Towards Uncertain QoS-aware Service Composition via Multi-objective Optimization

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***Abstract*—QoS-aware Web service composition has recently become one of the most challenging research issues. Although much work has been investigated to solve the problem, they mainly focus on certain QoS of Web services, while QoS with uncertainty exposes the most important characteristic in a real and highly dynamic environment on the Internet. In this paper, with the consideration of uncertain service QoS, we model the issue of Web service composition with QoS uncertainty that is translated into a multi-objective optimization problem via uncertain interval number, which can be solved by our proposed approach via an non-deterministic multi-objective evolutionary algorithm using the strategy of decomposition. Large-scale empirical experiments have been conducted on our simulated datasets. The experimental results demonstrate that our proposed approach can effectively and efficiently find an optimum composite service solution set with satisfactory convergence.**

***Keywords*—Uncertain QoS; Web service composition; Multi-objective optimization; Evolution algorithm**

I. Introduction

Web services are becoming the most important fundamental building blocks for fast developing next generation applications[1]. In many cases, however, no single Web service in a service repository can satisfy a given complex request. Thus, Web service composition (WSC) is proposed and is the task of combining a set of single Web services together to create a complex, value-added and cross-organizational business process[2].Quality of Service (QoS) is a broad concept that encompasses a group of nonfunctional properties, such as the cost, response time, throughput, availability and successability. For those Web services providing the same functionality, QoS has been one of the important criteria to differentiate them for Web service discovery, selection and composition. As a result, QoS-aware Web service composition (QWSC) is becoming a hot research issue. The challenge is how to construct a composite service effectively and efficiently such that its overall QoS is optimal, while all the QoS constraints are satisfied.

Many efforts on QoS-aware Web service composition have been made in recent years. Several works calculate the QoS value for single or composite Web service by Linear Programming (LP) or Mixed Linear Programming (MIP)[3][4][5][6][7][8][9] and get the global optimal component Web service. As the Artificial Intelligence (AI) algorithm applied on QWSC, the authors in [10][11][12] model the QWSC problem into a multi-objective optimization problem and solve it using a genetic algorithm. However, these approaches mainly focus on certain QoS of Web services. The value of QoS is always uncertain in realistic Internet environments. These approaches can not expressed the uncertainty of QoS fully, the MIP algorithm ignores the multi-objective proposition and Uncertain QoS-aware Web service Composition (UQ-WSC) problem is an NP-hard problem. Therefore, how to solve the UQ-WSC problem effectively and efficiently is still a challenging research issue.

To address the issue above, a new model and algorithm are respectively proposed in this paper. Firstly, we formulate our Web service composition with QoS uncertainty as an UQ-WSC problem that is modeled into an interval number multi-objective optimization problem (IMOP). Then, a Non-Deterministic multi-objective evolutionary algorithm based on decomposition (NDmoea/d) is proposed for solving an IMOP. Based on the MOEA/D algorithm[13], the algorithm presents an interval Pareto theory for interval number comparison and takes advantage of the Tchebycheff approach for decomposition. Finally, large-scale experimental evaluation has been on conducted and the results revealed that the proposed approach can be used to solve the UQ-WSC problem effectively and efficiently with satisfactory convergence.

The rest of this paper is organized as follows. Section II reviews related work on QoS-aware Web service Composition. The UQ-WSC problem is modeled into an interval number multi-objective optimization problem in section III. Section IV proposes an NDmoea/d algorithm for IMOP. Empirical experiments are shown in section V. Finally, section VI concludes the paper and discusses the future work.

II. Related Work

QoS-aware Web service composition problem has become one of the most popular research issue during the last years. To find the optimal composite service efficiently, lots of methods have been proposed. Zeng et al. [3][4] proposed a method based on linear programming. Based on a predefined workflow model, it transforms a QoS-aware WSC problem to an integer programming problem and finds the global optimal component services solution. With the consideration of loops peeling and stateful Web services, Ardagna et al. [5] modeled the Q-WSC problem into a mixed integer linear programming problem

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and solved it in the QoS constrained Web service selection problem. Based on QoS measurement metrics, Huang et al. [6] proposed multiple criteria decision making and integer programming approaches to select the optimal candidate service. To select service components with various QoS levels, Yu et al. [7] modeled the problem into the combinatorial model and the graph model. It took advantage of some heuristic algorithms in finding the solution. Taking into consideration of the probability and conditions of each execution path, Zheng et al. [9] proposed a approach to calculate QoS for composite services with complex structure and deal with different workflow composite patterns effectively.

