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# An Effect of User Experience on A Data-Driven Fuzzy Inference of Web Service Quality

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**Abstract**

Today, various stakeholders provide a large number of functionally similar Web Services (WS) to meet increasingly complex business needs. Therefore, to distinguish similar WS, some researchers have proposed using the non-functional characteristics, named Quality of Service (QoS), and user's needs, expressed through Quality of Experience (QoE). Thus, all those QoS and QoE attributes should be taken into account in predicting WS quality jointly, called WS QoSE (Quality of Service and Experience). However, these attributes are different in nature, i.e., QoS is data-driven and numerical, while QoE is expert-based and linguistic. Consequently, to predict WS QoSE, in this paper, we propose a hybrid fuzzy inference approach, composing both quantitative and qualitative data inputs into WS QoSE output by applying the adaptive neuro-fuzzy inference system (ANFIS). The developed prototype allows us to implement the proposed approach, investigate its performance, and study the effect of QoE attributes on WS QoSE. The results of the two experiments show good performance and suitability of the proposed hybrid fuzzy inference approach for predicting WS QoSE based on combining QoS and QoE attributes. We expect that those results inspire researchers and practitioners to understand the WS QoSE better and develop user needs matching WS.

**Keywords:** web service, fuzzy prediction, quality of service, quality of experience, ANFIS.

## 1 Introduction

Recently, service-oriented architecture (SOA) has been employed by stakeholders since it offers a standard way of achieving interoperability between heterogeneous systems, regardless of the technology and platform of their implementation [5].

However, an atomic web service (WS) has limited functionality and, therefore, cannot always satisfy complex and vaguely defined users' needs and appropriately reflect sophisticated business processes

[5]. For this reason, stakeholders provide a plethora of WSs with similar functionality. Therefore, to distinguish similar WSs, some researchers have proposed using the non-functional characteristics, like availability, reliability, response time, etc., named Quality of Service (QoS) [16],[11], source code metrics [39], assessing cloud QoS using OWA in neural network [18], QoS (Response Time and Throughput) prediction based on the deep fusion of features [12], etc. These characteristics depend on WS implementation and development quality (i.e., taken from the technological level and data-driven) and can be evaluated automatically.

Other attributes, like a service design, ease of use, cost, reputation, satisfaction, etc., depend on the user satisfaction with WS. They are subjective and significantly depend on the user's preferences, mood, morale, interests, and other subjective factors and unpredictable reasons [27],[33]. These informal and human-dependent characteristics are known as the Quality of Experience (QoE) for WS [21]. They are qualitative and can be evaluated through surveys.

Summing up, both QoS and QoE attributes [47] should be taken into account in predicting WS quality jointly, called Quality of Service and Experience (WS QoSE).

Nevertheless, some authors propose WS QoS/QoE determining approaches, they are insufficiently personalized and accurate [4],[31],[1]. It is unclear what quality attributes should be considered and how to measure them [16]. In addition, QoS values from WS providers do not reflect the real WS QoE value, i.e., they differ for various users, depend on a context, and dynamically change over time according to several parameters [38]. Moreover, for incorporating QoE into WS quality assessment, we need real data on the user's experience or/and satisfaction. However, QoE data is missing in many problem domains. In [41], the authors used a real-world QWS Dataset [2] for QoS attribute values and the Amazon customer review feedback dataset [3] for QoE values. However, QoE remains subjective, and its evaluation is expensive and tedious, requiring a high human involvement [6]. So, considering that users cannot invoke all WS to obtain QoE due to increased time cost and huge resource overhead [49],[53], the involvement and use of domain experts to obtain WS QoSE values makes sense and is applicable in this paper. Authors of [29] use interviews, questionnaires and web-based surveys to get subjective information from users about products or services. Authors of [21] created a synthetic dataset for WS recommendation that contained actual user reviews of services published on service portals, and mapped these reviews to the services in WS-DREAM dataset. In [7], the WS-DREAM dataset is used for WS quality prediction in Cloud computing and the Internet of Things (IoT) using Graph Convolutional Network. Authors of [17] use the same the WS-DREAM dataset with the collaborative filtering (CF) method for QoS prediction.

Authors of [26] showed that three analysed QoS metrics (i.e., packet loss, latency, and jitter) have a very significant relationship with the QoE of IoT services. The authors [34] have stated that the QoS and QoE concepts are often studied separately, and making the comprehensive quality analysis is problematic and not trivial. Therefore, they have studied QoS and QoE in mobile applications and found that QoS attributes directly impact QoE perceived by the user.

Summing up, the question under consideration is *how to combine QoS and QoE into QoSE?* and *how does the inclusion of QoE attributes in the prediction affect the final QoSE?*

The Bayesian approach is popular to combine subjective judgment or prior experience with test samples data [40], to personalise manufacturing service recommendations [52], to evaluate multivariate QoS attributes at run-time [51]. However, the authors proposed weighted Bayesian Runtime Monitor [50] approach sometimes produces false positives and false negatives errors that decrease the capacity of making decision. The main advantage of using the Bayesian approach is augmenting the quality of data, thereby reducing the uncertainty of decision-making [40].

Since quality is a vague and subjective concept, it is recommended to model and assess it by applying a fuzzy inference [36],[45]. Fuzzy controllers, such as Mamdani, Sugeno, etc., are the most widely used in practice since they provide satisfactory results with quantitative numerical data input [48]. Also, the adaptive neuro-fuzzy inference system (ANFIS) it allows us to get more successful and accurate results in prediction [24]. Therefore, in this research, we apply ANFIS for data-driven WS QoS prediction.

The main aim of this paper is to extend the concept of WS QoSE by investigating how to combine QoS and QoE into QoSE employing fuzzy inference approach, and investigating how the inclusion of

QoE attributes in the prediction affects the final QoSE. Consequently, this paper proposes a hybrid fuzzy inference approach for predicting WS QoSE with ANFIS. The advantage of the research is that we have supplemented and combined objective measures of real WS from the WSDream dataset by collected real-world subjective measures (expert evaluations) of QoE on the same WS dataset. Consequently, a complete picture of service quality is obtained during the WS planning process.

The main advantages and scientific contribution of this paper are as follows:

1. A proposed new hybrid fuzzy inference approach composes both quantitative and qualitative data inputs and formalize the vague concept of QoSE.

2. The proposed approach assesses the WS quality from the user's perspective, not just from a numerical perspective.

3. The proposed approach employees the content separation principle of the subjective and objective quality attributes, which are combined into WS QoSE through their combination by fuzzification and normalization.

4. The successful implementation and demonstration of the hybrid fuzzy inference WS QoSE planning system demonstrates its design contribution.

5. The proposed approach and its implementation into the hybrid fuzzy inference WS QoSE planning system allows us to investigate the impact of subjective attributes on WS QoSE by statistical, correlation and similarity analysis.

6. The obtained experiments of hybrid fuzzy inference WS QoSE planning showed a significant influence of QoS attributes on whole WS QoSE Performance value.

The novelty of the current study is that we combined quantitative and qualitative WS characteristics into the hybrid WS QoSE concept, which encompasses both objective and subjective attributes. This WS QoSE concept is implemented into hybrid fuzzy inference WS QoSE planning system, used to predict, plan and investigate the impact of subjective and objective attributes on WS QoSE.

