

Comprehensive Quality-Aware Automated Semantic Web Service Composition

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Abstract—Semantic web service composition has been a pre-vailing research area in recent years. There are two major challenges faced by researchers, semantic matchmaking and QoS optimisation. Semantic matchmaking aims to discover interoperable web services that can interact with each other to provide rich functionalities through language understanding and reasoning. QoS optimisation aims to optimise the non-functional requirement of service users, e.g., minimum cost, maximal reliability. Many scholars have looked into QoS optimisation problems in QoS-aware web service composition applying AI planning and Evolutionary Computation techniques. To meet users' requirement, one often needs to consider both semantic matchmaking quality and QoS simultaneously. Existing works on web service composition often concerns either semantic service composition or QoS-aware service composition. However, there are few works concerns both semantic matchmaking quality and QoS at the same time and achieve a more desirable tradeoff in consideration of both sides. Therefore, In this paper, proposed a genral comprehensive quality model that can achieve a more desirable balance in consideration of both semantic matchmaking quality and QoS. This model is also suitable to be tackled through EC algorithms, and we develop a PSO-based service composition approach with explicit support for the comprehensive model, which can generate more desiable balanced web service composition that meet both senmantic matchmaking quality and QoS requirement by comparing existing QoS evaluation model using benchmark dataset. We also conduct an experiment shows our PSO-based mehtod performs better in finding more optimised solution by comparing one existing GP-based method.

I. INTRODUCTION

Web service composition pertains to a combination of multiple web services to provide a value-added composition service that accommodates customers' arbitrarily complex requirements. This application is developed by integrating interoperable and collaborative functionalities over heterogeneous systems. Due to the increase of the number of large-scale enterprise applications, the number of Web services has increased substantially and unprecedentedly. Therefore, manual and semi-automated web service composition are considered to be less efficient while automated web service composition enjoys less human intervention, less time consumption, and high productivity.

Two most notable challenges for web service composition are (1) ensuring interoperability of services and (2) achieving QoS optimisation [1]. *Interoperability* of web services presents challenge (1) in syntactic and semantics dimensions. The syntactic dimension is covered by the XML-based technologies (such as *WSDL*, *SOAP*). The semantics aspect, on the other hand, demands further research. Through ontology-based semantics [2], web services can understand and better

collaborate with each other. There are many ontology languages and formats for semantic service descriptions, such as OWL-S, WSMML, and SAWSDL [3], which make "machine understanding" possible through identifying and matching semantic similarity in input/output parameters of web services in heterogeneous environments. The second challenge (2) is related to finding *optimised solutions* to Quality of Service (*QoS*). This problem gives birth to *QoS-aware service composition* that considers the composition of service-level agreements (SLA) [4] involving a collection of SLA rules and policies for supporting QoS-based composition.

Existing works on service composition focus mainly on addressing the one of challenges above. A lot of works have been conducted to optimise the quality of compositions under a pre-defined abstract workflow, which is generally considered as *semi-automated Web service composition* approach [5], [6]. Meanwhile, many research works consider the possibility of generating a composition plan automatically in discovering and selecting suitable web services, which are considered to be NP-hard [7]. *Semantic web services composition* is distinguished from the syntactic service composition, with the hope of eliminating conflicts by the semantic level of web services. In the past few years, substantial works have been done on semantic web service composition [8], [9], [10]. However, few works have enabled truly automatic semantic web service composition, where both QoS and quality of semantic match making will be optimised simultaneously. To a given service request, the quality of service composition solution depends on both QoS and quality of semantic matchmaking.

The overall goal of this paper is to *develop an comprehensive approach to automated QoS-aware 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 both QoS optimisation and semantic matchmaking quality optimisation in our proposed comprehensive quality model. Particle Swarm Optimisation (PSO) has show its promise in searching near-optimised service composition solutions [11]. We will propose a PSO-based service composition approach using our comprehensive quality model to measure semantic matchmaking in automated semantic web service composition. We will achieve three objectives in this work as follows:

- 1) To propose a general comprehensive quality model that address QoS and semantic matchmaking quality in considering different matching types with corresponding concept similarity.
- 2) To propose a PSO-based service composition algorithm

that utilises the proposed quality model. To do that we will first propose a representation of semantic service composition, which can model the quality of semantic matchmaking and QoS together. A particle is then used to represent a queue of services that can be used to decoded into a near-optimised semantic service composition solution.

- 3) To evaluate our proposed approach, we conduct experiment to compare our comprehensive quality model with QoS evaluation model, we also compare an one existing GP approach with our approach using our comprehensive model. Both comparison utilise benchmark datasets from Web Services Challenge 2009 (WSC09) [12]

II. RELATED WORK

Substantial work on web service composition either focused on semantic web service composition [13], [14], [15] or QoS-aware web service composition [11], [16], [17], [18], [19]. However few researchers addressed both semantic matchmaking quality and QoS requirements at the same time for web service composition problems. To the best of our knowledge, [8], [9], [10] reported some recent attempts on service composition that considers both aspects.

