QoE estimation for web service selection using a Fuzzy-Rough hybrid expert system

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***Abstract*—With the proliferation of web services on the Internet, it has become important for service providers to select the best services for their clients in accordance to their functional and non-functional requirements. Generally, QoS parameters are used to select the most performing web services; however, these parameters do not necessarily reflect the user's satisfaction. Therefore, it is necessary to estimate the quality of web services on the basis of user satisfaction, i.e., Quality of Experience (QoE). In this paper, we propose a novel method based on a fuzzy-rough hybrid expert system for estimating QoE of web services for web service selection. It also presents how different QoS parameters impact the QoE of web services. For this, we conducted subjective tests in controlled environment with real users to correlate QoS parameters to subjective QoE. Based on this subjective test, we derive membership functions and inference rules for the fuzzy system. Membership functions are derived using a probabilistic approach and inference rules are generated using Rough Set Theory (RST). We evaluated our system in a simulated environment in MATLAB. The simulation results show that the estimated web quality from our system has a high correlation with the subjective QoE obtained from the participants in controlled tests.**

***Keywords*-Web Services, QoS, QoE, intelligent systems.**

I. Introduction

Web Services (WSs) are self-contained software systems that can be published, advertised, located and invoked through the web, usually relying in standardized XML technologies (REST, SOAP, WSDL, and UDDI [1]) for description and publication, and on Internet Protocols for invocation[2]. Popularity of web services is growing rapidly which leads to large number of web services or applications with similar features. This offers users a number of options and introduces a higher demand on price, response time, availability, reliability, service performance and other non-functional attributes for selecting a web service.

The availability of large number of web services providing similar functionalities and features has increased the need for sophisticated discovery and selection processes that can better meet the user's needs. The discovery process is a process of identifying or locating a web service that fulfills certain functional properties. On the other hand, the selection process refers to evaluating and ranking the discovered web services for selecting the one that fulfills a set of non-functional properties [3]. As indicated in [3], the "functional properties describe what the service can do and the non-functional properties depict how the service can do it ". Non-functional properties involve qualitative or quantitative features such as, throughput, latency, response time, integrity, availability, security, etc. ([4] and [5]). However, a selection process which relies only on a partial set of non-functional properties can be misleading as this will not necessarily reflect the user's satisfaction. Thus, as we propose here, we need a methodology that considers several parameters to estimate the expected user experience, with each having a greater or lesser impact on the resulting estimation.

Quality of Experience (QoE) has become an important indicator, useful for network operators and service providers to help them understand the user acceptability towards a particular service or application. The paradigm is shifting towards user-centric evaluation of a services or application performance. To attract or bind users to a service, real time estimation of QoE is a must for network operators and service providers. QoE is defined in different ways depending on the application field [6] [7]. ITU-T defines QoE as: The overall acceptability of an application or a service, as perceived subjectively by the end user. QoE usually requires tests with actual users in a controlled environment to properly estimate it; but this is often costly and time consuming. Therefore, it is necessary to provide some tools or methodologies that can objectively represent the subjective QoE [8].

User's demand and expectation for web technology is accelerating with time. Users gets intolerant if the content is not served in expected time and easily switch to other options if their needs are not fulfilled[9]. About 90% of the people do not want to complain for the low service quality. They just leave the service and move to another ones [10]. So service providers and operators should not wait for user feedback for improving the service quality, instead they should continuously monitor QoE and improve it as required. They should provide users with services that can offer high QoE values.

Generally, web QoS parameters are used for selecting web services, which do not necessarily reflect the user's satisfaction towards a particular web service. Web QoS parameters reflect network and service level performance; however, they do not address the user's reaction to the service or application. In contrary, web QoE reflects user's satisfaction towards a particular web service however, it is evaluated subjectively. Therefore, it is necessary to derive a correlation between the web QoS parameters and the subjective web QoE, so that it can be used to identify the impact of different web QoS parameters on the web QoE of the users and moreover, estimate the web QoE objectively. This motivates research communities for further studies in quality estimation of web services. In recent years, a high amount of research work has been done on QoE assessments for voice and video services. However, little has been done on QoE assessment of web technology.

