

UDC 656.007.4: 656.007.4(045)
DOI:10.18372/1990-5548.80.18691

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QUALITATIVE QOE ASSESSMENT WHEN CHOOSING A WEB SERVICE USING AN EXPERT HYBRID SYSTEM

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Abstract—In the article proposes a new method, based on a hybrid fuzzy expert system, for assessing the QoE of web services. It also shows how different QoS parameters affect QoE. To do this, a subjective test was conducted in a controlled environment with real users to correlate QoS parameters with a subjective QoE score. Based on the test results, affiliation functions and rules for the fuzzy system were obtained. The membership function is derived using a probabilistic approach, and the derivation rules are generated using fuzzy set theory. The evaluation of the results was carried out in a simulation environment using the Matlab software package. The results of the simulation show that the quality of the website is rated and has a high correlation with the subjective quality assessment received from the participants of the control test.

Index Terms—Web services; QoE; intelligent systems; information and communication technologies.

I. INTRODUCTION

In recent years, the popularity of web services has been growing rapidly, leading to the emergence of web services or applications with similar features. Web services (WS) are self-contained software systems that can be published, advertised, located, and invoked over the Internet, typically relying on standardized XML TECHNOLOGIES (REST, SOAP, WSDL, and UDDI [1] for description and publication, as well as Internet protocols for calling [2]. This offers users a range of options and places higher demands on price, response time, availability, reliability, service performance, and other non-functional attributes for web service selection.

The availability of many web services that provide similar functionality has increased the need for complex processes and an increase in the number of web services that can better meet the needs of users. The discovery process is the process of identifying or locating a web service that performs certain functional properties. On the other hand, the selection process refers to the evaluation and ranking of discovered web services to select the one that corresponds to a set of non-functional properties [3]. As stated in [3], "functional properties describe what a service can do, and non-functional properties describe how a service can do it." Non-functional properties include qualitative or quantitative characteristics such as throughput, latency, response time, integrity, availability, security, etc. [4], [5]. However, a selection process that relies on only a

partial set of non-functional properties can be misleading, as it will not necessarily reflect user satisfaction. Thus, a certain methodology is proposed, which considers several parameters to assess the expected user experience, and each of them has a certain impact on the score obtained.

II. PURPOSE AND TASK STATEMENT

Quality of Experience (QoE) has become an important metric useful for network operators and service providers to help them understand user acceptability for a particular service or application. The paradigm is shifting towards user-centered performance evaluation of services or applications.

To attract users to the service, real-time QoE assessment is a must for network operators and service providers. QoE is defined differently depending on the application [6], [7]. ITU-T defines QoE as the overall acceptability of an application or service that is subjectively perceived by the end-user. QoE is analyzed by tests with real users in a controlled environment for a correct assessment, but it is time-consuming. Therefore, tools or methodologies are used that can objectively represent subjective indicators of the use of a service that affects the quality of life [8].

Users' demand and expectations for web technologies are constantly growing. Users are reluctant to wait if content is not served at the expected time and are easily changed to other options if their needs are not met. About 90% of people do not want to complain about the poor

quality of services. The web service that provides the service changes to another. Therefore, service providers and operators do not wait for feedback from users to improve the quality of service, instead, they constantly monitor the quality of the services provided and improve it as needed. By providing services to users, operators offer high QoE.

Generally, QoS parameters are used to select web services, which do not necessarily reflect the user's satisfaction with a particular web service. QoS parameters reflect network performance and service levels, but they do not address how a user responds to a service or application. In contrast, QoE reflects a user's satisfaction with a particular web service, however, it is evaluated subjectively. Thus, it is necessary to derive a correlation between the parameters of web QoS and subjective web QoE so that it can be used to identify the impact of different parameters and, objectively, evaluate QoE. This motivates research communities to further research in the field of assessing the quality of web services, where in recent years many studies have been conducted to assess the quality of services provided for voice and video services [2]. However, this is not enough.

III. PRESENTATION OF THE MAIN MATERIAL OF THE RESEARCH

This paper examines the problem of assessing the quality of web services based on a hybrid algorithm. Fuzzy expert systems [11] can effectively make decisions with inaccurate information, but they cannot automatically formulate rules for decision-making.