[13], [14], [15] captures the semantics of the parameters of web services using some kind of logic (e.g., description logic) for enabling semantic web service composition, where the number of web services or length of the graph is minimised to reach the optimised graph-based composition solutions. However, these approaches always need to improve their scalability for a large number of web services, and the evaluation method does not fit for today's customers' requirements properly.

A heuristic service composition method is proposed by Qi et al. [19] for QoS-aware web service composition, 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-to-optimal for QoS consideration. but obviously there exists scalability problem for enumeration techniques.

Evolutionary Computation (EC) techniques are used to improve the scalability for solving NP-hard problems. Gupta et al. [18] employ an Genetic Algorithm to the problem of QoS-aware web service composition, and a set of binary strings are used as individuals, which demands to be decoded into composition solutions. Genetic Programming are employed by [17] with direct representation of composition solutions, the overall quality of solutions are measured by a fitness function that is liable for penalising infeasible solutions. A hyper approach employs both a greedy search algorithm and Genetic Programming (GP) is introduced in [20] to generate locally optimised solution with functionality correctness. In particular, the greedy search is used to generate directed acyclic graph as composition solutions, which is further transferred to tree structure using unfolding techniques for initialisation and mutation during the evolutionary process. To eliminating the transformation process from DAG, A promising GraphEvol is proposed in [16], where web service composition are in a form of Directed Acyclic Graph(DAG) employing Graph-based evolutionary operators like crossover and mutation. PSO

has shown its efficiency in solving combinatorial optimisation problems [21], an indirect PSO-based approach was introduced in [11]. An optimised queue is used as indirect representation as composition solution that decoding into Direct Acyclic Graph (DAG). These QoS-aware approaches does not consider semantic matchmaking quality, which could lead to over-general outputs to be produced by selected services, The finding is evidently supported by our first comparison experiment. In fact, customers' perspectives, application domains and ontology granularity all could have significant impact on the outputs requested by users. In some scenarios, the output is too broad to bear any specific meaning for the customers, even though those web services selected leads to a very good overall QoS.

Few works [8], [9], [10] employ EC technique for considering both semantic matchmaking quality and QoS simultaneously. Lecue et al. [8] employ Genetic Algorithm for semi-automated web service composition considering semantic matchmaking quality and QoS, where the semantic matchmaking quality is measured the quality of semantic links that requires formal definition of ontology in Description logic. This evaluation takes huge cost and time for the domain experts to establish required ontology. Another GA-based approach work [9] employs a sequence of fitness functions are used in the binary selection of chromosomes, where semantic matchmaking quality is evaluate in two fitness functions considering concept similarity and parameter similarity respectively, However, different semantic matchmaking types are ignored in evaluation model. The work [10] as an immune-inspired web service composition approach employ indirect representation that a binary alphabet to encode a planning graph, where the semantic matchmaking quality is measured by the similarity using information retrieval technique.

In summary, composition solutions from semantic web service composition does not consider QoS [13], [14], [15], and QoS-aware web service composition [11], [16], [17], [18], [19] does not consider distinguished matchmaking quality in their fitness function. Few works do consider both quality aspects, but some limitations lie in semi-automated approach [8], less general semantic quality measurement [8], [10], or semantic matchmaking types ignorance [10]. In addition, experiments design for [8], [9], [10] are not conducted using benchmark dataset for the scalability, only small datasets are utilised that might suffer scalability. Results analysis for [8], [9], [10] also do not evidently point out what desired balance could be reached by considering semantic matchmaking quality and QoS. Therefore, we proposed a general comprehensive quality model which achieve a more desirable balance in consideration of both semantic matchmaking quality and QoS to fill the gaps discussed above, and then we proposed a PSO-based method with explicit support for the comprehensive model, and evaluate its performance by comparing with one existing GP-based approach.

III. PROBLEM DESCRIPTION

The aim of web service composition is to fulfil customers' requirements, which could be denoted as a composition goal:

$Comp.G(F(I_T, O_T), NF(QoS_T))$. This overall composition goal is demonstrated in two parts: functional part and non-functional part. The functional part is defined by a given task input and a desired task output. The nonfunctional part specifies QoS. To accomplish the composition goal, two stages are involved, services discovery and service selection. Service discovery is to find matching web services: $S_n(F(I_S, O_S), NF(QoS_S))$ from a Service Repository: $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$ for the given I_T . If no atomic web service could satisfy the composition goal, a composition of web services will be found to meet $Comp.G$. To ensure the composition solution returns the desired $Comp.G$, we use a quality model that take care of QoS and semantic matchmaking quality.

