table (LUT). An LUT contains a set of input/output pairs of a given circuit: if for the input **i** the circuit produces an output **o**, then the pair **i**/**o** is included into the LUT (see, for example, Table 1).

An LUT can be used as the specification when deriving a logic network that implements the given system of Boolean functions, and there exist a number of methods how to synthesize such a logic network.

If a given system of Boolean functions is completely specified then a 2-level network can be synthesized based on a corresponding Disjunctive Normal Form (DNF) or a Sum of Products (SoP) (McCluskey, 1965). If the system of Boolean functions is only partially specified, then other methods are used for

Figure 1. A) A Circuit S, B) A Circuit S'



logic synthesis (see, for example, Kuehlmann, 2003). In this case, each input pattern where the circuit behavior is not specified is usually treated as a 'Don't_Care' pattern, i.e., a circuit under design can produce any output to this input. Correspondingly, the circuit behavior is specified for such 'Don't_Care' patterns according to the designer's needs. It can be guarded by optimal criteria of a circuit under design, such as a number of logic gates, time needed to produce an output, etc. In this paper, we are interested in deriving a circuit that models the QoE evaluation of multimedia services, thus, one of optimal criteria could be the accuracy of the circuit prediction.

We derived the circuit *S* for the system of partially specified Boolean functions in Table 1 using the software tool ABC (Berkeley Logic Synthesis and Verification Group, ABC). For this purpose, we run the ABC tool against the LUT corresponded to Table 1. The set on input/output vectors was presented using the PLA format. The resulting circuit *S* with 11 gates is shown in Figure 1a.

2.2. Fuzzy Logic and Expert System

A *fuzzy logic* is represented as a set of mathematical principles for knowledge representation based on degrees of membership rather than on the membership of classical binary logic (Zadeh, 1965). Contradictory to two-valued Boolean logic (1 or 0), fuzzy logic is

Table 1. An example of an LUT

x_0	x_1	x_2	x_3	z_0	z_1
1	1	1	1	1	1
0	1	1	1	1	1
1	1	0	0	1	0

multi-valued, i.e. *fuzzy constants* belong to the interval between 0 and 1.

A *fuzzy set* can be represented as a set that contains fuzzy boundaries (Negnevitsky, 2002). Let X be the universe of discourse and its elements be denoted as x. In the fuzzy theory, the fuzzy set A of the universe X is specified by function $\mu_A(x)$ that is called a *membership function* of the set A. This membership function is defined as follows: $\mu_A(x)$: X -> [0,1], where $\mu_A(x) = 1$, if x is *totally* in A, $\mu_A(x) = 0$, if x is not in A, and $0 < \mu_A(x) < 1$, if x is *partially* in A.

For any element x of the universe X, the membership function $\mu_A(x)$ determines the degree of each x to belong to the set A. This degree is a value between 0 and 1, which represents a *membership value* or a so called *degree of membership* of the element x in set A.

A *fuzzy inference rule* can be defined as a conditional statement in the following form:

IF <antecedent> THEN <consequent>.

For example, IF x is in A THEN y is in B.

Usually, in the fuzzy inference rules the variables x and y are linguistic (for example, Height, weight etc.), while A and B are linguistic values determined by fuzzy sets (for example, tall, short, heavy etc.) on the universe of discourses X and Y, correspondingly.

Fuzzy set operators are used to manipulate with different fuzzy sets. Different operators like union, intersection, complement, etc. are used for the purpose. In this section, we will describe two fuzzy operators, namely *union* and *intersection*, as those are used throughout this paper.

The *fuzzy union operator* of two fuzzy sets A and B over the universe X can be represented by a membership function

$$\mu_A \cup_B(x) = max\ [\mu_A(x), \mu_B(x)],$$

where μ_A and μ_B are membership functions for the sets A and B correspondingly. The fuzzy union operator is equivalent to the OR operator in Boolean algebra.

The *fuzzy intersection operator* of two fuzzy sets A and B on the universe X can be represented by a membership function

$$\mu_A \cap_B(x) = min\ [\mu_A(x), \mu_B(x)],$$

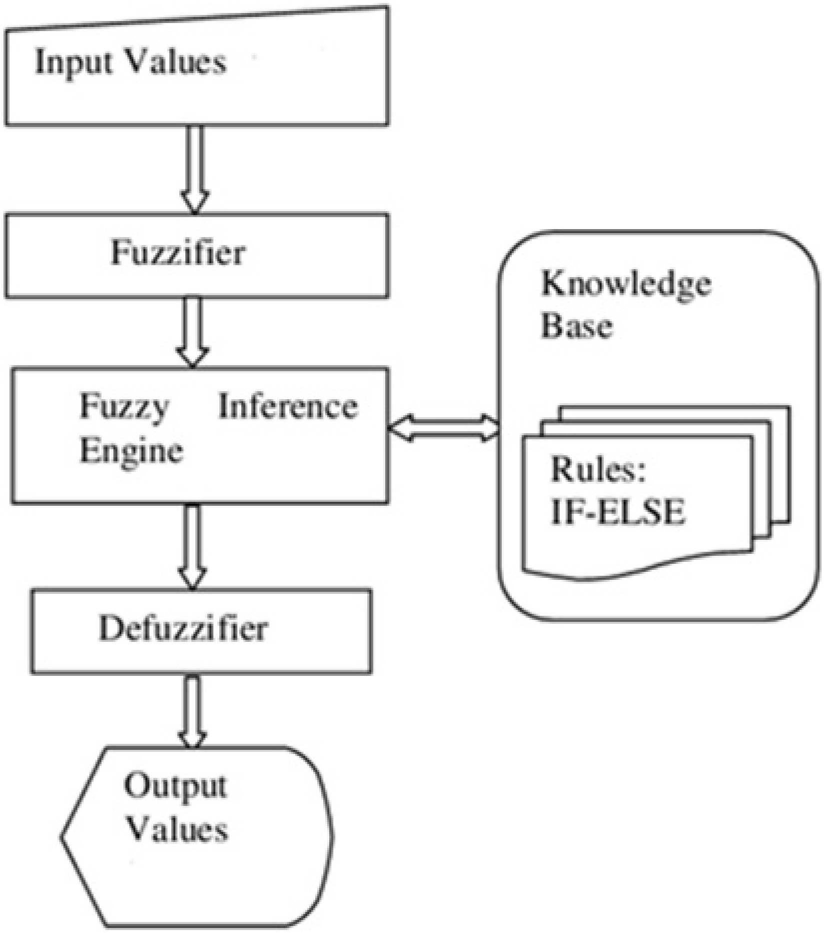
where μ_A and μ_B are membership functions for the sets A and B correspondingly. The fuzzy intersection operator is equivalent to the AND operator in Boolean algebra.

Fuzzy logic expert system is one of the well-known estimation/prediction techniques that is used for making decisions based on imprecise/ambiguous information in various fields (Baghel & Sharma, 2013). For instance, Adeli and Neshat (Adeli & Neshat, 2010) proposed a fuzzy expert system approach for diagnosis of heart diseases while in (Ngai & Wat, 2003) a fuzzy expert system is used for a hotel selection. Usually, the aim of a fuzzy logic expert system is to draw a concise result based on ambiguous information. A fuzzy logic expert system has three main components, namely *fuzzifier*, *fuzzy interference engine* and *defuzzifier* as shown in Figure 2 (Attaullah et al., 2008), and such a system can be used to establish the QoS/QoE correlation. In (Attaullah et al., 2008), the authors consider the signal strength, network load, available bandwidth, required bandwidth and jitter as QoS parameters for evaluating the performance of GPRS, WiFi and WiMax networks. With the help of membership functions and inference rules utilized in the fuzzifier and the inference engine correspondingly, the fuzzy expert system decides which network has a higher performance. Therefore, fuzzy expert systems have various applications, and the better membership functions and inference rules are defined the higher is the system intelligence. Components of the fuzzy expert system (Figure 2) are described below.