It is proposed to create a hybrid expert system, where set theory is used to determine the rules necessary for expert evaluation. The quality of web services is assessed based on three quality of service (QoS) parameters: lead time, availability, and reliability. These options are chosen because of their impact on the performance of web services and the overall user experience. However, the technique can also easily integrate other parameters for better performance. The paper describes a new approach to the use of QoS as a criterion for selecting WS, including an analysis of the various influencing factors affecting perceived quality, as well as a methodology for measuring QoE and establishing a correlation model between QoS / QoE. In addition, several real-world experiments were conducted with a group of end-users, and the results were illustrated.

Quality of Experience Assessment Methodology was first defined in the context of multimedia services. Much research has focused on assessing the QoE and correlation of network QoS as shown in

[8], [13], and [14]. Web Services (WS) are self-contained software systems that can be published, advertised, hosted, and called over the Internet, usually relying on standardized XML technologies (SOAP, WSDL, and UDDI [1]) to describe and publish, as well as the Internet protocols for the call.

The main advantage of web services is the encapsulation of the provided functionality, which can be automatically found by other applications or even combined [2] with other services to provide more complex functionality. With the increase in the supply of new services, choosing the most profitable service from several alternative options is impossible without means of comparing different providers. For this reason, QoS extensions for discovering web services have been proposed [3], as well as numerous papers on QoS-oriented methods for selecting web services. However, network QoS metrics such as load time, bandwidth, round-trip time, or QoS metrics of web services, such as availability, runtime, and accuracy, do not necessarily reflect the perceived quality of the end-user (who will use the created service) or satisfaction with the service. This is the main motivation for the Quality of Experience research [8], [9].

In article [19], the authors propose models that allow web services to be selected based on client constraints and QoS information collected by service providers at runtime. A new QoS-based web service selection scheme that uses fuzzy logic to find and select the right service based on customer preference or satisfaction is presented in [4]. However, the papers presented in [19] and [4] do not have any experiments or confirmation of the results.

In article [20], the authors analyze the methodology for choosing a web service based on contextual ontology and quality of service. In article [21], the authors propose a dynamic QoS computing model for selecting a web service based on general and business-specific criteria. The overall quality criterion includes lead price, lead time, and reputation, as well as business-specific criteria, including usability. In article [22], the authors present QoS-based criteria for selecting web services, where they propose to introduce web service ping operations across all web services to measure web service latency and service availability. All of the above methods for assessing the quality of web services ([19], [20], [21],[22], and [4]) are based on QoS parameters that do not have end-user input and do not classify the estimated quality in MOS scores.

A method for estimating the QoE of a web service, based on the correlation function between

web QoS (runtime, reliability, and availability) and QoE, is presented in [2]. It uses a regression analysis tool to compute the scores of the correlation function from subjective test data; however, the quality assessed by this method has a high MOS (Mean Opinion Score) error.

The main purpose of the study is to use the new Fuzzy expert method, based on a hybrid model used to assess the QoE of web services. With fuzzy expert systems that operate based on fuzzy logic, rules derived from fuzzy expert preferences provide results. A hybrid system that combines a neural network and a rule-based expert system is called a neural expert system (or a connectionist expert system). The basis of the neural expert system is the inference mechanism. It controls the flow of information in the system and initiates inference from the neural knowledge base.

The proposed Fuzzy expert method reflects the expected user preferences and the degree of satisfaction with the services provided, which can be useful for choosing a web service. The method of assessing the quality of a web service is based on the correlation between the quality of service (QoS) and the quality of user experience (QoE), obtained by conducting subjective tests. Thus, the proposed method will serve as an effective tool for choosing the most reliable web service in terms of expected user needs.

The expert system takes into account the QoS-QoE correlation, and the evaluation of the web service using the QoE indicator (which ranges from 1 to 5). Internet QoE metrics effectively reflect the level of user satisfaction (excellent, good, fair, bad) about a particular web service. Accordingly, assessments can be used to evaluate different service providers. It is also used to improve service by distributing web clients among different web service providers.

The methodology that is proposed relies on subjective tests. The data is influenced by the customer's feelings and experience. Thus, the correlation between the participant's QoS and QoE parameters remains inaccurate, and uncertain due to the different mental states and profiles of the individual, making it difficult to quantify preferences over the criteria. A fuzzy approach [11] can deal with consumer inaccuracy, creating an advantage through the use of fuzzy inferences. The advantage of using fuzzy expert systems is that they are simple and less computationally intensive. Fuzzy expert systems are good at making decisions with inaccurate information; However, they can't automatically learn the rules they need to make decisions. Therefore, a hybrid expert system Fuzzy

expert is proposed. Such a system is used to identify patterns, rules, and knowledge from a set of indicators [23] and [24] and has many advantages, is flexible and advanced compared to other data mining technologies [25].