A. Quality of Service and Composition Constructs

According to [22], four most often considered QoS parameters are response time, cost, reliability and availability described as follows:

- *Response time (T)* measures the expected delay in seconds between the moment when a request is sent and the moment when the results are received.
- *Cost (C)* is the amount of money that a service requester has to pay for executing the web service
- *Reliability (R)* is the probability that a request is correctly responded within the maximum expected time frame.
- *Availability (A)* is the probability that a web service is accessible.

The aggregation value of QoS attributes for a composite service varies with respect to different constructs, which reflects how services associated with each other in a service composition [22]. Here we consider two composition constructs: sequence and parallel constructs, in building the composition web service. The QoS calculation models are described as follows:

1) *Sequence construct*: The composition web service executes each atomic service associated with a sequence construct in a definite sequence order. The aggregation value for total time (T) and total cost (C) is as the sum of time and cost of web services involved respectively. The overall availability and reliability in a sequence construct are calculated by multiplying their corresponding availability and reliability of each web service in probability theory. This construct is shown in Fig. 1.

2) *Parallel construct*: Web services in a parallel construct are executed concurrently. The QoS aggregation value for total cost, availability and reliability are the same as these in sequence construct while the Total time (T) is determined by the most time-consuming path in the composition flow of the solution. This construct is presented in Fig. 2.

IV. COMPREHENSIVE QUALITY-AWARE SERVICE MODEL

In this section, we propose a comprehensive quality-aware service model to achieve a more desirable balance in consideration of both semantic matchmaking quality and QoS for semantic web service composition.

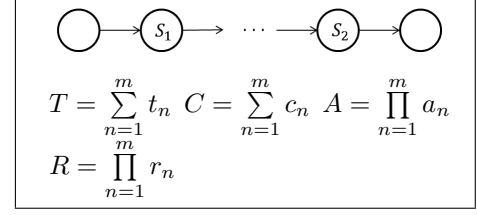


Fig. 1. Sequence construct and calculation of its QoS properties [17].

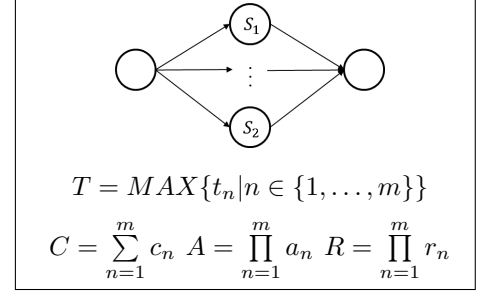


Fig. 2. Parallel construct and calculation of its QoS properties [17].

A. Semantic Web Service matchmaking Type

The semantic service matchmaking aims to discover appropriate services from service repository. A semantic web service is defined by $S(F(I_S \in C_1, O_S \in C_2), NF(QoS_S))$, where both Input and Output are linked to concept C_1 and C_2 in an ontology O respectively, satisfying $O = \{C, Taxonomy\}$. A web service matching process is to match the output and input concepts of two services according to the Taxonomy within an ontology. To measure the quality of semantic matchmaking, different matching levels are typically considered in the literature [23]. To understand these levels, let us define two web services associated with concept-related parameters in a particular domain. $S_1 (F(I_S \in C_1, O_S \in C_2), NF(QoS_S))$ and $S_2 (F(I_S \in C_3, O_S \in C_4), NF(QoS_S))$ and an ontology(O) with C_1, C_2, C_3 , and C_4 . The matching levels to be considered are:

- *Exact (\equiv)*: Output of Web service S_1 and Input of Web service S_2 are Exact match ($O_S \in S_1 \equiv I_S \in S_2$), if Concept C_2 and Concept C_3 are equivalent.
- *Plugin (\sqsubseteq_n)*: Output of Web service S_1 and Input of Web service S_2 are Plugin match ($O_S \in S_1 \sqsubseteq_n I_S \in S_2$), if Concept C_2 is a sub-concept of Concept C_3 , and $n = \{1, 2, \dots, n\}$ presents the levels of children concepts ($n = 1$ stands for direct children).
- *Subsume (\sqsupseteq_n)*: Output of Web service S_1 and Input of Web service S_2 are Subsume matched ($O_S \in S_1 \sqsupseteq_n I_S \in S_2$), if Concept C_2 is a sub-concept of Concept C_3 , and $n = \{1, 2, \dots, n\}$ presents the levels of parent concepts ($n = 1$ stands for direct parent).
- *Fail (\perp)*. Output of Web service S_1 and Input of Web service S_2 are not matched (Fail) ($O_S \in S_1 \perp I_S \in S_2$), if none of the previous matches discovered.

