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QOS-AWARE WEB-SERVICES RANKING: NORMALIZATION TECHNIQUES COMPARATIVE ANALYSIS FOR LSP METHOD

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ABSTRACT

Service-oriented architecture (SOA) and Internet services technologies offer advanced solutions for creating distributed business processes and applications. At the same time, services must be available to a growing number of users and satisfy their requirements for both functional and non-functional properties of services. The problem of services selection based on the quality of services is formulated as a multi-criteria decision-making (MCDM) problem. MCDM methods typically require preliminary normalization of the criteria, which in turn can significantly affect the results of multi-criteria problem resolving. In this paper, the effects of commonly known normalization techniques (MAX-MIN, VECTOR, MAX, SUM and LOG) on the ranking Web services using a method of Logic Scoring of Preference (LSP) are investigated. As an outcome of study conducted, the approach to the usage of the Vector, Sum and Max techniques to normalize the criteria when applying the LSP method has been proposed.

Keywords: QoS, web service, logic scoring of preference, normalization, ranking.

INTRODUCTION

Over the past decades, the Internet service technologies, e.g., Web services, Internet of Things (IoT) services, cloud and network services, services provided by Cyber Physical Systems have become an inalienable part of business infrastructures in many industries. It has become possible to automatically synthesize complex Web services from a set of elementary Web services (orchestration) and organize their joint work (choreography) to achieve the goals in different areas of business due to paradigm of the Service-oriented Architecture (SOA) [1]. In addition, providers offer a huge variety of simple, complex and composite Web services for integrating them into business processes. For instance, in the IoT-domain, Web services are commonly considered as the building blocks for business and application layers of IoT-infrastructure [2, 3]. Another demonstrative example of Web services usage is grounded on “smart home” scenarios, e.g., home appliances control [4]. Moreover, the service consumers face the challenge of choosing a suitable service for a specific application. Firstly, the service needs to possess the appropriate functionality for its correct integration into the business process. Secondly, the service is supposed to meet the consumer’s requirements to the quality properties of the service, called quality of service or QoS.

Nowadays, it has become a de-facto to express the functionality of Web services using the Web Service Definition Language (WSDL). The WSDL descriptions of available Web services are applied to form a list of candidate Web services that can provide the expected functionality. There have been a lot of developments, researches and proposals to formalize the description of the service QoS-properties; however, a generally accepted and standard approach has not yet been adopted. Therefore, the consumer of the service cannot determine in advance the quality of the proposed Web service. Against the background of a constantly growing market for the Web services brought to the use, the consumer needs to select the Web service from a list of service candidates with identical functional characteristics [5, 6]. This selection is further complicated because the consumer usually wants a Web service to satisfy several quality requirements at the same time. Thus, the QoS-aware service selection problem can be formulated as multi-criteria decision-making (MCDM) problem [7]. A comprehensive review of the Web service selection and MCDM methods can be found in [8].

Quality criteria have different measurement units and magnitudes, therefore, these criteria values must be transferred to a common scale by normalization to obtain a single aggregated score of the service’s quality. Various types of normalization techniques can be applied in MCDM, e.g., the MAX-MIN, VECTOR, SUM, MAX, Logarithmic (LOG), etc. These and other normalization techniques descriptions can be found, e.g., in [9, 10]. It is known that the deformations of the initial values of the criteria caused by the use of normalization can affect the final result obtained by the MCDM methods [9-11]. Therefore, the MCDM method must be consistent with the normalization method applied, otherwise, the best choice of service may be overlooked. The objective of this paper is to verify the effect of normalization techniques on pair with the LSP method on Web services QoS-aware ranking.

LITERATURE REVIEW

In this paper, the literature review has been focused on the research related to ranking the alternatives using MCDM methods and the impact of different normalization methods on ranking results. At the same time, special attention has been paid to applying these methods to QoS-based ranking Web services to select the best candidates in terms of satisfying user requirements.