The rest of this research paper is formed as follows. Section 2 overviews related works. Section 3 describes a hybrid fuzzy inference approach for predicting WS QoSE Performance. Section 4 presents the two experiments, and Section 5 discusses the obtained results. Finally, Section 6 concludes the paper.

## 2 A Fuzzy Inference Approach for WS QoSE Planning

This section describes a new hybrid fuzzy inference approach for WS QoSE planning (Figure 1), which consists of the following main parts: 1) Fuzzy Inference Design of domain experts' knowledge on WS QoE; 2) Fuzzy Inference Controller (FuzzIC); 3) Data-Driven Optimization with ANFIS, for which an external domain dataset for optimization of fuzzy rules and membership function (MF) parameters is used; and 4) Linguistic Approximation, which transforms crisp results into linguistic form.

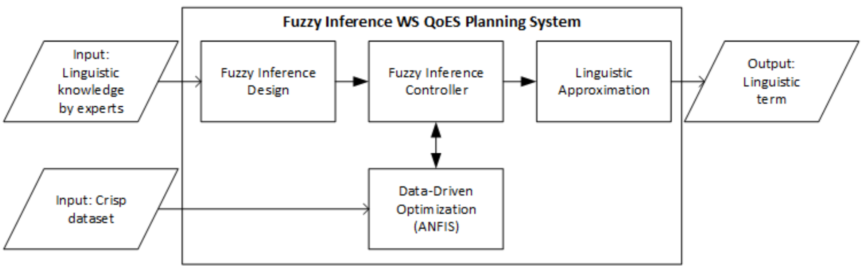


Figure 1: The proposed approach reference schema

The main advantage of this proposed approach is the synergy between expert knowledge and an external domain dataset for the planning of WS QoSE.

### 2.1 Fuzzy Inference Design

This component transforms User Experience expressed in a linguistic form into crisp data. It corresponds to the QoSE modelling, when experts express their opinion on WS QoSE attributes. WS

QoS is a tuple $Q_S$ ($q_1$,$q_2$,...,$q_n$), where $q_i$ denotes the objective attributes of WS QoS, like response time, execution cost, availability, etc.

Applying a fuzzy set theory, a linguistic variable of WS QoSE Q consists of linguistic attributes $Q_S$, whose value set T, in turn, can be divided into meaningful crisp intervals. Linguistic meaning of these intervals denotes the end-user's satisfaction level as "Good" (G), "Moderate" (M), "Low" (L). In general, the WS QoSE Q is expressed by eq. 1:

$$Q = \{Q_S, T, U, M(T)\}, \tag{1}$$

where $U$ is the universe of discourse with elements $u$ in interval $(0, +\infty)$.

$T$ is a set of linguistic terms $l_1, l_2, \ldots, l_n$ of $Q_S$. $M(T)$ is a set of semantic rules used to link each term with its meaning, where $M(T)$ is a sub-set of $U$ and defined by different types of membership functions (MF). In this research, a triangular MF (eq. 2) is used as an initial shape, and a trapezoidal MF – the revised one (eq. 3) [36],[10].

$$\mu_{A_i}^{Triang}(x) = \begin{cases} 0, & \text{if } x < c_1, c_3 \leq x, \\ \frac{x-c_1}{c_2-c_1}, & \text{if } c_1 \leq x < c_2, \\ \frac{c_3-x}{c_3-c_2}, & \text{if } c_2 \leq x < c_3, \end{cases} \tag{2}$$

$$\mu_{A_i}^{Trap}(x) = \begin{cases} 0, & \text{if } x < c_1, c_4 \leq x, \\ \frac{x-c_1}{c_2-c_1}, & \text{if } c_1 \leq x < c_2, \\ 1, & \text{if } c_2 \leq x < c_3, \\ \frac{c_4-x}{c_4-c_3}, & \text{if } c_3 \leq x < c_4, \end{cases} \tag{3}$$

where: $c_1$, $c_2$, $c_3$, $c_4$ are the parameters of MF.

Since user's satisfaction is vague by its nature, a semantic rule *M(T)* determines the grade of membership $\mu_{(l_i)}(u)$ of $u$ to a particular linguistic term $l_i$. So, the closer the value $\mu_{(l_i)}(u)$ is to 1, the more u belongs to $l_i$. Experts $E$ express their opinion on partition intervals of linguistic terms $l_i$ in U of WS QoS attributes (eq. 4):

$$E = \{(ex_j) \mid j \in [1; m], m \in \mathbb{N}^+\},$$

$$Inter_i^{l_i} = \{[u_1^{l_i}; u_2^{l_i}] \mid u_1^{l_i} \in \mathbb{R}_{>0}, u_2^{l_i} \in \mathbb{R}_{>0}, u_1^{l_i} < u_2^{l_i}\}, \tag{4}$$

$$\forall ex_j : T(l_i) \rightarrow Inter_i^{l_i},$$

where each expert $(ex_j)$ assigns a partition interval $(Inter_i^{l_i})$ to each linguistic term $T(l_i)$. All these assignments form a set of expert rules $r_{ij}^{ex}$ and used as the output of the Fuzzy Inference Design component.

## 2.2 Fuzzy Inference Controller (FuzzIC)

FuzzIC is a classical fuzzy inference controller [23],[43], consisting of the following parts: Fuzzification, Fuzzy Inference, and Deffuzification.

**Fuzzification**, employing a particular fuzzification method to convert a crisp dataset input into a fuzzy dataset. Since measured quality attributes can have different measurement units, they should be normalized applying different techniques. Here, a linear max-min normalization [46] (eq. 5), which map fuzzy numbers to the interval from 0 to 1, is used.

$$\textbf{Benefit criteria: } \tilde{u}_i = \frac{u_i - min(u_i)}{max(u_i) - min(u_i)}, \tag{5}$$

$$\textbf{Cost criteria: } \tilde{u}_i = \frac{max(u_i) - u_i}{max(u_i) - min(u_i)}.$$

In particular, weights can be assigned to experts according to their experience in the application domain, etc. [25]. Moreover, the fuzzified data is presented for balancing, since consensus should be found between different expert opinions. For balancing of intervals, the labelled equilibrium fuzzy relation $\rho_{eqlb}^{T(l_i)'}$ of normalized terms of linguistic variable $T(l_i)'$ is suggested in [22]. After balancing, the MFs shapes are redefined using trapezoidal (eq. 3), $L$-shaped [13] and $\Gamma$-shaped [15] MFs.

**Fuzzy Inference** applies a set of fuzzy rules and a particular fuzzy inference approach, like Mamdani or Takagi-Sugeno (T–S), to fuzzy inputs for generating a fuzzy output.

**Defuzzification** translates the obtained fuzzy output into a crisp user understandable output, using a particular defuzzification method, like centroids, max-membership, weighted average, etc. [8].