The semantic matchmaking is achieved by utilising OWL2 and OWL-S or other semantic markup languages for web services. In this paper, we use MECE (Mediation Contract Extension) [24] and OWL-DL. MECE is considered to be an alternative semantic annotation for WSDL. MECE defines

the service-related inputs and outputs with parameter-related concepts. OWL-DL is a sublanguage of OWL extended from RDF. It specifies semantic information of concepts involved in MECE.

B. Comprehensive Quality-Aware Model

In this paper, we propose a comprehensive quality model to evaluate the overall quality of semantic web service composition. This model overcome the disadvantages of current prevailing QoS-aware optimisation that ignores quality of semantic matchmaking.

Semantic Web Service link Semantic matchmaking model. Due to the discretisational characteristics of different match types and values assigned to matching types that driven by the cost of data integration and manipulation [8], partial ordering match types are considered to be one factor for the semantic matchmaking quality. For example, Exact matching type demands less time for computation compared to that of Plugin match. Another factor in our proposed model is concept similarity, which could be evaluated based on the edge counting method defined in [25]. This formula (1) is used to estimate the similarity between concept-related parameters for selecting web services. Therefore, given the quality match type and the concept similarity of two parameters-related concepts, the semantic matchmaking quality of matched parameters is defined by Formula (2), where the value of $q(p_{mt})$ follows the same settings in [8]. Particularly, 1 (Exact), 0.75 (Plugin), 0.5 (Subsume) or 0.25 (Intersection).

$$q(p_s) = \frac{2N \cdot e^{-\lambda L/D}}{N_1 + N_2} \quad (1)$$

$$q(p_{sm}) \doteq (q(p_{mt}), q(p_s)) \quad (2)$$

Further more, edges represent services connections in our weighted graph representations, where assigned weight value $q(e_{sm})$ is considered to be semantic matching quality on edge level according to parameter aggregations. The weight value $q(e_{sm})$ is defined in 3, where $q(e_{mt})$ and $q(e_s)$ are the average value of concept-related parameters quality in $q(p_{mt})$ and $q(p_s)$ respectively.

$$q(e_{sm}) \doteq (q(e_{mt}), q(e_s)) \quad (3)$$

Comprehensive quality model. Compared to QoS evaluation model, the comprehensive quality model is established to investigate both functional and non-functional requirements. The comprehensive quality of our service composition representation refers to QoS of service vertices and Semantic matching quality of Edges in weighted graphs. Consequently, the comprehensive quality model is defined in Formula (4), which could be further broken down into Formula (5).

$$q_{cq} \doteq (q(e_{sm}), q(v_{QoS})) \quad (4)$$

$$q_{cq} \doteq (q(e_{mt}), q(e_s), q(v_a), q(v_r), q(v_c), q(v_t)) \quad (5)$$

Quality aggregate matrix. The quality aggregation is defined based on the constructs of composition web services, in consideration of functional and non-functional properties. The

TABLE I
QUALITY AGGREGATE MATRIX FOR SEMANTIC WEB SERVICE COMPOSITION

Composition Construct		Sequence	Parallel
Quality	F	$Q(e_{mt})$	$\prod_{n=1}^m q(e_{mt})$
		$Q(e_s)$	$(\sum_{n=1}^m q(e_s))/m$
	NF	$Q(v_a)$	$\prod_{n=1}^m q(v_a)$
		$Q(v_r)$	$\prod_{n=1}^m q(v_r)$
		$Q(v_c)$	$\sum_{n=1}^m q(v_c)$
		$Q(v_t)$	$\max(q(v_t))$

quality on construct level is further calculated by following the rules summarised in Table I.

C. Objective Function

In real life, given a unique and optimised solution is always easier for customers to pick up directly when many quality criteria involved into decision making, rather than provided a set of solutions. Therefore, it is very practical to define a single fitness as a weighted sum of all the quality related components in Formula (6), where weights setting is very flexible, it could be adjusted according to users' preferences. The fitness value of 1 means the best comprehensive quality and 0 means the worst. For this purpose, MT , S , A , R , T , and C must be normalised so that the fitness value falls within the range from 0 to 1. Therefore, the service composition problem in this paper is treated as a fitness maximisation problem.

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

where $\sum_{i=1}^6 w_i = 1$

$$\hat{Q}_k = \begin{cases} \frac{Q_k - Q_{k,min}}{Q_{k,max} - Q_{k,min}} & \text{if } Q_{k,max} - Q_{k,min} \neq 0. \\ 1 & \text{otherwise.} \end{cases} \quad (7)$$

where $k = 1, 2, 3$, and 4, where Q_1 as MT , Q_2 as S , Q_3 as A , and Q_4 as R .

$$\hat{Q}_j = \begin{cases} \frac{Q_{j,max} - Q_j}{Q_{j,max} - Q_{j,min}} & \text{if } Q_{j,max} - Q_{j,min} \neq 0. \\ 1 & \text{otherwise.} \end{cases} \quad (8)$$

where $j = 1$, and 2, where Q_1 as T and Q_2 as C .

