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Comprehensive Quality-Aware Automated Semantic Web Service Composition

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August 28, 2017

Submitted in partial fulfilment of the requirements for
PhD.

Abstract

Automated web service composition is an NP-hard problem and it has been raising much attention in the research community due to the computational challenge and real-world applicability. The focus of our studies on service composition is to find effective and efficient approaches to comprehensive quality-aware semantic web service composition, which aims optimize semantic matchmaking quality and Quality of service (QoS) simultaneously. This problem is not fully explored before in the following considerations: (1) developing EC-based approaches that could explicitly support a comprehensive quality model that jointly the two quality aspects, (2) developing multi-objective approaches for optimizing the quality criteria that involved in the comprehensive quality model, (3) developing EC-based composition approaches for dynamic service composition while handling various changes of composition environment, and (4) developing EC-based approaches for semantic web service composition, particularly, considering precondition and effects.

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Chapter 1

Introduction

1.1 Problem Statement

Service-oriented computing (SOC) is a novel computing paradigm that employs services as fundamental elements to achieve the agile development of cost-efficient and integrable enterprise applications in heterogeneous environments [75, 76]. SOC aims to be platform neural and language agnostic to enable integrable and seamless communication among those existing or newly built independent services. *Service Oriented Architecture* (SOA) could abstractly implement service-oriented paradigm of computing. This accomplishment has been contributing to the reuse of software components, from the concept of functions to units and from units to services during the ongoing development of SOA [10, 72]. One of the most typical implementation of SOA is *web service*, which is designated as "modular, self-describing, self-contained applications that are available on the Internet" [20]. Several standards play a significant role in registering, enquiring and grounding web services across the web, such as UDDI [19], WSDL [50] and SOAP [32]. Since an atomic web can not always satisfy users' requirements, *web service composition* aims to loosely couple a set of web services to provide a value-added composite service that accommodates complex functional and non-functional requirements of service users.

The first notable challenges for web service composition are ensuring interoperability of services [32]. *Interoperability* of web services presents challenges in syntactic and semantic dimensions. On the one hand, the syntactic dimension is covered by the XML-based technologies [115], such as $WSDL$ and $SOAP$. In this dimension, most services are composed together merely based on the matching of input-output parameters. On the other hand, the semantic dimension enables a better collaboration through ontology-based semantics [71], in which many standards have been established, such as OWL-S [64], Web Service Modeling Ontology (WSMO) [51], SAWSDL [47], and Semantic Web Services Ontology (SWSO) [79]. This dimension brings around some other underlying functionality of services (i.e., precondition and postcondition) that could effect the execution of web services and their composition. The interoperability challenge gives birth to *Semantic web services composition*, as a different technique from traditional service composition methods (i.e., only syntactic dimension is presented in web services). The interoperability of services is presented as a semantic matchmaking relationship between provided information (i.e. one service output) and required information (i.e., another service input), which do not often perfectly match with each other based on their semantic descriptions. Therefore, the quality of matchmaking becomes an aspect of the quality concern for users, which also raise researchers' interests.

The second notable challenges for web service composition are achieving Quality of Service (QoS) optimization [32]. QoS represents non-functional attributes of service composition (e.g, cost, time, reliability and availability). Often, a global search method is employed

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to minimize the cost and maximize the reliability of composite services. This challenge gives birth to *QoS-aware service composition* that aims to find composition solutions with optimized QoS. Furthermore, QoS-aware service composition problem is facilitated by *Service Level Agreement (SLA)* [87], i.e., binding constraints on QoS. This results in the *SLA-aware web service composition*, e.g., constraints on cost, execution time, availability and reliability are separately specified with both lower and upper bounds. In addition, when QoS preference is provided by users, optimization problem often returns a single near-optimal solution, and it is considered as a *single-objective optimization* problem. Otherwise, a set of composition solutions are returned when QoS preference is not clearly by users. This problem is considered as a *multi-objective optimization problem*.

Apart from the two notable challenges discussed above, the service composition problem is dynamic in the real world, rather than *static*. For example, QoS of services are fluctuating over time. These services chosen at the planning stage may not be available during the run-time, it may due to imprecise interface description [42] or hardware failures [37]. New services can also be registered in the service repository from time to time. Existing techniques for *static web service composition* cannot cope with such a changing environment. Therefore, *dynamic web service composition* becomes a very important research field with growing research interest and practical value. Particularly, some mechanisms are required to automatically detect the changes or recover from the faults [16]. Additionally, in the context of semantic web service composition, dynamic web service composition must also handle the changes in the ontology.

Different service composition approaches [23, 26, 38, 52, 62, 81, 86, 117, 102] have been proposed to cope with those composition challenges discussed above and they can be classified into two main categories: *semi-automated web service composition* and *fully automated web service composition*. The first category of composition approach requires human beings to manually create abstract service workflows. It is generally assumed that a pre-defined abstract workflow is given a priori. The optimization problem in this approach turns to selecting concrete services with the best possible quality for each abstract service in the given workflow. Due to a tremendous growth in industries and enterprise applications, the number of web services has increased dramatically at an unprecedented pace. The process of designing abstract workflows manually is fraught with difficulties in effectively and efficiently solving composition problems [52], such as QoS-aware service composition problem. Therefore, full automation of composition process is introduced in web service composition for less human intervention, less time consumption, and high productivity [83]. The differences in fully automated approach is that an abstract workflow is not provided, but instead created automatically with the service selection process.

Generating composition plans automatically in discovering and selecting suitable web services is an NP-hard problem [67], which means the near-optimized composition solution is not likely to be found in a reasonable computation time. To effectively and efficiently solve this problem, *Artificial Intelligence (AI) planning-based approaches*, *Evolutionary Computation (EC) techniques* and hybrid techniques have been introduced. AI planning is utilized to solve the automated web service composition problems as a plan making process, from initial states to a set of actions to desired goal states-composite web services, where services are considered as actions triggered by one state (i.e., inputs) and resulted in another state (i.e., outputs). In the second approach, heuristics have been employed to generate near-optimal solutions using a variety of EC techniques, e.g., Genetic Algorithms (GA), Genetic Programming (GP) and Particle Swarm Optimization (PSO). EC-based techniques have been effectively developed to solve the *QoS-aware web service composition* problem. Many representations have been carefully investigated in QoS-aware web service composition problems, since they could significantly affect the performance of fully automated service composi-

tion approaches. In the third approach, a hybridization of AI planning-based approaches and EC-based approaches [23, 62] have been proposed to simultaneously ensure the correctness in constructing workflows and optimize the quality of composition solutions (e.g., QoS). These methods are considered to be more effective in finding more optimal solutions. As summarized here, a few challenges previously addressed, but not solved for fully automated service compositions lies in jointly optimizing QoS and semantic matchmaking quality, dealing with multi-objective semantic web service composition for simultaneously optimizing different quality aspects, handling environment changes (i.e., changes in QoS, ontology and service repository) in dynamic service composition, and composing semantic web services considering precondition and effects while optimizing QoS and semantic matchmaking quality. Those challenges are addressed with some key limitations in Section 1.2.

The overall goal of this thesis is to propose effect and efficient approaches to comprehensive-quality aware automated web service composition. This comprehensive quality aims to jointly optimize semantic matchmaking quality and QoS. Meanwhile, this new approach also tackles several service composition problems, such as multi-objective optimization, dynamic web service composition and semantic web service composition based on preconditions and postconditions.

1.2 Motivations

The motivations of this proposed research lies in five key aspects that simultaneously account for. 1. *Various techniques of combining AI planning and EC for automatic service composition*. 2. *Simultaneous handling quality of semantic matchmaking and quality of service*. 3. *Muti-objective optimization*. 4. *Dynamic semantic service composition*. 5. *Service composition based on preconditions and effects*. Herein these key aspects are explicitly discussed below.

Various Techniques of Hybridization

Various techniques have been utilized to solve service composition problems, such as AI planning, local searching and EC-based techniques [31, 77, 81, 102]. AI planning is a prominent technique for handling web service composition problems while always ensuring the correctness of the solution (i.e., all the inputs of involved services are satisfied) [102]. Local search is a exhaustive search technique for solving optimization problems. In local search, solutions keep moving to the neighbor solutions, driven by some local maximization criterion until near-optimal solution found [77]. However, this technique has the shortage of being trapped in local optimal. On the other hand, EC-based techniques are outstanding at solving combinatorial optimization problems and are less prone to premature convergence in complex search spaces. To take the benefits from various techniques, various techniques of hybridization allows escaping local optima easily and improving the rate of convergence rate [85].

Various techniques have been employed to handle service composition problems in the literature [31, 63, 77, 78, 81, 102]. Many researchers investigated AI planning techniques for service composition problems using classical planning algorithms (e.g., GraphPlan [9]), where inputs, outputs, preconditions and effects are well defined along with the actions (i.e., services) [63, 78]. On the one hand, AI planning ensures both the correctness of functionality and satisfactory of constrains, but it is always considered to be less efficient and less scalable, incapable of solving complicated optimization problems [77]. On the other hand, some researchers combined AI planning and local search to handle optimization problems,

e.g., a combination of Graphplan and Dijkstras algorithm is proposed by [31] to find a correct solution with optimized QoS. Many EC techniques have been utilized to handle service composition problems, due to their promising performance in handling combinatorial optimization problems in a huge searching space. This problems usually have no mathematical models utilized for solving them. A few researchers also combined both local search and EC-based techniques for efficiently finding composition solution with optimized QoS [77]. From the techniques discussed above, they are problem-specific for either optimizing QoS or number of services. In this thesis, more complicated and realistic service composition problems are addressed. To cope with this composition problems featured in all the motivations discussed below (i.e., comprehensive quality-aware service composition, multi-objective optimization, dynamic service composition, and composing semantic web services based on preconditions and postconditions), EC-based hybrid techniques, optionally combing with AI planning or local search, are motivated to be proposed in our problems. For example, one heuristic in an EC-based technique is initially utilized for a purpose of global search. Meanwhile, another heuristic is additionally designed for a purpose of a local search, which determining neighborhood of composition solutions. This hybrid method may lead to more effective performance.

Comprehensive Quality of Semantic Web Service Composition

Web service compositions are optimized by the well known non-functional attributes (i.e., QoS). In the domain of semantic web services, often, the provided information (i.e., outputs) does not perfectly match the required information (i.e., inputs) according to their semantic descriptions [54]. Then, the quality of these matches (i.e., quality of semantic matchmaking) become one part of the goal for achieving service compositions with better semantic matchmaking quality [52]. Therefore, a comprehensive quality is proposed for simultaneously considering both QoS and semantic matchmaking quality as a novel combinatorial optimization problem. One motivated example from a practical perspective is explained here: 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.

Existing works on service composition focus mainly on addressing only one quality aspect discussed above. For the semantic matchmaking quality, it is mainly addressed in works that focus on the discovery of atomic services, i.e., one-to-one matching of user requirements to a single service. Some works [6, 11, 66] on semantic service composition often minimize the number of services or the size of a graph representation for a web service composition. These approaches do not even guarantee an optimized overall QoS. On the other hand, huge efforts have been devoted to studying QoS-aware web service composition [21, 26, 38, 62, 81, 117]. Some of these works do consider different semantic matchmaking types (e.g., Exact and Plugin matches [74]) when they compose services, but do not recognize the importance of semantic matchmaking quality. It is not sufficient to only consider one quality aspect for optimizing service composition. However, only very few works address both semantic matchmaking quality and QoS for web service composition problems.

To the best of our knowledge, [30, 52, 80] reported about first attempts that consider both aspects together, but only semi-automated approaches have been studied in their works. For these reasons, there is a need to device a comprehensive quality for jointly optimizing the two quality aspects. Apart from that, new fully automated approaches need to be proposed to handle this optimization problem and explicitly support the comprehensive quality.

Multi-Objective Composition Optimization

Existing approaches for handling web service composition problems fall into two groups, depending on different goals of optimization, either a single objective or multiple objectives. In single-objective service compositions, one composition solution is always returned by a composition task, where the preferences of each quality component within the single objective (e.g., a weighted sum of different quality criteria) is known by users. However, users do not always have clear preferences for many quality criteria in advance, and trade-offs presented by two or more conflicting criteria are also taken into optimal decisions. Therefore, multi-objective optimization is a natural requirement to provide a set of trade-off solutions that concern about the conflicting and independent quality criteria. For example, premium users do not care cost as much as price-sensitive users do, so premium users may prefer a composition solution with lowest execution time with no limit on a budget, rather than the one with a relatively lower execution time without exceeding a budget. Therefore, multi-objective web service composition approaches are motivated to be proposed for producing a set of solutions, since the preferences of different quality is not clear and hard to determine in advance, and single-objective optimization using weighted sum method cannot reach solutions in the non-convex regions [44].