The concept of quality of experience (QoE) refers to the subjective quality of a system, service, or program perceived by a user. A more commonly cited definition can be found in [10] as: "*the overall acceptability of an application or service as subjectively perceived by the end user.*" However, there is an understanding that while QoS corresponds to objective parameters of the quality of a network or service, QoE corresponds to a measurable property that represents the subjective quality, the service assigned by the end user, the property affected by the QoS, as well as other factors. The hypothesis, of course, is that correlation, or predictive model, is created to reflect the relationship between QoS and QoE.

Quality of Experience is a concept first introduced to describe the perceived quality of audio and video transmission [12], and the correlation between QoE and QoS networks has been explored in the literature [13], [14], [16]. However, it has been expanded to describe the quality of a wider range of services, including web-based applications. Here, the tasks are different from the measurement of multimedia QoE, especially because the usability [20] becomes an important factor. Nevertheless, even though work has been done to measure QoE on the Internet, these works only look at the impact of network QoS network parameters such as bandwidth, round-trip data time, and download times. It is known that no work has considered the effect of the QoS parameters of a service on the measured QoE. To effectively use QoE as a criterion for choosing a web service, a parallel is drawn between the QoS parameters of the network and the service. The paper describes a solution for using the quality of experience as a criterion for choosing web services, including the analysis of various influencing factors that may affect the end-user's perception of quality, as well as the methodology for measuring QoE and creating a correlation model between QoS / QoE. A consultant conducting consumer surveys provides an online analysis tool to help their clients in decision-making by obtaining initial information about promotions using a web service from one or more providers. Since all WS providers return the same data, the analysis tool can select the best provider according to the QoS to ensure the best quality for end-users.

The choice usually works as follows [21], [7]: providers advertise a service with a certain QoS score,

which is usually divided between lead time (q_1), reputation (q_2), success rate (q_3), availability (q_4) and execution price (q_5). The service requester (analysis tool) assigns a weight to each QoS parameter (w_1 for q_1 , w_2 for q_2 , etc.) and selects the best service according to the evaluation function, for example

$$score(s_i) = \sum_{j=1}^5 w_j q_j(s_i). \quad (1)$$

Used in [7] to describe the evaluation of the SI service (from the service provider i). Obviously, when we are dealing with web service composition (calling multiple services in a workflow), the choice is much more difficult, however, a single service example is sufficient for our research. Temporarily exclude the execution price from the QoS parameters (since it does not indicate the quality of service) and rename the score function to

$$QoS(s_i) = score(s_i) = \sum_{j=1}^4 w_j q_j(s_i), \quad (2)$$

with the weight of w_i as unknowns, suppose we can establish a relationship with QoE in this way,

$$QoS(s_i) = F(QoS(s_i)) = F\left(\sum_{j=1}^4 w_j q_j(s_i)\right), \quad (3)$$

where F and w_i depend on the QoS / QoE ratio. With this formula, the tool can now use QoE as a selection criterion. In other words, the tool can use a formula to select the service that will provide the best QoE for the end user, and if there is a strike price defined for the service, then the tool only needs to optimize

two variables (the best QoE given price constraints). The first step in this process is to determine the F and w_i values and to establish whether there is a good match between QoS and QoE for web services. This is exactly the basis that is in this work. As can be seen from the above description, it is possible to distinguish several entities involved in the research methodology that ensures the use of the web service. Figure 1 shows the path between the web service provider and the end user, as well as the factors that affect QoE.

Web Service Provider: Provides the requestor with a web service interface to perform the operation. Figure 1 shows only one provider, there may be multiple providers for one type, or for multiple services in the case of composition.

WS requester: it accesses one or more web services to provide a value-added service. In the example above, the WS requester corresponds to an online inventory analysis tool.

In the case of a composition of several web services, a WS querier may also be called an orchestrator.

End Customer: Provides an access interface between the end user and the value-added service provided by the WS requester.

To establish a relationship between QoS and QoE for web services, QoS attributes are defined that describe the performance of a web service and how they can be measured.