V. PSO-BASED APPROACH TO QoS-AWARE SEMANTIC WEB SERVICE COMPOSITION

PSO has shown its efficiency in solving combinatorial optimisation problems [21]. Therefore, we will employ a PSO-based approach, which is considered to be simple and efficient without penalising or repairing that often required by GP [11]. Fig. 3 shows the overview of our approach with five steps. Step 1: The composition process is triggered by a composition goal defined in Subsection III, which describes customers requirements both functional and non-functional. Step 2: This composition goal are used to discover all relevant web services, which lead to a shrunken service repository that is subsequently used by PSO as a searching space. Step 3: A weighted graph representation is randomly built up from the an initial service queue that mapped to the particle's location, interleaving with semantic matchmaking process utilising ontology-based index cache. In the weighted graph, graph edges are assigned with

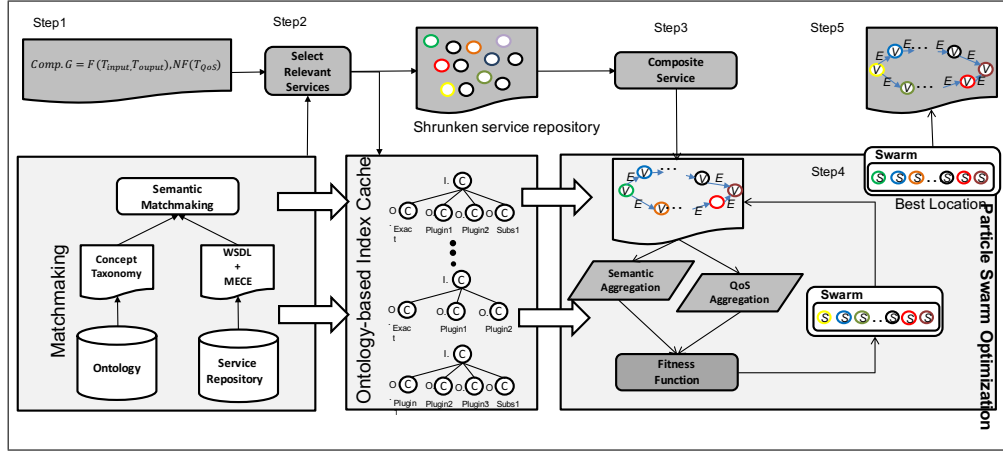


Fig. 3. Overview of POS-based automated semantic web service composition approach.

semantic matchmaking quality as weights. Step 4: The fitness value of the weighted graph is evaluated to update the position of particle under PSO algorithm in Sect. V-C, where the position is mapped to the index of service queue. later on, the updated service queue is used to decode a new weighted graph as the composition solution. Step 4. Lastly, the best position found in the searching space is selected and decode into the final optimised solution. This PSO-based approach is similar to [11], but we employ weighted graphs as a different solution presentation.

A. Ontology-based Index Cached Optimisation

In PSO, particles represent weighted graphs with edges and vertices associated with quality of semantic matchmaking and QoS respectively, the bottlenecks of generating weighted graph lie in building edges and nodes, which are related to the cost of semantic quality calculation and the size of service repository respectively. To effectively construct weighted graphs, we pre-calculate semantic matchmaking quality. The key idea of the index is to create a mapping from the output-related concepts to potentially matched input-related concepts while considering different levels of match types. Meanwhile, this index size could also be reduced by only considering the concepts related in the shrunken service repository, which means the index cache is filtered by those task-relevant web services. This optimised cache also contributes to less and constant time for weighted graphs building through the whole evolutionary process.

B. Composition Weighted Graph

We defined our semantic web service composition solution as a weighted graph $WG = (V, E)$, where V is a set of services as vertex: $V = [S1, S2...Sn]$ and E is a set of edges $E = e_1, e_2, ...e_n$. Each e is associated with $q(e_{sm})$ as weight value that mapped to a pair of quality values $q(e_{mt})$ and $q(e_s)$ on the edge level, and e_m is expressed as $(S_a, S_b) = q_{mt}, q_s$. Here we provide an example of the web service composition, which is described in Fig. 4. The data of composition web service flows from the start to the end, where five web services

involved and linked with each other using edge connections. Besides that, $q(s_{mt})$ and $q(s_s)$ are calculated for all edges $e_1, e_2, ...e_n$ assigned as weights.