Existing research on the automated web service composition mainly concentrates on single objective problems for QoS-aware web service compositions. That is, only one solution is promoted by a unified QoS ranking score to the users. However, to our best knowledge, existing works on multi-objective service composition [59, 97, 110, 111] are only approached by semi-automated methods to handle the conflicting QoS attributes independently. Simultaneously constructing workflows and selecting proper services for optimizing multi-objectives is a very challenge work to complete. On the other hand, some constraints on SLA have also been taken into account in some approaches discussed above. These constraints raise the complexity of absolute Preto priority relation [35]. Apart from SLA constraints, users often have vague thoughts about what solutions are preferred. For example, a maximally acceptable trade-off for service execution cost and reliability. These partial preferences should be used for searching the most preferred region. Many preference articulation techniques for multi-objective optimization have been studied [**?**, 13, 14, 18, 36], these approaches can be classified into three groups based on the articulation of preferences [95]. The first group is priori approaches, where the articulation is done before optimization process; the second group is interactive approaches, where the articulation is done during optimization process; the third group is posteriori approaches, where the articulation is done after optimization process. As argued in [36], the third approaches are capable of generating more desired solutions in the preferred region by utilizing biased crowding distance [13] or reference vectors [18]. However, all these approaches have not been used for solving service composition problem considering user preferences on a comprehensive quality. In particular, more practical and effective user preference models are required along with modifications of posteriori methods for effective cope with for service composition problems. From above discussion, these is a lack of fully automated approaches to multi-objective web service composition problems for QoS-aware web service composition abiding by constrains on SLA. Meanwhile, the insufficiency of handling only non-functional attributes (i.e., QoS)

has given rise to adding semantic matchmaking quality into simultaneous consideration for this multi-objective problem. Further, user preference articulation techniques have not been studied in service composition problem so far.

Dynamic Semantic Web Service Composition

In a dynamic environment, QoS of atomic services in a service repository is fluctuating over time. Static service composition solution is no longer enough, and remedy actions must be taken if the original composition solution changes in QoS or is no longer executable due to any service involved goes offline. Apart from that, newly registered services could also alter the composition plan as it might significantly contribute to the overall QoS or quality of semantic matchmaking. Therefore, dynamic web service composition is proposed to effectively and efficiently update composition solutions when their performance and executability cannot be guaranteed any further [56].

Most approaches work on effective and efficient methods for service re-selection for each component services in a service composition solution, which do not allow the changes of service composition structure. Apart from that, the cost of initial planning is ignored and separated from the adaption of dynamic environment. On the one hand, some techniques [4, 7, 46] endeavored to update outdated or incorrect compositions, and they allow for dynamic adaptation of the solutions based on implementation of variability constructs at the language level. For example, a composition language extending a typical WS-BPEL [4] is proposed for supporting the dynamic adaption using ECA (Event Condition Action) rules, which is utilized for guiding the operations for self-reconfiguration. This approach is difficult to manage, and error-prone. Based on and by extending the previous approaches, variability model based approaches [3] have been proposed to support the adaption of service composition solutions. Meanwhile, some other works [68, 88, 98, 112] utilize decision tree learning, reinforcement learning and Rtree query techniques for dynamic service composition problem. Those non-EC based approaches focus on developing efficient methods for service re-selection, which is utilized for replacing services once negatively contributed changes are detected. On the other hand, EC-based techniques can overcome two limitations. That is, the changes of composition structure is allowed and avoiding re-planning cost through re-using known plans (composite services) obtained prior. First, a proper amount of individuals stored could be used for retrieving an alternative composition solution in the case of failure. This is a save of computation cost for re-planning. Second, the stored individuals could be further evolved resulting in changes of component services or composition structure. However, existing EC-based approaches to web service composition are only studied in static scenarios, rather than dynamic ones. Although some works [31, 59] claimed that their approaches fit the dynamic problems due to the natural features of their adopted algorithm (i.e., a continuous optimization process), there is no definition or discussion about dynamic service composition problems in their papers. Therefore, there is a lack of research in the area of EC-based dynamic service composition. Given above discussion, it is very advisable to study the effectiveness of EC approaches in a dynamic composition context.

Automated Web Service Composition Based on Preconditions and Effects

Since conditions and effects do not apply to most of web services, we achieve valid service composition merely on inputs and outputs previously. However, some web services include conditions and effects, these conditional constraints also determine the executability of services, which lead to more complex service composition constructs (i.e., choice and loop) to

be considered when services are composed together. For example, in a scenario of an online book shopping system [102], services are composed to provide an operation for book shopping. Users expect a purchasing outcome (e.g., receipt) returned if books and customer details (e.g., title, author, customer id) are given. In this case, users may have specific constraints. If the customer has enough money to pay for the book in full amount, then they would like to do so. Otherwise, the customer would like to pay by installments. Therefore, the constraints on their current account balance needs to be handled during the execution of the service composition.

Most of the existing approaches to automated web service composition are approached through services represented by only inputs and outputs. However, a underlying functional knowledge base of services (i.e., in the form of preconditions and effects) is not covered [73]. On the one hand, a few approaches [6, 12] have been explored to achieve compositions that consider precondition and effects using AI planning, since AI planning ensures both the correctness of functionality and satisfaction on constrains. Meanwhile, exhaustive methods are utilized with AI planning for tackling optimization problems. These methods suffer hugely in terms of efficiency, scalability, and computation cost. On the other hand, EC techniques (i.e., heuristic methods) are considered to be more flexible and more efficient. Given the benefits of both AI planning and EC-based techniques, they are motivated to be collectively explored for automated web service composition based on preconditions and effects.

1.3   Research Goals

The overall goal of this thesis is to *develop new and effective EC-based hybrid approaches for comprehensive quality-aware automated semantic web service composition*. More specifically, the research focus will be on: (1) developing EC-based approaches that could explicitly support a proposed comprehensive quality model that jointly optimizes QoS and semantic matchmaking quality, (2) developing multi-objective approaches for optimizing multiple quality criteria involved in the comprehensive quality model, (3) developing EC-based composition techniques to handle various changes in composition environment, and (4) developing EC-based approaches for semantic web service composition, particularly, considering precondition and effects. This research aims to develop EC-based approaches, optionally combined with some local search, for effectively and efficiently handling the research focus above. The research goal described above can be achieved by completing the following set of objectives:

1. **Develop EC-based approaches to comprehensive quality-aware automated web service composition that simultaneously optimizes both QoS and semantic matchmaking quality**. Particularly, we extend existing works on QoS-aware service composition by considering jointly optimizing both quality aspects, which will be covered collectively through a comprehensive quality model. Meanwhile, representations of the composition solutions are the key aspect of the approaches, since they must maintain all the required information for the evaluation. Therefore, we will investigate the following sub-objectives to handle this objective.

   (a) *To propose a comprehensive quality model that addresses QoS and semantic matchmaking quality simultaneously to reach a desirable compromise.* We aim to establish a quality model with a simple calculation and good performance. This model is utilized for evaluating QoS and quality of semantic matchmaking of service composition solutions. Meanwhile, to perform a feasible evaluation, it must support most of existing benchmark datasets, e.g., Web Service Challenge 2009 (WSC09)[45] and OWLS-TC [49].

(b) *To propose direct solution representations for comprehensive quality-aware web service composition.* Graph-based and tree-based representations are widely used for directly representing service composition solutions. Graph-based representations are capable of presenting all the semantic matchmaking relationships as edges, but hardly supporting some composition constructs (e.g., loop and choice). Tree-based representations could be more ideal for practical use, since they can present all composition constructs as inner nodes of trees. However, they could hardly maintain all the edge-related relationships supported by graphs. To take advantage of the graph-based and tree-based representations, we aim to propose a tree-like representation. In particular, any isomorphic copy in the traditional tree-based representations is removed, and insert an edge to the root of the copy. Meanwhile, particular genetic operators will be developed without breaking the functionality of the inserted edge.

(c) *To propose indirect solution representations for comprehensive quality-aware web service composition.* The *indirect representations* do not present the final service composition solutions directly, they must be decoded to produce executable service composition solutions. Previous studies have shown their good performance in searching optimal solution for QoS-aware web service composition [25, 26]. However, the decoding process could increase the computation time. Apart from that, the indirect representation potentially increases the searching space as discussed in [26]. To overcome these disadvantages, it is advisable to propose more effective indirect representations.

(d) *To propose EC-based hybrid methods to effectively and efficiently handle the problem for comprehensive quality-aware automated web service composition.* The reasons of utilizing hybrid techniques are briefly discussed in Subsection 1.2, and they aim to efficiently and effectively handle service composition problems. Herein, memetic approaches are developed for supporting both the proposed indirect and indirect representations. In particular, new and effective genetic operators are to be developed for EC-based algorithms, and local search techniques will also be developed to avoid being trapped by the local optimal. For the local search, properly designed structures will be studied for neighboring solutions. Apart from that, these approaches must explicitly support the comprehensive quality model. Further more, AI planning techniques will be incorporated into the newly memetic approaches to expedite the convergence speed.

2. **Develop multi-objective approaches to fully automated comprehensive quality-aware semantic service composition**. In practice, many quality criteria proposed in our comprehensive quality model are often conflicting in natural, such as an amount of money paid for service execution and a possibility of service availability. Existing works [17, 106, 111, 59, 114, 120] mainly concentrated on semi-automated QoS-aware web service composition. Therefore, research must be carried out not only for a better understanding of inherent trade-offs among different objectives (e.g., quality of semantic matchmaking and QoS are naturally considered as two conflicting objectives), but also for developing fully automated approaches for overcoming the limitations of semi-automated approaches. It is approached by utilizing cutting-edge multi-objective optimization algorithms (e.g, NSGA-II [29], SPEA2 [123] and MOEA/D [119]). These algorithms are needed for finding a Pareto front of evolved solutions. Meanwhile, different representations may not perform equally well, so a study on improving the effectiveness of different representations along with different Evolutionary Multi-Objective Optimization (EMO) techniques also arouses researchers' interest. Apart from that,

SLA consideration needs to be taken into account. It is also necessary to consider customized matchmaking levels to bring the flexibility for meeting different requirements from segmented users (e.g., platinum users, gold users and normal users). Further more, Most EMO algorithms work on achieving evenly distributed non-dominated Pareto solutions. However, users are often interested in certain regions of the Pareto Front, and often have vague ideas about what solutions will be mostly preferred. Therefore, more effective and efficient methods should be conducted for determining the potentially preferred solutions and yielding a smaller set of most preferred solutions. The development of this approach can be divided into the following four sub-objectives:

(a) *To develop a EMO-based approaches for multi-objective fully automated semantic web service composition*. Herein we will propose useful modifications of multi-objective EC algorithms (for example, NSGA-II [29], SPEA2 [123] and MOEA/D [119]) simultaneously to improve the effectiveness and efficiency of our service composition approaches. This sub-objective is also established for in-depth investigation of each quality criteria based on our proposed comprehensive quality model in Objective 1. In particular, both quality of semantic matchmaking and QoS must be optimized separately, since they can conflict each other. It would be interesting to examine different tradeoffs among the service composition solutions with respect to the different quality criterion. Apart from that, fully automated approaches are also developed to achieve high practical usefulness without replying on given abstract workflows.

(b) *To develop EMO-based hybrid approaches for multi-objective fully automated semantic web service composition*. Once we achieve the sub-objective 2(a), the effectiveness and efficiency are the next focus. The EC-based approaches should be extended by introducing an effective local search mechanism. In particular, we aim to design an effective mechanism to decide how often, how long, which solutions we use the local search for targeting the neighboring solutions. For example, a local search is designed and to target the neighborhood of the best the individual of each current population, and it is performed with a highest possibility with respect to its fitness values.

(c) *To develop EMO-based approaches for multi-objective fully automated semantic web service composition subject to constraints on SLA and customized matchmaking level*. In real world, sometimes, satisfaction on given SLA constraints is required in addition to optimizing QoS. Therefore, this sub-objective consider some additional constraints on QoS (i.e., multilevel constraints with lower and upper bound for different individual QoS criterion [111]). Meanwhile, to satisfy the customized different semantic matchmaking levels (e.g., exact matchmaking level and less strict matchmaking level), these methods are also required to cope with the constraints on the different accepted matchmaking level. We aim to propose a vector that represents QoS and semantic matchmaking constraints, which is modeled as a set of lower and upper bounds for each quality criterion. To effectively handle the constrains, the vector could be utilized in the fitness function for penalizing the individuals that breach the constraints.

(d) *To develop EMO-based approaches for multi-objective fully automated semantic web service composition subject to preference articulation*. The articulation of user preferences could be achieved either before (i.e., a priori), during (i.e., interactive), or after (i.e., a posteriori) an EMO process. As argued in [36], a posteriori preference articulation often results in more and more desired solutions on the preferred

region of a Pareto Front. We aim to develop fully automated multi-objective semantic web service composition approach integrating posteriori preference articulation methods. In particular, an effective preference model is created to cope with full or partial preference information according to users' preferences. Meanwhile, this preference model must be explicitly supported by posteriori articulation techniques, which guild the solutions towards both true Pareto Front and the most preferred region.

3. **Develop EC-based techniques to achieve dynamic semantic web service composition effectively**. Objectives 1 and 2 are proposed for solving static service composition problems. In our context, composition environment refers to the registered services in the service repository, non-functional attributes advertised by service providers, and the ontology utilized for describing the resources of web services. On the one hand, after using existing EC-based approaches to generate an initial composition plan from a given composition task, some factors could significantly impact the execution of the plan, such as changes in QoS, ontology and service repository. On the other hand, existing non-EC based approaches [70, 88, 98, 112] work on effective and efficient methods for service re-selection for repairing each service employed. Technically, their approaches do not allow changes in service composition structure. Also, the cost of initializing a composition plan is ignored and separated from their approaches. To overcome the two limitations above, three studies are conducted as three sub-objectives below:

   (a) *To develop EC-based techniques to re-optimize solution candidates in response to changes in QoS and Ontology.* Traditionally, initial population is created with solution candidates that are further evolved for searching optimal solutions. During the evolutionary computation process, most of service candidates are discarded except the best service candidate identified. Those discarded solution candidates may be promising, since some of them could turn to be alternative best due to the changes in services or the ontology. Therefore, instead of discarding the solution candidates, we always create an archive for remaining candidates, which are utilized to re-optimization since these candidates preserve both diversity and elitism. This diversity and elitism motivate us to continue the evolutionary process without wasting the computation time in the stage, where an initial composition plan is produced.