The *fuzzifier* contains the membership functions (fuzzy sets). In the *fuzzifier*, input parameters are mapped into membership functions to determine the membership of these parameters to appropriate fuzzy sets.

The *fuzzy inference engine* contains a collection of IF-THEN rules, which are obtained

Figure 2. A fuzzy expert system



from experts or learned using other intelligent techniques. The justified inputs taken from the fuzzifier (i.e. membership values) are applied to the antecedents of the fuzzy rules. In case of multiple antecedents, AND or OR (intersection or union) operators are used to get the result of the antecedent evaluation (the truth value). This value (the truth value) is then applied to the consequent membership function, i.e., the output QoE membership function. In other words, the consequent membership function is clipped or scaled to the level of the truth value of the rule antecedent. If more than one rule is trigged from one set of input parameters, then the outputs of all the rules are aggregated into the *aggregated output fuzzy set*.

The *defuzzifier* is used to perform a *defuzzification*, namely a single output value is obtained from the defuzzifier with the use of the *aggregated output fuzzy set*. There exist various defuzzification techniques (Ross, 1995) such as the centroid method, the weighted average method, the maximum method, etc.

3. USING DIFFERENT LOGICS TO PREDICT THE QOE VALUE OF MULTIMEDIA SERVICES

In this section, we present two self-adaptive techniques that we have used when evaluating/predicting the QoE of the multimedia services. The first technique is based on using Boolean formulae effectively represented by corresponding logic circuits (Kushik et al., 2014) while the second technique utilizes fuzzy logic formulae represented by corresponding expert systems (Pokhrel et al., 2014).

3.1. Using Logic Circuits for Predicting the QoE Value of Multimedia Services

In this subsection, the approach based on Boolean formula represented by a corresponding logic circuit is briefly described. The translation from the Boolean formula to a logic circuit is made by the use of an LUT. Such LUT can be written using various formats to further use some tools supporting a logic synthesis technique; for instance, PLA or BLIF formats can be used. In this paper, we represent an LUT in the PLA format and rely on using the ABC tool to derive and to resynthesize a logic circuit (if necessary) (Berkeley Logic Synthesis and Verification Group, ABC). ABC is a growing software system for synthesis and verification of binary synchronous sequential logic circuits. It provides scalable logic circuit synthesis and optimization based on And-Inverter Graphs (AIGs) and other internal circuit representations. Moreover, ABC includes a number of commands for synthesis, resynthesis, optimization and verification of logic circuits as well as for providing the circuit statistics and parameters. The ABC can be easily downloaded from its official web site and run against a LUT to synthesize a corresponding circuit S.

The QoE prediction approach relies on logic circuit learning and we first discuss how the initial circuit can be derived and then turn to a learning procedure itself.

Consider a multimedia service W and a collection of service parameters $p_1, p_2, \ldots, p_k$ that are used for the QoE evaluation. For the sake of scalability, we consider each parameter p_i value as a nonnegative (unsigned) integer, bounded by the maximal value M_{p_i}, $p_i\_value \in \{0, \ldots, M_{p_i} - 1\}$. In order to evaluate the QoE of the service W, written $QoE(W)$, a logic circuit S is derived. Inputs of the circuit S correspond to service parameters $p_1, p_2, \ldots, p_k$ which values are encoded as Boolean vectors of length $]\log_2 M_{p_i}[$, where $]t[$ denotes the minimal integer that is not less than t; thus, the number of primary inputs of S equals $\sum_{i=1}^{k}]\log_2 M_{p_i}[$. The circuit calculates the $QoE(W)$ value for given integers $p_1\_value, p_2\_value, \ldots, p_k\_value$ and $QoE(W)$ that is bounded by the maximal value M_{QoE}, $QoE(W) \in \{0, \ldots, M_{QoE} - 1\}$ also represented as a Boolean vector. The length of a corresponding Boolean vector is $]\log_2 M_{QoE}[$, as $]\log_2 t[$ bits are needed to represent an unsigned integer t. Therefore, the circuit S has $\sum_{i=1}^{k}]\log_2 M_{p_i}[$ primary inputs and $]\log_2 M_{QoE}[$ primary outputs.

In order to derive the initial circuit S, we use statistics gathered by multimedia service experts as well as by the automatic evaluation of service parameters by end-users, who have an experience of using the service W. The logic circuit S that is derived based on the provided statistics, evaluates and predicts the QoE value of the multimedia service W for any values of input parameters. In Algorithm 1, we present an algorithm for deriving the initial circuit S.

Given an integer x, let $\mathbf{B}(x)$ denote a corresponding Boolean vector for x. Due to Steps 2 and 3 of the above algorithm, the following statement holds.

Proposition 1: Given a multimedia service W and a statistic pattern $p_1\_value, p_2\_value, \ldots, p_k\_value$, $UserSatisfaction\_value$, a circuit S returned by Algorithm 1 produces

Algorithm 1. For deriving an initial logic circuit to evaluate the QoE value

Inputs: Service parameters p_1, p_2, …, p_k with nonnegative (unsigned) integer values bounded by M_{p_1}, M_{p_2}, …, M_{p_k}; maximal value of the QoE M_{QoE};

Statistics, i.e., feedbacks from experts/users U_1, …, U_r represented as a list of patterns p_1_*value*, p_2_*value*, …, p_k_*value*, *UserSatisfaction_value*.

Output: a logic circuit *S*

1. Determine the number of primary inputs and primary outputs of *S*:

The number of primary inputs equals $\sum_{i=1}^{k}]\log_2 M_{p_i}[$ while the number of primary outputs equals $]\log_2 M_{QoE}[$.

2. Derive an LUT for the corresponding statistics.

2.1 For each user U_i, $i \in \{1, …, r\}$, convert its statistic scores p_1_*value*, p_2_*value*, …, p_k_*value*, *UserSatisfaction_value* into Boolean vectors and add the corresponding line to the LUT.

3. Synthesize the circuit *S* for a system of possibly partial, Boolean functions and **Return** *S*.

□

the output **B**(*UserSatisfaction_value*) when the concatenation **B**(p_1_*value*) · **B**(p_2_*value*) · … · **B**(p_k_*value*) is applied as an input vector.

In order to improve the prediction ability of the circuit *S* derived by Algorithm 1, one may consider an input confidence interval of length τ_*in*. In this case, the LUT derived at Step 2 of Algorithm 1 can be extended by patterns that are not specified in the statistical data. Given a statistical vector **B**(p_1_*value*) · **B**(p_2_*value*) · … · **B**(p_k_*value*) added to the LUT, all Boolean vectors located not farther than at the distance on τ_*in* from **B**(p_1_*value*) · **B**(p_2_*value*) · … · **B**(p_k_*value*) can be also appended to the LUT with the same **B**(*UserSatisfaction_value*) value. As an example, consider an LUT derived for two service parameters p_1 and p_2 such that maximal value of each parameter equals 5 and the QoE value also ranges from 0 to 5. Consider a statistical pattern (p_1_*value* p_2_*value*, *UserSatisfaction_value*) = (3 2, 5). This pattern is converted into the corresponding Boolean vector (011 010, 101). If τ_*in* equals 1, then the vectors (011 001, 101) and (011 011, 101), (010 000, 101) and (100 000, 101), are added to the LUT if they do not contradict the existing statistics.

Once a circuit *S* is derived, the circuit can be used for evaluating the QoE of the multimedia service. The circuit accepts Boolean vectors as inputs representing current values of considered parameters and the output is a Boolean vector corresponding to an integer that evaluates the QoE value. As in this paper we are interested in self-adaptive models, we discuss how such circuit can be modified if the circuit behavior does not match new statistical data that can appear when a new end-user agrees to leave his/her feedback about the service quality. Therefore, the circuit behavior has to be modeled under a corresponding input **i** and if the result produced by the circuit differs significantly from the expected one then the circuit has to be resynthesized. To evaluate the difference between the circuit output and the user satisfaction value we introduce some value τ_*out* that represents an output confidence interval, i.e., the *QoE*(*W*) produced by the circuit *S* has to belong to the interval [*UserSatisfaction_value*

$-\tau\_out$, $UserSatisfaction\_value + \tau\_out$]. Given a new pattern **i/o** where the vector **o** represents the *UserSatisfaction_value* for a new user and *QoE*(*W*) is an integer that corresponds to the *S* output for the input **i**, if |*QoE*(*W*) – *UserSatisfaction_value*| ≤ τ_out then the circuit *S* is not resynthesized.