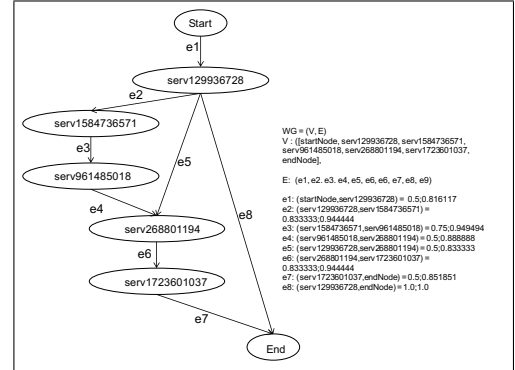


Fig. 4. Composition weighted graph solution

C. QoS-aware Semantic Web Service Composition Algorithm

The overall algorithm investigated here is made up of the PSO-based web service composition algorithm 1 and the decoding algorithm 2. In algorithm 1, the idea is to translate the particle location produced by PSO into a service queue as an indirect representation, such that finding the best fitness of the weighted graph is to discover the optimised location of the particle in the search space. In PSO, the dimension of each particle equals to the number of relevant web services. The index of each services is mapped to a separate location component in a particle. Services in a queue follow the ascending order, from which we decode a weighted graph using Algorithm 2. It is a simple forward graph building algorithm, and this method can lead to more services and edges connected to the graph as redundancies that must be removed. Also, semantic quality value are assigned to all the edges, which is calculated from a quality aggregation function from all involved concept-related parameters.

VI. EXPERIMENT DESIGN

In this section, a quantitative evaluation approach is adopted in our experiment design. The objectives of the evaluation

 ALGORITHM 1. Steps of the PSO-based Web service composition technique.

Input : relevant Web services rws
Output: Optimised service queue $queue$, Optimised Weighted Graph $OPTWG$

- 1: Map each relevant service to an index in the particle's position vector;
- 2: Randomly initialise each particle in the swarm;
- 3: **while** $max. iterations not met$ **do**
- 4: **foreach** $particles in the swarm$ **do**
- 5: $queue \leftarrow$ particle's position vector;
- 6: $WG \leftarrow generateWeightedGraph()$;
- 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;
- 15: **return** $OPTWG$;

 ALGORITHM 2. Create a composition weighted graph from a queue.

Procedure $generateWeightedGraph()$
Input : Task inputs I , task outputs O , Optimised service queue $queue$, IndexCache $IndexCache$
Output: Weighted Graph WG

- 1: $WG \leftarrow null$;
- 2: $WG \leftarrow new endNode(), new startNode()$;
- 3: $OutputSet \leftarrow \{I\}$;
- 4: **while** $all O \notin OutputSet$ and $queue \neq null$ **do**
- 5: **foreach** $ws in queue$ **do**
- 6: **if** $ws.inputs \in OutputSet$ **then**
- 7: **foreach** $I in ws.inputs$ **do**
- 8: $p_{mt} \leftarrow query IndexCache$;
- 9: $p_s \leftarrow query IndexCache$;
- 10: $e_{sm} \leftarrow aggregation(p_{mt}, p_s)$;
- 11: $WG.edge \leftarrow e_{sm}$;
- 12: $WG \leftarrow new wsNode()$;
- 13: $OutputSet add \{ws.outputs\}$;
- 14: $queue.remove ws$;
- 15: remove $dangling nodes$;
- 16: remove $dangling edges$;
- 17: **return** WG ;

 TABLE II
 FEATURES OF THE WSC09 DATASETS

Dataset	No.Concept	No.Individual	No.Service
WSC09_01	1578	3102	572
WSC09_02	12388	24815	4129
WSC09_03	18573	37316	8138
WSC09_04	18673	37324	8301
WSC09_05	31044	62132	15211

are to (1) measure the effectiveness of the comprehensive quality model in automated semantic web service composition approach; (2) explore the impacts of the semantic matchmaking that contributes to overall composition quality; and (3) compare solutions generated by QoS-aware approach with our method; and (4) compare our method with one existing GP-based approach.

We utilise benchmark dataset web service challenge 2009 (WSC09) [12] to perform the evaluation. WSC09 provides problems with five tasks corresponding to variable number of services, and ontologies. Therefore, it is a challenge dataset for measuring the scalability of our quality evaluation model. Table II presents the features of the WSC09 dataset. The number of concepts, individuals in the ontology and services in each data set is shown in the second, third, fourth column respectively. Also, we extend all the datasets with QoS attributes from service providers to enable our evaluation.