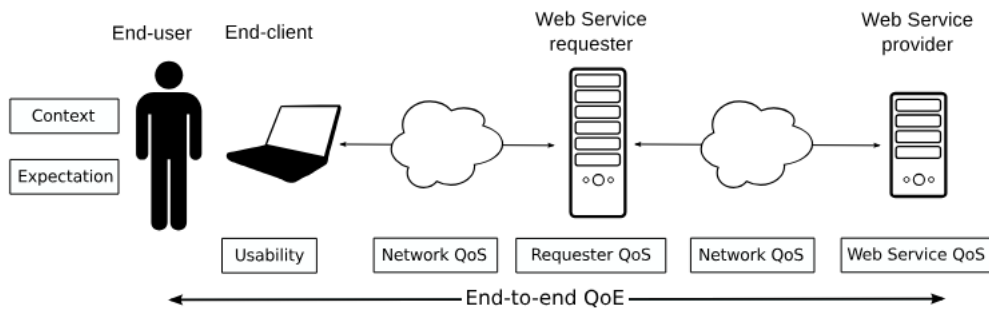


Fig. 1. Influence on QoE (factors)

Many QoS attributes are defined in the works [22], [3], so we will only list and briefly describe only those that have a direct impact on the quality perceived by the user. They are described as follows.

Lead time: The time between sending a request and receiving a response. In some works, [3] is also referred to as productivity. In the paper [3], it consists of:

1) duration of transmission, i.e. the time elapsed between sending / receiving a request and sending / receiving a request, which is added to the time between sending/receiving and sending/receiving a response;

2) delay, i.e. the time elapsed between the receipt of the request and the request served by the web service; iii) processing time, the time it takes for the provider to process the service request.

For the service s , the execution time (q_{du}) of the service to perform the op operation is given by the formula

$$q_{du}(s, op) = T_{trans}(s, op) + latency(s, op) + T_{process}(s, op), \quad (4)$$

Availability: The probability that a service is available. It is defined as the ratio between the time

when the service was available $T_{av}(s)$ and the given I_{av} testing interval. Denoted by,

$$q_{av}(s) = T_{av}(s) / I_{av}, \quad (5)$$

Reliability: This is the probability that the request will be fulfilled within the maximum time. It is calculated as the ratio between the number of successful $N_{su}(s)$ calls and the total number of $N_{total}(s)$ hits. Denoted by the formula

$$q_{su}(s) = N_{su}(s) / N_{total}(s). \quad (6)$$

Although they are not directly related to performance, it is also important to mention two other attributes that are usually taken into account in the QoS composition literature [7].

Execution Price: This is the cost that the requesting web service must pay to perform the web service operation. But this may not directly affect the end user but should be considered when choosing a service. The price of the operation performed by the service s is denoted as $q_{pr}(s, op)$.

Reputation: Corresponds to the average rating given to the service by previous requesters. Since we intend to use end-user perception as a metric for a web service in this paper, we do not consider this attribute. However, it can be interesting to compare the selection results when the end-user's perception is considered and when the rating of the requesters is considered to see which approach produces better results. Such a comparison, however, goes beyond this work. To create a robust model for QoE, it is necessary to identify the factors that can influence how the user perceives the service. Figure 1 shows the various factors that can affect end-to-end QoE that need to be monitored to isolate the factors that affect the quality of service in the network. The various factors are described below.

Network QoS: Described by factors such as bandwidth, packet loss, etc. Notice in Fig. 1 that it is necessary to distinguish between two network connections to be distinguished: the relationship between the requester and the selected service and the communication between the specific client and the requester. In general, it is assumed that the quality of the connection between the requester and the service is constant, given the static nature of both nodes. This can be seen in the definition of runtime, where the transmission time is considered as part of the metric. However, the same cannot be the case when there is a connection between the end customer and the requester, as the customers can be anywhere. Sequential requests from the same entity

should have a slight variation that we can use to measure *QoE*.

Requester QoS: Considers factors such as response time and throughput. This factor can be controlled in the experimental setup, however, the requester must be provided with a good *QoS* to avoid bias in the results.

Usability: refers to the ease of use and ease of learning of the application interface between the end user and the end client [20]. Although in an experimental setup, usability remains more or less constant, usability guidelines are taken into account to minimize the impact on the results.

Context: Takes into account factors such as user experience, age, gender, environment, etc. These factors must be controlled under experimental conditions.