### 2.3 Data-Driven Optimization (ANFIS)

In order to improve the performance of the proposed system, MF parameters and fuzzy rules are optimized, using a particular optimization method such as genetic algorithm, Particle Swarm Optimization, pattern search, adaptive neuro-fuzzy inference, etc. [22]. For better performance and feasibility, ANFIS, which is a combination of a fuzzy inference system (FIS) and an adaptive neural network [20], is used for optimization. It is based on a set of fuzzy IF-THEN rules (eq. 6) to generate the predefined input-output pairs.

$$R_i : \text{if } \ (x_1 is A_1^{(i)}) \ \ldots \text{ and } \ldots \ (x_n is A_n^{(i)}) \ \text{ then } \ f_i = a_i^T \cdot x + b_i, \tag{6}$$

where $(x \in \mathbb{R}^n)$ is an inputs vector in the premise part characterized by a particular MF, and $(a_i, b_i)$ is a pair of the coefficients of linear Takagi–Sugeno consequents. ANFIS training is the process of determining the premise and consequence parameters using a particular optimization algorithm. It can be presented in five layers as follows:

**Layer 1**: Fuzzification: inputs $((x_1, x_2), n = 2)$ are fuzzified using trapezoidal MFs (eq. 3) whose parameters $c_1, c_2, c_3, c_4$ are adapted by the learning process. In the result, as the parameter values change, MFs of the linguistic terms $A_n^{(i)}$ change too.

**Layer 2**: Evaluation of the rule strength: each node has the rule strength $w_i$ (eq. 7):

$$w_i = \prod \mu_i(x). \tag{7}$$

**Layer 3**: Normalization: all rule strengths $w_i$ are normalized $(\bar{w}_i)$ (eq. 8):

$$\bar{w}_i = \frac{w_i}{\sum_i w_i}. \tag{8}$$

**Layer 4**: Application: the rule $(R_i)$ is obtained to get the output $f_i$ (eq. 6).
**Layer 5**: Computation: the global model response *(f)* is determined (eq. 9):

$$f = \sum_i \bar{w}_i f_i. \tag{9}$$

After training, the ANFIS performance is determined by various statistical tests. Here, we applied the following statistical tests.

The ***coefficient of determination*** $(R^2)$ [9] measures how differences in one variable can be explained by differences in another variable (eq. 10). The higher $R^2$, the higher the percentage of points through which the drawn line passes when the data points are plotted.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{10}$$

$$SS_{tot} = \sum_i (f_{train_i} - \bar{f}_{train})^2 \ and \ \ SS_{res} = \sum_i (f_{train_i} - f_i)^2,$$

where $SS_{res}$ denotes the sum of the squares of residuals, and $SS_{tot}$ – the total sum of squares.

The ***mean squared error (MSE)*** [9] (eq. 11) measure the average of the squares of errors between the output $f$ and the training $f_{train}$.

$$MSE = 1/n \sum_{i=1}^{n} (f_i - f_{train})^2, \tag{11}$$

where $f_i$ and $f_{train_i}$ show the ANFIS output and the measured value from the i-th element. The closer MSE is to zero, the more accurate the predicted results are.

The ***root mean squared error (RMSE)*** is the square root of the average squared distance between the actual and the predicted scores [9] (eq. 12).

$$RMSE = \sqrt{\frac{\sum_i (f_i - f_{train_i})^2}{n}}. \tag{12}$$

RMSE is always positive, and a value of 0 indicates the perfect fit of the data. Generally, a lower RMSE would be better than a higher one. Since RMSE can vary in the interval $[0, +\infty)$, some authors, like [19], propose using normalized RMSE (eq. 13).

$$NRMSE = \frac{RMSE}{(max_{f_i} - min_{f_i})}. \tag{13}$$

Then, the ***normalized RMSE (NRMSE)*** ranges in the interval [0; 1], where values closer to 0 represent better fitting predictions.

The ***sum of squares due to error (SSE)*** is the total deviation of the response values from the fit to the response values [28] (eq.14).

$$SSE = \sum_{i=1}^{n} (f_i - f_{train_i})^2. \tag{14}$$

An SSE value closer to 0 indicates a smaller random error component in the prediction model, i.e., the fit is more useful for prediction.

### 2.4 Linguistic Approximation

After FuzzIC gives us the result in the form of a mathematical expression, it should be translated into a linguistic expression, which is better comprehensible and interpretable by the user [14]. For example, the end-user understands a linguistic expression, like “high quality” or “low quality”, better than the crisp number, like, “the quality equals to 0.24”.

*Linguistic approximation* is a process of assigning linguistic expressions to various mathematical objects that are obtained as outputs of fuzzy models [42]. In the literature, we can find various approaches to linguistic approximation, like the “best-fit” methods, linguistic hedges and connectives, etc. In this research, we employ the most frequently used the “best-fit” approach for linguistic approximation [42].

In this paper, the “best-fit” linguistic approximation of the crisp output Out, obtained from FuzzIC, is a process of finding the most suitable linguistic term $l_i^{Out}$, such that the fuzzy-number meaning of the approximating linguistic term $l_i^{Out}$ is the closest to the approximated fuzzy set (eq. 15).

$$l_i^{Out} = arg\ min_i\ d(l_i, Out). \tag{15}$$

For the aim of linguistic approximation, the Euclidean distance (the “best-fit” technique), is applied (eq. 16 [35]).

$$d(l_i, Out) = \sqrt{\frac{1}{D}\sum_{i=1}^{D}(\mu_{l_i}(u_i) - \mu_{Out}(u_i))^2}, \tag{16}$$

where: $l_i$ and $Out$ are fuzzy sets in $U$, and $D$ is the fuzzy number (i.e., $D$=3 for triangular MF, $D$=4 for trapezoidal MF). For $n$, the Euclidean distance matrix $[n \times n]$ is developed and the minimum distance to the nearest linguistic term is found. It is treated as a linguistic term for the approximated fuzzy number $Out$.

If the approximated fuzzy set Out corresponds to the meaning of some of the linguistic values of $l_i$ and, the correct linguistic label that fits 100 % is found, the distance will be minimal. However, this rarely happens, and in reality $0 < d(l_i, Out) < 1$, even with the "best fitting" linguistic label. This is due to the transformation of fuzzy sets into natural language descriptions. In addition, ambiguous situations occur, where the minimal distance from several meanings of linguistic labels is the identical or similar. In this case, a more suitable label can be chosen from the provided. Summing up, the result of the "best-fit" linguistic approximation depends on the choice of distance/similarity measure and the underlying linguistic variable.

Finally, the *Output* of the proposed fuzzy inference WS QoSE planning system in the form of a set of linguistic terms is obtained.

# 3 Results

This section describes a new hybrid fuzzy inference approach for WS QoSE planning (Figure 1), which consists of the following main parts: 1) Fuzzy Inference Design of domain experts' knowledge on WS QoE; 2) Fuzzy Inference Controller (FuzzIC); 3) Data-Driven Optimization with ANFIS, for which an external domain dataset for optimization of fuzzy rules and membership function (MF) parameters is used; and 4) Linguistic Approximation, which transforms crisp results into linguistic form. Two experiments are conducted to validate the proposed approach as follows:

1. Experiment 1, using objective and subjective attributes for predicting WS QoSE by the proposed approach; and

2. Experiment 2, using only objective attributes for predicting WS QoS applying only ANFIS.

## 3.1 Obtaining WS QoSE Performance (Experiment 1)

In this section, we describe Experiment 1 for WS QoSE Performance prediction with the proposed WS QoSE Planning System (see Figure 1) using objective and subjective attributes of WS. The flowchart of this experiment is presented in Figure 2.