We run the experiment on computing grid comprising of 170 NetBSD (Unix operating system) workstations operated by the Sun Grid Engine. The parameters were chosen based on general settings from [26] for our PSO-based approach. In particular, PSO population size is 30 with 100 generations. We run 30 times independently for each dataset. We configure weight of fitness function to properly balance functional side and nonfunctional side. 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 accordingly. However, the settings of these weight values does not impact the method. In general, weight settings are adjusted according to users' preferences.

VII. RESULTS AND ANALYSIS

A. Comparison Test with QoS Evaluation Model

In this section, we analyse the composition solution generated by using our approach comparing with QoS-aware approach. First, we look at mean value of Q_{mt} , Q_s and Q_{QoS} at optimum at the 100th generation for two approaches, shown in Table III. The QoS-aware approach record Q_{mt} , Q_s and utilise fitness function $Fitness = w_1\hat{A} + w_2\hat{R} + w_3(1 - \hat{T}) + w_4(1 - \hat{C})$ when $\sum_{i=1}^4 w_i = 1$, but MT and S are recorded, and $Q(QoS)$ is normalised from 0 to 0.5 to make it comparable to Q_{QoS} in our approach. We observe an interesting pattern from Table III using statistic analysis: mean value of Q_{mt} and Q_s at optimum by our approach is consistently higher than those by QoS-aware approach. Meanwhile, Q_{QoS} generated by QoS-aware approach can obtain a slightly higher value than that of our approach. In conclusion, we can perceive that our evaluation could find out better functional quality with a reasonable trade off in QoS.

TABLE III
MEAN QUALITY FOR COMPREHENSIVE QUALITY-AWARE METHODS AND QoS-AWARE APPROACH

WSC09		QoS-aware Evaluation	Comprehensive Quality Evaluation
Task1	Q_{mt}	0.189787 ± 0.039278686	$0.221862 \pm 0.009582 \uparrow$
	Q_s	0.884962 ± 0.014140	$0.894082 \pm 0.009206 \uparrow$
	Q_{QoS}	0.278730 ± 0.007786	0.280222 ± 0.008212
Task2	Q_{mt}	0.001795 ± 0.000719	$0.001977 \pm 0.001566 \uparrow$
	Q_s	0.906971 ± 0.005855	$0.923970 \pm 0.006898 \uparrow$
	Q_{QoS}	$0.239979 \pm 0.000578 \uparrow$	0.238596 ± 0.001264
Task3	Q_{mt}	0.158526 ± 0.014028	$0.245830 \pm 0.007761 \uparrow$
	Q_s	0.949109 ± 0.002331	$0.972765 \pm 0.002980 \uparrow$
	Q_{QoS}	$0.247002 \pm 0.000661 \uparrow$	0.245631 ± 0.000431
Task4	Q_{mt}	0.000000 ± 0.000000	$0.000004 \pm 0.000002 \uparrow$
	Q_s	0.879514 ± 0.007456	$0.920733 \pm 0.000001 \uparrow$
	Q_{QoS}	$0.242297 \pm 0.000507 \uparrow$	0.236677 ± 0.002211
Task5	Q_{mt}	0.000042 ± 0.000030	$0.000078 \pm 0.000020 \uparrow$
	Q_s	0.915933 ± 0.012888	$0.927678 \pm 0.002578 \uparrow$
	Q_{QoS}	$0.238189 \pm 0.000240 \uparrow$	0.237485 ± 0.000328

Second, to compare the results generated from two evaluation approaches, we demonstrate an example solution that shows the differences in web services composition obtained through two different methods. Fig. 5 (1) and (2) show two composition weighted graphs as the two optimised solutions to Task 3 with (1) QoS-aware approach and (2) Comprehensive quality-aware method respectively. Two approaches generate exactly the same service workflow structure where those service vertices and edges denoted in red are different. We make a comparison of the quality among these different edges (e_1 to e_4) associated service vertices in terms of quality of semantic matchmaking and QoS attributes in Fig. 5 (3). We also look at ΔQ which reveals the amount of variation on quality between two methods, where the positive values means the benefits gained under our approach while the negative values means the trade-off. To demonstrate the benefits of the positive value, we analyse the smallest positive ΔQ corresponding to e_4 and demonstrate how the output and required input are different under two approaches in Fig. 5 (4). *Ser1640238160* and *Ser1947554374* are selected service vertices with output concept-related parameters *Inst795998200* and *Inst582785907* corresponding to two concepts *Con103314376* and *Con2037585750* respectively, and *Inst658772240* are the required parameter related to concept *Con2113572083*. There exist *Inst795998200* \in *Con103314376* \sqsubseteq_2 *Inst658772240* \in *Con2113572083* and *Inst582785907* \in *Con2037585750* \sqsubseteq_3 *Inst658772240* \in *Con2113572083*. It is obvious that our approach selects the service providing *Inst795998200* that are closer to the users' requirements suggesting that our method can produce better semantic matchmaking quality.