The confidence interval [*UserSatisfaction_value* – τ_out, *UserSatisfaction_value* + τ_out] specifies the permissible distance between the circuit behavior and new statistical data. If the *QoE*(*W*) value produced by the circuit *S* does not belong to this interval several cases are possible:

1. The input part **i** of a new statistical pattern **i/o** where **o** is a Boolean vector for the expected *UserSatisfaction_value*, was not in the initial LUT (not described in the previous statistics); and thus, the circuit *S* was not correctly synthesized for a Don't_Care input **i**. In this case, the new input pattern **i/o** is added to the LUT for the circuit and the circuit is resynthesized.
2. The output of the circuit *S* for the input **i** was defined in the initial LUT but the output is not within the confidence interval. If this mismatching is caused by an expert error that provides initial statistics, we consider an end-user as an expert and resynthesize the circuit w.r.t. the new output for the input **i**.
3. The output of the circuit *S* for the input **i** is not within the confidence interval and this mismatching is due to different end-user opinions. In other words, for the same service parameter values, two different users specify the user satisfaction values with the difference greater than the constant τ_out. In this case, a problem arises of solving a conflict of user opinions. In this paper, we do not go deep into solving this problem, since the probability of such situation is very low when the number of service parameters is large enough. Thus, we again rely on the last end-user opinion and resynthesize the circuit in a corresponding way, presented in Algorithm 2.

Similar to Proposition 1, the following statement holds.

Proposition 2: Given a multimedia service *W*, a statistic pattern p_1_value, p_2_value, …, p_k_value, *UserSatisfaction_value* and the length τ_out of an output confidence interval, a circuit *S* returned by Algorithm 2 produces the output **B**(*x*), such that | *x* – *UserSatisfaction_value* | ≤ τ_out when the concatenation $\mathbf{B}(p_1\_value) \cdot \mathbf{B}(p_2\_value) \cdot \ldots \cdot \mathbf{B}(p_k\_value)$ is applied as an input vector.

Consider an LUT in Table 1 as the statistics gathered from a user and/or an expert for a given multimedia service. In this case, the circuit *S* in Figure 1a is a circuit derived for predicting the QoE of this service based on statistics provided in Table 1. As an example, consider another user that agrees to provide a feedback about using the multimedia service; then an output of the circuit *S* is computed according to his/her feedback. If *S* provides the output that does not belong to the user confidence interval with τ_out, then the circuit should be resynthesized. Consider a score of the user represented as Boolean vector (1001)/(10). The circuit *S* in Figure 1a outputs (00) which correspond to 0 score when an input (1001) is applied and thus, the circuit has to be resynthesized taking into account this new input/output pair, if the length of the output confidence interval $\tau\_out < 3$. We have performed such resynthesis using ABC and obtained another circuit *S′* with 17 gates (Figure 1b).

Additional experimental research is also needed to evaluate the optimal length of confidence intervals for different services, since the length of both input and output confidence intervals significantly influences both, the prediction accuracy and the computational complexity which contradict each other. The bigger are the τ_in/τ_out values the less resynthesis steps are needed, along with reducing the accuracy of the circuit prediction. Studying optimal values for the length of input and output confidence

Algorithm 2. For learning the logic circuit that evaluates/predicts the QoE value for multimedia service

Inputs: QoE parameters p_1, p_2, …, p_k with nonnegative values bounded by M_{p_1}, M_{p_2}, …, M_{p_k}; maximal value of the QoE M_{QoE};
The circuit *S* that evaluates the QoE value for multimedia service *W*;
A new user feedback p_1*_value*, p_2*_value*, …, p_k*_value*, *UserSatisfaction_value*;
Maximal difference τ*_out* for a corresponding output confidence interval.
Output: a modified logic circuit *S*
1. Integers p_1*_value*, p_2*_value*, …, p_k*_value*, *UserSatisfaction_value* are converted into Boolean vectors **v_p1**, **v_p2**, …, **v_pk**, **v_us**.
2. The output *QoE*(*W*) of the circuit *S* is computed for the input **v_p1**, **v_p2**, …, **v_pk**.
3. If | *QoE*(*W*) - *UserSatisfaction_value* | > τ*_out* then
3.1 *If* the line **v_p1**, **v_p2**, …, **v_pk** is specified as an input in the LUT, then change the corresponding output to **v_us**,
Otherwise,
Add the new line **v_p1**, **v_p2**, …, **v_pk**, **v_us** to the LUT.
Synthesize the new circuit *S'*; assign *S* = *S'* and **Return** *S*.
□

intervals remains one of challenging topics for a future work.

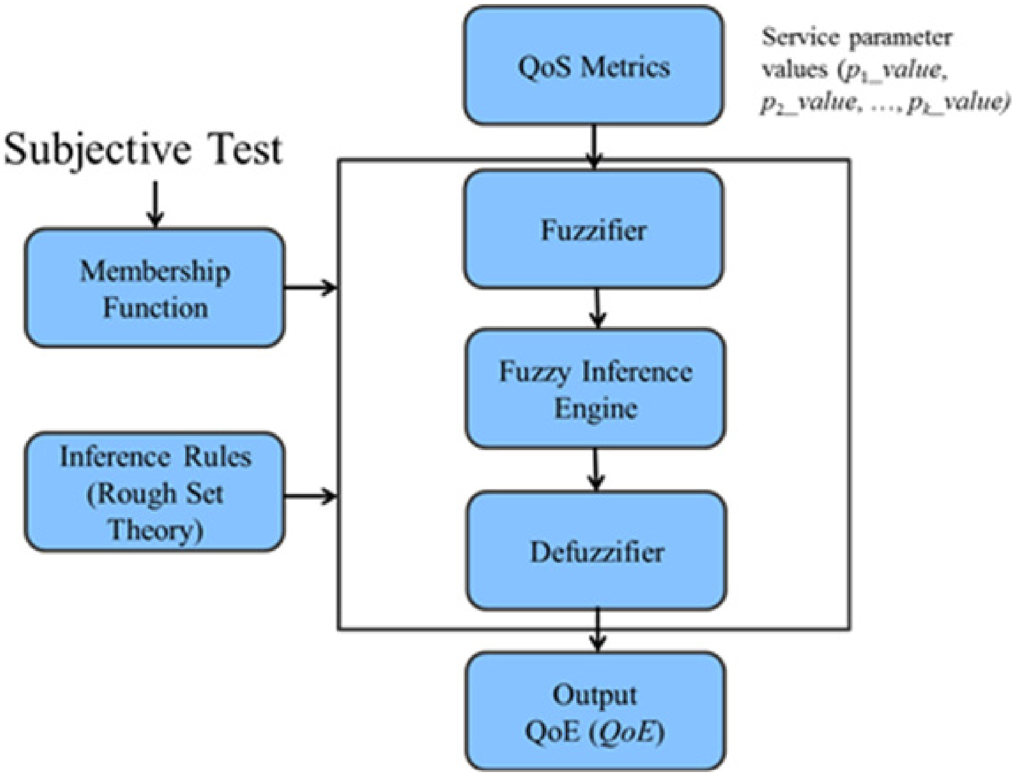
3.2. Using Fuzzy Logic Expert Systems for Predicting the QoE Value of Multimedia Services

In this section, we describe how a fuzzy logic expert system can be learned or trained for predicting the QoE value of multimedia services. Figure 3 represents the basic block diagram of the fuzzy logic expert system construction. The inputs of the system are service parameter values and the output of the system is an estimated QoE value. The *fuzzifier* contains the membership functions for service parameters and the *fuzzy inference engine* contains the collection of IF-THEN rules for evaluating the QoE of a multimedia service. The *defuzzifier* performs the defuzzification of the *aggregated output fuzzy set* to obtain the single QoE value.

