

# PROVIDING A FUZZY SYSTEM FOR EVALUATING AND COMBINING SERVICES IN THE SERVICE-ORIENTED ARCHITECTURE

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**Abstract.** Today, service oriented architecture is recognized as an effective way for organizations to select, evaluate, and combine services, including key activities that take place in different phases of the service life cycle of the service oriented architecture. Service evaluation is one of the key activities in implementing a successful service project. Our goal is to assess the appropriateness of the services identified and the choice of service means using specific techniques to select a service from a set of client profiles. In this research, we are looking at how to use fuzzy logic to evaluate a set of suggested services and combine them. In order to adapt the results of the research with actual values, actual data was used. In this paper we were able to work with the actual data by presenting a suitable combination method to achieve this goal and then, by testing this method with actual data, we were able to evaluate the efficiency of the proposed algorithm, and it was found that this algorithm has the highest accuracy in choosing the optimal combination of services.

**Keywords:** Fuzzy logic, service evaluation, service mixing, service oriented architecture, service selection.

**1. Introduction.** Service Oriented Architecture (SOA) is a new and evolving technique for building distributed applications with Distributed Application. Services are distributed components with defined and cleared interfaces that process and exchange XML messages (12). With a service-oriented approach, solutions can be provided that are not limited to the domain, organization, company or department (2). Using SOA, in a company with different systems and applications on different platforms, it is possible to create a loosely coupled fabrication solution that ensures a smooth and inconsistent flow of work (3). Service-oriented architecture refers to a conceptual level at the level of architecture, and therefore it is about something basic and high level, which basis is the experience gained in the production of CBD-based software systems and two basic principles in the software engineering industry that are production of software with "high cohesion and at the same time with low coupling" (6). Therefore, service oriented programming ideas are not new ideas and you may have used it before (7). However, the collection of the best experiences from the production of such systems integrating and contemplating the technological state of human today, which is the same concept in the service architecture, is new (9).

In fact, the application of fuzzy logic in the field of service-oriented architecture has grown significantly over the past few years. The scientific contribution of this study is to examine the application of fuzzy logic and provide a fuzzy system in the process of selection and evaluation of service-oriented services architecture. The results obtained in this study can be used to select a service set appropriate to the goals of the organization to identify services, and we will answer the question whether the fuzzy decision maker tool can choose the best available system for selecting a service from among the services offered?

## **2. Background**

The theory of fuzzy set and fuzzy logic was first introduced by Professor Lotfizadeh in a dissertation entitled "Information and Control Fuzzy Collections" in 1965 (5). His primary goal of this era was to develop a more effective model for describing the process of natural language processing. He introduced mathematical and engineering sciences into modifications such as fuzzy sets, fuzzy events, fuzzy numbers, and fuzzification (10). Since then, Professor Lotfizadeh has been successful in numerous awards due to the introduction of an exquisite theory of fuzzy logic and his efforts in this field. After introducing the fuzzy logic into the world of science, there were initially many resistances against the acceptance of this theory. (14 and 11) are part of these resistances as mentioned. It was due to false perceptions of fuzzy logic and its efficiency. Interestingly, fuzzy logic was more welcomed in the first years of its birth in the Oriental world, especially in Japan, but the domination of zero and one thought in the West gave a slight boost to this theory. (18) However, as soon as this science was utilized, new electronic and digital devices were introduced into the market which worked based on fuzzy logic (19). The opposition also slightly decreased, in Japan, fuzzy logic was welcomed, mainly on robotics and intelligence. The subject was one of the main driving forces of this science after four years of immersion. In fact, it can be said that a large part of artificial intelligence is along with the history of fuzzy logic (21).

In this section, the four ways that have been used for service evaluation by the use of fuzzy logic are checked :

LAU and [18] YUNE proposed a distributed fuzzy qualitative evaluation system called DFQES to apply complex distributed assessment scenarios.

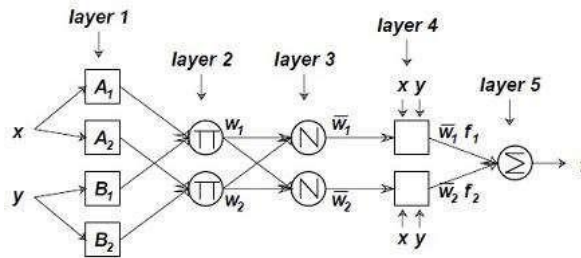
CHEN and colleagues [19] have presented a Qos based web service evaluation model. Concepts and communications are defined by the language, which identifies the web. When user access to web services is provided, the functions of the front-end service are upgraded and Qos limits are also progressing. This model can automatically capture valuation characteristics from a knowledge base that reflects the requirements of the task, user area, and Qos constraints.