In this paper, we propose a methodology to estimate the quality of web services based on a fuzzy-rough hybrid algorithm. Fuzzy expert systems [11] are good at making decision with imprecise information; however, they cannot automatically formulate rules that they require for making the decisions. Therefore, a fuzzy-rough hybrid expert system is proposed where rough set theory is used to define the rules necessary for the fuzzy expert system. We consider three web QoS parameters: execution time, availability and reliability as important indicators for QoE estimation. These parameters have been selected because their variation affects efficiency of web services and the overall user experience; however, it must be noted that our method can also easily integrate more or other parameters. At first, we conducted subjective tests in a controlled environment with real users to correlate QoS parameters to subjective QoE, i.e., Mean Opinion Score (MOS) [12]. Based on the results from these subjective tests, we derived membership functions and rules for the fuzzy system. The probabilistic approach is used for deriving membership functions and the Rough Set Theory is used to derive rules from the subjective tests. We simulated our system in MATLAB and compared the estimated QoE output with the subjective QoE obtained from the participants in the controlled tests. The results from the experiments validated our methodology showing high correlation between our estimated QoE and the subjective QoE.

The rest of the paper is organized as follows. Section II describes the related work. In section III, the methodology for web service quality estimation is presented. In Section IV, web QoE estimation system is presented. In section V, we validate our methodology with experiments. Finally, section VI gives a conclusion and directions for future work

II. Related Works

The World Wide Web (WWW) has dominated the Internet since it has been commercialized in the year 1995. It has allowed interconnecting the world by sharing information related to daily life activities, such as, education, business, commerce, science, social networking and entertainment. This has fuelled the increase in an enormous amount of web services and applications based on web technologies.

QoE was first defined in the context of multimedia services. A high amount of research attention has been diverted towards estimating QoE and correlating network QoS with QoE of multimedia services as shown in [8], [13] and [14]. In the case of web services, user satisfaction is often measured in terms of response time. If users need to wait a longer time during web service session it will be perceived negatively. Due to the limitation of resources in mobile networks, the situation with this respect can become even more critical. The effect of response time on user behavior in the web is presented in [15], [16], and [17]. Response time is one of the important parameters; however, it is not sufficient to evaluate web services quality [18]. Two practical approaches to measure QoE are presented in [10], where a service level approach using statistical samples and a network management system approach using QoS parameters is used. Here the authors identify different key performance indicators for mobile services based on reliability (i.e., service availability, service accessibility, service access time, continuity of service) and comfort (i.e., quality of session, ease of use and level of support). However, it does not provide any methodology that could map QoS parameters to QoE.

In [19], authors propose models that allow selecting web services based on client constraints and QoS information gathered by the service providers at runtime. A new scheme for QoS-aware web services selection which exploits fuzzy logic to locate and select the right service based on the customer's preference or satisfaction degree is presented in [4]. However, works presented in [19] and [4] lack any experiments and validation of results.

In [20], the authors present a web service selection methodology based on context ontology and quality of service. In [21], the authors propose dynamic QoS computation model for web service selection based on generic and business specific criteria. A generic quality criterion includes execution price, execution duration and reputation, and business specific criteria including usability. In [22], the authors present a QoS based web service selection criteria, where they propose introducing web service ping operations in all web services for measuring web service latency and service availability. All the above web service quality estimation and selection methods ([19], [20], [21],[22] and [4]) are based on QoS parameters that lack end user participation and do not classify estimated quality into MOS scores.

A web service QoE estimation method based on a correlation function between web QoS (execution time, reliability and availability) and QoE is presented in [2]. It uses a regression analysis tool to calculate indexes of a correlation function from the subjective test data; however, the quality estimated by this method has high MOS error margin.

