Comprehensive Quality-Aware Automated Semantic Web Service Composition

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Abstract. Semantic web service composition has been a prevailing research area in recent years. There are two major challenges faced by researchers, semantic matchmaking and Quality of Service (QoS) optimisation. Semantic matchmaking aims to discover interoperable web services that can interact with each other by their resources described semantically. QoS optimisation aims to optimise the non-functional requirements of service users, e.g., minimum cost, maximal reliability. To meet users' requirements, one often needs to consider both semantic matchmaking quality and QoS simultaneously. Existing works on web service composition focus mainly on one single type of quality requirements. Therefore, we propose a comprehensive quality model considering semantic matchmaking quality and QoS simultaneously with an aim of achieving a more desirable balance on both sides. Further, we develop a PSO-based service composition approach with explicit support for the comprehensive model. We also conduct experiments to address the effectiveness of our PSO-based approach and a desirable balance achieved using our comprehensive quality model.

1 Introduction

Web service composition pertains to a chain of multiple web services to provide a value-added composite service that accommodates customers' complex requirements. Two most notable challenges for web service composition are ensuring interoperability of services and achieving Quality of Service (QoS) optimisation [5]. *Interoperability* of web services presents challenge in syntactic and semantic dimensions. The syntactic dimension is covered by the XML-based technologies, such as $WSDL$, $SOAP$. The semantic dimension enables a better collaboration through ontology-based semantics, such as OWL-S, WSML, and SAWSDL [12]. *Semantic web services composition* is distinguished from the syntactic service composition, the resources of semantic web services are described semantically to enable a better interoperability for chaining web services. Another challenge is related to QoS optimisation. This problem gives birth to *QoS-aware service composition* that aims to find composition solutions with optimised QoS.

Existing works on service composition focus mainly on addressing only one challenge above. In these works, huge efforts have been devoted to QoS-aware web service compositions assuming a pre-defined abstract workflow is given. This is generally considered as a *semi-automated web service composition* approach. Generating composition plans automatically in discovering and selecting suitable web services is a NP-hard problem [10]. In the past few years, many approaches [6,8,14,19,20,21] to QoS-aware web service composition employ Evolutionary Computation (EC) techniques to automatically generate composition solutions. Genetic Programming (GP) based approaches produce promising results, but these approaches often require repairing or penalising the solutions [8,21]. However, Particle Swarm Optimisation (PSO) is considered to be an easy way to maintain the correctness of solutions in solving combinatorial optimisation problems [19]. All these works have enabled an *automatic web service composition*, but do not optimise QoS and quality of semantic matchmaking simultaneously to achieve a desirable balance on both sides.

The overall goal of this paper is to *develop a PSO-based approach to comprehensive quality-aware automated semantic web service composition that satisfactorily optimises both QoS and semantic matchmaking quality*. Particularly, this paper extends existing works of QoS-aware service composition by considering jointly optimising QoS and semantic matchmaking quality, which is proposed as a comprehensive quality model. We will achieve three objectives in this work:

1. To propose a comprehensive quality model that addresses QoS and semantic matchmaking quality simultaneously with a desirable balance on both sides.
2. To propose a PSO-based service composition approach using the proposed comprehensive quality model. To do that, we aim to find a service candidate queue that can be decoded into a service composition with near-optimal comprehensive quality.
3. To address the effectiveness of our PSO-based approach and a desirable balance achieved using our comprehensive quality model, we first compare our PSO-based approach with one recent GP-based approach [8] using our proposed quality model, and then compare our proposed quality model with one widely used QoS model using our proposed PSO-based approach.

2 Related Work

Substantial works on web service composition focus on either semantic web service composition [1,3,9] or QoS-aware web service composition [6,8,14,19,20,21], However, only a few researchers address both semantic matchmaking quality and QoS for web service composition problems. To the best of our knowledge, [4,7,13] reported some attempts on service composition that considers both aspects.

Semantic web service composition [1,3,9] captures the semantic descriptions of web services' parameters using some kind of logic (e.g., description logic) that ensures the interoperability of web services. In these approach, the number of web services or length of a graph representation for web service composition is minimised to reach the optimised composition solutions. However, this evaluation approach does not guarantee an optimised QoS of composition solutions.