Based on above investigations, we proposed an non-deterministic multi-objective evolutionary algorithm for a multi-objective optimization problem with uncertain interval number, that is translated by an uncertain QoS-aware Web service composition. The method can find a Pareto optimal solutions set for composite services and also can select different QoS composite services for users, taking into account of users preference.

III. Modeling of UQ-WSC problem

In this section, the UQ-WSC problem is modeled as an interval multi-objective optimization problem. First, the uncertain QoS of Web service is represented as an interval number. Then, an interval multi-objective optimization problem is denoted for a UQ-WSC problem.

A. Uncertain QoS Calculating Model

A Web service has lots of invoked records, which is different and uncertain. In this section, the uncertain QoS of Web service is denoted as an interval number as follows.

Definition 1 (Interval Number)**.** Let $\Re$ is a set of real numbers. A closed interval X is a interval number, if $X = [x^L, x^U] = \{x | x \in \Re, x^L \leq x \leq x^U\}$, where x^L is the lower bound of interval and x^U is the upper bound of interval.

Interval number is a set of real numbers on a closed interval. If a interval number $X = [x^L, x^U]$ and $x^L = x^U$, the interval number X is a real number. The general rules of interval number on mathematical calculation are similar to the rules of the set.

Definition 2 (Interval Number of Uncertain QoS)**.** Given a Web service $ws \in W$ and its uncertain QoS matrix $M_{m \times n}$, denoted by definition 4, the matrix $M_{m \times n}$ can be represented as a vector by interval number of uncertain QoS, which can be denoted as

$$M_{m*n} = \begin{pmatrix} ws.Q_1 \\ ws.Q_2 \\ \vdots \\ ws.Q_m \end{pmatrix} = \left([{q_1}^L, {q_1}^U] \quad \cdots \quad [{q_n}^L, {q_n}^U] \right)$$

where q_i $(i = 1, 2, \cdots, n)$ is a QoS criteria of Web service, ${q_i}^L$ and ${q_i}^U$ are lowest and highest QoS value in each attribute, respectively.

Definition 3 (Computing on Interval Number)**.** Given two interval number $A = [a^L, a^U]$ and $B = [b^L, b^U]$, the addition and the multiplication between the interval numbers are denoted as $A + B = [a^L + b^L, a^U + b^U]$ and $A * B = [Min(a^L b^L, a^L b^U, a^U b^L, a^U b^U), Max(a^L b^L, a^L b^U, a^U b^L, a^U b^U)]$, respectively.

B. UQ-WSC Multi-objective Optimization Model

A traditional multi-objective optimization problem model can be stated as following:

$$\begin{cases} \dot{M}in\ F(x) = (f_1(x), f_2(x), \cdots, f_n(x))^T \\ s.t.\ x \in \Omega \end{cases} \tag{1}$$

where Ω is the decision variable space, $F : \Omega \rightarrow R^m$ consists of n real-valued objective functions $f(x)$ and R^m is called the objective space.

Following the traditional multi-objective optimization model, the UQ-WSC problem can be modeled an interval multi-objective problem based on the service QoS calculating model. The model is shown as below.

To determine the best combination, we firstly define variables s_{ij} as follows.

$$\begin{cases} s_{ij} = 1, \text{ if the service } j \text{ is selected for the task } i; \\ s_{ij} = 0, \text{ otherwise} \end{cases} \tag{2}$$

In a service composition, there is exactly one service which is selected for a task. Therefore, the variables before must have the following constraint.

$$\sum_{j=1}^{m} s_{ij} = 1,\ 1 \leq i \leq T \tag{3}$$

In an UQ-WSC problem, the user may be give multiple global QoS constraints $C = (c_1, c_2, \cdots c_n)$, where c_1 represents global cost constraint, c_2 represents global response time constraint, others are the same way.

From above all, the interval multi-objective optimization model for UQ-WSC problem consists of objective function (1) and the constraints (2), (3) and users' global QoS constraints C. In the next section, we will propose an interval non-deterministic multi-objective evolutionary algorithm to solve this model.

IV. Interval Non-deterministic Multi-objective Evolutionary Algorithm

Given a multi-objective optimization problem, many methods have been proposed in recent years, such as greedy algorithm, evolution algorithm, dynamic planning, etc. However, these approaches cannot solve the interval multi-objective optimization problem directly that is proposed in this paper. Based on moea/d algorithms, we proposed an NDmoea/d algorithm to solve an IMOP for UQ-WSC problem.