   (b) *To develop EC-based hybrid techniques to re-optimize solution candidates for changes in QoS and Ontology.* Once the EC-based techniques to re-optimize solution candidates for changes in QoS and ontology are achieved, it should be further studied in developing more effective approach to handle this problem. We aim to propose an adaptive and hybrid approach to this dynamic problem. On the one hand, we firstly assign a higher priority to a group of services with changes. This priority is utilized in service selection for building up new individual (i.e., service composition solutions), and must be adaptively handled with a proper decreasing rate with respect to each service, when they are actually used in service selection. On the other hand, the hybrid refers to a memetic approach that combines EC-based approach and a local search, where the local search is developed to accelerate the convergency and decrease the number of evaluation times. In this sub-objective, we aim to achieve more effective performance compared to the EC-based approaches in Objective 3(a).

(c) *To develop EC-based hybrid techniques for handling service failure and new service registration using updated candidates in the population.* Apart from the changes in the QoS and the ontology of services, occasionally, existing services may fail and/or new service may become available. For the case of new service registrations, efficient methods need to be proposed to update the plan with new services in timely manner. When new services are registered in the service repository, we discard a portion of the current population. This discarded population is associated with low fitness values. Then, we replenish population based on updated services repository. For the case of service failure, efficient approaches need to be proposed to either mutate on an un-invokable component service of an individual, or a pre-defined parent structure of the component service, or effectively re-generate whole solutions using invokable services in the service repository.

4. **Develop EC-based approaches for semantic web service compositions based on preconditions and effects (Optional).** We plan to extend the service composition approaches (i.e., satisfaction on inputs and outputs) to include preconditions and effects. These conditional constraints also necessitates the study of various of composition constructs for automated semantic web service composition, e.g., loop and choice. Therefore, three sub-objectives have been proposed as our targets as follow.

   (a) *To develop EC-based techniques for semantic web service composition based on preconditions and effects.* In this objective, inputs and outputs are not everything for the execution of web services, our composition problem is extended by considering not only inputs and outputs, but also preconditions and effects. In particular, we need to establish a general matchmaking mechanism for satisfaction on preconditions and effects, since there is no systematic studying for that in existing works. We aim to model inputs and outputs as variable names and further referenced in preconditions and effects, which can be distinguished as different instances from the knowledge base. In particular, preconditions are assigned to the description of requirements of inputs using logic formula. The effects are restricted to the description of constraints on returned outputs, relationships between inputs and outputs, and changes caused by the service in the knowledge bases. Based on the mechanism, two simple composition constructs (i.e., sequence and parallel) are automatically constructed for considering preconditions and effects. Meanwhile, we aim to develop EC-based approaches to effectively handle this problem. In particular, we will propose new representations to copy with preconditions and effects.

   (b) *To develop EC-based hybrid techniques for semantic web service composition based on preconditions and effects.* Once the EC-based techniques to semantic web service composition based on preconditions and effects are proposed. More effective techniques shall be developed. In particular, we aim to create a memetic approach that utilize a EC-based approach and a local search for avoiding trapped by local optimal. This memetic approach is expect to benefit in an accelerated convergency rate and a decreasing the number of evaluation times.

   (c) *To develop EC-based techniques for semantic web service composition based on preconditions and effects for supporting loops and choice.* We initially extend the matchmaking mechanism of satisfaction on preconditions and effects to include loops and choice composition constructs. To extensively cope with these two constructs, new and effective representations must be studied since the old representation

only consider sequence and parallel constructs. Apart from that, EC-based approaches will be developed to effectively solve this problem.

1.4 Published Papers

During the initial stage of this research, the preliminary work was carried out on establishing the comprehensive quality model. Afterwards, some studies on the direct and indirect representations are completed for one part of Objective 1, but the earlier works focus on static web service composition using single-objective optimization technique. The following are the publications made from the preliminary studies:

- WANG, C., MA, H., CHEN, A., AND HARTMANN, S. "Comprehensive Quality-Aware Automated Semantic Web Service Composition". *AI 2017: Advances in Artificial Intelligence: 30th Australasian Joint Conference*. 2017, pp. 195-207.

- WANG, C., Ma, H., CHEN, A., AND HARTMANN, S.: "GP-Based Approach to Comprehensive quality-aware automated semantic web service composition". In: SEAL2017: International Conference on Simulated Evolution and Learning(To appear)

1.5 Organization of Proposal

The remainder of the proposal is organized as follows: Chapter 2 provides a fundamental definition of the web service composition problem and performs a literature review covering a range of works in this field; Chapter 3 presents a formal definition for our service composition problem, and discusses the preliminary work explores direct and indirect representations for comprehensive quality-aware semantic web service composition using a hybridization of AI planning techniques and EC-based techniques; Chapter 4 presents a plan detailing this project's intended contributions, a project timeline, and a thesis outline.

Chapter 2

Literature Review

In this chapter, we first introduce the background knowledge of web service composition in Subsection 2.1.1 and 2.1.2, i.e., properties of web service and web service composition, and service discover mechanisms. Second, EC techniques are also briefly introduced in Subsection 2.1.3. Followed that Section 2.2 reviews the single-objective service composition using EC and non-EC based techniques in Subsection 2.2.1. Subsection 2.2.2 reviews existing works on multi-objective approaches and many-objective approaches. Dynamic web service composition is covered in Subsection 2.2.3. Subsection 2.2.4 discussed semantic service composition based on preconditions and effects. Lastly, Subsection 2.2.5 summarizes some key reviews and limitations in the literature review.

2.1 Background

2.1.1 Web Service

Web services are self-describing modules offering functionalities over the internet. The idea of web services is to allow customers to use them without prior specific knowledge. The functionalities of web services are often specified by their functional attributes, which satisfy users' functional requirements and provide mechanisms to allow users to search desired service. Web services are classified into two groups based on their functionalities: *information-providing services* and *world-altering services* [65]. The first type of services expect some data returned by giving inputs or nothing. For example, an air velocity transducer web service reads the wind speed and returns the velocity at the time. This service does not require any inputs. On the other side, a city weather web service requires a city name and returns weather information for that city. Information-providing services do not produce any side effect to the world. The functionalities of these services are only inputs and outputs. The second type of services not only provide data information but also alters the status of the world by producing side effects. For example, a PayPal service will cause a deduction in the balance of users' bank account. *In this proposal, we mainly focus the first type of services for first three objective. Later on, an extensive study is optionally carried for the second type of services*

As demonstrated above, the functional attributes determine what service really does, while the non-functional attributes often refers to some quality criteria, which is considered for raking services [2]. In realistic scenarios, the non-functional are also important. For example, users may not prefer a service with higher cost with the same functionality provided by another one. Herein we will demonstrate both the functional and non-functional properties in following subsections.

Figure 2.1: Functional Properties of a Web Service.

Functional Properties of Web services

The operational characteristics of web services are related to the functional properties, which demonstrate the behaviors of web services, i.e., how services can be successfully invoked and what information are returned after execution. In other words, a set of inputs I is required by a service and a set of output O is returned by a service. For semantic web services, ontology reasoner is employed to reason about the properties (i.e., inputs and outputs) of web services, where a knowledge base is created to better enable the interoperability of the functional properties. Sometimes, the preconditions ϕ must be hold in the knowledge base before service execution, and they must remain consistent before passing the input I. Side effects are also created as effects φ along with outputs O. All functional properties of web services are demonstrated in Fig. 2.1.

Nonfunctional Properties of Web services

Apart from the functional properties of web services discussed above, the non-functional properties of web services play an important part in composing services and often refer to QoS. For example, customers prefer lowest execution cost with highest response time and reliability. According to [118], four most often considered QoS parameters are 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.

Web Service Discovery

To generate service compositions, web service must provide mechanisms for discovery required services. Therefore, service discovery becomes a fundamental technique to be considered in all service composition approaches. [1] discussed three mechanisms of semantic web service discovery: classification-based approach, functionality-based approach and hybrid approach. Those service discovery techniques are further demonstrated below.

The first service discovery technique makes use of the classes provided by service semantic annotation in WSMO-Lite language. Therefore, service requesters can use class names to express a goal, which is a straightforward discovery from a set of classes. However, classes

without clear meaning definition could lead to the issue of incomprehensibility of web service discovery. For example, several classes may declared in either different terms for the describing the same content or same terms for describing different content.

The second service discovery technique does not take classes into account, but consider functional properties of web service to include pre-conditions and effects. In particular, a desired functionality description is defined. A discovery algorithm must be developed to handle a matching for different input, output, precondition and effects with associated concepts and relations in the provided domain knowledge base. The key idea of the matchmaking is to check whether services accept all the desired inputs provided by users and whether the desired outputs is delivered by services. In addition, this discovery technique also checks for the satisfiability of implications that actual precondition and actual effects must imply the desired precondition and desired effects respectively. The strength of the second is that it potentially meet the demands of all the comprehensible discovery, while the weakness is a lack of efficiency and scalability.

The third service discovery technique is based on a hybridization of classification and functionality-based discovery. Classification hierarchy is proposed to achieve automatic semantic reasoning in hierarchical functionality. For example, a functionality class is associated with super classes and sub classes for more general functionality class and more specific functionality class respectively. However, to make a consistency of classification hierarchy, the inputs, outputs, precondition and effects of a functionality class must satisfy the conditions that contains all the inputs, outputs, precondition and effects of all the classes it is subsumed by. The advantage of this approach is to achieve better performance combining strengths of the previous two pure classifications based and functionality based approaches. While the classification hierarchy needs to be kept consistent when a new web service is published or updated.

As discussed above, the first and third approach is considered either less effective or demands to build up a consistent ontology for classes and their functional attributes. It is not the focus of our research to build up any ontology for supporting classes or properties. *In the proposal, we use the second service discovery technique for meeting a comprehensible discovery. That is, different types of ontology reasoning are utilized to approach the matchmaking as a fundamental part of service composition algorithm.*

2.1.2   Web Service Composition

Since an atomic web service could not satisfy or fully satisfy users' complex functional requirements, web service composition is approached by composing web services together to meet the requirements. Manual service composition is very time-consuming and less productive. Therefore, many approaches have been developed to achieve semi-automated or fully automated service composition. The semi-automated service composition is inspired by the business process that required prior knowledge to build up abstract workflows. These workflows consist of abstract services, each of which is defined by input-output pairs. The details of these steps are further discussed in Subsection 2.1.2. On the other hand, when we are composing services, the interoperability of services is very important in both semi-automated and fully automated web service composition. In particular, several problems are simultaneously taken into account. That is I/O matchmaking (i.e., a mechanism for ensuring the interoperability), discovery relevant services to the optimizing the quality of service composition, e.g., overall QoS. Consequently, the following concerns are required to consider in generating composition solution.
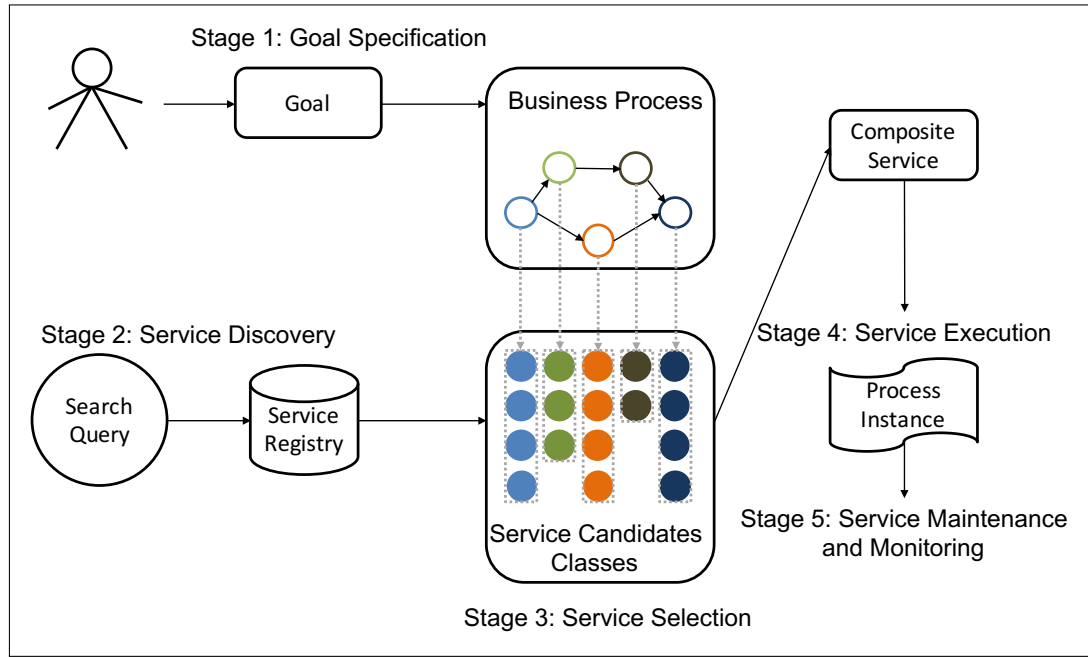
Figure 2.2: Web service composition lifecycle [67].