The main contribution of this paper is to present a novel method based on fuzzy-rough hybrid model to estimate the QoE of web services. Experiments performed show that this method correctly reflects the expected customer's preferences and satisfaction degree; and, thus, can be useful for selecting the right web service. The proposed web service quality estimation method is based on QoS-QoE correlation which is obtained through subjective tests. A fuzzy-rough hybrid expert system takes into consideration QoS-QoE correlation to rate each web services with a QoE score (which is in the range of 1 to 5 as in the case of MOS scores). The web QoE scores can effectively represent the level of the user's satisfaction (excellent, good, fair, poor or bad) towards a particular web service. Correspondingly, the scores can be used to rate different service providers. It can also be used for improving the service experience by distributing web clients towards different web service providers. For instance, the high priority web clients are served with excellent quality web services and the low priority web clients with lower quality services.

The methodology we propose relies on subjective tests. Subjective data are strongly influenced by the customer's feeling and experience. Therefore, the correlation between QoS parameters and the participant's QoE remains imprecise, uncertain or ambiguous due to various human mental states and profiles, making the preferences over the criteria hard to quantify. The fuzzy approach[11] can deal with the consumer's imprecision by creating preference relations through the use of fuzzy sets and inference rules. An advantage of using fuzzy expert systems is that they are simple and computationally less intensive. Fuzzy expert systems are good at making decisions with imprecise information; however, they cannot automatically acquire the rules they require for making the decisions. Therefore, a fuzzy-rough hybrid expert system is proposed where rough set theory is used to acquire the rules for the fuzzy expert system. Rough Set Theory is used for discovering patterns, rules and knowledge from the datasets as in [23] and [24]. Rough Set Theory has many advantages, for instance, it does not have information loss and it is flexible and extendable as compared with other data mining technologies [25].

III. Methodology

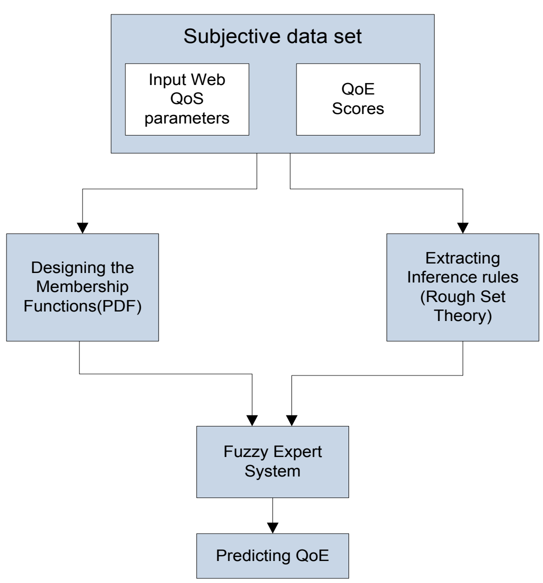

Fig. 1. Methodology for Web QoE estimation

In order to develop our web QoE estimation technique, we followed a methodology that consists of conducting subjective tests with end user participants in order to build a learning set that correlates web QoS parameters with the subjective QoE. This correlation was then used to build the membership functions and inference rules of our fuzzy expert system for web QoE estimation. The methodology for designing web QoE estimation is shown in the Fig. 1.

A. Subjective Tests

A subjective test platform used in [2] has been established to perform the subjective tests. In the experiment, an interactive web application has been developed to simulate typical web service architecture. Each user is asked to use this web application. From the user's responses a MOS score is obtained. Three QoS parameters: reliability, execution time (in seconds) and availability (in seconds) are measured during the performance of the tests.

- Execution time is measured as a delay at the server level.
- Availability: readiness for correct service [26]. In our case, it is measured as a period of server downtime, in which the service responds with *"Service unavailable, please retry again in a few moments"*after each request until a certain time has elapsed.
- Reliability: continuity of correct service [26]. In our case, it is measured as a number of consecutive erroneous responses, in which the service responds with *"An error has occurred, please try again"*, until the subject has retried the number of times defined by the test variable.

A total of 88 users have registered so far for the test which is considered reasonable for subjective tests [27]. The details of the experiments can be found in [2].