QoS-aware web service composition is studied using traditional approaches or EC techniques for finding near-optimised solutions. Qi et al. [14] propose a local optimisation and enumeration method, where a small number of promising candidates related to each task are considered by local selection, and composition solutions are enumerated to reach the near optimal QoS. EC techniques are widely used to automatically generate solutions with optimal QoS. Gupta et al. [6] employ a modified Genetic Algorithm (GA) using a binary string as an individual, which demands to be decoded into composition solutions. Yu et al. [21] use GP for finding near-optimal solutions that are reached by penalising infeasible solutions using a fitness function. A hybrid approach employing a greedy search and GP is introduced in [8] to generate functionally correct tree-based representations, which are transformed from graph-based representations. To eliminating the transformation process, a promising GraphEvol is proposed in [20], where graph-based evolutionary operators are employed. An indirect PSO-based approach was introduced in [19]. An service queue is used as an indirect representation that is decoded into a *directed acyclic graph* (DAG). These QoS-aware approaches [6,14,8,19,20,21] do not consider semantic matchmaking quality.

Only a few works [4,7,13] consider both semantic matchmaking quality and QoS simultaneously. Lecue et al. [7] propose a semi-automated web service composition using GA to encode a given abstract service workflow, where the evaluation of semantic matchmaking quality requires a complete and formal definition of ontology using description logic, which is associated to the resources of web services. Another GA-based approach [4] utilise process description language to encode pre-stored cases-based workflows, where workable services are composed to complete this workflow. An automated immune-inspired web service composition approach [13] employs a clonal selection algorithm to proliferate decoded planning graphs, but this approach is only evaluated with some simple cases.

In summary, despite a large number of approaches for semantic web service composition and QoS-aware service composition approaches, there is a lack of a fully automated semantic service composition approach to optimise semantic matchmaking quality and QoS simultaneously.

3 Motivation and Problem Description

Our goal is to develop a PSO-based approach for automatically generating good service compositions. Often, many different service compositions can meet a user request but differ significantly in terms of QoS and semantic matchmaking quality. For example, in the classical travel planning context, some component service must be employed to obtain a travel map. Suppose that two services can be considered for this purpose. One service S can provide a street map at a price of 6.72. The other service S' can provide a tourist map at a price of 16.87. Because in our context a tourist map is more desirable than a street map, S' clearly enjoys better semantic matchmaking quality than S but will have negative impact on the QoS of the service composition (i.e., the price is much higher). One can easily imagine that similar challenges frequently occur when looking for service compositions. Hence, a good balance between QoS and semantic matchmaking quality is called for. We therefore propose a *comprehensive quality model* in considering semantic matchmaking quality and QoS simultaneously.

We consider a *semantic web service* (*service*, for short) as a tuple $S = (I_S, O_S, QoS_S)$ where I_S is the set of service inputs that are consumed by S, O_S the set of service outputs that are produced by S, and $QoS_S = \{t_S, c_S, r_S, a_S\}$ the set of non-functional attributes of S. The inputs in I_S and the outputs in O_S are concept-related parameters with the concepts in an ontology $\mathcal{O}$. The attributes t_S, c_S, r_S, a_S refer to the response time, cost, reliability, and availability of service S, respectively. These four QoS attributes are most commonly used [22].

A *service repository* $\mathcal{SR}$ is a finite collection of services with a common ontology $\mathcal{O}$. A *service request* (also called *composition task*) over $\mathcal{SR}$ is a tuple $T = (I_T, O_T)$ where I_T is the set of task inputs, and O_T the set of task outputs. The inputs in I_T and the outputs in O_T are concept-related parameters with the concepts in the ontology $\mathcal{O}$.