Web Service Composition Lifecycle

Typical steps in a workflow-based automated Web service composition solution are shown in Fig. 2.2. The detail of the service lifecycle is discussed as follows:

1. *Goal specification:* The first step in service composition is to collect users' requirements for composition goal that comprises of the functional (i.e., correct data flow) and non-functional side (i.e., QoS). This step is achieved by building up an abstract workflow including a series of tasks with clearly defined functionalities. Those tasks could be completed by selecting proper concrete services to reach desired QoS.

2. *Service discovery:* Once the goal is clearly specified, concrete web services will be selected for each task regarding its functional requirement. Often, more than one concrete web service is likely to be found to match one service discovery task. However, those matched web services are always different in QoS.

3. *Service selection:* At this stage, many techniques have been studied to select web services to best match each task for the satisfying functional requirement of each task and overall business process. Therefore, a plan of service composition is created ahead of execution.

4. *Service execution:* the process instance is monitored for any changes or services failures during service execution. In this stage, some actions are to be taken for adapting the changes.

The web service lifecycle discussed above is a typical *semi-automated approach*. There is a distinction between semi-automated and fully automated approaches. On the one hand, during the goal specification stage of semi-automated approach, the abstract workflow is already provided. An abstract workflow is not provided at the stage of goal specification for *fully automated service composition*. Often, fully automated service composition rely on some algorithms (e.g., Graphplan algorithm [9]) to achieve service composition. Service workflow
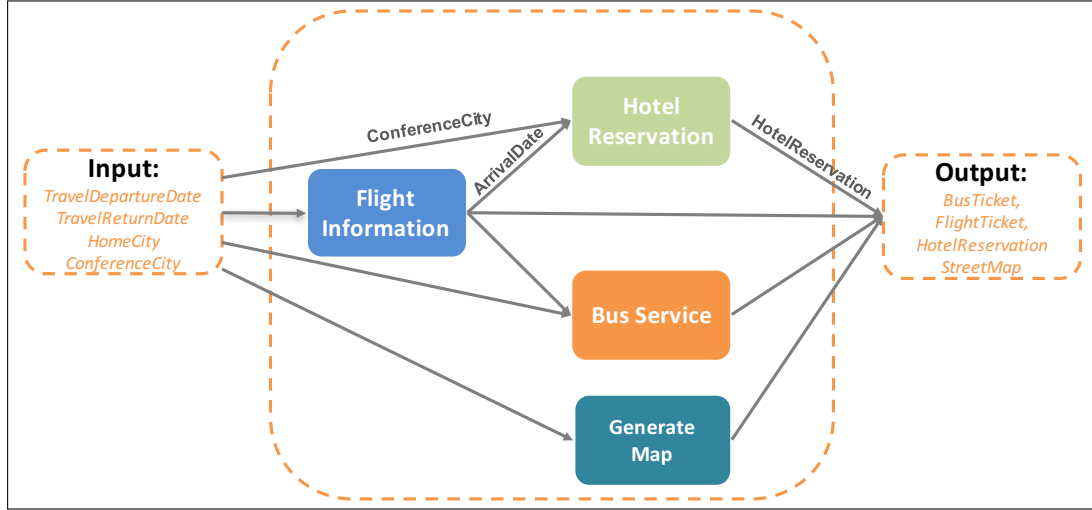
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Figure 2.3: An example of traveling agency service.

is gradually built up along with service discovery and service selection. In our thesis, I concentrate on developing methods for fully automated service composition, where service discovery and service selection are considered as interrelated tasks that are interleaved with the composition algorithm.

An Example of web service composition

Fig. 2.3 shows a popular web service composition example from a travel domain. In this scenario, the agency provides customers a serial of services to satisfy their complex requirements. These services include flight bookings, accommodation reservations, bus services and map generations. In Fig. 2.3, the task inputs (i.e., $TravelDepartureDate$, $TravelReturnDate$, $HomeCity$ and $ConferenceCity$) are gathered from customers, and task outputs (i.e., $BusTicket$, $FlightTicket$, $HotelReservation$ and $StreepMap$) are expected to be returned. Apart from those, the inputs of all the component services must be satisfied. In this example, we begin by executing the FlightBooking Service and GenerateMap Service, the FilightInformation service books the flights and determines a $arrivalDate$. Then, we use the $arrivalDate$ together with the other given data, we can book the hotel and bus, and generate Map for conference city. Together, these four services produce all required outputs for customers.

Functional Properties of Web Service Composition

From the example demonstrated above, two characteristics are addressed for the functional attributes of web service composition. One is that all the inputs of component services must be matched by given task inputs or produced outputs, so that service composition can be successfully executed. Another is that users' required inputs must be a subset of all the outputs of component web services, so that a service composition goal is successfully completed.

In the first characteristics, often, the given task inputs or produced outputs often do not perfectly match the required services' inputs. For example, one component service from previous service composition example is pick up for further demonstration regarding the semantic matchmaking quality of the required inputs. The generateMap service requires inputs $MappedLocation$ and producing output $StreetMap$. Given that $instance - of(ConferenceCity, City)$, $instance - of(MappedLocation, Location)$ and $City \sqsubseteq Location$.

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Figure 2.4: An example for demonstrating semantic matchmaking quality.

We can see that $ConferenceCity$ is less preferable. Therefore, Semantic matchmaking quality between ConferenceCity and MappedLocation is relatively lower.

Description logic (DL) makes it possible to measure the quality of semantic matchmaking. Substantial work [6, 52, 53, 55, 84] utilizes Description logic (DL) reasoning between input and output parameters of web services for matchmaking, where different matchmaking types are considered for matchmaking, and they usually result in *different matchmaking quality*. Therefore, exploring a effective mechanism for measuring the quality of semantic matchmaking in service composition is one of crucial tasks in our thesis.

Firstly, we demonstrate different *Matchmaking Types* discussed above here. Given two concepts a, b in ontology $\mathcal{O}$, four commonly used matchmaking types are often used to describe the level of a match between outputs and inputs [74]:

- *exact* returned, if a and b are equivalent ($a \equiv b$),

- *plugin* returned, if a is a sub-concept of b ($a \sqsubseteq b$),

- *subsume* returned, if a is a super-concept of b ($a \sqsupseteq b$),

- *fail* returned, if none of previous matchmaking types is returned.

Secondly, to our best knowledge, three methods [53, 80, 89] are utilized for measuring the quality of semantic matchmaking in the domain of service composition. We will demonstrate these three methods below.

The first method measures the quality of matchmaking regarding the different matchmaking types. In [53], the quality of semantic matchmaking is measured by the two quality criterion, matchmaking types and common description rate. They additionally consider *interaction* matchmaking type ($a \sqcap b$), i.e., if the intersection of a and b is satisfiable. In their work, a causal link $sl_{i,j} \doteq \langle S_i, Sim_T(Out\_s_i, In\_s_j), S_j \rangle$ is created between a input and a output. In particular, both *exact* match and *plugin* match are presented as robust causal links, while both *subsume* match and *intersection* match are presented as valid casual links. However, valid casual links are not specific enough to be utilized as the input of another web service. Thus the output requires Extra Description, denoted as $In\_s_x \setminus Out\_s_y$, to enable proper service composition using Eq. 2.1. As a result, *subsume* and *intersection* are transferred to be *exact* and *plugin* respectively to formulate a robust link, so common description rate, $q_{cd}(sl_{i,j})$ is calculated based on Extra Description and Least common subsume, denoted as $lcs(In\_s_x, Out\_s_y)$, using Eq. 2.1..

$$In\_s_x \setminus Out\_s_y \doteq \min_{\preceq d}\{B | B \sqcap Out\_s_y \equiv In\_s_x\}, since\ Out\_s_y \sqsupseteq In\_s_x \tag{2.1}$$

$$q_{cd}(sl_{i,j}) = \frac{lcs(In\_s_x, Out\_s_y)}{In\_s_x \setminus Out\_s_y + lcs(In\_s_x, Out\_s_y)} \tag{2.2}$$

The second method for measuring the quality of semantic matchmaking adopts a similarity measurement from information retrieval. In [80], the similarity is calculated by the

average value of $F\_Measure(S_i.out_k, S_j.in_k)$. $F\_Measure(S_i.out_k, S_j.in_k)$ measures the similarity of two matched output $S_i.out_k$ and input $S_j.in_k$, and it is calculated based precision and recall between the provided output and required input.

The third method for measuring the quality of semantic matchmaking is discussed in [89] using semantic similarity. For concepts a, b in $\mathcal{O}$, semantic similarity, denoted as $sim(a, b)$, is calculated based on an edge counting method in a taxonomy like WorldNet or Ontology using Eq. (2.3) [89]. This method has the advantages of a simple calculation and a good performance . In Eq. (2.3), N_a, N_b and N_c measure the distances from concept a, concept b, and the closest common ancestor c of a and b to the top concept of the ontology $\mathcal{O}$, respectively. L is the shortest distance between the two concepts, a and b, while D is the depth of ontology tree. Also, λ equals 1 for neighborhood concepts or 0 for concepts from same hierarchy.

$$sim(a, b) = \frac{2N_c \cdot e^{-\lambda L/D}}{N_a + N_b} \tag{2.3}$$

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

In this paper we are only interested in robust compositions, where only exact and plugin matches are considered, and we suggest to consider the semantic similarity of concepts when comparing different plugin matches. As argued in [52] *plugin* matches are less preferable than *exact* matches due to the overheads associated with data processing

Nonfunctional Properties of Web Service Composition

The nonfunctional properties of web service composition is determined by all the QoS of involved concrete web services in the solution. The aggregation value of QoS attributes for web services composition varies with respect to different constructs, which reflects how services associated with each other in a service composition [118].

- *Sequence construct*: service composition executes each atomic service associated with a sequence construct in a definite sequence order. The aggregation time (T) and execution cost (C) is as a sum of time and cost of web services involved respectively. The overall availability and reliability in a sequence construct are calculated by multiplying the availability and reliability of each conponent web service in the probability theory. This construct is shown in Fig. 2.5.

- *Parallel construct*: web services in a parallel construct are executed concurrently. The QoS aggregation execution cost, availability and reliability are calculated in the same way as these in the sequence construct while the total time (T) is determined by the most time-consuming path in the composite flow of the solution. This construct is presented in Fig. 2.6.

- *Choice construct*: Only one service path is executed in a choice construct depending on the satisfaction of the conditions on each path. In Fig. 2.7, assuming the choice construct has n branches, $p_1, \ldots, p_n$ with $\sum_{k=1}^{d} p_k = 1$ denote the probabilities of the different branches of the choice construct. For example, The aggregated total cost C is the multiplication of the cost of each branching service and the possibility p of the branch.

- *Loop construct*: web services in a loop construct are executed repeatedly until a certain condition is satisfied. In Fig. 2.8, assuming the average number of iterations is ℓ, and t, c, r, and a are corresponding aggregated value of a composite service. Therefore, For a

loop construct, aggregated response time (T) and execution cost (C) are $p_n \cdot t$ and $p_n \cdot c$ respectively while aggregated availability A and reliability R are the ℓth power of the value of one iteration, i.e., $A = a^\ell$ and $R = r^\ell$.

$$T = \sum_{n=1}^{m} t_n \qquad C = \sum_{n=1}^{m} c_n \qquad A = \prod_{n=1}^{m} a_n \qquad R = \prod_{n=1}^{m} r_n$$
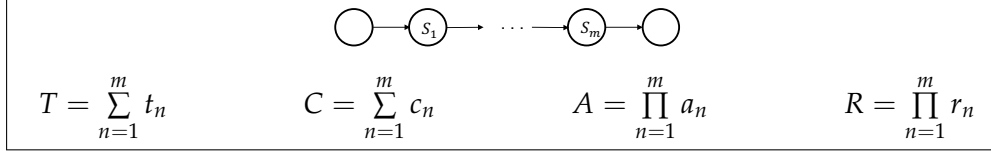
Figure 2.5: Sequence construct and calculation of its QoS [117].

$$T = MAX\{t_n | n \in \{1, \ldots, m\}\}$$

$$C = \sum_{n=1}^{m} c_n \qquad A = \prod_{n=1}^{m} a_n \qquad R = \prod_{n=1}^{m} r_n$$
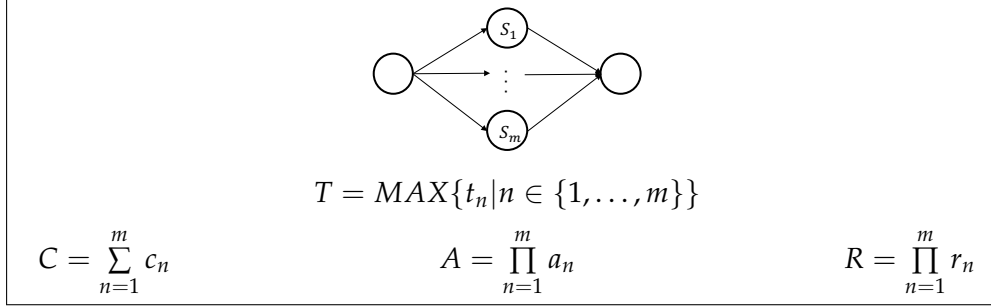
Figure 2.6: Parallel construct and calculation of its QoS [117].

$$T = \sum_{n=1}^{m} p_n \cdot t_n \qquad C = \sum_{n=1}^{m} p_n \cdot c_n \qquad A = \prod_{n=1}^{m} p_n \cdot a_n \qquad R = \prod_{n=1}^{m} p_n \cdot r_n$$
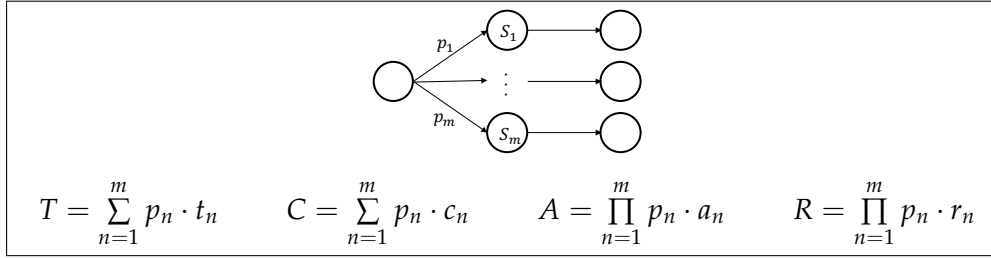
Figure 2.7: Choice construct and calculation of its QoS [117].

$$T = \ell \cdot t \qquad C = \ell \cdot c \qquad A = a^\ell \qquad R = r^\ell$$
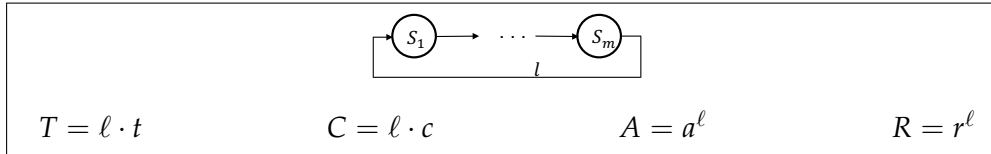
Figure 2.8: Loop construct and calculation of its QoS [117].