As the same as MOEA/D algorithm, the NDmoea/d algorithm decomposes the interval number multi-objective optimization problem into N single objective subproblem, which can be optimized simultaneously in a single run.The algorithm makes use of interval Pareto approach for comparison and Tchebycheff approach for decomposition. The NDmoea/d algorithm works specifically as follows:

Algorithm 1: NDmoea/d algorithm

Input:

- INMOP
- N: the number of the subproblems considered in NDmoea/d (population size)
- $\lambda^1, \lambda^2, \cdots, \lambda^N$: a uniform spread of N weight vectors
- T: the number of the neighborhood of the each weight vector
- a stopping criterion

Output:

- EP: an external population, which is used to store non-dominated solutions found during the search

Step 1 Initialization:

Step 1.1 Set EP = $\varnothing$.

Step 1.2 Compute the Euclidean distances between any two weight vectors, and find out the T closest weight vectors to each weight vector as the neighborhoods. Set $B(i) = \{i_1, i_2, \cdots, i_T\}$, where $\lambda^{i_1}, \lambda^{i_2}, \cdots, \lambda^{i_T}$ are the T closest weight vectors to λ^i.

Step 1.3 Generate an initial population $x^1, x^2, \cdots, x^N \in \{0,1\}^n$ randomly, where $x^1, x^2, \cdots, x^N$ meet the constraint equation (3). Set $FV^i = F(x^i)$, $i = 1, 2, \cdots, N$.

Step 1.4 Initialize $z = (z_1, z_2, \cdots, z_m)^T$ randomly.

Step 2 Update:

For $i = 1, 2, \cdots N$, do

Step 2.1 **Reproduction:** Select two neighborhoods $\{k, l\}$ from $B(i)$ randomly, and then generate a new solution y' from x^k and x^l by using genetic operators.

Step 2.2 **Update of z:** For each $j = 1, 2, \cdots, m$, if $z_j < f_j(y')$, then set $z_j = f_j(y')$.

Step 2.3 **Update of Neighboring Solutions:** Following the ranking methods about interval numbers, if $g^{ws}(y|\lambda^j) \geq g^{ws}(x^j|\lambda^j)$ for each index $j \in B(i)$, then set $x^j = y$ and $FV^j = F(y)$.

Step 2.4 **Update of EP:** Remove all the vectors dominated by $F(y)$ from EP; Add $F(y)$ to EP, if no vectors in EP dominate $F(y)$.

Step 3 **Stopping Criteria:** If stopping criteria are satisfied, then stop and output EP. Otherwise, go to **Step 2**.

The NDmoea/d algorithm consists of three steps: Initialization, Update and Stopping Criteria. In initialization phrase, the algorithm initializes the population and the reference points, and gets the the neighborhoods by computing the Euclidean distances between two weight vectors; In update phrase, the algorithm reproductions a new feasible solution by genetic operators, such as crossover and mutation. Then, update the reference points, neighboring solutions and EP using the new feasible solution. Finally, the algorithm can be stopped and output the interval Pareto solution set, when the stopping criteria are satisfied in Step 3.

Different from MOEA/D algorithm, the NDmoea/d algorithm generates an initial population in initialization phrase (step 1.3), which must satisfy the constraint equation (2) and (3) from the interval multi-objective optimization model for UQ-WSC problem. In Update phrase, the NDmoea/d algorithm uses interval pareto approach for comparison between two values in step 2.2, step 2.3 and step 2.4.

V. Experimental Evaluation

A. Experimental Setup and Datasets

In order to evaluate the effectiveness of our proposed method, we implemented the algorithm in Python. Some empirical experiments are conducted on a PC with Intel Dual Core 2.8GHZ processor and 3G RAM in window 7.

We took advantage of response time, latency time, availability, reliability and successability as uncertain QoS criteria and generated a synthetic uncertain QoS dataset based on QWS2[14] dataset, which includes measurements of 9 QoS attributes for 2507 real-world Web services. In experiment, we firstly generated a normal distributions interval number for uncertain QoS value of Web services in QWS2. Then, for Ndmoea/d algorithm, the crossover probability was 0.8 and the mutation probability was 0.1. Next, we set dynamically the number of abstract services tasks T, the candidate services number N, the iteration stopping criterion M and the population P to evaluate the algorithm. Finally, we evaluation the algorithm from two aspects, such as optimal solution set and the convergence.

B. The Experiment Results and The Performance Evaluation

We assume there exists $T = 5$ abstract services tasks, $N = 3$ candidate Web services contained in every tasks and there are 3 QoS properties, including response time, availability and latency time. Let the interval possibility $\lambda = 1/2$, the population $P = 100$ and the iteration numbers $M = 500$. Using our proposed approach, we can effectively find the optimal solutions set as shown in the Table I.