Expectation: refers to the quality that the user expects from the service received and it may vary from service to service. For example, a user is likely to expect higher quality from a paid service than from a free one.

The measurement methodology consists of introducing a controlled variation of some variables of interest (WS QoS attributes) and the remaining variables are either captured through a controlled experiment or keeping accurate measurements of the remaining variables of variation.

For this reason, the service downtime is used as a variable instead of the previously provided formula.

1) The test suite is determined based on combinations of control variables q_i ($1 \leq i \leq n$, for n variables). Each test subject is assigned a subset of tests.

2) Before starting the test, the subject is asked to evaluate the service under normal conditions (without supervision) in order to establish a baseline for measurement. The assessment is carried out using the MOS (Mean Opinion Score – MOS) scale [24]. The baseline serves to isolate the variables of interest from other factors that may influence the results, but it is expected that they will remain the same for the same subject of study. The experiment is designed in such a way as to measure $\Delta q_{oe} / \Delta q_1 \dots \Delta q_n$, where the variation of the constant factors is zero (e.g., $\Delta_{suitability} = 0$).

3) Each subject undergoes the tests assigned to him one by one, and evaluates the service on the MOS scale.

4) Normalized values for each q_i variable, represented in terms of q_i and correlated with the value obtained from the MOS score, show the effect (w_i weight) of each factor on QoE. The value is calculated using Pearson's linear correlation

coefficient, which is determined by the following formula:

$$w_i = \frac{\sum_{k=1}^n (q_{i,k} - q_i)(q_{oek} - q_{oe})}{\sqrt{\sum_{k=1}^n (q_{i,k} - q_i)^2} \sqrt{\sum_{k=1}^n (q_{oek} - q_{oe})^2}}. \quad (7)$$

where q_{ik} is the normalized value of the parameter. To conduct subjective tests, a test platform was created, which is used in [2]. The variable \tilde{q}_i in test k , and q_{oek} is the score given by the user in the same test.

5) A regression analysis is carried out between results $score(q_1 \dots q_n) = \sum_{j=1}^n w_j g_j$ and results QoE in order to obtain the function $q_{oe} = f(q_{os})$, and $q_{os} = score(q_1, \dots, q_n)$.

6) Since the basic line of operations was used for the previous operations, the final function is obtained using

$$q_{oe} = \int f(q_{os}) dq_{os}, \quad (8)$$

An experiment was conducted to test our methodology. A web application that imitates the typical architecture of a web service has been developed. The service used for the experiment is very simple, to minimize usability problems, consists of a simple form where the user of the service (the subject) enters two numbers, and the simulated WS corresponds with the sum of the numbers. The variation in quality is counted when generating a response. For the experiment, only three variables are controlled: – execution time, controlled as server-level latency. In addition, both the total server response time and the client response time (calculated using client-side JavaScript) are stored for analysis. The following values are used for this variable [0.0, 0.2, 0.5, 1.0, 1.5, 2.0, 3.0, 4.0, 8.0] in seconds - Availability, controlled as a period of server downtime, during which the service responds "Service unavailable, please try again in a few minutes" after each request until the time runs out. The number of requests executed during this time is also recorded for analysis. The values used for this variable are [0.0, 1.0, 2.5, 5.0, 8.0] in seconds – reliability, controlled as the number of consecutive false responses, to which the service responds "An error occurred please try again" until the subject tries a few more times. The values used for this variable are [0, 1, 2]. The test suite is defined by all combinations of the three variables, meaning there are 135 alternative tests. Each study subject was assigned 10 random tests during registration. The experiment was posted online using Google's cloud service App Engine 2. This service was chosen because of its high reliability and distributed

architecture. The hired service was of the F2 type, which is equivalent to a server with a clock speed of 1200Mhz and 256MB. Some contextual information was requested to support the analysis.

Eighty-eight people registered to participate in the experiment, of whom eighty-one started testing, and only sixty-one passed the full set of tests. This means that a total of 671 data points were collected, but unfortunately about 4.5 scores on average for each of the 135 possible tests. The average of the scores predicted that respondents are more confident about QoE only when the quality is too poor or too good.