A service composition is commonly represented as a DAG. It nodes correspond to the services in the composition. Two services S and S' are connected by an edge e if some output of S serves as input for S'. Apparently, such outputs and inputs must semantically match to ensure the correct execution of the service composition. The mechanism to compose services relies on the semantic descriptions of inputs and outputs, which enables inputs of services to be matched by outputs of other services. The following *matchmaking types* are often used to describe the level of a match [11]: For concepts a, b in $\mathcal{O}$ the *matchmaking* returns *exact* if a and b are equivalent ($a \equiv b$), *plugin* if a is a sub-concept of b ($a \sqsubseteq b$), *subsume* if a is a super-concept of b ($a \sqsupseteq b$), and *fail* if none of previous matchmaking types is returned. In this paper we are only interested in robust compositions where only *exact* and *plugin* matches are considered, see [7]. As argued in [7] *plugin* matches are less preferable than *exact* matches due to the overheads associated with data processing. We suggest to consider the semantic similarity of concepts when comparing different plugin types. For concepts a, b in $\mathcal{O}$ the *semantic similarity* $sim(a, b)$ is calculated based on the edge counting method defined in the formula (1) from [15], where N_a, N_b and N_c measure the distances from concept a, concept b, and a closest common ancestor c of a and b to the top concept of the ontology $\mathcal{O}$, respectively.

$$sim(a, b) = \frac{2N_c \cdot e^{-\lambda L/D}}{N_a + N_b} \tag{1}$$

For our purposes, λ can be set to 0 as we do not measure the similarities of neighbourhood concepts, which is not the matching type considered in this paper.

Given a service request $T = (I_T, O_T)$, we represent a service composition solution for T with services $S_1, \ldots, S_n$ by a weighted DAG, $WG = (V, E)$ with node set $V = \{Start, S_1, S_2, \ldots, S_n, End\}$ and edge set $E = \{e_1, e_2, ...e_m\}$. $Start$ and End are two special services defined as $Start = (\emptyset, I_T, \emptyset)$ and $End = (O_T, \emptyset, \emptyset)$ that account for the input and output requirements given by the request. Each edge e from a service S to a service S' means that service S produces an output

$a \in O_S$ that is matched (*exact* or *plugin*) to an input $b \in I_{S'}$ to be consumed by service S' in the composition. Based on the matchmaking type the *semantic matchmaking quality* of edge e can be defined as follows:

$$type_e = \begin{cases} 1 & \text{if } a \equiv b \ (\textit{exact} \text{ match}), \\ p & \text{if } a \sqsubseteq b \ (\textit{plugin} \text{ match}) \end{cases} \tag{2}$$

$$sim_e = sim(a, b) = \frac{2N_c}{N_a + N_b} \tag{3}$$

with a suitable parameter $p, 0 < p < 1$ to chosen, for discussion see 4.1. However, if more than one pair of matched output and input exist from services S and S' respectively, $type_e$ and sim_e will take on their average values.

The *semantic matchmaking quality* of the service composition can be obtained by aggregating over all edges in E as follows:

$$MT = \prod_{j=1}^{m} type_{e_j} \tag{4}$$

$$SIM = \frac{1}{m} \sum_{j=1}^{m} sim_{e_j} \tag{5}$$

The QoS of the service composition can be obtained by aggregating the QoS values of the participating services. For a service composition with services $S_1, S_2, ...S_n$ we obtain the reliability $R = \prod\limits_{k=1}^{n} r_{S_k}$, the availability $A = \prod\limits_{k=1}^{n} a_{S_k}$, the cost $C = \sum\limits_{k=1}^{n} c_{S_k}$, and the response time T is the time of most time-consumption path in the composition, i.e.,

$$T = MAX\{\sum_{k=1}^{\ell_j} t_{S_k} |\ j \in \{1, \ldots, m\} \text{ and } P_j \text{ is a path of length } \ell_j\}.$$

When multiple quality criteria are involved into decision making, then the overall fitness of a solution is proposed as a *comprehensive quality model*, which can be defined as a weighted sum of the individual criteria:

$$Fitness = w_1 \hat{MT} + w_2 S\hat{I}M + w_3 \hat{A} + w_4 \hat{R} + w_5(1 - \hat{T}) + w_6(1 - \hat{C}) \tag{6}$$

with $\sum_{k=1}^{6} w_k = 1$. The weights can be adjusted according to users' preferences. Herein, the individual criteria are normalised to a range between 0 to 1, where 1 means the best value and 0 means the worst. For this purpose, we normalise MT, SIM, A, R, T, and C so that the function value falls within the range from 0 to 1 using formula (7). To simplify the presentation we also use the notation $(Q_1, Q_2, Q_3, Q_4, Q_5, Q_6) = (MT, SIM, A, R, T, C)$. MT and S have minimum value 0 and maximum value 1. The minimum and maximum value of A, R, T, and C are calculated across all task-related candidates in the service repository $\mathcal{SR}$ using greedy search, for discussion see 4.1.