2.1.3 Evolutionary Computation Techniques Overview

Evolution Computing (EC) techniques are founded based on the principles of Darwin natural selection. The nature evolution and selection of individual in a population are automated simulated in EC techniques. In particular, a population of individuals is initialized for directly or indirectly presenting the solutions. Those individual candidates are evolved and evaluated using a fitness function to evaluate the degree of how good (or bad) of each individual. Therefore, it is possible to reach solution with near-optimal fitness. EC have been shown its promise in solving combinatorial optimization problems [5]. This is due to its flexibility in encoding the problems for the representation and its good performance in many scenarios. In particular, to manage the constraints in the problems, five main methods have been proposed deal with the constraints: coding, penalty functions, repair algorithm,

indirect methods of representation and multi-objective optimization [33]. In the context of service composition. Many EC techniques have been approached for handling optimization problems for web service composition, such as Genetic Algorithms (GA) [105], Genetic Programming (GP) [48], Particle Swarm Optimization (PSO) [43], and Clonal Section Algorithm [28]. These techniques are briefly introduced here.

GP is considered as a particular application of GA with a set of different encoded genes. In particular, the representation of GA is commonly represented as a linear structure. However, In GP, each individual is commonly represented as a tree structure. the tree structure has a terminal set and a function set, where variables, constants and functions are consisted of respectively. Also, the tree structure is considered be efficiently evaluated recursively. Three genetic operators consisting of reproduction, crossover, and mutation are involved in to generate next generation for both GA and GP. Reproduction operator retains the elite individuals without any changes. Crossover operator replaces one node of one individual with another node of another individual. Mutation operator replaces a randomly selected node in an individual. The whole evaluation process won't stop unless an optimized solution found or a pre-defined number of generation reached.

PSO is one of swarm intelligence (SI) techniques that is based on the behavior of decentralized, self organized system. PSO algorithm is initialized by a group of random particles, which direct or indirect present the solutions. Those particles explores for the optimization position, which is approached by repeating the process of transferring particles position according to both their own best-known position and global best position.

Artificial immune system (AIS) has been studied for performing machine learning, pattern recognition and solving optimization problems. Clonal Section Algorithm (CSA) is one of AIS for handling optimization problems, and the principle of utilizing Clonal Section Algorithm lie in the features of immune memory, affinity maturation. In particular, the antigen is considered as a fitness function instead of the explicit antigen population, and a proportion of antibody, rather than the best affinity antibody, are chosen to proliferation. Further more, speed and accuracy of the immune responses grow higher and higher after each infection even confronting cross-reactive response. Apart from that, hypermutation and receptor editing contribute to avoiding local optimization and selecting optimized solution respectively.

2.2 Related Work

2.2.1 Single-Objective Web Service Composition Approaches

In this section, approaches to QoS-aware web service composition will be discussed in two distinct groups: EC-based approaches, which mainly rely on the EC techniques to reach the optimal solutions, and non-EC based methods, which do not utilize any bio-inspired methods. However, most of these approaches employ a single-objective fitness function for optimizing a united QoS score as a simple Additive Weighting (SAW) technique [40].

EC-based Composition Approaches

EC-based web service composition mainly relies on evolutionary computation algorithms for searching optimal solutions. These algorithms are inspired by the behavior of human, animals or even T-cells. To use different EC algorithms, proper representations need to be designed. These representations directly or indirectly represent the service composition solutions. Herein we mainly discuss some promising research works on QoS-aware

web service composition using Genetic Algorithm (GA), Genetic Programming (GP), Particle Swarm optimization (PSO), and Clonal Selection Algorithm (CSA).

Genetic Algorithm. GA is a very reliable and powerful technique for solving combinatorial optimization problems [93]. It has been applied to solve optimization problems for QoS-aware web service composition [101]. [15] developed a GA-based approach for semi-automated QoS-aware service composition, where an abstract workflow is given. In their work, GA methods are compared to linear integer programming. The experimental finding reveals GA method is preferred when the size of service candidates are increasing. [94] proposed a hybrid approach utilizing GA and local search. In particular, a local optimizer is developed and only recalled in the initial population for improving QoS value. This local search contributes to a better overall performance compared to GA-based methods without local search. In [52], a semi-automated service composition approach is developed in their paper for optimizing the quality of semantic matchmaking and some quality criteria of QoS. In particular, the quality of matchmaking problem is transferred to measure the quality of semantic links, which is proposed by two quality aspects: matchmaking type and degree of similarity.

Genetic Programming. Tree-based representations could be more ideal for practical use, since they can present all composition constructs as inner nodes of trees. GP technique is utilised for handling tree-based representations. [86] relies on GP utilizing a context-free grammar for population initialization, and uses a fitness function to penalize invalid individuals throughout evolutionary process. This method is considered to be less efficient as it represents a low rate of fitness convergence. To overcome the disadvantages of [86], [117] proposes a GP-based approach employing the standard GP to bypass the low rate of convergence and premature convergence. The idea of this paper is to increase the mutation rate while encountering low diversity in the population and adopt a higher crossover probability while trapped in local optimization. During the evolutionary process, the elitism strategy is adopted, in which the best individual produced is reproduced to next generation directly without crossover and mutation. [62] proposes a hybrid approach combining GP and a greedy algorithm. In particular, a set of DAGs that represent valid solutions are initialised by a random greedy search and transferred into trees using the graph unfolding technique. In each individual, terminal nodes are considered as task inputs, root node as outputs, and all the inner nodes as atomic web services. During the reproduction process, a randomly selected node on one individual is replaced with a new subtree generated by a greedy search to perform mutation while same atomic inner nodes in two random chosen individuals are swapped to perform crossover. However, [23] proposes a different transformation algorithm to present composition constructs as the functional nodes of trees. On the whole, all these GP-based approaches [62, 86, 23, 117] consistenly ignore the semantic matchmaking quality, and their representations do not preserve semantic matchmaking information and composition constructs simultaneously.

Graph-Based Genetic Programming. A graph-evolutionary approach is introduced in [21] with graph-based genetic operators, which is utilised to evolve graph-based representation. Although graph-based representations are capable of presenting all the matchmaking relationships as edges, they hardly present some composition constructs (e.g., loop and choice). Another paper [24] investigated Directed Acyclic Graph with branches using GraphEvol approach [21] to find near-optimal QoS solution in web service composition comparing with GP approach in [22]. The experiment results reveal a significant improvement in execution time while slightly tradeoff in the fitness value. However, the service composition problem for handling branches is not generally formulated, i.e., only works for one choice construct. If more one nested choice constructs, their approach does not work any more.

Particle Swarm optimization. PSO is considered to a simple and effective approach for solving combinatorial optimization problems with few parameters settings [60]. The paper [60] proposed an environmental-aware PSO approach for QoS-aware web service composition. In particular, an improved discrete PSO algorithm is developed for adapting the changes of composition environment (i.e., services) when a same service composition request is called more than one time. The paper [58] proposed a hybrid Genetic Particle Swarm optimization Algorithm (GPSA). In their work, GA is employed with only crossover operator to produce new individuals with n_1 iterations while PSO is only utilized for local searching (i.e., C_2 parameter is set to 0 in the standard velocity updating functional) with n_2 iterations. This approach achieves a good balance of global and local optimization through a mechanism based on two thresholds, which determine the values of n_1 and n_2. However, these works [58, 60] handle only semi-automated service composition problems. On the other hand, [26] proposes a PSO-based fully automated approach to generate a composition graph from a queue. The idea is to translate the particle location into a service queue as an indirect representation of composition graph, so finding the best fitness of the composite graph is to discover the optimized location of the particle in the search space. [26] proposes a PSO-based fully automated approach to generate a composition graph from an indirect representation, i.e., a service queue. This service queue is mapped to particles' locations, so finding the best fitness of the composite graph is to discover the optimized location of the particle in the search space. In particular, the dimension of the particle is set up as the same number as relevant web services, and the index of services is mapped to the location vectors in a particle and put services in a queue in ascending order, from which a graph is decoded using a forward GraphPlan Algorithm. However, These fully automated approaches only optimize QoS.

Clonal Selection Algorithm. The paper [109] introduces a novel web service composition approach using an immune algorithm for global optimization considering optimum time under a constraint on cost. As a given abstract graph could be broken into several single pipelines, the optimization problem is transferred into getting the optimum executing plan for the single pipelines. In a pipeline, each involved tasked could be slotted with several alternative web services with QoS values labelled to their edges so that a weighted multistage graph is established for a longest path selection. In the immune algorithm, the service composition problem is encoded using a binary string as an antibody for evaluating the affinity value regarding the antigen (fitness function), and the antibody with low concentration will be selected in a high probability of crossover and mutation for new antibody generation. However, the efficiency of creating the weighted multistage graph would be considered to be less efficient. The paper [80] introduced an immune-inspired web service composition approach combining an enhancing planning graph (EPG) and a clonal selection algorithm to solve optimization problem considering both semantic link quality and QoS. The EPG model is characterized with action and layer involved in multiple stages, where each action represents clustered web service, and each layer represents input or output parameters grouped in concepts. During the clonal selection process, the antigen is represented as a fitness function, and the antibody is represented as a binary alphabet to encode EPG. The remaining steps are standard computation procedure for CLONALG, which consists of clones generation from selected antibody, affinity maturation process, low-affinity antibody replacement. We re-select antibody and repeat all the procedure. At last, the approach is proved to reach an optimal solution or a near-optimal solution in the experiments under trip and social event attendance planning domains.

AI Based Approaches

AI Planning techniques have been widely employed for service composition [63, 78]. The main idea of these techniques considers services as actions that are defined with functional properties (i.e., inputs, outputs, preconditions and effects) to generate validate service compositions using classic planning algorithms.

Various AI planning approaches [31, 39, 82, 99, 102] have been presented to solve semantic web service composition problems using the Graphplan [9] algorithm. [102] employs the Graphplan to secure the correctness of overall functionality, which enables atomic web services to be concretely selected and accurately matched for achieving desired functionality. In particular, conditional branch structure is also correctly handled. The pitfalls of this approach are procuring only linear sequences of actions, and it is hard to deal with QoS optimization. In paper [31], service-dependent QoS is modeled and considered for QoS-aware web service composition. This dependent QoS model is formed in three cases: a default QoS attribute, a partially dependent QoS attribute, and a completely dependent QoS attribute, and they are used for the dependency checking base on a backwards Graph building with a breadth-first strategy. However, computation of service dependencies is very intensive for initialization and updating. Some approaches [53, 92] rely some frameworks supported by particular agent programming languages (e.g., Golog [92] and SHOP2 [91]) to composite web services. In [92], a service composition framework supported by Golog. Golog is used to present the generic procedure, and situation calculus and first order language (FOL) are used to describe the properties of services and users' preferences. Therefore, Golog can effectively perform a constant search to reach a terminating situation as a service composition solution. As summarized here, given the desired solutions generated to meet users' complex requirements, AI planning techniques are considered to be less efficient, and not capable of dealing with optimization solutions for service composition (e.g., generate either optimal QoS or number of services) independently. In addition, they may suffer scalability issues when large repositories are given.

Other Approaches

The non-EC based approaches do not rely on bio-inspired approaches. They target the optimized service composition solutions by some other methods. For example, integer programming, exhaustive search, local search and so on.