Figure 3 in combination with Fig. 2 gives an idea of the most influencing factors on user perception of quality. Worst Quality Quality is worst when the availability and reliability scores take on high values, indicating that these values have a greater impact on QoE than lead time. This is supported by the correlation index in Table I, which show that the reliability variable has the greatest impact, with a weight of 0.412. With such weights, it is best to approximate the q_{oe} function $f(q_{os})$ exponentially and the cubic function, as determined using a regression analysis tool to calculate function indices, and using the R_2 index and χ_2 red (reduced chi-squared) when comparing. However, given the first results, none of these curves are optimal: the result $R_2 = 0.483$ and χ_2 red = 0.404 was obtained for the cubic fit, and $R_2 = 0.327$, χ_2 red = 0.519 for exponential fit. The display of the results on the curve is shown in Fig. 4.

The results do not consider contextual information (country, language, age, and gender) and the impact of network latency between the user and the server, as both factors may have affected the quality rating given by the respondents. A more detailed analysis will be provided when the results are available. In this article, we have presented our new solution for selecting web services using Quality of Experience as a criterion for selecting web services. Value of $R_2 \sim 1$ or χ_2 in red ~ 1 indicates a "good" match for the data. By establishing a correlation between the user's perception of quality, user-perceived quality, and traditionally used WS QoS parameters, it is considered that service providers can provide value-added services that better meet users' quality expectations. The paper analyzes the factors that affect QoE in WS, as well as a methodology for establishing a correlation function between QoS and QoE of a web service. The results show how the runtime of a web service, runtime, availability, and reliability of a web service affect the quality perceived by the end user and indicate that both availability and reliability have a much greater impact on QoE than the runtime of a web service.

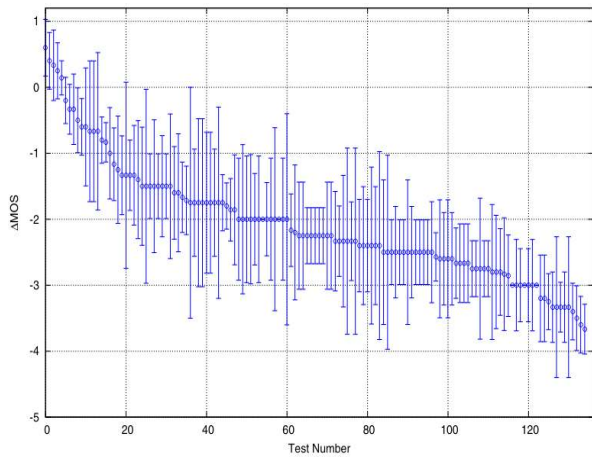


Fig. 2. Quality is ordered by decreasing MOS

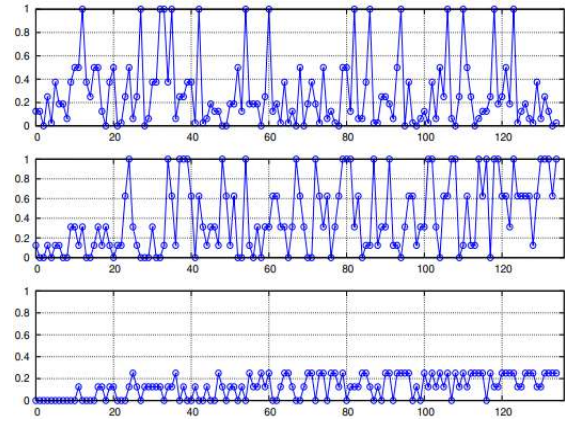


Fig. 3. The value of the QoS variables per test number is ordered by decreasing MOS (1 – runtime; 2 – availability; 3 – validity)

TABLE I. PEARSON CORRELATION SCORES

q_i	w_i
Exec. Time	0.0343100527874
Availability	0.328105361312
Reliability	0.41278445043