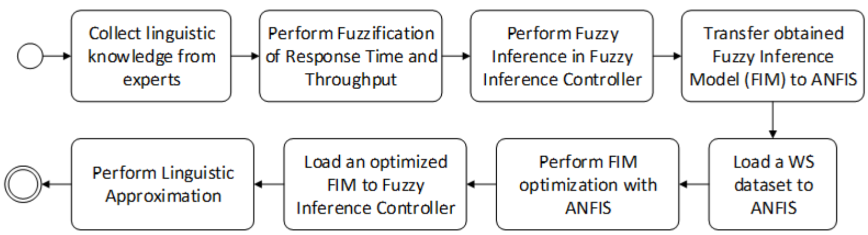


Figure 2: The flowchart of obtaining WS QoSE Performance with the proposed system.

## 3.2 Processing subjective attributes

According to Figure 2, linguistic knowledge about Response time and Throughput is collected from experts (i.e., "Collect linguistic knowledge from experts") and an input of the fuzzy inference WS QoSE planning system is formed in Table 1. This table presents the experts' ($ex_n$) opinions on partition intervals of linguistic terms $l_i$ in UoD of WS QoS attributes.The experts were from various role groups as follows: four domain users ($ex_1 - ex_4$) and four application developers ($ex_5 - ex_8$).

Table 1: Throughput and Response time WS QoSE data collected from experts

| | **Response Time (sec)** | | | | | | **Throughput (mbps)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **High** | | **Moderate** | | **Low** | | **Very High** | | **High** | | **Moderate** | | **Low** | |
| $ex_1$ | 0.80 | 2.9 | 2.9 | 6.4 | 6.4 | 24.0 | 760 | 947 | 458 | 779 | 219 | 531 | 107 | 205 |
| $ex_2$ | 0.10 | 2.3 | 2.3 | 4.6 | 4.6 | 21.0 | 607 | 972 | 604 | 608 | 204 | 464 | 118 | 199 |
| $ex_3$ | 0.70 | 4.8 | 4.8 | 8.7 | 8.7 | 19.0 | 698 | 912 | 626 | 784 | 198 | 421 | 83 | 190 |
| $ex_4$ | 0.80 | 3.0 | 3.0 | 6.6 | 6.6 | 18.0 | 812 | 986 | 404 | 747 | 208 | 292 | 68 | 208 |
| $ex_5$ | 0.50 | 4.5 | 4.5 | 8.9 | 8.9 | 18.5 | 650 | 976 | 426 | 666 | 208 | 284 | 97 | 200 |
| $ex_6$ | 0.01 | 6.6 | 6.6 | 9.3 | 9.3 | 18.0 | 651 | 917 | 596 | 806 | 203 | 497 | 83 | 250 |
| $ex_7$ | 0.10 | 5.5 | 5.5 | 10.3 | 10.3 | 19.0 | 741 | 922 | 446 | 749 | 204 | 430 | 112 | 180 |
| $ex_8$ | 0.50 | 7.2 | 7.2 | 11.2 | 11.2 | 21.5 | 831 | 978 | 437 | 653 | 218 | 346 | 103 | 218 |

This data is transferred to FuzzIC (Figure 1) (i.e., "Perform Fuzzification of Response Time and Throughput" in Figure 3a). When the Response Time is "High", the user feels an uninterrupted flow of thoughts, even if he/she notices the delay [44],[37] (Figure 3a). The "Moderate" Response Time is about the limit for keeping the user's attention on the dialogue. For a longer delay (the Response Time is "Low"), the user would like to perform other tasks while awaiting the computer to finish.

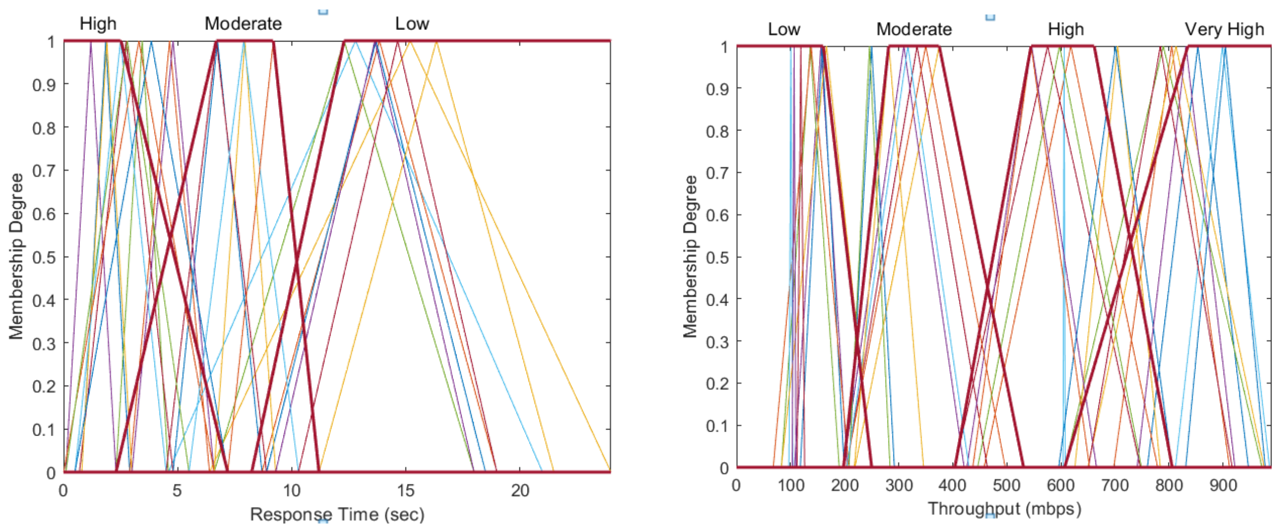


Figure 3: Input MFs from experts: a) Response Time (sec); b) Throughput (mbps).

Similarly, for Throughput, presented in Figure 3b, the values that fall under the "Very High" and "High" ranges shall exhibit no interruptions of user's work. Moreover, under the "Very High" Throughput the user feels that the system is reacting instantaneously. Meanwhile, under the "Moderate" Throughput user notices the delay, but it is acceptable for keeping his/her attention on the work. Finally, the "Low" Throughput disturbs with the user's focus on the work.

After processing all of the WS QoSE data collected from the experts, Response time and Throughput datasets are combined into combinatorial variants of the QoSE characteristic Performance see Table 2.

The fuzzified pair of inputs then goes through the Sugeno-type Fuzzy Inference component (see Section 2.2) consisting of fuzzy IF-THEN rules for determining the defuzzified crisp values of WS QoSE Performance.

In FuzzIC, we have a 12 ($3^1 \times 4^1$) verbose fuzzy rule set (see Table 2). It should be noted that increasing the partitions of the input space exponentially increases the number of rules and significantly slows down the learning and application speed of the system.