As mentioned above, the intelligence of a fuzzy expert system significantly depends on the membership functions and inference rules. The more accurately the membership functions and inference rules are specified the higher is the prediction ability of the expert system. Therefore, in order to effectively apply the fuzzy logic expert system for the QoE estimation, one has to carefully specify the membership functions as well as the inference rules. In this paper, we focus on deriving the membership functions and the inference rules based on the subjective data set; namely, statistics gathered from end-users and/or experts are utilized in order to derive the initial fuzzy expert system.

Once a fuzzy logic expert system is derived based on the initial statistical data (Figure 3), it can be used for the QoE prediction. Nevertheless, at any moment of utilizing of such 'prediction engine' the system can be updated. More formally a feedback loop can be considered in the above diagram. In other words, the difference between the observed output value and the QoE provided by end-users can be considered as a 'teacher' to resynthesize the system, i.e.,

Figure 3. A fuzzy logic expert system for QoE estimation



to update the membership functions as well as the inference rules. We further discuss how such system can be used when estimating the quality of a multimedia service. Given a multimedia service W and a collection of service parameters $p_1, p_2, \ldots, p_k$ that are used for the QoE evaluation, the output QoE of the multimedia service is represented by the variable *QoE(W)*.

Each service parameter p_i, $i \in \{1, \ldots, k\}$ is classified into A_j classes, $j \in \{1, \ldots, l\}$, and a membership function $\mu^{pi}_{Aj}(x)$ is derived for each class of service parameters. In this paper, we use the MOS score (ITU-T Recommendation P.800.1, 2006), thus $l = 5$ and the score belongs to the set {*excellent*, *good*, *fair*, *poor*, *bad*}. Similar classes are considered for the output QoE. As mentioned above, the membership functions are constructed based on the subjective data set, i.e., statistical data provided by end-users and/or by experts. In this paper, we focus on using a so called *trapezoidal function* to derive the membership functions for the fuzzy logic expert system. In particular, the Rough Set Theory (Pawlak, 2002) is used to generate inference rules based on subjective data sets. For this purpose, the Rosetta software (Rosetta, 2009) is used, which is a Rough Set toolkit for analysis of datasets to generate inference rules.

In order to estimate the QoE of a multimedia service, different patterns (p_1*_value*, p_2*_value*, …, p_k*_value)* are submitted to the fuzzy logic expert system. The output of the system represents the QoE value for a multimedia service. Below, we provide the algorithm for evaluating the QoE value based on the fuzzy logic expert system.

There exist various defuzzification techniques (Step 3) (Ross, 1995), for example, the centroid method, the weighted average method, the maximum method, etc, and, in this work

Algorithm 3. For evaluating/predicting the QoE value for multimedia service

Inputs: A multimedia service W, service parameters p_1, p_2, …, p_k and their values p_1_value, p_2_value, …, p_k_value;
Inference rules given in the form: IF <antecedent> THEN <consequent>;
Membership functions $\mu^{pi}_{Aj}(x)$, $i \in \{1, ..., k\}$, $j \in \{1, ..., l\}$, where x is the service parameter value and A_j represents different classes of corresponding parameter values.
Output: The QoE value (*QoE*)
1. Map the service parameter values p_1_value, p_2_value, …, p_k_value into the membership functions $\mu^{pi}_{Aj}(x)$ and get the membership value in the *fuzzifier*.
2. Apply the justified inputs (membership values) taken from the fuzzifier to the fuzzy inference rules in fuzzy inference engine.
Rule: IF p_i is A_j AND IF p_i is A_j then QoE is A_j.
The output of the rule evaluation is the consequent membership function (*output fuzzy set*) clipped or scaled to the level of the truth value of the rule evaluation. If more than one rule is triggered the outputs of all the rules are aggregated into the *aggregated output fuzzy set*.
3. Defuzzify the aggregated output fuzzy set and get a single QoE value (*QoE*) in the defuzzifier.
4. Return *QoE value*.

we use the *centroid* method. The mathematical basis of this method relies on the *center of gravity (COG)* that can be expressed by the following formula.

Center of Gravity (COG)

$$y = \frac{\int \mu_i(x) \bullet x dx}{\int \mu_i(x) dx},$$

where y is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable.

Once an initial machine (a fuzzy expert system or a logic circuit) is derived, one may use it to predict the QoE value. However, the new statistical data can help in 'upgrading' the system by increasing its prediction ability. To improve the fuzzy logic expert system, fuzzy membership functions and inference rules are updated based on the new subjective data set. One may notice that such improvement requires a 'teacher' to be involved in the machine learning process. In other words, differently from the logic circuit, the fuzzy expert system is not adapted automatically when new statistical data appear. We further present experimental results of comparing fuzzy and logic network approaches for the QoE prediction.

4. EXPERIMENTAL RESULTS

In this section, we present the service environment for the performed experiments as well as the experimental results of the application of both approaches to a multimedia service that delivers a video traffic to an end-user. Taking into account the fact that the user/service provider is involved in a manual update of the inference rules, we further compare the prediction ability of two approaches. In the case of logic circuits, we estimate the performance as well, by measuring the time needed for the circuit

Table 2. Characteristics of video files considered when performing experiments

Video Content	Resolution	Frame rate (frame per second)
Movie1	1280x544	47
Animation1	1280x720	50
Interview1	1280x720	50
Sport	1280x720	50
Animation2	1980x818	48
Interview2	1280x720	60

resynthesis when the wrong circuit behaviour has been discovered for some statistical pattern.

4.1. A Service Under Experiment and a Subjective Dataset Collection

In order to compare logic network and fuzzy logic expert system based approaches, we performed experiments with a multimedia service that delivers a video traffic to an end-user. Experiments have been performed based on the following steps: a) constructing a dataset of video clips to be presented to end-users; b) deriving a subjective dataset with the use of end-users' scores; c) using the proposed techniques for the QoE prediction.

Step 1: Construction of the video clips with impairments due to impact of the network QoS

We considered six different video contents of different type (movie, animation, interview and sport) for the experiments. Considered videos are of HD (High Definition) quality and their characteristics (content, resolution and frame rate) are shown in Table 2. Each video clip was streamed from a source node to a destination node and, correspondingly different QoS parameters were considered. We used a VLC server (source node) to stream a video to a VLC client (destination node) and injected the QoS parameters through the emulated network using the *Netem* tool (Netem, 2009). We considered two QoS parameters (a packet loss rate and a jitter) as the network condition indicators. The procedure was repeated for all six video content types. This combination resulted in a database of 228 video clips with different perturbations.

Step 2: Conduction of the video subjective test with end-users to obtain a QoS-QoE dataset

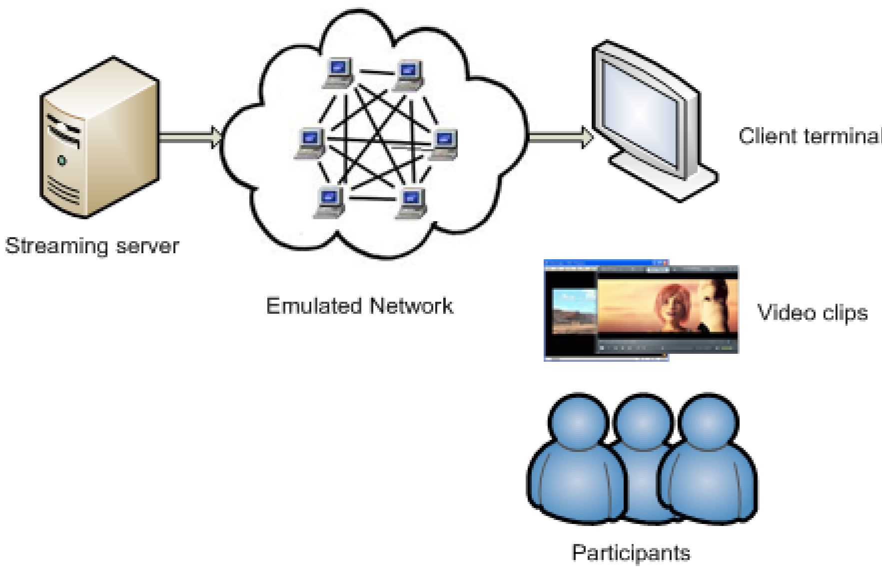
In order to derive a subjective test data set, we presented the modified video clips (Step 1) along with the original video clips to end-users. After watching each video clip, end-user participants rated these clips according to the perceived impairment providing one of the MOS scores (ITU-T Recommendation P.800.1, 2006): Excellent (score 5), Good (score 4), Fair (score 3), Poor (score 2), and Bad (score 1).