Many MCMD methods can be applied to QoS-aware Web service selection. In paper [12], a comparative analysis of the methods, namely Analytic Hierarchy Process (AHP), Logic Scoring Preference (LSP), Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) and Web service relevancy function (WsRF), has been conducted. Perhaps some hybrid methods and approaches, such as Fuzzy AHP [13], Fuzzy TOPSIS [14], a combination of the AHP and the TOPSIS [15, 16], will be promising for QoS-based Web services selection. The soft computing methods for selecting the suitable Web service, including evolutionary algorithms, have been discussed in [17].

The AHP method has been applied to rank Web services [7]. The authors describe the types of Web services QoS-parameters (numeric, Boolean, string, ordered and unordered sets, enumeration) and their value comparison rules exhaustively. To facilitate the ranking of Web services with a large number of QoS-parameters, a flexible hierarchy of these parameters has been proposed. However, the comparison with other MCDM methods and QoS-parameters normalization techniques has not been discussed. Nevertheless, the list of QoS-parameters taken into consideration for ranking, their value ranges and criteria importance weights can be a good example for testing other Web services ranking methods and criteria normalization techniques.

The authors of the paper [18] have introduced an approach to QoS-aware Web services discovery and ranking by applying the WsRF. Later, this approach has been implemented in other works [19, 20], but they have not analyzed the effect of normalization on the ranking result.

A detailed analysis of the most suitable normalization methods, especially for AHP has already been conducted [11]. In [9, 10], the effect of four normalization methods (MAX-MIN, VECTOR, MAX and SUM) on the results of the TOPSIS method of the ranking has been investigated. In paper [9], a method for evaluating the consistency of normalization techniques using the Rank Consistency Index (RCI) has been proposed. In [21], six normalization methods (MAX-MIN, VECTOR, MAX, SUM, LOG and Fuzzification) have been investigated and RCI has also been applied to assess the impact of these techniques on ranking results. However, in this work, in contrast to work [9], the authors have used RCI to assess the quality of ranking, taking into account the order of each alternative in the rankings. In the papers [9, 21], the consistency has been additionally checked by calculating the correlation between the rankings using the Pearson and Spearman correlation methods.

The essence of the LSP method has been presented in plenty of works, in particular in [22, 23]. The description of the application of this method in different domains, e.g., job selection problem, home selection problem, evaluation of medical conditions, evaluation of Internet search engines, etc., can be found in [23]. However, only the MAX-MIN normalization technique has been used in all applications the authors are aware of. The applying of the LSP method for Web services ranking is covered in literature sparsely. This gap has been partially filled by several works, e.g., [24-27]. In work [24], the LSP method with Ordered Weighted Averaging (OWA) operators has been applied for semantic Web service ranking, but solely the MAX-MIN normalization technique has been utilized. In [25], the authors propose a method for automatic selection of Web services based on QoS using the LSP method, taking into account the fact that service's suitability significantly depends on the user's context. This work uses the MAX-MIN normalization method. A modified LSP method has been proposed in [26], this method involves the MAX-MIN normalization technique. In [27], the LSP method has been broadened to a Type-based LSP Extension for service selection using context-aware criteria. This method uses the MAX-MIN normalization technique.

MATERIALS AND METHODS

In this paper, an example the Web services list and their properties, given in [7], have been utilized. To simplify the QoS-based ranking algorithm, the authors of this work have grouped the criteria that have similar characteristics and priorities. Groups and criteria and their weights can be represented as a tree or hierarchy shown in Figure-1.

Our study has not used such grouping; therefore, direct (or immediate) weights of the relative importance of each criterion have been calculated in accordance with the tree shown in Figure-1. The list of criteria, their ranges of values and calculated weights are provided in Table-1.

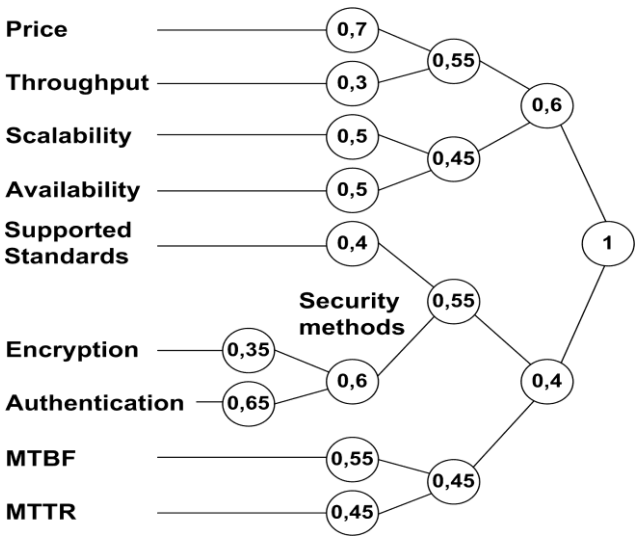

Figure-1. The hierarchical structure of criteria weights.