Jui-Che Tu and Chi-Ling Hu [20] solve service ranking problems using AHP and fuzzy logic. The method is presented in the pre-negotiation phase. Arun Sharma [21] presented a fuzzy logic approach to assess the capability of maintaining components, which was more effective than previous ones.

**3. Adaptive Neural Fuzzy Inference system (ANFIS).** Adaptive neural fuzzy inference system provides an adaptive network that can be used for estimating membership by means of post-propagation algorithms or hybrid (least squares and back propagation estimates). The system performance is obtained by using the difference between the observed outputs and the output of the trained network, which is displayed with the error rate. Different steps of the FIS system can be identified as sequential layers of the neural network. The structure of the ANFIS system is described below:

The model is similar to FL: the **IF** sector is the same as the fuzzy proposition, and the **Then** section is similar to the mathematical function. The model uses a fuzzy inference system based on the TSK fuzzy if-then rules [1].

Assume that the FIS system has two inputs  $x, y$  and one output  $f$  such that  $x, y$  are the qualitative parameters and  $f$ , QoS is the total, TSK rules of the system are according to the following formulas:



**Figure1. ANFIS model**

$$1: \quad \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1(x,y) \quad (1)$$

$$2: \quad \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2(x,y) \quad (2)$$

Figure 1 shows the ANFIS architecture equivalent to an adaptive network that is functionally equivalent to the TSK fuzzy inference.

As shown in Fig. 1, the output of Figure 1 is the input of the fourth layer of Fig. 2.

In Figure 1,  $o_{L,i}$  represents the output of node  $i$  in the  $L$ -layer. In Layer 1, each node is a square node that generates membership degrees according to Equation 3.

$$o_{L,i} = \mu_{A_i}(x) \quad (3)$$

$x$  is the input of the node  $i$ ,  $A_i$  is the language tag that is dependent on this node,  $\mu_{A_i}$  represents the parameter membership functions.

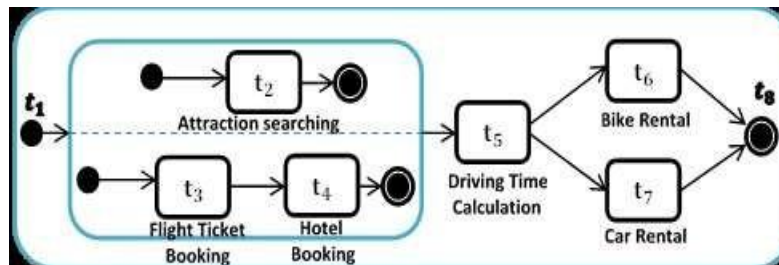
$o_{L,i}$  is the degree of membership of a fuzzy set  $\{A_1, A_2, A_3, A_4\}$ .

**4. Proposed model**

The combination of services results from the need for a predetermined purpose that is not achieved by the initial services. The two most important factors in creating an appropriate combination of services are the functional and qualitative features of the services. The services available in a combination must be functionally integrated and coordinated, and the quality features of the services must be such that the quality of the product is matched to the needs of the user. To quantify the quality of services and their combination, QoS quantifies quality quantitatively [11].

**1-4- execution plan**

Today, different languages and models are used to describe a combination of services, the state diagram is one of the most common methods for describing the combination of services. For example, a conjunction mode diagram for a trip plan is shown in Figure 3-3 [4].



**Figure 2: Conjunction mode charts related to the travel plan [11]**

The appointment of a service from members of a community to execute any action during the execution of a compound service leads to the formation of a map. It should be noted that due to the existence of multiple routes and the possibility of multiple choices among the services of an association, there are always several executable maps for the execution of a composite service (16 and 17). The quality of each service is determined by the qualitative criteria associated with that service. According to the quality criteria (cost, response time, availability, reliability and operational capability) for the initial services, the qualitative vector service S is defined as Equation (4).

$$Q(s) = (q_{cost}(s), q_{Rt}(s), q_{Av}(s), q_{Re}(s), q_{thp}(s)) \quad (4)$$

The methods for calculating the values of qualitative criteria are different. These values are used to compute the QoS of service combinations. There are collective functions used to calculate QoS for each of the qualitative criteria of a hybrid service based on sequencing, branching, parallel, and loop structures; Table 3.1 shows some of these functions for the execution plan [4].