Based on the defined fuzzy IF-THEN rules by eq. 6 and applying values from Table 2, the WS QoSE Performance surface (Figure 4) is pictorized by FIS, which is configured in MATLAB Fuzzy

Table 2: The 12 fuzzy IF-THEN rules according to the experts' opinions in the FuzzIC (C – Constant, VH – Very High, H – High, M – Moderate, L – Low, VL – Very Low).

| **No** | | **Response Time is** | | | **Throughput is** | | | **QoSE Performance** | |
|---|---|---|---|---|---|---|---|---|---|
| | | $T(l_1)$ | $Inter_i^{(l_1)}$ | | $T(l_2)$ | $Inter_i^{(l_2)}$ | | Output | $Inter_i^{Out}$/C |
| 1. | | H | (0; 7.2) | | H | (404; 804) | | M–H | (0.333; 0.667) |
| 2. | | M | (2.3; 11.2) | | M | (195; 531) | | M | 0.333 |
| 3. | | L | (8.25; 20) | | L | (0; 250) | | L–M | (0; 0.333) |
| 4. | | H | (0; 7.2) | | VH | (607; 987) | | H | 0.667 |
| 5. | **IF** | H | (0; 7.2) | **AND** | L | (0; 250) | **THEN** | M | 0.333 |
| 6. | | H | (0; 7.2) | | M | (195; 531) | | M–H | (0.333; 0.667) |
| 7. | | M | (2.3; 11.2) | | L | (0; 250) | | L–M | (0; 0.333) |
| 8. | | M | (2.3; 11.2) | | H | (404; 804) | | M | 0.333 |
| 9. | | M | (2.3; 11.2) | | VH | (607; 987) | | M–H | (0.333; 0.667) |
| 10. | | L | (8.25; 20) | | M | (195; 531) | | M | 0.333 |
| 11. | | L | (8.25; 20) | | H | (404; 804) | | M | 0.333 |
| 12. | | L | (8.25; 20) | | VH | (607; 987) | | M–H | (0.333; 0.667) |

Logic Toolbox for analyzing, designing, and simulating fuzzy logic systems.

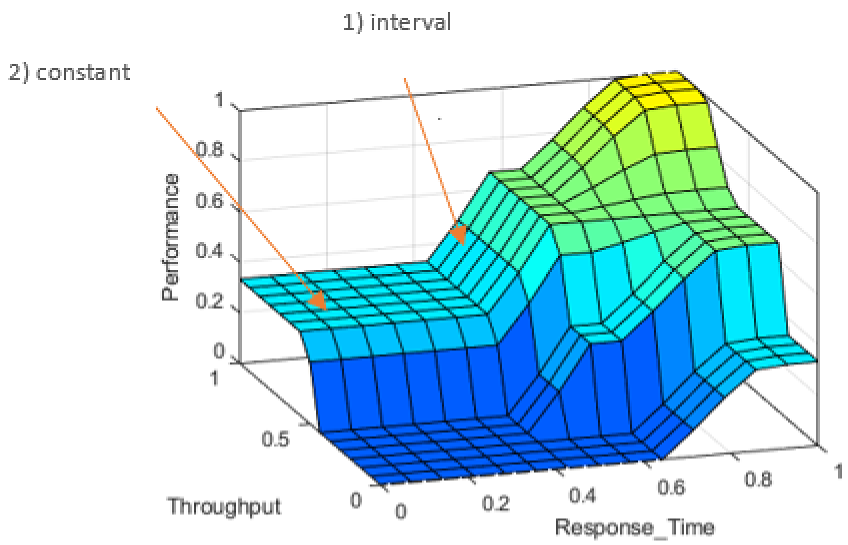


Figure 4: The WS QoSE Performance surface using FIS.

During the implication process of Response Time and Throughput, we have got two cases of QoSE Performance: 1) interval (like High–Moderate (0.333; 0.667) in Figure 4), where the surface varies (see Figure 4); and 2) constant (like Moderate (0.333) in Figure 4), where the surface remains constant (see Figure 4).

Consequently, constant QoSE Performance values belong to one linguistic term. Meanwhile, interval QoSE Performance values cannot be assigned to a single linguistic term, rather to the interval of two linguistic terms with different membership degrees.

Therefore, QoSE Performance can be categorized into revised seven linguistic terms as follows: Low, Low–Moderate, Moderate, Moderate–High, High, High–Very High, and Very High. All these obtained information form FIM, which is transferred to ANFIS (i.e., "Transfer obtained Fuzzy Inference Model (FIM) to ANFIS" in Figure 2).

### 3.3 Employing ANFIS for optimization with crisp data

Here, the following steps are performed "Load a WS dataset to ANFIS" and "Perform FIM optimization with ANFIS" (Figure 2).

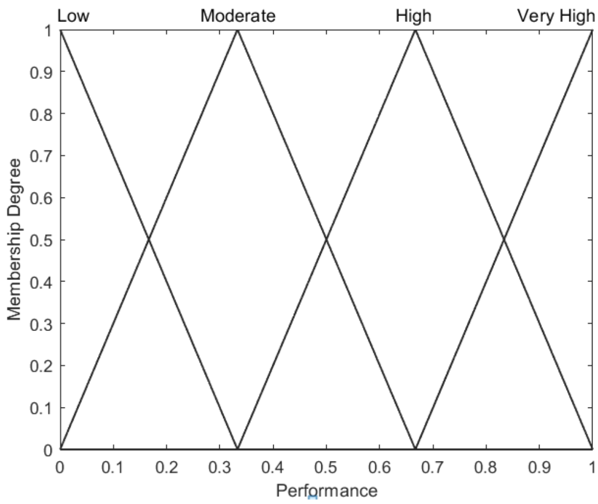


Figure 5: The MFs of the output of WS QoSE Performance obtained using FIS.

For the Data-Driven Optimization (see Section 2.3), we have used a WS dataset collected from WSDream dataset [54],[55], which presents Response Time and Throughput values from 339 users on real-world 5 825 WSs. ANFIS hyper-parameters for optimization with crisp data are shown in Table 3.

Table 3: ANFIS hyper-parameters

| **Hyper-Parameters** | **Description/Value** |
|---|---|
| Fuzzy structure | FIS training data Sugeno/genfis1 |
| Generation of FIS object | grid partition on the data |
| MF type (Input / Output) | trapmf (trapezoidal) / constant |
| Number of variables (inputs/outputs) | 2 / 1 |
| Number of terms (Input1 / Input2) | 3 / 4 |
| Optimization method | hybrid |
| Training algorithm to model the training data | least-squares and backpropagation gradient descent methods |
| Maximum number of training epochs | 100 |
| Initial step size | 0.001 |
| Step size decrease rate / increase rate | 0.9/2 |
| AndMethod / ImpMethod / AggMethod / DefuzzMethod | prod / prod / sum / wtaver |
| Data for training / Data for testing | 80/20 |

The principal schema of the fuzzy inference with ANFIS is presented in Figure 6.