$$\hat{Q}_k = \begin{cases} \frac{Q_k - Q_{k,min}}{Q_{k,max} - Q_{k,min}} & \text{if } k = 1, \ldots, 4 \text{ and } Q_{k,max} - Q_{k,min} \neq 0, \\ \frac{Q_{k,max} - Q_k}{Q_{k,max} - Q_{k,min}} & \text{if } k = 5, 6 \text{ and } Q_{k,max} - Q_{k,min} \neq 0, \\ 1 & \text{otherwise.} \end{cases} \tag{7}$$

The composition task is to find the maximum value of objective function in (6).

4 PSO-based Approach to Comprehensive Quality-Aware Automated Semantic Web Service Composition

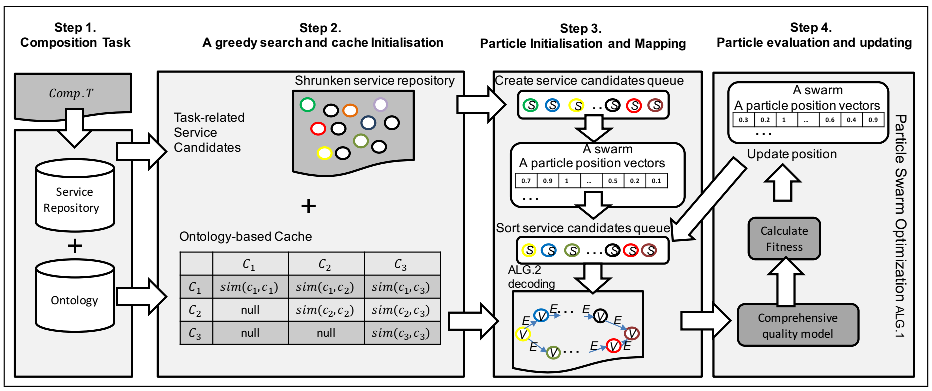


Fig. 1: An overview of POS-based approach to comprehensive quality-aware automated semantic web service composition.

4.1 An Overview to PSO-based Method

As PSO has shown promise in solving combinatorial optimisation problems, we propose a PSO-based approach to comprehensive quality-aware automated semantic web service composition. Fig. 1 shows an overview of our approach consisting of four steps:

Step 1: The composition process is triggered by a composition task, which is clearly defined in 3.

Step 2: This composition task is used to discover all task-related service candidates using a greedy search algorithm adopted from [8], which contributes to a shrunken service repository. This greedy search algorithm keeps adding outputs of the invoked services as available outputs (initialised with I_T) , and these available outputs are used to discover task-related services from a service repository and updated with the outputs of these discovered services. This operation is repeated until no service is satisfied by the available outputs. During the greedy search, an ontology-based cache (*cache*) is initialised, which stores the concept similarities of matched inputs and outputs of task-related candidates. This *cache* is also used to discover services by checking whether *null* is returned by given two output-related and input-related concepts.

Step 3 and Step 4: These two steps follow the standard PSO steps [16] except for some differences in particles mapping and decoding processes. In particular, these two differences are related to sorting a created service queue using service-to-index mapping for a particle' position vectors and evaluating the fitness of a particle after decoding this service queue into a WG respectively. Those differences are further addressed in Algorithms 1 and 2 in 4.2.

4.2 PSO-based Approach Algorithm

The overall algorithm investigated here is made up of a PSO-based web service composition Algorithm 1 and a decoding Algorithm 2. In Algorithm 1, the steps 4, 5, 6 and 7 are different from those of standard PSO: In step 4, the size of task-related service candidates generated by a greedy search determines the size of each particle's position. Each service candidate in a created service candidates queue is mapped to an index of a particles position vectors, where each vector has a weight value between 0.0 and 1.0. In step 5, service candidates in the queue are sorted according to their corresponding weight values in descending order. In step 6, this sorted queue is used as one of the inputs of the forward decoding Algorithm 2 to create a WG. In step 7, the fitness value of the created WG is the fitness value of the particle calculated by the comprehensive model discussed in 3.