B. Membership functions

The membership functions required for fuzzy expert system are designed using subjective data sets. A membership function curve values represents the degree to which a particular QoS parameter value belongs to different QoE scores. We used a Probabilistic Distribution Function (PDF) to derive a membership function as described in [8] and [28]. For every QoS parameter, we built different probability distribution functions (PDF) (one function per QoE score) that provide the variation of the participant's ratio (%) with the QoS metric for a specific QoE score. This probabilistic information was changed into a fuzzy set by dividing the PDF by its peak value (normalized PDF) [29]. The triangular or trapezoidal fuzzy set represents the membership functions for the different QoS metrics. In our case, we reduce the five scale MOS classes to three scale MOS classes (low, medium and high) for QoS parameters because it was very difficult to find the boundary region between fair and good, and bad and poor.

Fig. 2 illustrates the QoE scores membership functions associated with the execution time QoS parameter. For example, the execution time of 2.5 seconds has membership values of 0, 1, and, 0 respectively to the QoE scores low, medium, and, high. We note that a membership value of 1 represents a high degree of membership to the corresponding class and decreasing membership value represents deviation from the class. Fig. 3 and Fig. 4 illustrate the membership functions for availability and reliability respectively. Similarly, in Fig. 5, the membership functions for the estimated QoE are defined according to the standard MOS definition [12].