B. Comparison Test with GP-based approach

We compare one GP-based approach [20] with our PSO method, where the individuals are tree structure with strict constraints transferred from a DAG employing unfolding techniques. We further mark all the service nodes in the tree representation with all their outgoing edges for considering semantic matchmaking quality, and those edges information

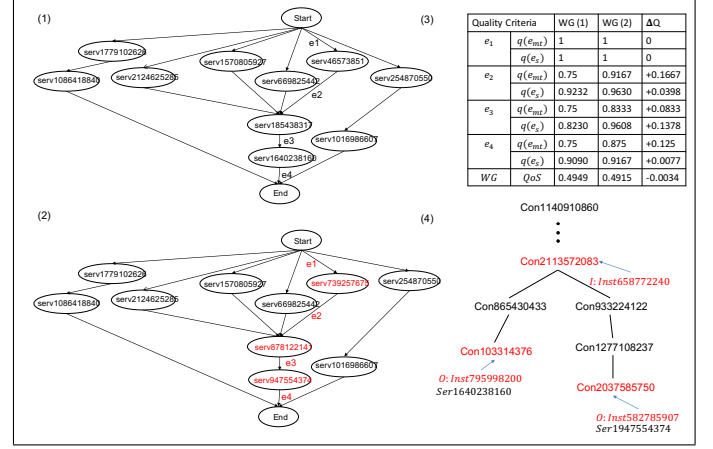


Fig. 5. Example Comparison of solutions to Task 3 under different approaches.

TABLE IV
MEAN FITNESS RESULTS FOR COMPARING GP-BASED APPROACH

Dataset	PSO-based approach	GP-based approach
WSC09 01	$0.559207 \pm 0.012780 \uparrow$	0.518411 ± 0.018470
WSC09 02	0.470083 ± 0.001106	$0.471594 \pm 0.002436 \uparrow$
WSC09 03	$0.559207 \pm 0.012780 \pm \uparrow$	0.552947 ± 0.007094
WSC09 04	$0.468942 \pm 0.001670 \pm \uparrow$	0.442934 ± 0.010154
WSC09 05	$0.469424 \pm 0.000800 \pm \uparrow$	0.256425 ± 0.038916

are maintained correctly in the crossover and mutation. At last, we evaluate both semantic matchmaking quality and QoS simultaneously using the discussed the comprehensive quality model to investigate the performances of two approaches. To make a fair comparison with our PSO approach considering the same number of evaluations (3000 times), we adjust the parameters settings for GP approach [20] to 30 individual for 100 generations.

The Table IV shows the mean fitness values accomplished by two methods and Table ?? shows the average execution time required by them. We employ statistical analysis to test the significant differences in mean fitness value and execution time. The results show that the PSO-based approach performs better in four of five tasks. However, there is also a trade-off between optimised solution and execution time. We can see the PSO-based approach takes longer execution time, it due to that every individual in each generation must be decoded into a solution from optimised queue, and this process is very time-consuming. However, In GP, the initialisation first population is costly in time as transformation process from a DAG, but following new individuals are generated through mutation and crossover, which demands much less time comparing decoding process.

At last, We also compare the average fitness value with optimum through the evolutionary process for both two approaches over 30 independent runs. Fig. 6 is an example of convergence rate from Task 3, where the behaviour of PSO-based approach presents a very clear evidence of fast convergence and reaches a better-optimised solution, while the performance of GP is barely satisfactory, as GP-based method improves its fitness value gradually.

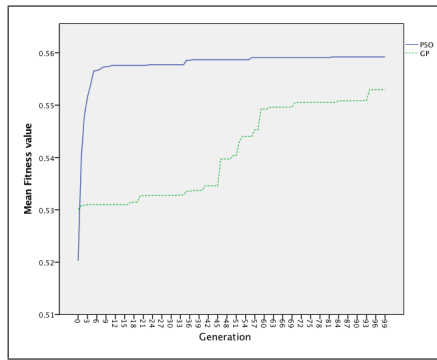


Fig. 6. An example of comparing convergency rate of PSO and GP approaches for task 3

VIII. CONCLUSION

This work introduces a comprehensive evaluation model employed our PSO-based method for QoS-aware automated semantic automated web service composition that combines the quality of semantic matchmaking with QoS. The results show that our approach obtain better functional quality with a reasonable trade-off in QoS. Also, we compare one GP-approach with our PSO-based method to show our performance results in finding better-optimised solution. Future works could investigate other direct or indirect representations of semantic web service composition on semantic web service composition, and look into other EC techniques to evaluate their performance. Also, we could reshape the problem on providing customers with a set of solutions to choose from, rather than a single solution, so research question is redefined as multi-objectives or many objective problems.

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