ALGORITHM 1. Steps of PSO-based service composition technique [19].

```
1:  Randomly initialise each particle in the swarm;
2:  while max. iterations not met do
3:      foreach particles in the swarm do
4:          Create a service candidates queue and map service candidates to a
              particle's position vectors;
5:          Sort the service queue by position vectors' weights;
6:          Create a WG from the service queue (Algorithm2) ;
7:          Calculate the WG fitness value;
8:          if fitness value better than pBest then
9:              Assign current fitness as new pBest;
10:         else
11:             Keep previous pBest;
12:     Assign best particle's pBest value to gBest, if better than gBest;
13:     Calculate the velocity of each particle;
14:     Update the position of each particle;
```

Algorithm 2 is a forward graph building algorithm extended from [2]. This algorithm take one input, a sorted service queue from step 5 of Algorithm 1. Note that different service queues may lead to different WGs. In addition. I_T, O_T and *cache* are also taken as the inputs. Firstly, *Start* and *End* are added to V of WG as an initialisation, and *OutputSet* is also created with I_T. The following steps are repeated until O_T can be satisfied by *Outputset* or the service queue is *null*. If all the inputs I_S of the first popped S from *queue* can be satisfied by provided outputs from *OutputSet*, this S is added to V and its outputs are added to *OutputSet*, and S is removed from *queue*. Otherwise, the second popped S from *queue* is considered for these operations. Meanwhile, e is created with $type_e$ and sim_e if S is added, and calculated using information provided from *cache*. This forward graph building technique could lead to more services and edges connected to the WG, these redundancies should be removed before WG is returned.

ALGORITHM 2. Create a WG from a sorted service queue.

Input : I_T, O_T, *queue*, *cache*
Output: WG

$WG = (V, E)$;
$V \leftarrow \{Start, End\}$;
$OutputSet \leftarrow \{I_T\}$;
while O_T *do not satisfied by OutputSet* **do**
  foreach S *in queue* **do**
    if *all* I_S *satisfied by OutputSet* **then**
      V add S;
      $OutputSet$ add $\{O_S\}$;
      queue.remove S;
      $e \leftarrow$ calculate $type_e$, sim_e using *cache*;
      E add e;
remove *dangling nodes*;
remove *dangling edges*;
return WG;

5 Experiment Study

In this section, we employ a quantitative evaluation approach with a benchmark dataset used in [8,18], which is an augmented version of Web Service Challenge 2009 (WSC09) including QoS attributes. Two objectives of this evaluation are to: (1) evaluate the effectiveness of our PSO-based approach, see comparison test in 5.1. (2) evaluate the effectiveness of our proposed comprehensive quality model to achieve a desirable balance on semantic matchmaking quality and QoS, see comparison test in 5.2.

The parameters for the PSO are chosen from the settings from [16], In particular, PSO population size is 30 with 100 generations. We run 30 times independently for each dataset. We configure the weights of fitness function to properly balance semantic matchmaking quality and QoS. Therefore, w_1 and w_2 are set equally to 0.25, and w_3, w_4, w_5, w_6 are all set to 0.125. The p of $type_e$ is set to 0.75 (*plugin* match) according to [7]. In general, weight settings and parameter p are decided by users' preferences.

5.1 Comparison Test for GP-based approach and PSO-based approach

To evaluate the effectiveness of our proposed PSO-based approach, we compare our PSO-based method with one recent GP-based approach [8] using our proposed comprehensive quality model. We extend this GP-based approach by measuring the semantic matchmaking quality between parent nodes and children nodes. To make a fair comparison, we use the same number of evaluations (3000 times) for these two approach. We set the parameters of that GP-based approach as 30 individuals and 100 generations, which is considered to be proper settings referring to [17].

The first column of Table 1 shows five tasks from WSC09. The second and third column of Table 1 show the original service repository size and the shrunk service repository size after the greedy search respectively regarding the five tasks. This greedy search helps reducing the original repository size significantly, which contributes to a reduced searching space. The fourth and fifth column of Table 1 show the mean fitness values of 30 independent runs accomplished by two methods. We employ independent-samples T tests to test the significant differences in mean fitness value. The results show that the PSO-based approach outperforms the existing GP-based approach in most cases except task 3. Note that all the p-values are consistently smaller than 0.01. In task 5, the PSO-based approach performs significantly better than the GP-based approach in finding optimal solutions. It may be that the GP-based approach is stuck in local optima in a very large search space due to its evolutionary operators. On the other hand, the decoding process used by the PSO-based approach allows for small changes that more effectively prevent this from happening.