Table-1. The ranges and weights of Web services criteria.

Criterion	Range	Weight
Price	1,8 to 2,7 USD	0,231
Throughput	415 to 1425 Kbps	0,099
Availability	92 to 96%	0,135
Scalability	0,8 to 0,92	0,135
Supported Standards	2 to 5	0,088
Data Encryption	5 to 9	0,0462
Authentication Method	5,84 to 17	0,0858
Mean Time Between Failures (MTBF)	$3{,}6\cdot 10^7$ to $4{,}1\cdot 10^7$s	0,099
Mean Time to Restoration (MTTR)	1580 to 1800 s	0,081

J. Dujmović presented the LSP method [22], which allows reconfigure aggregation function with the special r parameter:

$$\mathrm{E}_i = \left(w_1 E_{i,1}^r + w_2 E_{i,2}^r + \ldots + w_m E_{i,m}^r\right)^{\frac{1}{r}}, \quad (1)$$

where E_i is an aggregation function of all m criteria for the global score of the ith Web service; $E_{i,j}$ – normalized elementary preferences, that indicate the degree of satisfaction of user's requirement by the jth criterion of the ith Web service; w_j – the weight of criterion, that reflects the relative importance of jth criterion, and $0 \le w_j \le 1$, $\sum_{j=1}^{m} w_j = 1$; r – a real number that presents a logical relation between the criteria. The value of E_i aggregation function can be interpreted as the global degree of satisfaction of the m specified user requirements by the ith Web service.

By varying the value of r, a spectrum of aggregation functions can be obtained, including functions, e.g., weighted harmonic mean ($r=-1$), weighted geometric mean ($r=0$), weighted arithmetic mean ($r=1$), weighted square mean ($r=2$), etc.

The r values are determined by the number of criteria and the α parameter, which is the simultaneity/ replaceability degree of the aggregated criteria. The α parameter can take values from 0 to 1 and is known as *orness degree* or *orness*. In [22], seventeen symbolic names (C, C+ +, C+, C+ -, CA, C- +, C-, C- -, A, D- -, D-, D- +, DA, D+ -, D+, D+ +, D) of aggregation functions and the r values for the case of 2–5 aggregated criteria for different α are presented. For a larger number of criteria, the r can be calculated using the approximation function [23]:

$$r(\alpha) = \frac{c_0 + c_1 x + c_2 x^2 + c_3 x^3 + c_4 x^4}{\alpha(1-\alpha)}, \quad (2)$$

where $x = \alpha - 1/2$ and $0 < \alpha < 1$; $c_0 = 0{,}25$, $c_1 = 1{,}89425$, $c_2 = 1{,}7044$, $c_3 = 1{,}47532$, $c_4 = -1{,}42532$.

The values of criteria must be normalized first to use any aggregation function. The values of all criteria, which usually have different measurement scales, are transformed by normalization into normalized ratings, i.e. the values of all attributes are mapped onto a single scale. Normalization gives the way to the comparison of all criteria on a common scale and, therefore, to apply the weighted aggregation. There are many normalization techniques, the lists of normalization types of and their descriptions can be seen, for instance, in [9-11, 21]. The normalization procedure takes into account two properties of the criterion: the first one is "benefit", which means the higher value of the criterion, the better (e.g. throughput); and the second one is "cost", which means the lower criterion value, the better (e.g. price).