Table I
The optimal solutions set found by NDmoea/d algorithm

No.	*Interval Pareto Solutions*	*Quality of Composite Services*
1	$< ws_1, ws_5, ws_9, ws_{10}, ws_{13} >$	$([713.24, 727.69], 0.58, [348.84, 364.33])$
2	$< ws_1, ws_6, ws_9, ws_{10}, ws_{13} >$	$([714.16, 728.10], 0.53, [309.98, 324.74])$
3	$< ws_1, ws_5, ws_9, ws_{10}, ws_{15} >$	$([733.31, 747.40], 0.56, [289.31, 304.18])$
4	$< ws_1, ws_6, ws_9, ws_{10}, ws_{15} >$	$([734.23, 747.82], 0.52, [250.45, 264.59])$
5	$< ws_1, ws_6, ws_9, ws_{11}, ws_{15} >$	$([773.74, 787.33], 0.46, [219.07, 232.52])$
6	$< ws_2, ws_5, ws_9, ws_{10}, ws_{13} >$	$([892.85, 906.42], 0.55, [162.24, 177.58])$
7	$< ws_2, ws_6, ws_9, ws_{10}, ws_{13} >$	$([893.77, 906.83], 0.51, [123.38, 137.99])$
8	$< ws_2, ws_5, ws_9, ws_{10}, ws_{15} >$	$([912.93, 926.13], 0.54, [102.71, 117.43])$
9	$< ws_2, ws_6, ws_9, ws_{10}, ws_{15} >$	$([913.84, 926.55], 0.49, [63.856, 77.847])$
10	$< ws_2, ws_6, ws_9, ws_{11}, ws_{15} >$	$([953.35, 966.06], 0.44, [32.469, 45.774])$

From Table I, the approach gets 10 interval Pareto solutions to make the response time and latency time lowest and availability highest. The solutions consist of an optimal solution set and cannot be dominated by each other from the quality of composite services.

The convergence is one of the most important index to evaluate the algorithm. We evaluate the convergence by computing and observing the number of interval Pareto solutions. Let assume the number of abstract service tasks and candidate services, $T = 5$ and $N = 5$, respectively. The population sizes are altered from 20 to 100. The iterative times are from 1000 to 20000. The experimental results are shown in Figure 1.

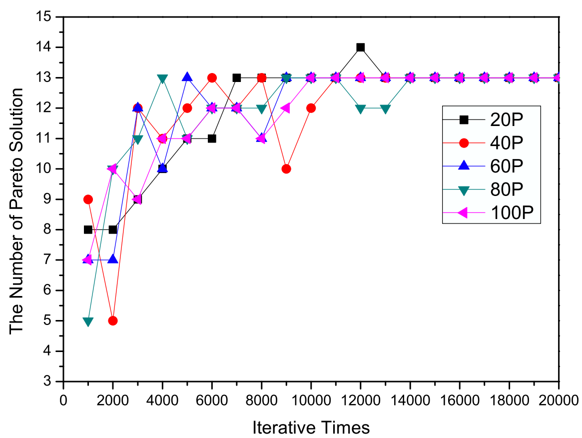

Figure 1. The number of Pareto solutions with different populations

As shown in Figure 1, however population change, the number of Pareto solutions is 13 all the same from iterative times 14000 to 20000. As a result, the number of Pareto solutions to the same interval number multi-objective optimization problem is steady at last, as the populations and the iterative times are growing up. So, the algorithm is convergence from the number of Pareto solutions changing.

From the experimental results above, we conclude that our approach can solve the uncertain QoS-aware Web service composition with QoS uncertainty effectively. More specifically, our proposed algorithm NDmoea/d can solve the interval number multi-objective optimal problem effectively and has satisfactory convergence.

VI. Conclusion and Future work

This paper presents a non-deterministic multi-objective optimization method for UQ-WSC problem. The method firstly models an UQ-WSC problem into an multi-objective optimization problem with uncertain interval number. Then, an NDmoea/d algorithm is proposed to solve the interval number multi-objective problem and gets the optimal solutions set. Experimental results indicate that our proposed approach can solve the UQ-WSC problem effectively and efficiently, which has satisfactory convergence.

In this paper, we focus on finding the optimal composite services for an UQ-WSC problem. For our future work, we will improve the algorithm to optimize more multi-dimensional uncertain QoS criteria and conduct compared experimental evaluation to emerging service composition approaches. We also consider how to recommend an optimal single or composite Web service for users.

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