Integer Linear Programming (ILP). ILP methods are utilized for achieving web service composition. Generally, an ILP model is created with three inputs provided: a set of decision variables, an objective function and a set of constraints. On the other hand, the outputs are maximized/minimize objective function and values of decision variables. Therefore, ILP is flexible in taking QoS into account, handling constraints for QoS and optimizing the objective function for QoS-aware service composition problem. [34] define a zero-one IP model for web service composition based on an abstract service workflow, where services may be different in QoS, but classified into the same classes. [113] formulated web service composition problem based on the model introduced in [34]. Apart from that, compared with the previous work, they simultaneously take both QoS and constraints on QoS into account. However, on the one hand, due to the increase in the number of decision variables, ILP may lead to exponentially increase the complexity and cost in computation [57]. The resulted huge delay is not allowed in the real world scenarios. In addition, if non-linear function is utilized, the scalability is a big problem.

Dynamic Programming Approach. Dynamic programming is an effective method for solving problems, where many repetitions of their break-down subproblems and optimal substructures are presented. In [39], an efficient pruning approach is developed includ-

ing a forward filtering algorithm for searching task related service candidates, a modified dynamic programming approach for dealing a subproblem of service composition (i.e., a problem on satisfaction of each concept pool of each graph layer), and a backward-search method for searching optimal composition results. This paper [107] forges a problem to solve large-scale service composition efficiently with QoS guarantee, where a dynamic programming algorithm named QDA is developed to for ensuring the optimization of the composition problem. The optimization problem is solved by optimizing every subproblem based consideration of web service composition with fewest services involved in. In particularly, best-known QoS are recorded and updated for all added web services, and service parameters by the maximum of the path using the traceback depth-first search to derive an execution plan. However, the global best QoS could be never reached since a trade-off in the efficiency of QoS guarantee in solutions.

ER Model-Based Approach (ILP). Most of the small and medium business rely on ER database to process information and data. [108] employs ER model to construct domain ontology and semantic web services. It potentially benefits large groups of organizations. With regard to the ontology construction, it realizes the transformation from ER to OWL-DL, which has maximum expressiveness while retaining computational completeness and decidability. Also, it constructs semantic web service described by OWL-S from ER. Therefore, the semantic web service composition problem is transferred to reason composite service based on a link path between entities in the ER model corresponding to the classes. However, other constructs such as loop and switch constructs cannot be effectively expressed in their approach, which demands many further research. They do not consider optimization problem at all.

2.2.2 Multi-objective, and Many-objective Web Service Composition Approaches

Maximizing or minimizing a single objective function is a most commonly used way to handle optimizing problems in automated web service composition. That is a Simple Additive Weighting (SAW) [40] technique, which presents a utility function for all the individual quality criteria as a whole. This technique optimizes and ranks each web service composition using a single value for each solution. However, the limitation of this technique lies in not handing the conflicting quality criteria. Those conflicting quality criteria are always presented trade-offs. To overcome this limitation, a set of objectives corresponding to different independent quality criteria are optimized simultaneously. Consequently, a set of promising solutions that presents many quality criteria trade-offs are returned.

Multi-objective approaches

Many multi-objective techniques [59, 120, 114, 111, 106, 17] have been investigated to extensively study QoS-aware web service composition problems. A set of optimized solutions is ranked based on a set of independent objectives, i.e., different QoS attributes. In particular, solutions are compared according to their relationship for domination. That is, figure out solutions that clearly dominate the others. For example, given two service composition solutions that are compared based on execution cost c and execution time t, solution one, $wsc_1(c = 10, t = 1)$ and solution two, $wsc_2(c = 13, t = 1)$. In our context, wsc_1 dominate wsc_2 as wsc_1 has the same execution time and a lower execution cost. If given $wsc_3(c = 10, t = 2)$, wsc_2 is a *non-dominant* solution in the relation to wsc_3 because of its longer execution time and cheaper execution cost. Therefore, If those non-dominant solutions are globally produced among both the dominant and non-dominant solutions, i.e., they do not dominate themselves. These solutions are called a *Pareto Front*, which provide a

set of non-dominant solutions for users to choose.

Multi-objective techniques with GA Many approaches to multi-objective web service composition employs GA [59], but other EC algorithms are also considered. For GA, [59] employs a service composition model, called MCOOP (i.e., multi-constraint and multi-objective optimal path) as web service composition solution, where only a sequence composition construct is considered in the paper. In this model, different paths are selected from a service composition graph that includes N service group. In each group, services present same functionality with different QoS. Apart from that, GPDSS is proposed to generate the outputs of Pareto optimal composition paths. In particular, two points crossover and mutation are applied to speed up the astringency of this algorithm. The work [97] investigates a semi-automated approach to SLA-aware web service composition problem. Each linear representation presents three service composition solutions designed for three group users' categories. The individuals are randomly initialized, evaluated and optimized with objectives from all the possible combinations of throughput, latency, cost and user category. In this work, two multi-objective genetic algorithms: E-MOGA and Extreme-E are developed. E-MOGA is proposed to search a set of solutions that equally distributed in the searching space by the means of fitness function, where the production of domination value, Manhattan distance to the worst point and sparsity (i.e, Manhattan distance to the closest neighbor individual) is assigned to the feasible individual as fitness value, and SLA violation /domination value is assigned to the infeasible solutions. On the other hand, Extrem-E provide extreme solutions by employing fitness functional, where weights use a term 1/exp(p-1), where p is the number of objectives and is assigned to the pth objective.

Multi-objective techniques with PSO The work [111] combines genetic operators and particle swarm optimization algorithm together to tackle the multi-objective SLA-aware web service composition problems. The method proposed in the paper is considered to be more effective for considering different scare of cases. It is called as HMDPSO, i.e., hybrid multi-objective discrete particle swarm optimization. In particular, the updates of particle's velocity and position are achieved by the crossover operator, where both velocity and position of new individual are updated in accordance with positions of *pbest*, *gbest*, and current velocity. On the other hand, mutation strategy is introduced to increase the diversity of particle, and it perform on the *gbest* particle if the proposed swarm diversity indicator is below some value. For the evaluation, the fitness values of individuals are assigned in the same way as the E-MOGA method in [97].

Multi-objective techniques with ACO Generally, ACO simulates foraging behaviors of a group of ants for optimizing the traversed foraging path, where the strength of pheromones is taken account for. The work [120] turns the service composition problem into path selection problem for a given abstract workflow with different service candidate sets. It employs a different strategy of "divide and conquer" for decomposing a given workflow. That is, two or more abstract execution paths are decomposed from the workflow and have no overlapped abstract services. This decomposing strategy results in a much smaller length of the execution paths compared to those in the works [116]. Also, a new ACO algorithm is proposed to handle the multi-objective QoS-aware service composition problem. In particular, the phenomenon is presented as a k-tuple for k objectives, rather than a single value. Apart from that, a different phenomenon updating rule is proposed by considering an employment of a proposed utility function as a global criterion. The paper [100] introduces non-functional attributes of web services to include trust degree according to the execution log. Also, a novel adaptive ant colony optimization algorithm is proposed to overcome the slow convergence presented from the traditional ant colony optimization algorithm. In particular, the pheromone strength coefficient is adjusted dynamically to control both the updating and evaporation of pheromone. The experiment results are analysed in an alternative way. That

is, the total Pareto solutions are combined from different compared ACO algorithms, then the accurate rate of each algorithm is calculated based on the compared Pareto solutions identified in the total Pareto solutions. The results also show more Pareto solutions found compared to the traditional ACO methods. However, the experiment is only conducted for the evaluation of a small case study, where only a simple abstract workflow is studied.

Many-objective approaches

Herein, more than three objectives in multi-objective problems (MOPs) are often considered as many-objective problems. Ishibuchi et al. [41] present an analysis of the multi-objective algorithm for handling optimization problems with more than 3 objectives. However, they address that the searching ability is deteriorating while the number of objectives is increasing, since the non-dominated solution is very large, which make it harder to move solutions towards the Pareto Front.

The work [27] employs NSGA-II to deal with five different quality criteria (i.e., runtime, price, reputation, availability and reliability) for semi-automated web service composition problem. To examine the techniques to decrease the deterioration, two preference relations proposed by [8] are applied to NSGA-II: Maximum Ranking (MR) and Average Ranking methods (AR). In particular, MR is the best of all the ranking scores from all the objectives, and AR is a sum of all the ranking scores from all the objectives. Therefore, three algorithms (NSGA-II, NSGA-II with MR and NSGA-II with AR) are evaluated for studying the five different performance metrics (i.e., hypervolume [121], Generational Distance [96], Spread and Coverage [122], and pseudo Pareto front (i.e, a combination of all non-dominated solutions)), where An empirical evaluation is performed on. The experiment shows NSGA-II with AR outperforms others in both GD and Spread (i.e., more balanced solutions). However, a certain region of Pareto Front is generated by NSGA-II, rather than a wider distribution for the solutions. NSGA-II with MR performs intermediately compared to the other two algorithms. On the whole, this work, for the first time, takes two preference relations into account for solving many-objective service composition problem, and contribute to finding better solutions with many performance metrics.

Preferences Articulation Techniques for Multi-and Many-objective Approaches

Most of the EMO algorithms focus on generating evenly distributed non-dominated Pareto solutions. Often, an indispensable decision must be made for choosing a small number of solutions, which satisfy customers' preferences. However, in some practical scenarios, some issues in EMO algorithms need to be handled when no or few solutions are gained in the preferred areas or far-optimal solutions are gained. To solve these issues, some user preferences-based approaches have been proposed to search only the space that preferred by users and to increases the density of solutions in that space. These approaches can be classified into three groups based on the articulation of preferences [95]. The first group is prior approaches, where the articulation is done before optimization process; The second group is interactive approaches, where the articulation is done during optimization process; The third group is posteriori approaches, where the articulation is done after optimization process. As argued in [36], the third approaches are capable of generating more desired solutions in the preferred region.

Most of the multi-objective service composition assumes that the user preferences are not known in advance. However, often, a vague preference is provided by users at least, and preferred solutions are roughly specified by them. These vague preferences should be taken into decision making and could guide us in searching the most interesting areas on the

Pareto front in a more effective and efficient way. In [13], they proposed two effective and efficient methods for finding the most relevant parts of Pareto solutions according to users' preferences. In particular, vague trade-offs between different objectives are taken into account when users have some rough thoughts about trade-offs. The first method is based on a guided multi-objective evolutionary algorithm in [14], and the second one is approached by a new biased crowding operator. In the first method, the dominance is specified for the maximally acceptable trade-offs of each pair of objectives, and the space of objectives is appropriately transferred into two auxiliary objectives. The second method works on finding a biased distribution on the Pareto solutions. The idea of this method is to introduce a biased crowding distance, which controls the expansion of solutions according to their location projected on a proposed hyper plane, i.e., users' specified direction vector. The experiment conducted shows that two methods achieve an effective and efficient way of finding relevant Pareto solutions for users. In [18], a posteriori articulation method is proposed to find Pareto solutions in the preferred areas. In particular, reference vectors are utilized by a decision maker according to users' preferences. The reference vectors can be easily defined either in a priori or a posterior. In their paper, a posteriori is adopted based on the observation of given Pareto solutions. The reference vectors divide the objective space into subspaces, where one individual is selected from each subspace and put into the next generation. Therefore, the newly generated individuals move towards optimal Pareto Front and reference vectors. The experiments show that this method could handle preferences effectively and efficiently as well as more optimal Pareto solutions found. On the whole, none of existing preference articulation techniques focus on web service composition, let alone applicability for comprehensive quality-aware semantic web service composition.

2.2.3 Dynamic Web Service Composition Approaches

All the previously discussed approaches can be classified into one group that assumes the composition environment is static. The rest approaches can be classified into another group that does not make that closed world assumption. Instead, a real world scenario taken a dynamic composition environment into account. For example, nonfunctional properties of web services may fluctuate over time or services are failed/newly registered. A few researcher works on the second group to cope with the dynamic composition environment. To address this problem [70], a suitable mechanism for effectively and efficiently handle this problem raise a significant challenge for the practical value.

Dynamic Web Service Composition Approaches For Changes in QoS

Service selection is one of the crucial steps when we compose services. In the context of static web service composition, we always selection services based on the QoS advertised by service providers. However, QoS is fluctuating over the time. The executed instances of a service for the run time indicate a real QoS value. This dynamic QoS is formally modeled as an uncertain QoS model. Based on this model, some studied [104] has been addressed recently. In [104], the QoS model describes the probabilities of different dominating relationships in the instances of all services within the same class. To efficient provide a relatively small set of services for selection that is based on the uncertain QoS model, the data structure of R-tree is introduced for spatial query on multidimensional data (i.e., many dimension of QoS attributes) since it can significantly reduce the searching space. This space index technique is one of the key contributions in this paper for efficiently store and retrieve services for service selection.

   Reinforcement learning (RL) is one technique of machine learning for solving sequential

decision-making problems to maximize some long-term rewards. RL is utilized to deal with how actions are taken in an uncertain environment. In our context, this uncertain environment is related to QoS. In [69], they combines multi-objective optimization and reinforcement techniques to solve multi-objective service composition problem in an uncertain and dynamic environment. In particular, we service composition is modeled based on Partially Observable Markov Decision Process (POMDP), and solutions to services composition are considered to be a set of decision policies. Each of the decision policies is considered as a procedure of service selection (i.e., a single workflow). They proposed approach in this paper to learn an optimal selection policy.