In this work, five of the most commonly used MAX-MIN, VECTOR, MAX, SUM and LOG normalization techniques have been investigated. These techniques are denoted as N_1, N_2, N_3, N_4 and N_5, respectively. Let n be a number of Web services ranked by the LSP method, m is a number of QoS criteria, $x_{i,j}$ is a value of jth criteria for i^{th} Web service, $i = 1,\ldots,n$ and $i = 1,\ldots,m$. The normalization techniques briefly described below.

a) Max-Min normalization (N_1). The normalized value $E_i(x_j)$ for benefit criterion is obtained with

$$E_i(x_j) = \frac{x_{i,j} - x_{\min}}{x_{\max} - x_{\min}}. \quad (3)$$

For cost criteria $E_i(x_j)$ is calculated as follows:

$$E_i(x_j) = \frac{x_{\max} - x_{i,j}}{x_{\max} - x_{\min}}. \quad (4)$$

b) Vector normalization (N_2). In this technique, the normalized value for benefit criterion is calculated as follows:

$$E_i(x_j) = \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{n} x_{i,j}^2}}. \quad (5)$$

For cost criteria $E_i(x_j)$ is calculated as follows:

$$E_i(x_j) = 1 - \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{n} x_{i,j}^2}} . \quad (6)$$

c) Max normalization (N_3)**.** In this technique, the normalized $E_i(x_j)$ value for benefit criterion is obtained as follows:

$$E_i(x_j) = \frac{x_{i,j}}{x_i^{\max}} . \quad (7)$$

For cost criteria, $E_i(x_j)$ is calculated as follows:

$$E_i(x_j) = 1 - \frac{x_{i,j}}{x_i^{\max}} . \quad (8)$$

d) Sum normalization (N_4)**.** With this technique, the normalized $E_i(x_j)$ value for benefit criterion is calculated as follows:

$$E_i(x_j) = \frac{x_{i,j}}{\sum_{i=1}^{n} x_{i,j}} . \quad (9)$$

For cost criteria, $E_i(x_j)$ is calculated as follows:

$$E_i(x_j) = \frac{1/x_{i,j}}{\sum_{i=1}^{n} 1/x_{i,j}} . \quad (10)$$

e) Logarithmic normalization (N_5)**.** The normalized $E_i(x_j)$ value for benefit criterion is obtained with respect to the following expression:

$$E_i(x_j) = \frac{\ln(x_{i,j})}{\ln\left(\prod_{i=1}^{n} x_{i,j}\right)} . \quad (11)$$

For cost criteria, $E_i(x_j)$ is calculated as follows:

$$E_i(x_j) = \frac{1 - \frac{\ln(x_{i,j})}{\ln\left(\prod_{i=1}^{n} x_{i,j}\right)}}{n-1} . \quad (12)$$

EVALUATION METHODOLOGY

This section presents the research methodology that has been successfully applied to evaluate of effects of normalization on the outcome of the QoS-aware ranking of Web service alternatives with LSP method. This methodology is similar to the approach proposed in [9], but slightly differs in terms of the creation of the decision matrix at each iteration of the simulation process and the algorithm for calculating the RCI. The criteria for Web services have been created by generating random values for criteria in the ranges shown in Table-1. The algorithm for the RCI calculation, proposed in [9], corresponds to the calculation in accordance with the following formula:

$$RCI(N_1) = \Big(T_{12345} + \frac{3}{4}(T_{1234} + T_{1235} + T_{1245} + T_{1345}) + \frac{2}{4}(T_{123} + T_{124} + T_{125} + T_{134} + T_{135} + T_{145}) + \frac{1}{4}(T_{12} + T_{13} + T_{14} + T_{15}) \Big) / N , \quad (13)$$

where T_{12345} is a total number of times when N_1 produced the same ranking as N_2, N_3, N_4 and N_5; T_{1234} is a total number of times when N_1 produced the same ranking as N_2, N_3 and N_4; T_{123} is a total number of times when N_1 produced the same ranking as N_2 and N_3; T_{12} is a total number of times when N_1 produced the same ranking as N_2; N is a total number of iterations in simulation process was run.

Formula (13) is written for the case of calculating the RCI of the first normalization technique (N_1) when evaluating five normalization techniques. RCI for the other normalization techniques can be calculated with formulae similarly to (13).