In Layer 1, the input data (Response Time ($x_1$) and Throughput ($x_2$) is fuzzified based on eq. 3 and MFs are obtained, where each MF is presented as an adaptive node (see Figure 6). The ANFIS network's Layer 2 is formed when the fuzzy rules are established by obtaining all possible combinations of MFs pairs. Consequently, we have got 12 pairs of ($x_1$) (Response Time) and ($x_2$) (Throughput). Using eq. 7, a firing strength (weight for each fuzzy rule is 1) are computed. In Figure 5, each obtained rule is presented as non-adaptive node. In Layer 3, the rule strengths are normalized (eq. 8) and presented as non-adaptive node. Consequently, in Layer 4, the defuzzification is performed, and fuzzy rules are applied (see eq. 6) by adopting each node. Layer 5 is the summation layer, which has a single fixed non-adaptive output of the overall ANFIS network obtained using eq. 9. The 12 fuzzy rules and MF parameters are taken from FuzzIC (shown in Table 1) and loaded to ANFIS. Thus, in ANFIS undergoes optimization of those MF parameters and fuzzy rules from FIS based on objective crisp data. After this optimization, those optimized parameters and fuzzy rules are translated back to FuzzIC (i.e., "Load an optimized FIM to FuzzIC" in Figure 2). Further, the FuzzIC makes inferencing

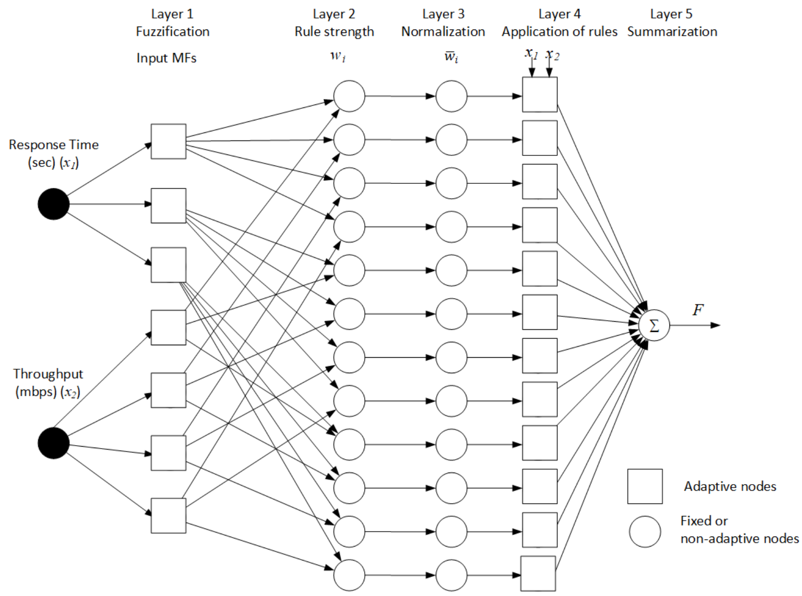


Figure 6: The proposed ANFIS network for WS QoSE Performance prediction.

based on the optimized MF parameters and fuzzy rules.

Based on this scenario, the WS QoSE Performance value may change after optimization and it may fall into another predefined linguistic term interval. For example, before the optimization, we have "Moderate" Performance, and after, it becomes "High".

The resulting surface of the optimised WS QoSE Performance is presented in Figure 7. As can be seen, it becomes smoother.

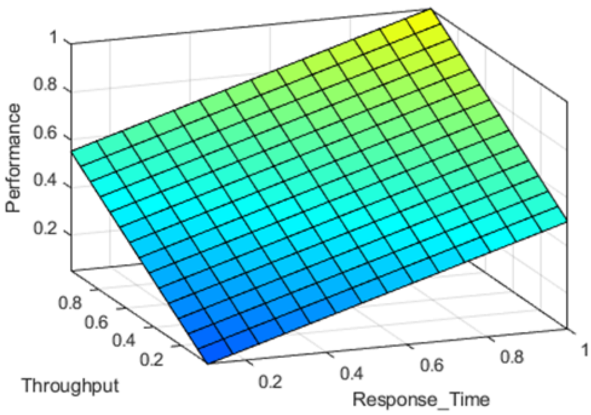


Figure 7: The resulting surface of the optimised WS QoSE Performance.

The obtained fuzzy IF-THEN rules after optimization are presented in Table 4. Note that QoSE Performance is characterized by a linguistic term, its interval, and a crisp value of the QoSE Performance in this interval.

The WS QoSE Performance after optimization employing ANFIS looks like presented in Figure 8.

The WS QoSE Performance linguistic terms have been changed after optimization applying ANFIS. As a result, we have got five linguistic terms: Low, Low–Moderate, Moderate, Moderate–High, High (i.e., "Perform Linguistic Approximation" in Figure 2). Thus, the first experiment (Experiment 1) is completed.

### 3.4 Obtaining WS QoS Performance with ANFIS (Experiment 2)

In this section, we describe Experiment 2 for WS QoS Performance prediction with ANFIS using only objective attributes of the same WSDream dataset (see Figure 9).

Table 4: The optimized 12 fuzzy IF-THEN rules (C – Constant, VH – Very High, H – High, M – Moderate, L – Low, VL – Very Low).

| **No** | | **Response Time is** | | | **Throughput is** | | | **QoSE Performance** | |
|---|---|---|---|---|---|---|---|---|---|
| | | *T(l_1)* | *Inter_i^(l_1 )* | | *T(l_2)* | *Inter_i^(l_2 )* | | *Output* | *Inter_i^Out/C* |
| 1. | **IF** | H | (0.552; 1) | **AND** | H | (0.334; 1) | **THEN** | H | (0.65; 1) / 0.83 |
| 2. | | M | (0.103; 1) | | M | (0; 0.667) | | M | (0.052; 0.835) / 0. |
| 3. | | L | (0; 0.552) | | L | (0; 0.338) | | L | (0; 0.386) / 0.05 |
| 4. | | H | (0.552; 1) | | VH | (0.667; 1) | | H | (0.823; 1) / 1.00 |
| 5. | | H | (0.552; 1) | | L | (0; 0.338) | | M | (0.277; 0.67) / 0.5 |
| 6. | | H | (0.552; 1) | | M | (0; 0.667) | | M–H | (0.666; 0.835) / 0. |
| 7. | | M | (0.103; 1) | | L | (0; 0.338) | | L–M | (0.052; 0.386) / 0. |
| 8. | | M | (0.103; 1) | | H | (0.334; 1) | | M–H | (0.66; 0.835) / 0.6 |
| 9. | | M | (0.103; 1) | | VH | (0.667; 1) | | M–H | (0.777; 1) / 0.77 |
| 10. | | L | (0; 0.552) | | M | (0; 0.667) | | L–M | (0.052; 0.38) / 0.2 |
| 11. | | L | (0; 0.552) | | H | (0.334; 1) | | M | (0.05; 0.777) / 0.3 |
| 12. | | L | (0; 0.552) | | VH | (0.667; 1) | | M | (0.33; 0.67) / 0.5 |

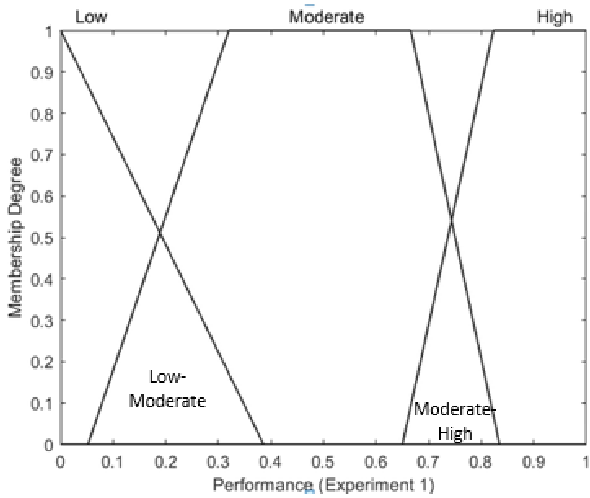


Figure 8: The MFs of the output of WS QoSE Performance obtained after ANFIS.