Dynamic Web Service Composition Approaches For Service Failure

Traditionally, re-selection of failed service is one of widely used approach to re-ensure the desired execution web service composition. The idea of this traditional approach restores many alternative service candidates for each component service involved in the composition solution. If component service confronts failure, the alternatives are used for the replacement. A framework, WS-Replication is introduced in [88], which mainly address service failure using the idea of the traditional method. [112] further introduce a more complicated model that address attributes of not only QoS but also transactionality for more reliable replacement. However, those approaches [88, 112] have a huge cost in computation due to the re-selection mechanisms [70]. To overcome the disadvantage of traditional resection approach, [70] proposes a QoS-aware performance prediction for self-healing web service composition system. This system consists of three main phases: monitoring, diagnosis and repair. The monitoring phase is to detect degradation, diagnosis is to identify the source of degradation, and repair is to reselect desired services. To minimising the number of re-selection in the phase of repair, decision tree learning is used to the prediction of the performance based on the QoS. This technique outperforms other classification techniques (i.e., back propagation neural network, support vector machine probabilistic neural network, and group method of data handling and regression tree) by accuracy in [68]. Those works mainly focus on services failure, and they do not recognise the importance of QoS changes of service in the repository. [98] proposes a method to cluster services that are back up for service failure. This method determines a set of backup services based on their functional properties for service repairing. By employing functional properties, services and their combinable services are identified. The fragmented clusters are formed based on the subsume relationship among their associated combinable services. Also, to merge these fragmented clusters, unified clusters are created by adding virtual services that subsume the fragmented clusters. Therefore, a set of backup services is provided in both the clusters that the failure services involved in and their sub-clusters, from which we could select suitable service.

2.2.4 Semantic Web Service Composition Approaches

Sophisticated real-world applications demand complex requirements in developing service composition. Apart from consideration of both the functional and nonfunctional properties of web services, more complex chaining strategies of semantic services are necessarily arranged to satisfy dependency constraints in the real world. To cope with these complicated requirements, preconditions and effects are semantically described using logic formula to enable the complex service composition. Many standards have been established for supporting the chaining ability of semantic web services, such as OWL-S. OWL-S accommodates varieties of structural constructs for service composition, namely: Sequence, Unordered, Choice, If-Then-Else, Iterate, Repeat-While, Repeat-Until, Split and "Split + Join"

[102]. For example, "Split+Join" calls for the process consisting of the parallel execution of a collection of process components with barrier synchronization. That is, "Split+Join" doesn't completes until all of its components processes have been completed. Additionally, "Split" and "Split+Join" can be applied for partial synchronization [102].

Most of the existing service composition approaches do not fully consider services associated with preconditions and effects. Therefore, it is hard to generate service composition solutions with branch structure in a fully automated way. The importance of preconditions and effects are ignored that specifies preconditions needed to be satisfied and effects resulted from service execution. The execution of these services could causes side effects in the world. However, some approaches do consider preconditions and effects using classic AI planning methods. The limitation of these approaches lies in the linear sequences of actions.

A generalized semantic web service composition is introduced in [6], preconditions and effects are effectively presented in a conditional directed acyclic graph where conditional nodes created with two outgoing edges representing the satisfied and the unsatisfied case at the run time. They filter the solutions based on the trust rate using Centrality Measure of Social Networks to find web service trusted by the customers. They also implement semantic web service composition engine for automated conditional service composition. The main limitation of this work is that the loops structure are not considered in their web service representation, and they leave optimization problems aside.

This paper [103] addresses a critical problem by considering services with preconditions and effects. In a real world scenario, this problem can significantly affect service composition solutions. In their paper, an extensive Graphplan technique is proposed to support the representation of the problem with execution effects. In particular, a two-level directed graph, called planning graph (PG) is utilized and comprises of two kinds of nodes (proposition and action ones) and three kinds of edges (precondition-edges, add-edges, and delete-edges). The proposition and action level is alternated between each other in the PG. By utilizing this presentation, the branch structure is supported in the service composition solution when some uncertain effects are produced by some services.

2.2.5 Summary and Limitations

An overview of recent related research on web service composition is presented in this chapter. The first related research discussed is **single-objective web service composition approaches**, which mainly works on generating composition solutions with optimal QoS or number of services based on the objective functions. On the one hand, EC-based approaches have been widely used for effectively and efficiently solving the above problems. On the other hand, non-EC based approaches, such as AI planning approaches, Integer Linear Programming, Dynamic Programming Approaches are employed in web service composition, but they may suffer scalability due to the increase in complexity of the problem or leave aside optimization problem. The key limitation of single-objective web service composition approaches is that the importance of semantic matchmaking quality is ignored, which should be simultaneously taken into account with QoS. To cover this necessity, new representations and quality model must be proposed along with service composition methods.

The second related research area discussed is **multi-objective, and many-objective composition approaches**, in which different independent quality criteria of QoS are separately optimized and a set of solutions is produced. These solutions present different tradeoffs among different quality criteria of QoS. Multi-objective composition approaches optimize two or three independently quality criteria, while many-objective composition approaches optimize more than three quality criteria. One limitation of multi-objective or many objec-

tives approaches is that one important quality criteria, i.e., quality of semantic matchmaking, is not considered. Apart from that, constraints on both SLA and quality of semantic matchmaking are not simultaneously taken into account. Meanwhile, none of existing preference articulation techniques focus on web service composition problems. Therefore, it is very interesting and challenging to simultaneously to take these interesting problems into account.

Dynamic web service composition approaches are discussed in the third related research area, where a closed world assumption is dropped. In particular, the composition environment is changing over time, which gives birth to two dynamic service composition problems. One is related to the changes in QoS, and another is to the changes in the availability of services. Existing dynamic web service composition mainly works on service selection using non-EC techniques. These techniques aim to adapt the changes in the solutions, such as re-selection of changed services. However, the cost of initial planning is consistently ignored and separated from the adaption of a dynamic environment. In addition, some interesting problems are not taken into account, such as the changes of ontology that is utilized to describe the functional properties of services, and new service may register in the services repository.

The last related research area focuses on **semantic web service composition approaches**, which explore a more complex and realistic service composition. Most of existing semantic web service composition is merely based on the inputs and outputs of services, Beside these functional properties, precondition and effects are occasionally considered when they compose services. However, The support for preconditions and effects is not fully investigated along with global optimization in existing works since they potentially bring various of composition constructs into consideration. Achieving semantic service composition considering all these composition constructs and global optimization on a comprehensive quality is a big challenge.

Chapter 3

Preliminary Work

This chapter exhibits the two initial works for comprehensive quality-aware semantic web service composition approach, which combines a hybridization of various techniques for optimising the quality of semantic matchmaking and quality of service. In particular, One direct representation and another indirect representation are proposed in two premilitary works using a PSO-based approach and a GP-based approach respectively. Apart from that, composition solutions are represented in a DAG or a tree-like representation, respectively, in the two approaches. These two works are discussed in the following sections.

3.1   Problem Formalisation

We consider a *semantic web service* (*service*, for short) as a tuple $S = (I_S, O_S, QoS_S)$ where I_S is a set of service inputs that are consumed by S, O_S is a set of service outputs that are produced by S, and $QoS_S = \{t_S, c_S, r_S, a_S\}$ is a set of non-functional attributes of S. The inputs in I_S and outputs in O_S are parameters modelled through concepts in a domain-specific 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 [118].

A *service repository* $\mathcal{SR}$ is a finite collection of services supported by 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 a set of task inputs, and O_T is a set of task outputs. The inputs in I_T and outputs in O_T are parameters described by concepts in the ontology $\mathcal{O}$.

Matchmaking types are often used to describe the level of a match between outputs and inputs [74]: 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 [52]. As argued in [52] *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* matches.

Robust causal link [54] is a link between two matched services S and S', noted as $S \rightarrow S'$, if an output a ($a \in O_S$) of S serves as the input b ($b \in O_{S'}$) of S' satisfying either $a \equiv b$ or $a \sqsubseteq b$. For concepts a, b in $\mathcal{O}$ the *semantic similarity* $sim(a, b)$ is calculated based on the edge counting method in a taxonomy like WorldNet or Ontology [89]. This method has the advantages of simple calculation and good performance [89]. Therefore, the *matchmaking*

type and *semantic similarity* of a robust causal link can be defined as follow:

$$type_{link} = \begin{cases} 1 & \text{if } a \equiv b \text{ (\textit{exact} match)} \\ p & \text{if } a \sqsubseteq b \text{ (\textit{plugin} match)} \end{cases}, \qquad sim_{link} = sim(a,b) = \frac{2N_c}{N_a + N_b} \qquad (3.1)$$

with a suitable parameter $p, 0 < p < 1$, and with N_a, N_b and N_c, which measure the distances from concept a, concept b, and the closest common ancestor c of a and b to the top concept of the ontology $\mathcal{O}$, respectively. However, if more than one pair of matched output and input exist from service S to service S', $type_e$ and sim_e will take on their average values.

The *semantic matchmaking quality* of the service composition can be obtained by aggregating over all robust causal links as follow:

$$MT = \prod_{j=1}^{m} type_{link_j}, \qquad\qquad SIM = \frac{1}{m} \sum_{j=1}^{m} sim_{link_j} \qquad (3.2)$$

We consider two special atomic services $Start = (\emptyset, I_T, \emptyset)$ and $End = (O_T, \emptyset, \emptyset)$ to account for the input and output requirements given by the composition task T, and add them to $\mathcal{SR}$.

We use formal expressions as in [61] to represent service compositions. We use the constructors $\bullet$, $\|$, $+$ and $*$ to denote sequential composition, parallel composition, choice, and iteration, respectively. The set of *composite service expressions* is the smallest collection $\mathcal{SC}$ that contains all atomic services and that is closed under sequential composition, parallel composition, choice, and iteration. That is, whenever $C_0, C_1, \ldots, C_d$ are in $\mathcal{SC}$ then $\bullet(C_1, \ldots, C_d)$, $\| (C_1, \ldots, C_d)$, $+(C_1, \ldots, C_d)$, and $*C_0$ are in $\mathcal{SC}$, too. Let C be a composite service expression. If C denotes an atomic service S then its QoS is given by QoS_S. Otherwise the QoS for C can be obtained inductively as summarized in Table 3.1. Herein, $p_1, \ldots, p_d$ with $\sum_{k=1}^{d} p_k = 1$ denote the probabilities of the different options of the choice $+$, while ℓ denotes the average number of iterations.

Table 3.1: QoS calculation for a composite service expression C

$C =$	$r_C =$	$a_C =$	$c_C =$	$t_C =$
$\bullet(C_1, \ldots, C_d)$	$\prod_{k=1}^{d} r_{C_k}$	$\prod_{k=1}^{d} a_{C_k}$	$\sum_{k=1}^{d} c_{C_k}$	$\sum_{k=1}^{d} t_{C_k}$
$\| (C_1, \ldots, C_d)$	$\prod_{k=1}^{d} r_{C_k}$	$\prod_{k=1}^{d} a_{C_k}$	$\sum_{k=1}^{d} c_{C_k}$	$MAX\{t_{C_k} \mid k \in \{1, ..., d\}\}$
$+(C_1, \ldots, C_d)$	$\prod_{k=1}^{d} p_k \cdot r_{C_k}$	$\prod_{k=1}^{d} p_k \cdot a_{C_k}$	$\sum_{k=1}^{d} p_k \cdot c_{C_k}$	$\sum_{k=1}^{d} p_k \cdot t_{C_k}$
$*C_0$	$r_{C_0}{}^{\ell}$	$a_{C_0}{}^{\ell}$	$\ell \cdot c_{C_0}$	$\ell \cdot t_{C_0}$

When multiple quality criteria are involved in decision making, the fitness of a solution can be defined as a weighted sum of all individual criteria using Eq. (3.3), assuming the preference of each quality criterion is provided by users.

$$Fitness = w_1 \hat{MT} + w_2 \hat{SIM} + w_3 \hat{A} + w_4 \hat{R} + w_5 (1 - \hat{T}) + w_6 (1 - \hat{C}) \qquad (3.3)$$

with $\sum_{k=1}^{6} w_k = 1$. We call this objective function the *comprehensive quality model* for service composition. The weights can be adjusted according to users' preferences. $\hat{MT}$, $\hat{SIM}$, $\hat{A}$, $\hat{R}$, $\hat{T}$, and $\hat{C}$ are normalised values calculated within the range from 0 to 1 using Eq. (3.4). To simplify the presentation we also use the notation $(Q_1, Q_2, Q_3, Q_4, Q_5, Q_6) = (MT, SIM, A, R, T, C)$.

Q_1 and Q_2 have minimum value 0 and maximum value 1. The minimum and maximum value of Q_3, Q_4, Q_5, and Q_6 are calculated across all task-related candidates in the service repository $\mathcal{SR}$ using the greedy search in [62, 23].

$$\hat{Q}_k = \begin{cases} \frac{Q_k - Q_{k,min}}{Q_{k,max} - Q_{k,min}} & \text{if } k = 1, \ldots, 4 \text{ and } Q_{k,max} - Q_{k,min} \neq 0, \\ \frac{Q_{k,max} - Q_k}{Q_{k,max} - Q_{k,min}} & \text{if } k = 5, 6 \text{ and } Q_{k,max} - Q_{k,min} \neq 0, \\ 1 & \text{otherwise.} \end{cases} \tag{3.4}$$

To find best possible solution for a given composition task T, our goal is to maximise the objective function in Eq. (3.3).