The way to calculate the RCI with (13) can be expressed in a compact form using the following formula:

$$RCI_i = \frac{1}{N(n-1)} \sum_{j=1}^{n-1} t_{i,j} \sum_{k=1}^{j} k \cdot C_j^k , \quad (14)$$

where $t_{i,j}$ is a total number of times when N_i normalization technique produced the same ranking as j other normalization techniques; C_j^k is a number of k-combinations from j; n is a number of normalization techniques.

From the point of view of the practical calculation, the rankings coincidences number, the considered calculation method contains a redundant number of rankings comparisons. So, for instance, if in a specific iteration of simulation for the N_1 normalization technique, the number of coincidences times of T_{1234} is obtained, then there is no need for the N_1 normalization to count the number of T_{123}, T_{124}, T_{134}, T_{12}, T_{13} and T_{14} coincidences times. In addition, the redundant number of comparison operations grows significantly with the number of normalization techniques compared.

Therefore, an easier way to calculate RCI is proposed, which corresponds to the following formula:

$$RCI_i^* = \frac{1}{N(n-1)} \sum_{j=1}^{n-1} j \cdot t_{i,j} \ . \quad (15)$$

The asymptotic time complexity of the algorithm based on (14) is equal to $\Omega(2^n)$. The asymptotic time complexity of the algorithm based on (15) is equal to $O(n^2)$. The difference between the RCI and RCI^* values obtained with (14) and (15), respectively, is always a known value and is equal to

$$RCI_i - RCI_i^* = \frac{1}{N(n-1)} \sum_{i=1}^{n-1} t_{i,j} \sum_{k=1}^{j} \left(k \cdot C_j^k - 1\right). \quad (16)$$

As it can be seen in (16), the difference between RCI and RCI^* is always positive and depends on a maximum number of coincidences, therefore, the result of normalization techniques ranking with (14) and (15) will be the same. The steps for calculating RCI^* in accordance with (15) are provided in Algorithm 1.

Algorithm 1	
	Input: $R = \{R_1, ..., R_n\}$, where R_j is the ranking of the normalization techniques; n is the number of the normalization techniques
	Output: $RCI^* = \{RCI_1^*, ..., RCI_n^*\}$, where RCI_j^* is the Ranking Consistency Index of jth normalization technique
1.	for $j \leftarrow 1$ to n do
2.	$c \leftarrow 0$
3.	$RCI_j^* \leftarrow 0$
4.	for $k \leftarrow 1$ to n do
5.	if $k \neq n$ then
6.	if $R_j \equiv R_k$ then
7.	$c \leftarrow c + 1$
8.	end
9.	end
10.	$RCI_j^* \leftarrow RCI_j^* + \frac{c}{n-1}$
11.	end
12.	end

Two simulation based experiments were conducted to evaluate the effect of normalization techniques on the result of ranking with LSP method. The first one has been conducted to assess the dependency the of normalization techniques consistency on the number of ranked Web services, and the second one to evaluate the dependency of the normalization techniques consistency on *orness* parameter of the LSP method.

The common part of experiments is conducted as follows:

a) In each iteration Web service alternatives have been generated by randomly generating criteria vectors. The values of the vector elements have been bound to the corresponding ranges specified in Table-1.

b) Then, taking into account the "benefit-cost" property, the required number of non-dominated vectors has been chosen. From these non-dominated vectors, the decision matrix has been formed. So, the decision matrix consists of the n rows (number of evaluated Web services) and the m columns (number of criteria).

c) Then, decision matrix has been normalized by with (N_1, N_2, N_3, N_4 and N_5) normalization techniques.

d) LSP method has been applied for calculating the preference value for each Web service considered.

e) The rankings produced by LSP at each iteration have been compared and the numbers of matches between the rankings have been stored.

f) After performing the specified number of iterations (10^4), the RCI^* for each normalization technique have been calculated with respect to Algorithm 1.

In Table-2, the example of the results of counting the number of rankings coincidences for one simulation iteration are provided. In Table-3, the results of RCI and RCI^* calculation with respect to (14) and (15), using the data from Table-2, are demonstrated.

Table-2. An example of counting the number of rankings coincidences with different normalization techniques.