Table 1: Mean fitness values for comparing GP-based approach

WSC09	Original $\mathcal{SR}$	Shrunken $\mathcal{SR}$	PSO-based approach	GP-based approach
Task 1	572	80	$0.5592 \pm 0.0128 \uparrow$	0.5207 ± 0.0208
Task 2	4129	140	$0.4701 \pm 0.0011 \uparrow$	0.4597 ± 0.0029
Task 3	8138	153	0.5504 ± 0.0128	$0.5679 \pm 0.0234 \uparrow$
Task 4	8301	330	$0.4690 \pm 0.0017 \uparrow$	0.4317 ± 0.0097
Task 5	15211	237	$0.4694 \pm 0.0008 \uparrow$	0.2452 ± 0.0369

5.2 Comparison Test for Comprehensive Quality Model and QoS Model

Recently, a QoS Model, $Fitness = w_1\hat{A} + w_2\hat{R} + w_3(1-\hat{T}) + w_4(1-\hat{C})$, where $\sum_{i=1}^{4} w_i = 1$, is widely used for QoS-aware web service composition [8,19,20]. To show the effectiveness of our proposed comprehensive quality model, we compare the best solutions found by this QoS model and our comprehensive model using our PSO-based approach. We record and compare the mean values of both SM ($SM = 0.5\hat{MT} + 0.5\hat{SIM}$) and $QoS(QoS = 0.25\hat{A} + 0.25\hat{R} + 0.25(1-\hat{T}) + 0.25(1-\hat{C}))$ of best solutions over 30 independent runs. To make a sense of the comparison, all these recorded values are normalised from 0 to 1, and compared using independent-samples T tests in Table 2.

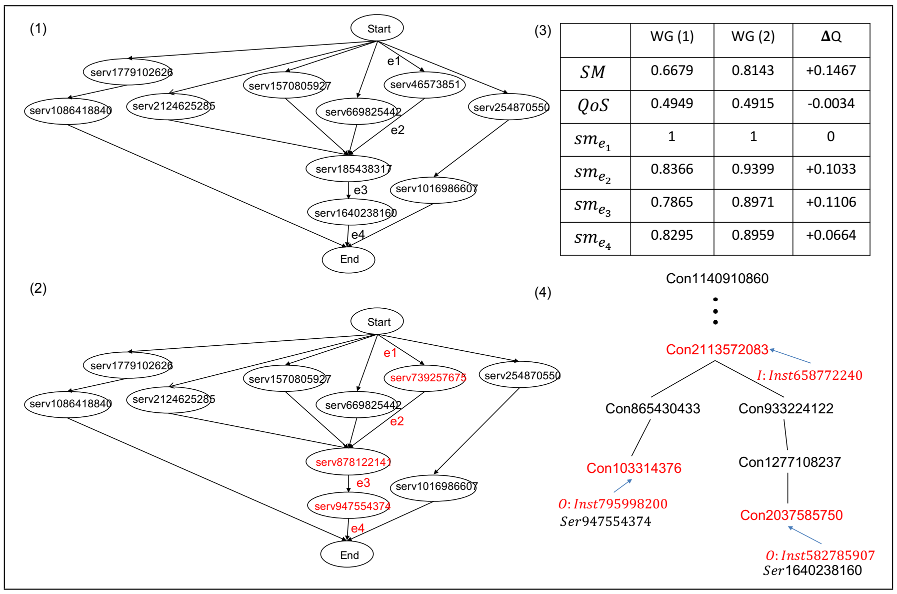
We observe an interesting pattern from Table 2. The mean values of QoS using QoS model are significantly higher than those using comprehensive quality model for Tasks 2, 3, 4 and 5. However, the mean value of SM using the comprehensive quality model are significantly higher than those using the QoS model, while a slight trade-off in QoS are observed in all tasks. In addition, our comprehensive model achieves a consistently higher comprehensive quality in terms of a combination of SM and QoS, which is significantly better in task 1, 2, 3 and 4.