We mention that the video clips were shown in a closed room in a random order. The duration of the subjective tests was around 2 hours and participants were allowed to take a pause of 5 minutes after watching 20 video clips. In total, 25 users registered for the test so far, which is considered reasonable for this kind of subjective tests (Nezveda et al., 2010). Figure 4 illustrates the experimental environment for the subjective tests.

Step 3: Modeling the logic network and fuzzy logic expert system using the QoS-QoE dataset

Figure 5 illustrates the modeling process for logic circuits and fuzzy expert systems. The

Figure 4. The experimental setup for the subjective tests



modeling process starts with a subjective test where participants are asked to rate different videos that contain impairments due to the QoS variation. As an outcome of the subjective test, the subjective dataset is obtained. This dataset provides the QoE values for different sets of QoS parameter values, namely, jitter and packet loss. The subjective dataset is used for the construction and the formulation of the membership functions and the inference rules for a fuzzy logic expert system as well as for the synthesis of a logic circuit. Once the corresponding self-adaptive system is derived, the QoE value can be predicted by the system for any pattern of QoS parameter values.

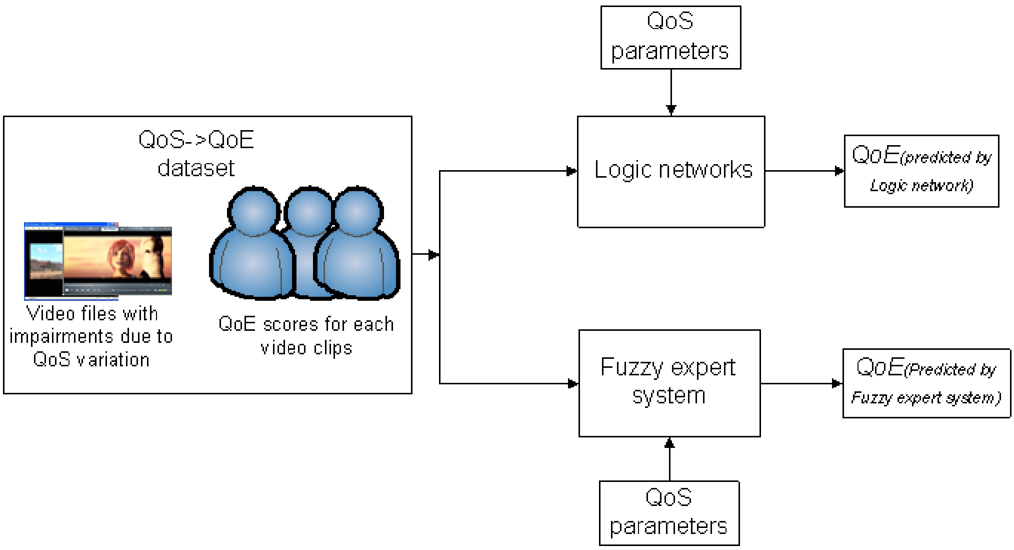
Both machines were trained/modeled several times in order to compare their prediction and self-adaptation ability. For this purpose, the total subjective dataset was divided into initial data set and six different iteration data sets, in order to perform experiments estimating the machine prediction ability.

4.2. Comparing the Logic Network and the Fuzzy Logic Expert System Approaches for the QoE Prediction

We have considered two service parameters when estimating the quality of the multimedia service. Those are the jitter and packet loss that are objective and can be automatically measured. When performing experiments, users were asked about their perception of the video quality. The jitter and packet loss values were automatically injected into the video transmission ranging from 0 to 20 and from 0 to 2%, correspondingly.

When comparing two different approaches for evaluating the QoE of the multimedia service we have considered 1) the QoE prediction ability of each approach, and 2) the performance of each approach. Both criteria remain crucial when estimating the quality of multimedia services. The reason is that more and more service parameters are taken into account nowadays, and, meanwhile, new methods and tools are being developed to estimate the parameter values more precisely. Thus, the size of corresponding adaptive models derived to predict the QoE

Figure 5. Modeling the process of the QoE prediction for logic circuits and fuzzy expert systems



value can grow exponentially w.r.t. the number of service parameters. Nevertheless, the prediction ability of such system needs to be high, i.e., should be thoroughly measured, while at the same time the system needs to be scalable. As the most 'hard' part for the system performance is its adaptation, we focus on measuring the time needed for the corresponding resynthesis. In order to compare the QoE prediction ability, we checked if the logic circuit/fuzzy logic expert system had to be resynthesized when new statistical data appeared. As mentioned above (Step 3), the whole number of iterations in the experiments was equal to 6, i.e., after the initial circuit/expert system had been constructed, new statistical data were taking into account exactly six times. A number N of patterns where the machine (a logic circuit or an expert system) behaved incorrectly was calculated and was considered as one of indicators to measure the machine prediction ability. For the sake of 'clear' comparison, we were interested in an absolute value of such indicator and thus, we did not consider any output confidence interval. Moreover, when evaluating and comparing the QoE prediction ability for both approaches we were interested in an average distance D between the QoE value produced by the machine and *UserSatisfaction_value* specified in the new statistical data. For example, if the new statistical data contain two patterns (p_1*_value*, p_2*_value*, *UserSatisfaction_value*) = (3, 2, 5) and (p_1*_value*, p_2*_value*, *UserSatisfaction_value*) = (2, 1, 3), and the current machine produces the QoE values 2 and 5, correspondingly, then the average distance $D = (|5 - 2| + |3 - 5|) / 2 = 2.5$.

Besides the QoE prediction ability, we evaluated the performance when adapting the logic circuit for the QoE prediction. In this case, whenever the corresponding machine had to be resynthesized after the new statistical data appeared, the time of such redesign had been measured. Below, we present the results of corresponding experiments with the multimedia service for both, Boolean and fuzzy logic based approaches.

4.2.1. Experimental Results for the Logic Circuit Based QoE Prediction for Multimedia Services

The initial statistics contained 26 vectors with a jitter ranging from 0 to 20 and a packet loss ranging from 0 to 2%. We introduced an input confidence interval when applying Algorithm 1 to derive the initial circuit *S*. In this case, the τ_in varied for different input vectors of the circuit under design. All initial vectors $\mathbf{B}(p_1\_value) \cdot \mathbf{B}(p_2\_value) \cdot \ldots \cdot \mathbf{B}(p_k\_value)$ added to the LUT had been ordered lexicographically and for each pair of neighbor vectors the τ_in value had been calculated. Given two input neighbor vectors $\mathbf{i}_1$ and $\mathbf{i}_2$, the τ_in value is the absolute integer distance between those vectors divided by two. For example, for the input vectors (011, 011, 101) and (011, 000, 100) the τ_in equals $]\,(3-0)/2\,[\, = 1$, and two vectors are added to the LUT, i.e. (011, 010, 101) and (011, 001, 100).

Having calculated necessary input confidence values for inputs, we respecified the circuit behavior and got 218 patterns in the corresponding LUT. This LUT was specified in the PLA format and the ABC tool has been used to derive the initial circuit *S*. The time needed for such logic synthesis was equal to 0.991 s.