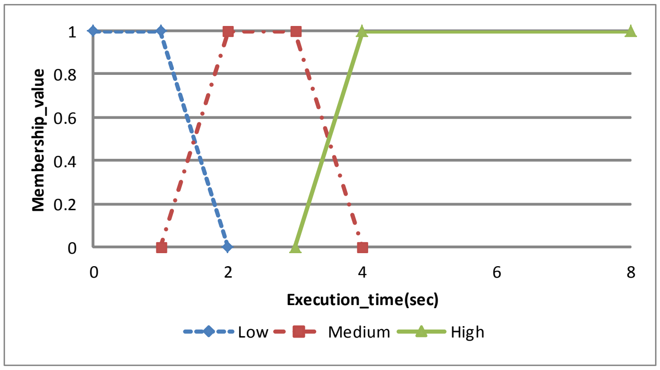

Fig. 2. Membership function for execution time

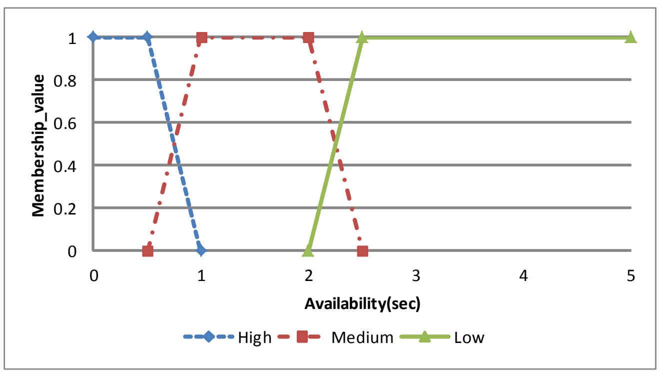

Fig. 3. Membership function for availability

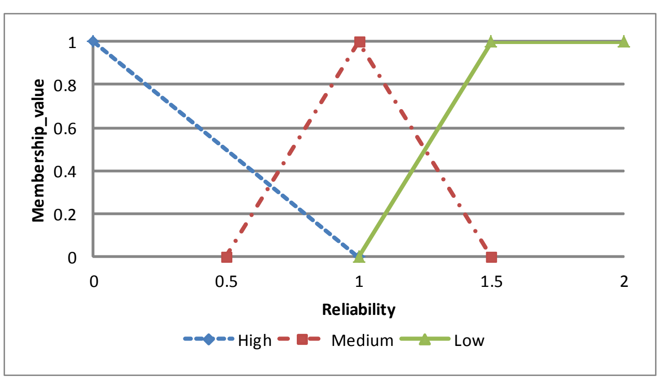

Fig. 4. Membership function for reliability

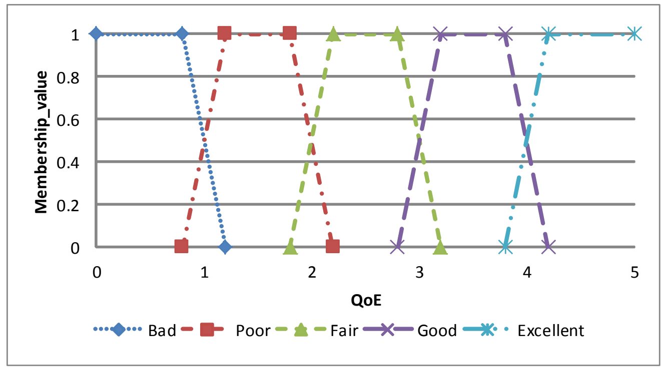

Fig. 5. Membership function for QoE

C. *Inference Rules*

We used the subjective data set to derive the inference rules for fuzzy expert system. Rough Set Theory is one of the well-known data mining techniques to generate classification/inference rules from the subjective data set [25] [23]. To apply Rough Set Theory on subjective data set, we represented subjective data set in the form of a conditional attribute set and a decision attribute set and processed it through discretization arithmetic. Here the QoS parameters represent the conditional attribute set and the QoE score represents the decision attribute set.

Out of the total subjective dataset, 10 of them are listed in Table I.

TABLE I
SUBJECTIVE TEST RESULTS

Execution time	**Availability**	**Reliability**	**QoE**
3	0	0	4
0	0	0	5
4	0	2	2
2	2.5	0	3
1.5	2.5	0	3
2	5	2	1
1	8	1	2
4	0	0	4
8	2.5	0	3
8	0	1	1

Table III is a QoE index decision making table derived from Table I and Table II. Attribute values for QoS parameters have been processed through discretization arithmetic as shown in Table II. These criteria's for different QoS parameters in Table II were selected based on observation from subjective datasets that contains only one QoS parameter variation.

TABLE II
DISCRETIZATION TABLE

Low	Medium	High
Execution time < 2 s	2 sec =< Execution time < 4 s	Execution time >= 4 s
Availability >=2.5 s	1<= Availability <= 2.5 s	Availability < 1 s
Reliability >=2	Reliability =1	Reliability =0

TABLE III
QOE INDEX DECISION MAKING TABLE

Execution time	Availability	Reliability	QoE
Medium	High	High	Good
Low	High	High	Excellent
High	High	Low	Poor
Medium	Medium	High	Fair
Low	Medium	High	Fair
Medium	Low	Low	Bad
Low	Low	Medium	Poor
High	High	High	Good
High	Medium	High	Fair
High	High	Medium	Bad

We used the Rosetta software [30] which is a Rough Set toolkit for analysis of datasets to generate inference rules. The Johnson's greedy algorithm [31] is used to find the reduct. If a rule predicts more than one QoE class then the QoE class with the highest accuracy is considered. 15 rules were generated, which were used by the fuzzy expert system for estimating the QoE. 3 out of 15 rules are shown below:

- *If (Execution_time is Low) and (Availability is High) and (Reliability is High) then (QoE is Excellent)*
- *If (Execution_time is Medium) and (Availability is High) and (Reliability is High) then (QoE is Good)*
- *If (Execution_time is Low) and (Availability is Low) and (Reliability is High) then (QoE is Poor)*

D. Web QoE Estimation System

Our proposed web QoE estimation system is based on fuzzy logic that is powered with a learned membership functions and a set of fuzzy inference rules. Fig. 6 illustrates the web QoE estimation system. The fuzzy expert system with pre-defined membership function and inference rules (Section III.B and Section III.C) acts as an intelligent system for web QoE estimation. The web QoS parameters are constantly fed to the fuzzy expert system that uses the pre-defined membership function and inference rules to estimate the web QoE.