	$t_{i,1}$	$t_{i,2}$	$t_{i,3}$	$t_{i,4}$
N_1	906	260	1508	657
N_2	1565	4740	2829	657
N_3	960	4619	2815	657
N_4	1326	2620	2829	657
N_5	747	281	1335	657

Table-3. The RCI and RCI^* values calculated using data from Table-2.

	N_1	N_2	N_3	N_4	N_5
RCI	1,028	1,887	1,856	1,869	0,983
RCI^*	0,214	0,554	0,532	0,542	0,199

RESULTS AND DISCUSSIONS

The obtained experimental results are presented in Figure-2 and Figure-3. The Vector (N2), MAX (N3) and SUM (N4) normalizations have higher RCI than the MAX-MIN (N1) and LOG (N5) techniques. The MAX-MIN (Nl) normalization has worst RCI on whole considered range of change in the number of competitive Web services. The peculiarity of these results is similar to the one presented by Chakraborty and Yeh in [9].

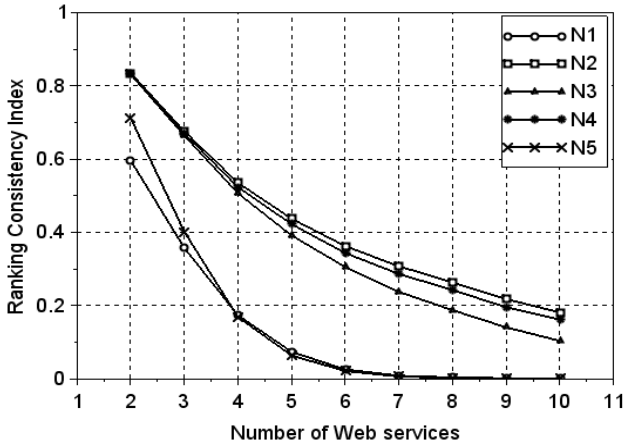

Figure-2. RCI of normalization techniques as the functions of Web services number.

The RCI of all five normalization techniques significantly depends on the *orness* parameter and has the maximum values at $orness = 0,\ 5\ (r = 1)$, which corresponds to the aggregating function weighted arithmetic mean (symbol A in Figure-3).

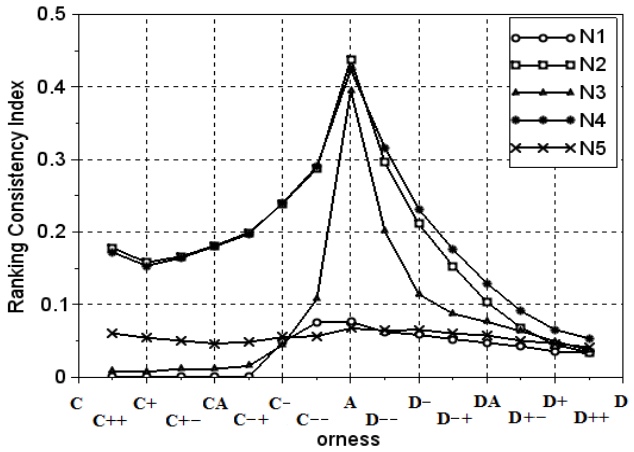

Figure-3. RCI of normalization techniques as the functions of aggregator simultaneity/replace ability degree (*orness*).

CONCLUSIONS

In this paper, the effects of commonly known MAX-MIN, VECTOR, MAX, SUM and LOG normalization techniques on the results of ranking Web services, using the LSP method, have been investigated. The experiment has shown a low consistency of Max-Min normalization technique in comparison with the rest of considered techniques. Our experiment has also confirmed the results of the Chakraborty and Yeh study [9] regarding the worst ranking consistency MAX-MIN normalization technique. However, it is the MAX-MIN technique that is usually used in the LSP method since the minimum value of the normalized criterion and zero or negative values of the *orness* parameter provide automatic rejection of a Web service that does not satisfy the mandatory requirements. Thus, to increase the consistency of ranking using the results of the LSP method, it is advisable to use VECTOR, SUM and MAX normalization techniques. At the same time, it is necessary to introduce a filter for automatic rejection of Web services that do not satisfy the mandatory requirements.

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