When new statistical data arrived, i.e., the first comparison iteration was executed, a wrong behavior of the circuit *S* was observed for $N = 9$ input vectors. The average distance *D* between the *User_Satisfaction* value and the QoE produced by the circuit *S* was equal to 12/9, $D = 12/9 \approx 1.33$. The circuit had been resynthesized and the timed needed for such resynthesis with the use of ABC was 1.112 s.

For the second iteration, i.e., for the new statistic data occurred at the second step, the circuit *S* already resynthesized once, behaved incorrectly for 10 input vectors. However, the average distance *D* in this case slightly decreased, namely $D = 12/10 = 1.2$. The time spent for the circuit resynthesis decreased as well and was equal to 0.946 s.

During the third iteration, the number *N* of 'misbehaving' vectors decreased together with the average 'misbehaving' distance *D*. In fact, *N* got equal to 9 and *D* was equal to 10/9, i.e. $D = 10/9 = 1.11$. Nevertheless, the better prediction ability did not decrease the resynthesis time that was 1.106 s.

At the forth iteration the *N* value did not change, i.e., $N = 9$, while the average distance between the QoE produced by the resynthesized circuit and the *User_Satisfaction* value increased slightly. In this case, $D = 12/9 \approx 1.33$ and the time for the resynthesis was 1,178 s.

During the fifth and the sixth iterations, one may clearly conclude the circuit starts increasing its prediction ability. This fact is proven by a number *N* of 'misbehaving' vectors that during the fifth iteration decreased up to 7 while after another resynthesis this number got equal to 5. The *D* value had been increased during the fifth iteration, $D = 12/7 \approx 1.71$, but it went down after another resynthesis and became equal to $6/5 = 1.2$. The time needed for the circuit resynthesis during the fifth and the sixth iterations was 0.947 s and 1.121 s, correspondingly. Experimental data for the multimedia service are represented in Table 3. One may notice that the number of 'misbehaving' vectors decreases on average, however, various fluctuations take place. The latter means that the logic circuit stabilizes from iteration to iteration being trained with the new statistical data. On the hand, the average distance *D* between the 'real' QoE value and the value produced by the logic circuit remains almost the same and is close to one.

4.2.2. Experimental Results for the Fuzzy Logic Expert System Based QoE Prediction for Multimedia Services

Similar to the case of logic circuit training, the initial statistics for the fuzzy expert system contained 26 vectors with a jitter ranging from 0 to 20 and a packet loss ranging from 0 to 2%. The initial fuzzy expert system was derived with the use of inference rules and membership functions. The inference rules were generated using the rough set theory and the membership functions were derived based on the initial statistics, i.e., on the subjective data set. Figures 6 and 7 represent membership functions for packet loss and jitter while Figure 8 represents the output QoE membership function.

A membership function curve values represent the degree of how 'much' a particular QoS parameter belongs to a given QoE class. The highest degree corresponds to the membership value that equals 1. As mentioned above,

Table 3. Experimental Results For The Logic Circuit Based Approach For The Qoe Prediction Of The Multimedia Service

Iteration #	*N*	*D*	Time (s)
1	9	1.33	1.112
2	10	1.2	0.946
3	9	1.11	1.106
4	9	1.33	1,178
5	7	1.71	0.947
6	5	1.2	1.121

when performing experiments we derived the membership functions based on the observation of subjective data sets. In this case, the trapezoidal fuzzy set represents the membership functions for different QoS parameters. Based on the diagram in Figure 6 one may conclude that participants provided excellent scores of the quality when the packet loss value varied from 0% to 0.02%, while for the packet loss values between 0.02% and 0.03% the scores were between excellent and good. Therefore, for the packet loss value from the interval [0, 0.02] the degree of membership equals 1 for the 'excellent' class. All the packet loss values from the interval [0.02, 0.03] share 'excellent' and 'good' classes with the degree of membership between 0 and 1. Corresponding membership functions derived for the packet loss and the jitter of the videos under experiment are presented in Figure 6 and Figure 7.

Figure 6. The membership function for the packet loss (%)

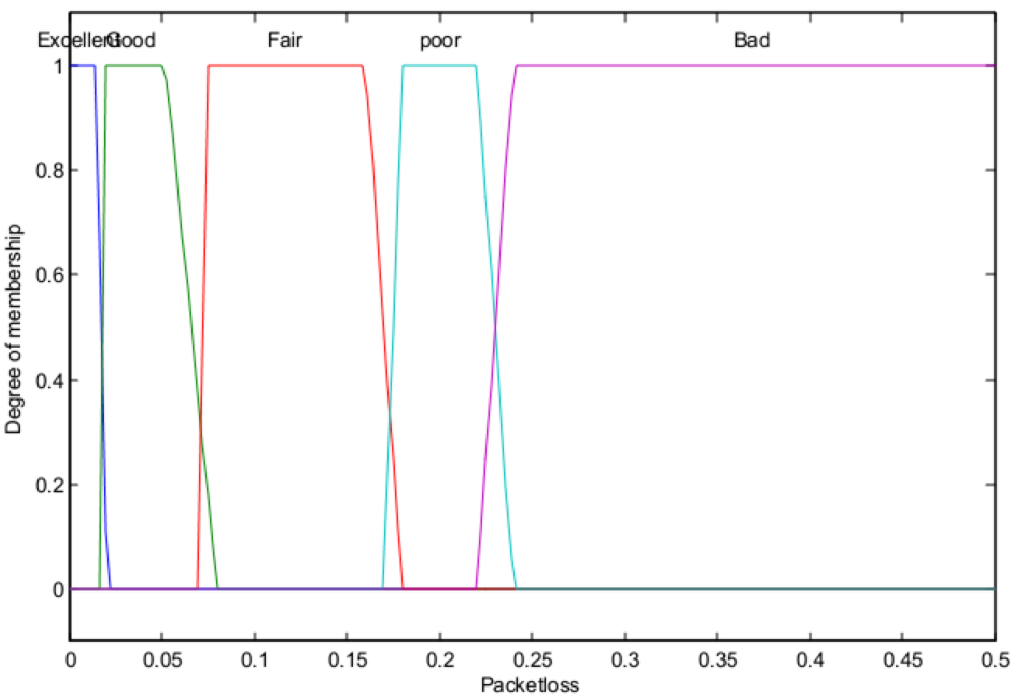


Figure 7. The membership function for jitter (millisecond)

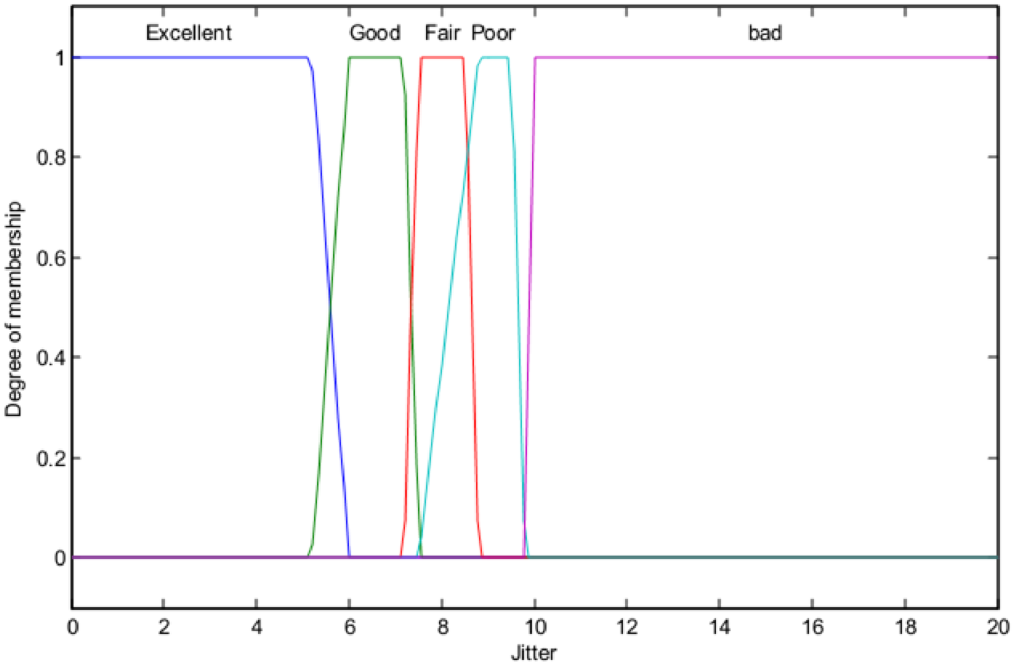


Figure 8. The membership function for QoE (MOS)