Note that in Experiment 1, in ANFIS we have used subjective attributes and fuzzy rules loaded from FuzzIC. In Experiment 2, we put to ANFIS only the Response Time and Throughput values of the WS Dream dataset, which is classified using the grid partition method, the Triangular MFs and the number of input partitions (i.e., "Load a WS dataset to ANFIS" in Figure 9).

Based on the described initial settings and using ANFIS intelligence, we have obtained the prediction surface (Figure 10) (i.e., "Perform Fuzzy Inference with ANFIS" in Figure 9). It represents the dependency between inputs (Response Time and Throughput) and output (Performance).

Note that the ANFIS structure is the same as in Experiment 1. However, the values of fuzzy rules and MF parameters differ because of the optimisation process in Experiment 1. A complete set of 12 ($3^1 \times 4^1$) fuzzy rules of Experiment 2 is presented in Table 5, where WS QoS Performance is characterized by a linguistic term, its interval, and a crisp value in this interval.

The defuzzified output of WS QoS Performance from ANFIS ranges into five intervals as follows (Figure 11): Low, Low–Moderate, Moderate, Moderate–High, High (i.e., "Perform Linguistic Approximation" in Figure 9).

Thus, the second experiment (Experiment 2) is completed.

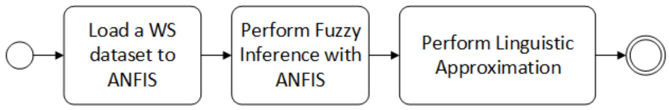


Figure 9: The flowchart of obtaining WS QoS Performance with ANFIS.

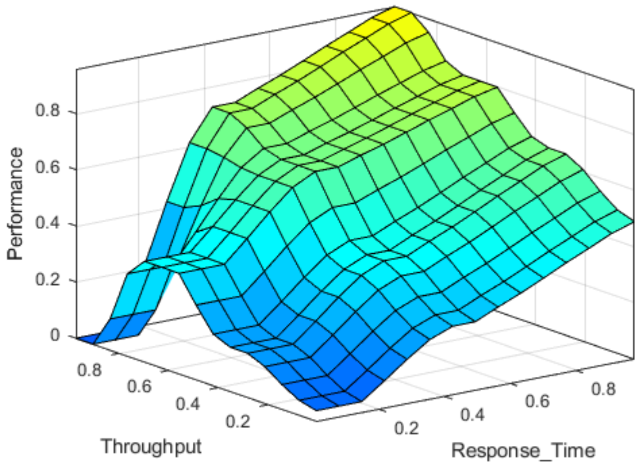


Figure 10: The WS QoS Performance surface obtained using ANFIS from objective data.

### 3.5 Comparison of Experiments

The obtained results of two experiments are compared as follows: 1) statistical tests ($R^2$, MSE, RMSE, and SSE) (Table 6); 2) correlation analysis (the Pearson's correlation coefficient); and 3) the Euclidian distances to measure the differences (i.e., similarity [32]) between the main linguistic terms High, Moderate and Low (Table 7).

As can be seen, both implemented WS quality prediction systems perform accurately enough and can be used for WS quality prediction.

The results of the correlation analysis show very strong linear relationship between QoS performance and QoSE performance (the Pearson's correlation coefficient equals 0.995).

The Euclidean distances, obtained using eq. 16, are presented in Table 7. They range in the interval from 0 to 1, where 0 means no distance between linguistic terms, i.e., they are the same, and 1 – the highest possible distance between linguistic terms, i.e., none similar. Consequently, we have characterized the obtained distances using five-point similarity scale as follows: (0.3; 0] – very strong similarity, (0.5; 0.3] – strong similarity, (0.7; 0.5] – moderate similarity, (1; 0.7] – weak similarity, and 1 – none.

As can be seen, the Low, Moderate and High linguistic terms obtained in Experiment 1 and Experiment 2 have very strong similarity.

## 4 Discussion

In this research, we have analysed an impact of users' subjective opinion on the data-driven WS quality planning and have proposed the fuzzy inference approach for WS QoSE planning and its implementing system that can deal with numerical objective data and linguistic subjective data inputs, i.e., enabling the expression of user experience through vague concepts. The main knowledge contribution of the proposed approach is deeper understanding of the WS quality planning problem. The obtained knowledge allows us to understand that quality planning is a subjective problem that cannot be solved by only objective and numerical data. In real-world problems, however, restrictions may arise based on modelling assumptions [30]. Moreover, the WS quality planning system is developed for users. Therefore, their subjective needs cannot be ignored. Consequently, we have proposed an approach to combine objective (measurable and expressed in a numerical form) and subjective (experienced and

Table 5: The 12 fuzzy IF-THEN rules obtained from ANFIS using the grid partition method (C – Constant, VH – Very High, H – High, M – Moderate, L – Low, VL – Very Low).

| **No** | | **Response Time is** | | | **Throughput is** | | | **QoS Performance** | |
|---|---|---|---|---|---|---|---|---|---|
| | | $T(l_1)$ | $Inter_i^{(l_1)}$ | | $T(l_2)$ | $Inter_i^{(l_2)}$ | | Output | $Inter_i^{Out}$/C |
| 1. | **IF** | H | (0.599; 1) | **AND** | H | (0.398; 0.899) | **THEN** | M–H | (0.446; 0.975) / 0.823 |
| 2. | | M | (0.236; 0.955) | | M | (0.002; 0.577) | | M | (0.127; 0.823) / 0.446 |
| 3. | | L | (0; 0.448) | | L | (0; 0.288) | | L | (0; 0.446) / 0 |
| 4. | | H | (0.599; 1) | | VH | (0.75; 1) | | H | (0.625; 0.975) / 0.975 |
| 5. | | H | (0.599; 1) | | L | (0; 0.253) | | M | (0.29; 0.637) / 0.489 |
| 6. | | H | (0.599; 1) | | M | (0.002; 0.577) | | M–H | (0.29; 0.823) / 0.666 |
| 7. | | M | (0.236; 0.955) | | L | (0; 0.288) | | L–M | (0.125; 0.665) / 0.290 |
| 8. | | M | (0.236; 0.955) | | H | (0.398; 0.899) | | M–H | (0.56; 0.975) / 0.650 |
| 9. | | M | (0.236; 0.955) | | VH | (0.75; 1) | | M–H | (0.65; 0.975) / 0.758 |
| 10. | | L | (0; 0.448) | | M | (0.002; 0.577) | | L–M | (0.122; 0.65) / 0.392 |
| 11. | | L | (0; 0.448) | | H | (0.398; 0.899) | | L–M | (0.244; 0.535) / 0.359 |
| 12. | | L | (0; 0.448) | | VH | (0.75; 1) | | M–H | (0.384; 0.758) / 0 |