Table 2: Mean values of SM, QoS and sum of SM and QoS for QoS model and comprehensive quality model using PSO-based approach

WSC09		QoS Model	Comprehensive Quality Model
Task1	SM	0.5373 ± 0.0267	0.5580 ± 0.0094 ↑
	QoS	0.5574 ± 0.0156	0.5604 ± 0.0164
	$SM + QoS$	1.0947 ± 0.0423	1.1184 ± 0.0258 ↑
Task2	SM	0.4549 ± 0.0033	0.4630 ± 0.0042 ↑
	QoS	0.4800 ± 0.0012 ↑	0.4772 ± 0.0025
	$SM + QoS$	0.9349 ± 0.0045	0.9402 ± 0.0067 ↑
Task3	SM	0.5538 ± 0.0082	0.6093 ± 0.0054 ↑
	QoS	0.4940 ± 0.0013 ↑	0.4913 ± 0.0009
	$SM + QoS$	1.0478 ± 0.0095	1.1006 ± 0.0063 ↑
Task4	SM	0.4398 ± 0.0037	0.4604 ± 0.0000 ↑
	QoS	0.4845 ± 0.0010 ↑	0.4734 ± 0.0044
	$SM + QoS$	0.9243 ± 0.0047	0.9338 ± 0.0044 ↑
Task5	SM	0.4580 ± 0.0065	0.4639 ± 0.0013 ↑
	QoS	0.4764 ± 0.0005 ↑	0.4750 ± 0.0007
	$SM + QoS$	0.9344 ± 0.0070	0.9389 ± 0.0020

5.3 Further Discussion

To analyse the effectiveness of achieving a good comprehensive quality at the expense of slightly reduced QoS, we demonstrate two best solutions produced using task 3 as an example. Fig. 2 (1) and (2) show two WGs as the best solutions obtained by employing the QoS model and the comprehensive quality model respectively. Both WGs have exactly the same service workflow structure, but some service vertices and edges denoted in red are different. To better understand these differences, we list the overall semantic matchmaking quality SM, overall QoS and semantic matchmaking quality associated to each edge in Fig. 2 (3) (Note: $sm_{e_n} = 0.5type_{e_n} + 0.5sim_{e_n}$), where ΔQ reveals the gain (positive ΔQ) or a loss (negative ΔQ) of the listed qualities for our comprehensive quality model. Therefore, we achieve an overall gain 0.1433, which is calculated from a sum of a SM gain (0.1467) and QoS loss (-0.0034). To understand the improvement of semantic matchmaking quality from these numbers, we pick up e_4 that is associated with the smallest ΔQ. The e_4 of Fig. 2 (1) and Fig. 2 (2) has two different source service vertices, $Ser1640238160$ and $Ser947554374$, and two same end vertices. $Ser1640238160$ and $Ser947554374$ are services with output parameters $Inst582785907$ and $Inst795998200$ corresponds to two related concepts $Con2037585750$ and $Con103314376$ respectively in an ontology shown in Fig. 2 (4). As $Inst658772240$ is a required parameter of the *end*, and related to concept $Con2113572083$, $Inst795998200$ is closer to the required output $Inst658772240$ compared to $Inst582785907$. Therefore, $Ser947554374$ is selected with a better semantic matchmaking quality compared to $Ser1640238160$.



	WG (1)	WG (2)	ΔQ
SM	0.6679	0.8143	+0.1467
QoS	0.4949	0.4915	-0.0034
sm_{e_1}	1	1	0
sm_{e_2}	0.8366	0.9399	+0.1033
sm_{e_3}	0.7865	0.8971	+0.1106
sm_{e_4}	0.8295	0.8959	+0.0664

Fig. 2: An example of comparison to best solutions for QoS model and comprehensive quality evluation model using Task 3.

6 Conclusion

In this work, we propose an effective PSO-based approach to comprehensive quality-aware semantic web service composition, which also has shown promise in achieving a better comprehensive quality in terms of a combination of semantic matchmaking quality and QoS compared to existing works. Future works can investigate multi-objective EC techniques to produce a set of composition solutions for the situations when the quality preference is not known.

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