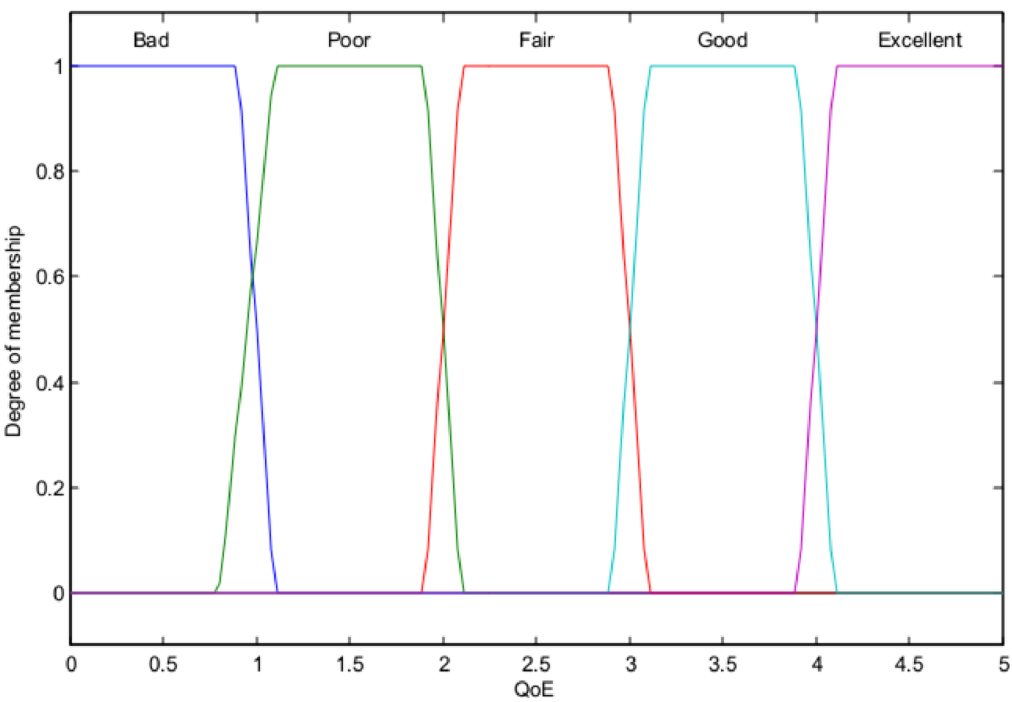


Table 4. Experimental results for the fuzzy logic expert system based approach for the qoe prediction of the multimedia service

Iteration #	*N*	*D*
1	8	1.00
2	5	0.702
3	9	1.44
4	2	0.610
5	3	0.676
6	3	0.699

The first comparison iteration was executed w.r.t. the initial fuzzy expert system. The system behaved incorrectly on $N = 8$ number of patterns. The average distance D between the *User_Satisfaction* value and the QoE produced by the expert system was equal to 1. Since the value of N was very high, the fuzzy expert system was updated by changing the rules and membership functions to correspondingly adapt a new dataset (i.e., the first comparison iteration). We mention that these changes were performed manually. The reason is that no tool support is available to make any automatic update of inference rules and membership functions as such system learning procedure requires a 'teacher' to be involved.

For the new statistic data at the second step, the fuzzy logic expert system already resynthesized once, behaved incorrectly for 5 input vectors, which is better than at the first iteration. Moreover, in this case, the average distance D slightly decreased up to $D = 0.7$. Again, the fuzzy logic expert system was updated w.r.t. the new statistical data.

During the third iteration, the number N of 'misbehaving' vectors increased together with the average 'misbehaving' distance D. In fact, N got equal to 9 and D was equal to 1.44. To adapt to the new scenario (the third iteration of the data set), the fuzzy logic expert system was resynthesized again.

During the fourth iteration, the number N of 'misbehaving' vectors decreased along with the average 'misbehaving' distance D. In particular, $N = 2$, and $D = 0.610$. This indicates that the system started to have the better prediction ability after the fourth iteration.

During the fifth and the sixth iterations, the fuzzy system remained stable w.r.t. the prediction ability, i.e., the number N of 'misbehaving' vectors decreased to 3. However, the D value remained between 0.65 and 0.7. Experimental results are presented in Table 4.

We mention again that differently from the logic circuit based approach for the QoE prediction, the time needed for the resynthesis was not evaluated for the fuzzy expert system. The reason is that the procedure of adapting the rules and membership functions was done manually.

4.3. Summary Of The Experimental Results

Experimental comparison of two approaches used for the QoE prediction of the multimedia services allows to draw some conclusions about advantages and disadvantages of using logic circuits and fuzzy expert systems for this purpose.

One may study Tables 3 and 4 to conclude that both machines are stabilized at some point when predicting the QoE value for the multimedia service. However, in both cases, fluctuations take place that can be caused, for example, by a mood of an end-user involved into the statistics gathering.

When comparing the prediction ability of both techniques, one may conclude that the fuzzy logic expert system 'shows' better results than the logic circuit. The number N of 'misbehaving' vectors evaluated at each iteration indicates that fact. Moreover, the fuzzy expert system starts to stabilize faster, namely, the fourth iteration made the system predict the QoE value 'almost' with no mistakes. The average distance *D* between the 'real' QoE value obtained from end-users and the QoE value produced by both machines is almost the same for both systems. Moreover, this distance is almost equal to one at each step of experiment. The latter means, that the output confidence interval with the distance $\tau\_out > 1$ should be sufficient for a clear prediction of a *User_Satisfaction*.

When comparing the performance of the two approaches for the QoE prediction, the logic circuit based approach 'wins' with no doubts. The reason is that the fuzzy expert system has to be manually resynthesized when 'misbehaving' patterns are detected. As for the logic circuit, such resynthesis can be effectively performed with the use of scalable tools developed for the logic synthesis, such as ABC, for example. Moreover, with the use of this tool the time needed for resynthesis almost never exceeds a second.

In other words, both systems have their own advantages. Correspondingly, based on the obtained experimental results a service provider can make his/her decision which approach is more suitable compromising between the machine scalability and its prediction ability at the same time.

5. CONCLUSION

In this paper, we have discussed two approaches for the QoE prediction of the multimedia services. Both approaches are based on logic formulae and their scalable representations. The Boolean logic formula is represented as a logic circuit while the fuzzy logic formula is represented by a corresponding expert system. Experimental results with an available multimedia service prove the effectiveness and applicability of both methods when evaluating/predicting the QoE value.

Experiments clearly prove the scalability of the use of logic circuits to predict the QoE value of the multimedia services. Meanwhile, fuzzy logic expert system requires a manual update of membership functions and inference rules and thus, the logic circuit approach 'wins' w.r.t. the performance factor. However, the accuracy of the QoE prediction is shown to be higher for the fuzzy logic expert system than for the corresponding logic circuit. Therefore, there is a trade-off between both approaches that a service provider faces in any case; in other words, one should compromise between the scalability of the logic circuit based approach and the accuracy of the fuzzy logic expert system.