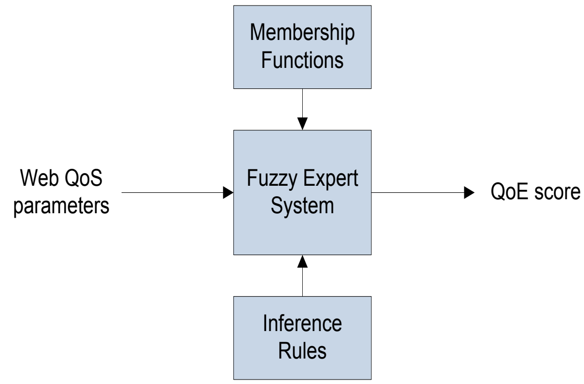

Fig. 6. Web QoE estimation system

IV. EXPERIMENTAL RESULTS

A. Validation of the Proposed Methodology

To validate the proposed methodology, we compared the results obtained from the subjective tests with those obtained from our proposed system. For this, we used the Fuzzy logic toolbox of MATLAB [32] and developed a simulation scenario with our membership function and rules for validation. Test cases with different input values were used for validation. For each test case, we obtained subjective QoE from subjective tests; and, estimated the QoE using our system simulated in MATLAB. Each red point in Fig. 7 represents the subjective QoE of a particular test case and blue points represent the estimated QoE. We should note here that the estimated QoE obtained by our system has a maximum value of 4.51 and a minimum value of 0.523. This is due to the centroid method used for defuzzification in the fuzzy expert system [11]. These results indicate that the proposed system succeeds in reflecting the user's perception. This is also illustrated in Fig. 8 that considers the probability distribution of the difference between the subjective scores of QoE and the estimated QoE scores. We can see that in around 80% of the test cases the score differences were less than 0.5. This estimation accuracy emphasizes the ability of the proposed system to measure the QoE of web services.

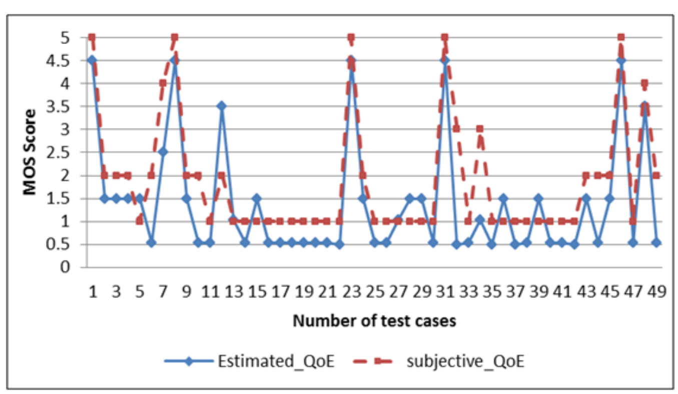

Fig. 7. Comparision between subjective and objective QoE

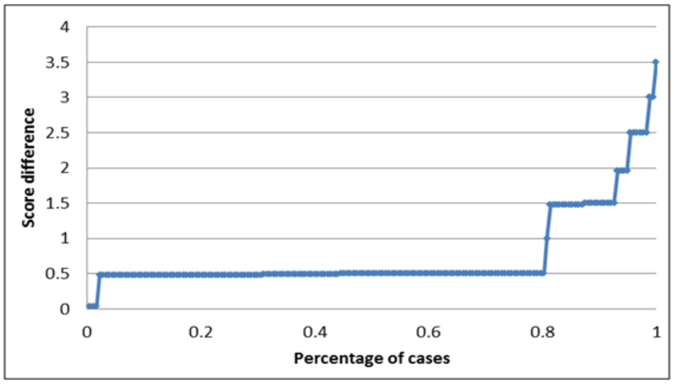

Fig. 8. Probabiltiy distribution of the subjective and estimated QoE difference

V. Conclusions

In this paper, we proposed a novel method based on fuzzy-rough hybrid expert system for estimating QoE of web services. We have performed a set of subjective tests with real participants in order to correlate web QoS parameters levels with the user perceived quality. The defined fuzzy membership functions were derived from the QoS/QoE correlation using probability distribution functions. We use a Rough Set Theory to generate estimation inference rules. The proposed methodology has been validated against the results of subjective tests. The validation results shows that our QoE estimation method is highly correlated to the participant's subjective QoE scores. The estimated QoE from web QoS parameters can be used as a selection criterion for different web services. In future work, we plan to also consider the contextual parameters for QoE estimation, as well as implement the solution in different web service frameworks.

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