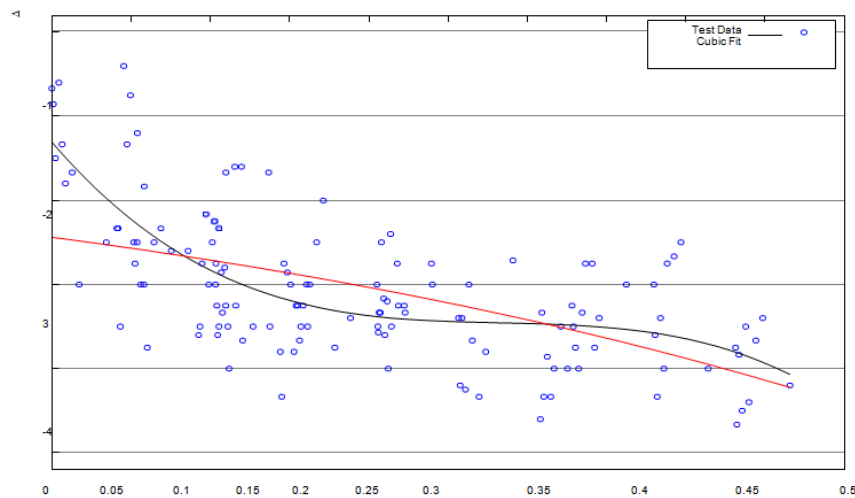


Fig. 4. Coefficient for the relationship between QoE and QoS (Exponential and Cubic)

VI. CONCLUSIONS

The conclusions drawn from the study allow us to note several key points. First, the analysis did not take into account contextual factors such as country, language, age, and gender of respondents, as well as the impact of network latency between the user and the server. These aspects could significantly influence the quality ratings given by users. A more detailed analysis that takes these factors into account will be provided later, allowing for a more accurate

assessment of the quality of web services. Secondly, the paper proposes a new solution for selecting web services based on the Quality of Experience (QoE) criterion. An R^2 value close to 1 or a χ^2 value of 1 indicates a good fit to the data, which confirms the correctness of the applied methodology.

Third, there is a significant correlation between users' perceived quality (QoE) and traditional web service quality (QoS) measures. This opens up the opportunity for service providers to offer value-added services that better meet user expectations. Fourth, the

analysis of factors influencing QoE showed that parameters such as the web service execution environment, availability, and reliability significantly influence the quality perceived by the end user. What stands out is that web service availability and reliability have a greater impact on QoE than the web service runtime environment. This suggests that to improve user satisfaction, web service providers should focus their efforts on improving the availability and reliability of their services.

Fifthly, the results of the study can be useful to web service providers to improve the quality of services provided. By focusing on improving availability and reliability, they will be able to significantly improve user satisfaction, which will ultimately lead to improved user experience and customer loyalty. Sixth, given the identified correlations between QoS and QoE, it can be concluded that traditional QoS parameters, such as response time and throughput, are important, but not the only aspects that influence user perception of quality. Seventh, the study shows that, despite the importance of technical characteristics, it is the subjective perception of the user, reflected in QoE, that is the decisive factor when choosing a web service.

Finally, a more detailed analysis will be conducted later to take into account contextual factors and the impact of network latency to more accurately assess the quality of web services. This will provide a more complete understanding of the factors that influence QoE and provide solutions that will more effectively meet user expectations. Thus, the findings can serve as a basis for further research and development of strategies to improve the quality of web services, taking into account various contextual factors and technical characteristics, which will ultimately enable service providers to provide better and more satisfying services to users. This study makes a significant contribution to the understanding of how various aspects of web services influence users' perceptions of quality and proposes a new approach to selecting web services based on the Quality of Experience criterion, which may lead to significant improvements in the field.

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Received March 19, 2024

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В. Г. Вовк, П. Р. Пелех. Оцінка Qoe для вибору веб-сервісу за допомогою гібридної експертної системи

У статті запропоновано новий метод, заснований на гібридній нечіткій експертній системі, для оцінювання QoE веб-сервісів. Також показано, як різні параметри QoS впливають на QoE. Для цього було проведено суб'єктивний тест в контрольованому середовищі з реальними користувачами, щоб співвіднести параметри QoS з суб'єктивною оцінкою QoE. На основі результатів тесту отримано функції належності та правила для нечіткої системи. Функція належності отримана з використанням імовірнісного підходу, а правила виводу згенеровані за допомогою теорії нечітких множин. Оцінювання результатів проведено в середовищі моделювання за допомогою програмного комплексу MATLAB. Результати моделювання показують, що якість веб-сайту, оцінена та має високу кореляцію з суб'єктивною оцінкою якості, отриманою від учасників контрольного тестування.

Ключові слова: веб-сервіси; QoE; інтелектуальні системи; інформаційно-комунікаційні технології.

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Кількість публікацій: 50.

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Напрямок наукової діяльності: інтелектуальні системи, веб-сервіси, QoE, QoS.

Кількість публікацій: 3.

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