More experimental results are needed to estimate the prediction ability as well as the performance for other services, for instance, for web services. Moreover, as the quality becomes a necessity for service compositions, especially those that are used in a Cloud, additional research is needed to estimate approaches for predicting the QoE of service compositions. Multimedia/web services and their compositions are planned to play a crucial role in the future Internet of Things and thus, new experiments should be performed in order to estimate the quality of the corresponding services and to draw a conclusion about 'potential' self-adaptive models that can be used for this purpose. Moreover, in the area of Clouds and the Internet of Things, other quality metrics can be also considered for further quality evaluation. These problems, as well as many others, remain for the future work.

REFERENCES

Adeli, A., & Neshat, M. (2010, March). A fuzzy expert system for heart disease diagnosis. In *Proceedings of International Multi Conference of Engineers and Computer Scientist*. Hong Kong (Vol. 1).

Attaullah, H., Iqbal, F., & Javed, M. Y. (2008). *Intelligent vertical handover decision model to improve QoS. Digital Information Management* (pp. 119–124). London, UK: ICDIM.

Baghel, A., & Sharma, T. (2013). Survey on Fuzzy Expert System. *International Journal of Emerging Technology and Advanced Engineering*, 230-233.

Berkeley Logic Synthesis and Verification Group. ABC: A System for Sequential Synthesis and Verification, Retrieved January 2, 2014, from http://www.eecs.berkeley.edu/~alanmi/abc/

Cisco. (2011). Cisco Visual Networking Index: Forecast and Methodology. 2010–2015. Whitepaper

ITU-T. (2006). *Mean opinion Score (MOS) terminology*. Recommendation P.800.1.

ITU-T. (2008). Q*uality of experience requirements for IPTV services*. Recommendation G.1080.

Johnson, D. S. (1974). Approximation algorithms for combinatorial problems. *Journal of Computer and System Sciences*, *9*(3), 256–278. doi:10.1016/S0022-0000(74)80044-9

Khirman, S., & Henriksen, P. (2002). Relationship between Quality-of-Service and Quality-of-Experience for public Internet service. *Passive and Active Network Measurement workshop*.

Kuehlmann, A. (Ed.). (2003). *The Best of ICCAD. 20 Years of Excellence in Computer-Aided Design*. Kluwer Academic Publishers.

Kumar, R., Rao, J. S., Turak, A. K., Chattopadhyay, S., & Rao, G. K. (2002). A Protocol to Support QoS for Multimedia Traffic over Internet with Transcoding. *Trusted Internet Workshop*. Banglore, India.

Kushik, N., Yevtushenko, N., Cavalli, A., Mallouli, W., & Pokhrel, J. (2014). Evaluating web service QoE by learning logic networks. *10th International Conference on Web Information Systems and Technologies (WEBIST)*. (pp. 3–5). Barcelona, Spain.

McCluskey, E. J. (1965). *Introduction to the theory of switching circuits*. NY: McGraw-Hill Book Company.

Mushtaq, M. S., Augustin, B., & Mellouk, A. (2012, June). Empirical study based on machine learning approach to assess the QoS/QoE correlation. *17th European Conference on Networks and Optical Communications (NOC)*. IEEE, (pp. 1-7). Vilanova i la Geltru, Spain. doi:10.1109/NOC.2012.6249939

Negnevitsky, M. (2002). *Artificial Intelligence, A Guide to Intelligent System. Addision-Weslay*. Pearson Education.

Netem. (2009). Linux Foundation, from http://www.linuxfoundation.org/collaborate/workgroups/networking/netem

Nezveda, M., Buchinger, S., Robitza, W., Hotop, E., Hummelbrunner, P., & Hlavacs, H. (2010). Test persons for subjective video quality testing: Experts or non-experts? *QoEMCS workshop at the EuroITV-8th European Conference on Interactive TV*. Tampere, Finland.

Ngai, E. W. T., & Wat, F. K. T. (2003). Design and development of a fuzzy expert system for hotel selection. *Omega*, *31*(4), 275–286. doi:10.1016/S0305-0483(03)00050-1

Pawlak, Z. (2002). Rough set theory and its applications. *Journal of telecommunications and information technology*, 3, 7-10.

Pokhrel, J., & Lalanne, F. Cavalli, & A., Mallouli, W. (2014). QoE Estimation for Web Service Selection Using a Fuzzy-Rough Hybrid Expert System. Advanced Information Networking and Applications (AINA), IEEE. (pp. 629-634). Victoria, Canada.

Pokhrel, J., Wehbi, B., Morais, A., Cavalli, A., & Allilaire, E. (2013). Estimation of QoE of video traffic using a fuzzy expert system. *Consumer Communications and Networking Conference (CCNC)*. IEEE, (pp. 224-229). Las Vegas, US. doi:10.1109/CCNC.2013.6488450

Rosetta - a rough set took kit for analysis of data. (2009). Retrieved March 10, 2014, from http://www.lcb.uu.se/tools/rosetta

Ross, T. J. (1995). *Fuzzy Logic with Engineering Applications*. McGraw-Hill, Inc.

Rubino, G., Tirilly, P., & Varela, M. (2006). *Evaluating users' satisfaction in packet networks using random neural networks. Artificial Neural Networks–ICANN* (pp. 303–312). Heidelberg: Springer Berlin.

Serral-Gracià, R., Cerqueira, E., Curado, M., Yannuzzi, M., & Monteiro, E. & Masip-Bruin. (2010). An Overview of Quality of Experience Measurement Challenges for Video Applications in IP Networks. *8th International Conference on Wired/Wireless Internet Communications* (pp. 252-263). Berlin, Heidelberg.

Wang, T., Pervez, A., & Zou, H. (2010, October). VQM-based QoS/QoE mapping for streaming video. *3rd IEEE International Conference on Broadband Network and Multimedia Technology (IC-BNMT)*. IEEE, (pp. 807-812). Beijing, China. doi:10.1109/ICBNMT.2010.5705202

Wijnants, M., Agten, S., Quax, P., & Lamotte, W. (2009, December). Investigating the relationship between QoS and QoE in a mixed desktop/handheld gaming setting. *Proceedings of the 5th international student workshop on Emerging networking experiments and technologies*. ACM, (pp. 29-30). Rome, Italy. doi:10.1145/1658997.1659013

Winckler, M. A., Bach, C., & Bernhaupt, R. (2013). Identifying user experience dimensions for mobile incident reporting in urban contexts. *IEEE Transactions on Communications*, *56*(2), 40–82.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353. doi:10.1016/S0019-9958(65)90241-X

Natalia Kushik has received her diploma degree in Applied Mathematics from Tomsk State University, Russia, in 2010. She has got a PhD degree in 2013 and worked as a PostDoc at Telecom SudParis, France. Her research interests include automata theory, service quality evaluation, software testing and verification.

Jeevan Pokhrel is currently working as a research engineer at Montimage, France and continuing his PhD degree in Institute Mines Telecom, France. He received a Dual Master degree from Institute Mines Telecom, France and Asian Institute of technology, Thailand in Communication and Network services (ComNETS) and Information Communication Technology (ICT) in 2011. He has been contributing in some of the European and French research projects. His PhD research is focused on network performance evaluation and security issues. His topics of interest cover performance evaluation, multimedia Quality of Experience (QoE), wireless networks, machine learning etc.

Nina Yevtushenko joined Tomsk State University in 1991 as a professor and presently she leads a research team working on the synthesis and analysis of discrete event systems. Her research interests include formal methods, automata theory, distributed systems, protocol and software testing.

Ana Rosa Cavalli is Full Professor at TELECOM SudParis since 1990, and nowadays she is the director of the Software for Networks department. Her research interests are on formal modeling, testing methodologies for conformance and interoperability testing, active testing and monitoring techniques, validation of security properties and their application to services and protocols.

Wissam Mallouli is a Telecommunication Engineer graduate from the National Institute of Telecommunication (INT) in 2005. He received his Masters degree from the Evry Val d'Essonne University also in 2005 and his PhD in computer science from Telecom and Management SudParis (France) in 2008. He is currently a research & development engineer at Montimage France. His topics of interest cover formal testing of functional behaviors and security aspects of distributed systems and networks. He worked in several Europeen and French research projects.