### 3-3-3- Optimal performance map selection

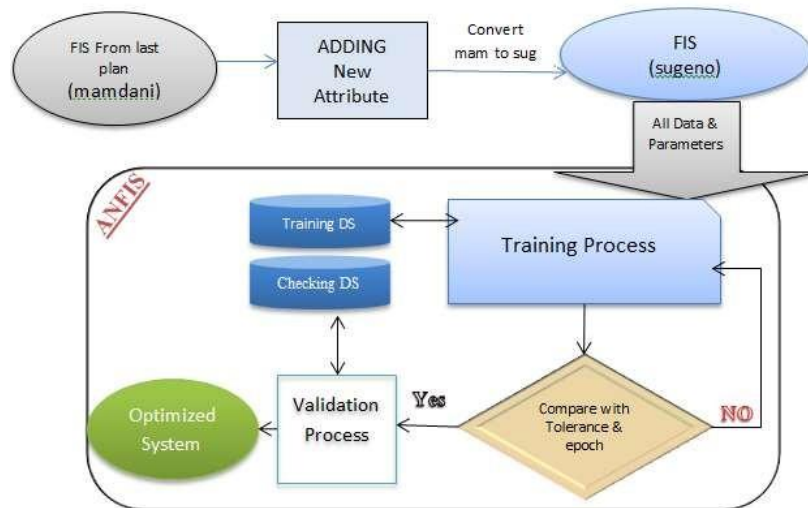
If one assumes that for each  $t_i$  there is a set of candidate services  $s_j$  that are ready for assignment, by selecting a service for each action in the run, the global planner produces a set of executable plans P as the equation 5.

$$P = [p_1, p_2, p_3, \dots, p_n] \quad (5)$$

n specifies the number of executable plans. After the qualitative vector of each execution plan is computed by cumulative functions, the Q matrix, each row of which represents the qualitative vector of an executable plan, is obtained as equation 6.

$$Q = \begin{pmatrix} Q_{1,1} & Q_{1,2} & Q_{1,3} & Q_{1,4} \\ Q_{2,1} & Q_{2,2} & Q_{2,3} & Q_{2,4} \\ \dots & \dots & \dots & \dots \\ Q_{n,1} & Q_{n,2} & Q_{n,3} & Q_{n,4} \end{pmatrix}$$

There are ways to select the optimal executive plan, but the purpose of this research is to design a fuzzy system that will scorecard the executive plans and select the top-level executive plan as the optimal execution plan.



**4.2 Architecture of the proposed model.** To improve the quality of the proposed method, automating some of the processes and completing the expert opinion are on the agenda. Our proposed scheme is to use a kind of adaptive neural fuzzy system by training through auxiliary data. In this way, the adaptive neural fuzzy model is implemented through training through input data as well as auxiliary data, for this purpose, a comparative neural fuzzy model with the basis of learning techniques is the introduction of the membership functions and the parameters of verbal variables, which is shown in Fig.3.

**Figure 3: Architecture of the proposed model**

The steps of the proposed method are as follows:

1- Use of a new non-obligatory feature:

In order to match the results of previous research with actual values and Web services, a new qualitative feature called "Throughput" was added to the collection to ensure that actual values for it would also affect the overall quality of the system.

2. Using Sugenu's Fuzzy Inference System:

In almost all of the previous methods, Mamdani's deduction system is used because of its simplicity of use and its intuition, while the Sugenu fuzzy inference system has the following advantages that are hidden by many scholars:

- Computational optimality
- Proper operation along with linear techniques
- Ensure continuity of the output level by this method

3- Applying real data sets

In order to match the results of the research, actual values will be generated with real data, derived from valid sources and from the recommendation of valid articles from valid journals.

4. Using the Adverse Neural Fuzzy Inference System:

In order to intelligently combine some of the stages of combination and theory, we have attempted to use a method that precisely determines the sectors of the inputs of the linguistic variables using qualitative knowledge of intelligent human. This results in closer results to actual values and consequently qualitative improvement of the system.

According to the scheme of the system, the first action performed in this section is the implementation of the variables and membership functions of the Mamdani fuzzy inference system. At this point, the membership function, language variables, and rules related to the throughput feature are designed and the other features will be designed similar to this feature.

The rules for the membership function of qualitative **Throughput** are as follows:

h h = h h = h h  
h h = h h = h h  
h h = =  
h h = =  
h h = =

The rules for the membership function of the qualitative value of **Cost** are as follows:

- CFcost IF Cost=very Low THEN Rank=very high
- CFcost IF Cost=Low THEN Rank=high
- CFcost IF Cost=moderate THEN Rank=moderate
- CFcost IF Cost=expensive THEN Rank=low
- CFcost IF Cost=very expensive THEN Rank=very low

The rules for the membership function of qualitative **Availability** are as follows:

- CFav IF Availability=very high THEN Rank=very high
- CFav IF Availability=high THEN Rank=high
- CFav IF Availability=moderate THEN Rank=moderate
- CFav IF Availability=low THEN Rank=low
- CFav IF Availability=very low THEN Rank=very low

For each qualitative feature, there will be five independent rules. There are five qualitative characteristics and 25 laws in this article.