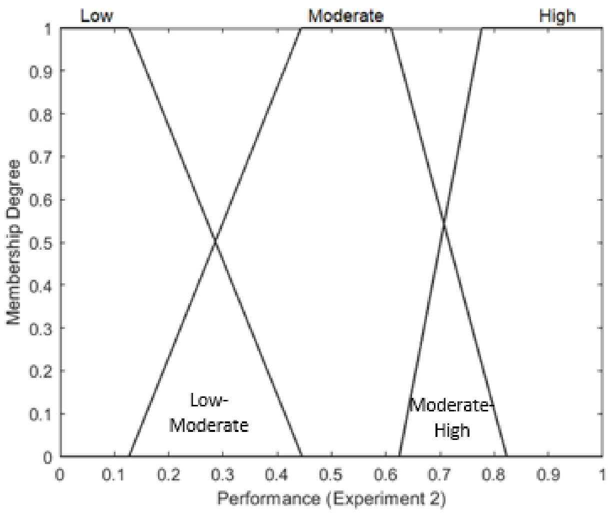


Figure 11: Output MFs for WS QoS performance from ANFIS using only objective attributes.

expressed in a linguistic form) WS quality attributes into QoSE. Another knowledge contribution is that in our proposed hybrid fuzzy inference WS QoSE planning approach, we have applied the content separation principle by distinguishing between the subjective and objective viewpoints to the quality attributes. Those QoS and QoE attributes are combined into QoSE through their combination by fuzzification and normalization (*answer to the research question how to combine QoS and QoE into QoSE*).

The design contribution of our research lies in the successful implementation and demonstration of the proposed hybrid fuzzy inference WS QoSE planning system. In order to demonstrate its suitability for WS QoSE performance prediction and feasibility, we developed a system prototype and conducted two experiments. In Experiment 1, objective and subjective attributes of WS were combined using the approach proposed in this research, and the WS QoSE performance prediction was carried out. In Experiment 2, only objective attributes were used for the WS QoSE performance prediction. Finally, the results of both experiments were compared using statistical tests ($R^2$, MSE, NRMSE, and SSE), the Pearson's correlation coefficient and the Euclidean distances among linguistic terms.

The statistical analysis shows a very good fitting prediction of both experiments. Nevertheless, the second experiment (Experiment 2) obtained more accurate results than the first one (Experiment 1). This small deviation shows the influence of subjective attributes on the WS QoSE prediction (*answer to the research question how does the inclusion of QoE attributes in the prediction affect the*

Table 6: The 12 fuzzy IF-THEN rules obtained from ANFIS using the grid partition method.

| **Statistical tests** | **Experiment 1 (FIS+ANFIS)** | **Experiment 2 (ANFIS)** |
|---|---|---|
| $R^2$ | 0.9839 | 0.999 |
| MSE | 0.0002 | 8.99743E-07 |
| NRMSE | 0.0143 | 0.0009 |
| SSE | 0.0797 | 0.0034 |

Table 7: The Euclidian distances between linguistic terms in Experiment 1 and Experiment 2.

| Experiment 2 \ Experiment 1 | Low | Moderate | High |
|---|---|---|---|
| Low | 0.059 (very strong similarity) | 0.464 (strong similarity) | 0.955 (weak similarity) |
| Moderate | 0.557 (moderate similarity) | 0.071 (very strong similarity) | 0.486 (strong similarity) |
| High | 1 (none similarity) | 0.516 (moderate similarity) | 0 (very strong similarity) |

*final QoSE*). The correlation analysis (0.999) shows a very strong linear relationship between WS QoS performance and WS QoSE performance. Consequently, the obtained results confirm that the similar prediction results can be obtained using both approaches, i.e., WS QoSE prediction and WS QoS prediction. Nevertheless, the user experience is related to the use and enjoyment of the user by the service, depending on the personality and current state of the user. So, the results of the WS quality prediction differ. Moreover, depending on the experts this difference can vary from a small to a significant deviation. Also, the small deviation obtained in our study can be explained by the fact that domain experts are well acquainted with the needs of users. Deeper research is also needed in this area with different users, experts and WS data to thoroughly investigate the variation in quality prediction and its dependence on user's needs.

The analysis of the comparison of linguistic terms showed that they do not contradict each other and the same terms in Experiment 1 and Experiment 2 have very strong similarity.

Summing up, the proposed fuzzy inference WS QoSE planning approach is feasible and suitable to be used for WS quality planning according to objective and subjective attributes by increasing the user satisfaction level. The performed research shows the impact of user experience on the WS QoSE prediction that helps us to plan WS quality matching user's needs.

Nevertheless, this paper has several limitations, they at once provide future research opportunities. First, the experiments show that they should be extended for bigger number of linguistic terms, which will allow us to see a greater difference and influence of subjective attributes on the whole WS QoSE performance. Second, we need a dataset for subjective and objective WS quality attributes from the same application domain. Now, the most researches use well-known several datasets, like WS Dream dataset, QWS dataset, etc. Therefore, the proposed approaches are limited to their realisation and experimentation. Moreover, the datasets become obsolete and do not correspond to the real-world problems as the data were collected with old technologies.

# 5 Conclusions

The analysis of the related work on WS QoS / QoE shows that most of the compared studies are based on quantitative data and well-known datasets (especially the WS-DREAM dataset is popular). Qualitative feedbacks are found in a few studies, because of the high time cost and huge resource overhead. Therefore, QoE data is missing in many problem domains. Consequently, WS planning based on QoS and QoE remains a challenging issue, since there is a knowledge gap in how to combine QoS and QoE into QoSE and how it affects the final QoSE. The newly proposed hybrid fuzzy inference approach for predicting WS QoSE allows us to assess the WS quality from the user's (subjective) and numerical (objective) perspectives combining them through their combination by their fuzzifying and normalizing.

Experiments have shown that the proposed approach is appropriate for the WS QoSE prediction, when input data is not only quantitative numerical but also qualitative. Both experiments produce sufficiently accurate results. However, the incorporation of subjective attributes into WS QoSE predictions gives a slight deviation that shows an effect of subjectivity.

The statistical analysis shows a very good fitting prediction of both experiments. The correlation analysis shows a very strong linear relationship between the WS QoS performance and the WS QoSE performance. Finally, the analysis of the comparison of linguistic terms showed that they did not contradict each other and the same terms in both experiments had a very strong similarity.

Summing up, the proposed fuzzy inference WS QoSE planning approach is feasible and suitable for the WS QoSE planning according to objective and subjective attributes.

The future research areas based on the obtained results are planned as follows:

- Extending related works review to systematic review in order to grasp the main trends and evoliution of WS QoSE application and new methods for WS QoSE prediction.
- Expanding the proposed approach with deep learning algorithms.
- Experimentation with bigger number of linguistic terms for WS QoSE performance prediction applying the proposed approach.
- Finding new datasets for wider experimentation.

Thus, the research topic under consideration remains relevant and with the emergence of new technologies and approaches, like deep learning, IoT, etc., new opportunities for its development open up.

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### Author contributions

The authors contributed equally to this work.

### Conflict of interest

The authors declare no conflict of interest.

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