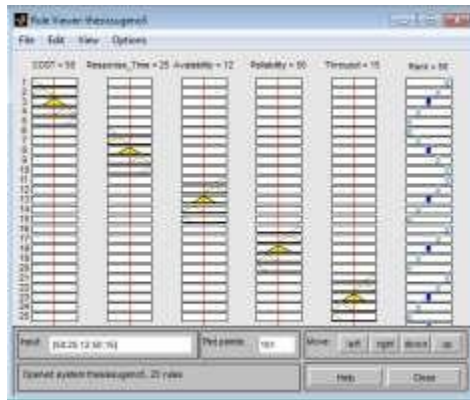
After this stage, the Mamdani fuzzy inference system will be converted to the Sugenu fuzzy inference system, all of which will be done in MATLAB software and in the fuzzy toolbox so that the conversion is carried out accurately without the user's opinion and accurate results are obtained. . Part of the space of the Mamdani fuzzy implementation rules is shown in Figure 4.

**Figure 4 - A part of the space of Fuzzy Mamadani implemented rules**



And part of the context of the Fugitive Implementation Rules of Sugenu is shown in Fig. 5

**Figure 5: Part of the context of the Fuzzy Sugnu Implementation Rules**



In Table 1, you can see that the Sugenu fuzzy results are much more precise than the Mamdani fuzzy, in that the worst input mode has the lowest number (27) and the best input mode has more numbers (40) in the results of the deduction of the Sugenu and in the data of the table. In Mamdani's deduction, the output is approximately constant (49 and 50), this precision will be effective in choosing the optimal combination of services. Table 1 shows part of the fuzzy comparison of the Mamdani and the Sugenu fuzzy.

30	32	15	30	0	40	20
32	33	0	52	12	38	20
02	45	30	12	43	33	20
00	42	54	10	3	31	20
00	40	1	1	1	51	40
CO2T	Response Time	Availability	Reliability	Throughput	(Sugeno) Mamdani	Sugeno Mamdani

**Table 1: Part of Fuzzy Comparison of Mamedani and Sugenu Fuzzy**  
4-4-Practicing Real Data and ANFIS Training:

In the previous method (11), the language variable parameters are entered by the human user / expert user, and the actual data did not interfere in their configuration. There was also no guarantee that membership functions and language variables would work well for all types of data, what we were looking for is to get the membership parameters dynamically, which is why we use a nervous way to teach real primitives data to determine the parameter of the linguistic variables in a smart way.

We implemented this method using ANFIS. In this section, our goal is to use real data to determine the parameter of language variables, so we need to use credible datasets that store Web service information. To extract these data, various sources such as (13 and 14) describe the methodology and data extraction models. Using these resources, the required data is extracted from (15).

The data in the data set is from 5825 different web services, which are obtained by 339 different users in different locations. Out of this large amount of data, we use 200 data from a specified user, of which 70% of the data that is 140 data will be used for training, and 30% of the data that is 60 data will be used for validation of the data. . Among the qualitative features provided by Throughput, we will examine

Response time by this mechanism and adjust the parameters of their linguistic variables.

The comparison of qualitative feature of Response time of results before training for the very low ([0 0 12.5]) and after training ([-5.06 0.99 3.06]) for the same language variable indicates that the results are closer to reality and the system's diagnostic capabilities are improved. For example, in pre-training mode, if the number 1 is given as input to this linguistic variable, it will be difficult to determine if the input is good or bad, but in the post-instruction data it can be easily understood that input 1 In the middle of the language variable is very low.

**Conclusion.** The findings showed that the Sugeno fuzzy results are much more accurate than the Mamdani fuzzy, in that the worst input mode has the lowest number and the best input mode has more numbers in the results of the Sugeno derivation and in its data. While in Mamdani's deduction, the output of the number is almost constant. This accuracy will be effective in choosing the optimal combination of services. Also, by applying real data, the parameter of the language variables is entered by the expert human user and the actual data did not interfere in their configuration, and it was not guaranteed that the membership functions and language variables for all The type of data work well, what we were looking for was dynamically integrate the membership functions, so we used the neural pathology to teach real data to make the parameter of the linguistic variables as smart. We implemented this method using ANFIS, which aimed to use real data in determining the parameter of language variables, so we would use valid datasets where different web services were stored. To extract these data, various sources, methodology and data extraction models were described and we extracted the required data using these resources. Comparing the results before the training for the same linguistic variable shows that the results are closer to reality and the system diagnostic ability is improved.

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