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

3.2.1 An Overview of our PSO-based Approach

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. 3.1 shows an overview of our approach consisting of four steps:
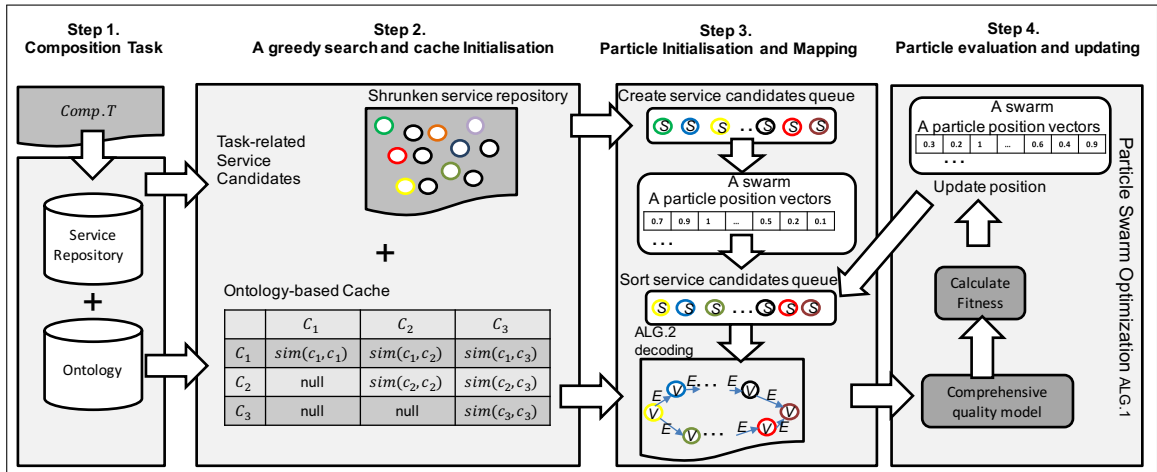
Figure 3.1: An overview of our PSO-based approach to comprehensive quality-aware automated semantic web service composition.

Step 1: The composition process is triggered by a composition task, which is clearly defined in Section 3.1.

Step 2: The composition task is used to discover all task-related service candidates using a greedy search algorithm adopted from [62], 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.

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Step 3 and Step 4: These two steps follow the standard PSO steps [90] 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 Section 3.2.2.

3.2.2 The Algorithms for our PSO-based Approach

The overall algorithm investigated here is made up of a PSO-based web service composition technique (Algorithm 1) and a *WG* creating technique from a service queue (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 Section 3.1.

ALGORITHM 1. Steps of PSO-based service composition technique [26].

1: Randomly initialise each particle in the swarm;
2: **while** *max. iterations not met* **do**
3:     **foreach** *particle 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:         Use Algorithm 2 to create a *WG* from the service queue;
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 [9]. This algorithm takes 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

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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

1: $WG = (V, E)$;
2: $V \leftarrow \{Start, End\ \}$;
3: $OutputSet \leftarrow \{I_T\}$;
4: **while** O_T *not satisfied by OutputSet* **do**
5: $\quad$ **foreach** S *in queue* **do**
6: $\quad\quad$ **if** I_S *satisfied by OutputSet* **then**
7: $\quad\quad\quad$ insert S into V;
8: $\quad\quad\quad$ adjoin O_S to $OutputSet$;
9: $\quad\quad\quad$ *queue*.remove S;
10: $\quad\quad\quad$ $e \leftarrow$ calculate $type_e, sim_e$ using *cache*;
11: $\quad\quad\quad$ insert e into E;

12: remove *dangling nodes* and *edges* from *WG*;
13: **return** *WG*;

3.3   Experiment Study for PSO-based Approach

In this section, we employ a quantitative evaluation approach with a benchmark dataset used in [62, 23], 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 Section 3.3.1. (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 Section 3.3.2.

The parameters for the PSO are chosen from the settings from [90], 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 [52]. In general, weight settings and parameter p are decided according to users' preferences.

3.3.1   GP-based vs. 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 [62] 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 [22].

The first column of Table 3.2 shows five tasks from WSC09. The second and third column of Table 3.2 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

Table 3.2: 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

space. The fourth and fifth column of Table 3.2 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 *p*-values are consistently smaller than 0.01. Using our PSO-based approach, small changes to sorted queues (particles in PSO) could lead to big changes to the composition solutions. This enables the PSO-based approach to escape from local optima more easily than the GP-based approach.

3.3.2 Comprehensive Quality Model vs. 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 [62, 26, 21]. 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 ($SM = 0.5\hat{MT} + 0.5S\hat{IM}$) 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 the comparison informative, all these recorded values have been normalised from 0 to 1, and compared using independent-samples T tests, see Table 3.3. Note that p-values are consistently smaller than 0.001 in the results indicating significant differences in performance.

In Table 3.3, 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 Tasks 1, 2, 3 and 4.

3.3.3 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. 3.2 (1) and (2) show two weighted DAGs, WG_1 and WG_2, which have been obtained as the best service compositions solutions based on the QoS model and on 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 sm_{e_n} associated to these different edges in WG_1 and WG_2. (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 a comprehensive quality gain (+0.1433), a result of a gain in semantic match-

Table 3.3: 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	$0.5580 \pm 0.0094 \uparrow$
	QoS	0.5574 ± 0.0156	0.5604 ± 0.0164
	$SM + QoS$	1.0947 ± 0.0423	$1.1184 \pm 0.0258 \uparrow$
Task2	SM	0.4549 ± 0.0033	$0.4630 \pm 0.0042 \uparrow$
	QoS	$0.4800 \pm 0.0012 \uparrow$	0.4772 ± 0.0025
	$SM + QoS$	0.9349 ± 0.0045	$0.9402 \pm 0.0067 \uparrow$
Task3	SM	0.5538 ± 0.0082	$0.6093 \pm 0.0054 \uparrow$
	QoS	$0.4940 \pm 0.0013 \uparrow$	0.4913 ± 0.0009
	$SM + QoS$	1.0478 ± 0.0095	$1.1006 \pm 0.0063 \uparrow$
Task4	SM	0.4398 ± 0.0037	$0.4604 \pm 0.0000 \uparrow$
	QoS	$0.4845 \pm 0.0010 \uparrow$	0.4734 ± 0.0044
	$SM + QoS$	0.9243 ± 0.0047	$0.9338 \pm 0.0044 \uparrow$
Task5	SM	0.4580 ± 0.0065	$0.4639 \pm 0.0013 \uparrow$
	QoS	$0.4764 \pm 0.0005 \uparrow$	0.4750 ± 0.0007
	$SM + QoS$	0.9344 ± 0.0070	0.9389 ± 0.0020

making quality (+0.1467) and a loss in *QoS* (-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 WG_1 and WG_2 has two different source nodes, $Ser1640238160$ and $Ser947554374$, and two the same *End* nodes. $Ser1640238160$ and $Ser947554374$ are services with output parameters $Inst582785907$ and $Inst795998200$ corresponds to two concepts $Con2037585750$ and $Con103314376$ respectively in the given ontology shown in Fig. 3.2 (4). As $Inst658772240$ is a required parameter of *End*, and related to concept $Con2113572083$, $Inst795998200$ is closer to the required output $Inst658772240$ than $Inst582785907$. Therefore, $Ser947554374$ is selected with a better semantic matchmaking quality compared to $Ser1640238160$.
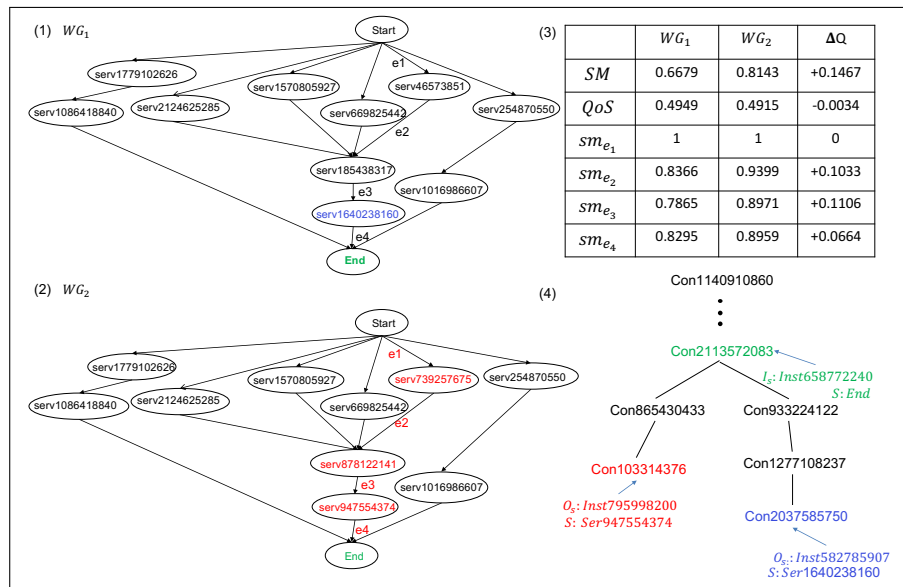

Figure 3.2: An example for the comparison of the best solutions obtained based on the QoS model and on the comprehensive quality model for Task 3.

3.4 Summary for PSO-based Approach

In PSO-based approach, 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.

3.5 GP-based Approach to Comprehensive Quality-Aware Automated Semantic Web Service Composition

In this section, we first introduce the tree-like representation that will be used in our approach, and then discuss the differences to the most widely used tree-based representations for GP-based service composition in the literature [38, 23, 117]. Finally, we present our GP-based approach with newly designed genetic operation methods.

3.5.1 A New Tree-like Representation for Web Service Composition

Let $\mathcal{G} = (V, E)$ be a DAG representation of a service composition. Let S be a service in $\mathcal{G}$, and let $S_1, \ldots, S_d$ be its successors in $\mathcal{G}$. We define the composite service expression relative to S as follows:

$$C_S = \begin{cases} \bullet(S, \| \ (C_{S_1}, \ldots, C_{S_d})), & \text{if } d \geq 2, \\ \bullet(S, C_{S_1}), & \text{if } d = 1, \\ S, & \text{if } d = 0, \end{cases} \tag{3.5}$$

which can be evaluated inductively starting with $Start$ which has no incoming edges in $\mathcal{G}$. The resulting expression C_{Start} is a composite service expression that is equivalent to $\mathcal{G}$.

Example 1. *Consider the composition task $T = (\{a, b, e\}, \{i\})$. Fig. 3.3 shows an example of a composition solution. It involves four atomic services $S_1 = (\{a, b\}, \{c, d, j\}, QoS_{S_1})$, $S_2 = (\{c\}, \{f, g\}, QoS_{S_2})$, $S_3 = (\{d\}, \{h\}, QoS_{S_3})$, and $S_4 = (\{f, g, h\}, \{i\}, QoS_{S_4})$. The two special services $Start = (\varnothing, \{a, b, e\}, \varnothing)$ and $End = (\{i\}, \varnothing, \varnothing)$ are defined by the given composition task T. The corresponding service composition expression is:*
$C_{Start} = \bullet(Start, \bullet(S_1, \| \ (\bullet(S_2, \bullet(S_4, End)), \bullet(S_3, \bullet(S_4, End)))))$.

Formal expressions can be visualized by expressions trees. For a composite service expression C let $\mathcal{T}$ denote the corresponding expression tree. Every leaf node in $\mathcal{T}$ is labelled by the corresponding atomic service, while every internal node in $\mathcal{T}$ is labelled by the corresponding composition constructor. For the sake of brevity we only consider $\bullet$ and $\|$ here, but our approach can easily be extended to $+$ and $*$, too. If a subtree of $\mathcal{T}$ (except for End) has an isomorphic copy in $\mathcal{T}$ then we remove it, label its root with a special symbol q, and insert an edge to the root of the copy. As a result we obtain a tree-like representation of a service composition. An example is shown in Fig. 3.3.

Fig. 3.3 shows for every atomic service S its sets of (least required) inputs $\mathcal{I}_S$ and outputs $\mathcal{O}_S$. Moreover, the set of available inputs $\mathcal{PI}_S$ is shown which is just the union of the input sets of all (direct and indirect) predecessors of S in the DAG. This can be easily generalized to composite service expressions. For a parallel composition $C = \| \ (C_1, \ldots, C_d)$ we define $\mathcal{I}_C = \cup_{k=1}^d \mathcal{I}_{C_k}$, and $\mathcal{O}_C = \cup_{k=1}^d \mathcal{O}_{C_k}$, and $\mathcal{PI}_C = \cup_{k=1}^d \mathcal{PI}_{C_k}$. For a sequential composition $C = \bullet(S, C')$ we define $\mathcal{I}_C = \mathcal{I}_S \cup (\mathcal{I}_{C'} - \mathcal{O}_S)$, and $\mathcal{O}_C = \mathcal{O}_S \cup \mathcal{O}_{C'}$, and $\mathcal{PI}_C = \mathcal{PI}_S$.

Example 2. *Consider the sequential composition $C_4 = \bullet(S_4, End)$ which is shown in the rightmost position in Fig. 3.3. We obtain $\mathcal{I}_{C_4} = \{f, g, h\}$ which represents the (least required) inputs for*

Figure 3.3: Example of a tree-like representation

this composition, and $\mathcal{O}_{C_4} = \{i\}$ which represents the outputs produced by this composition, and $\mathcal{PI}_{C_4} = \{a, b, e, c, d, j, f, g, h\}$ which represents the union of the input sets of all (direct or indirect) predecessors of S_4 in the DAG (i.e., S_1, S_2 and S_3).

Our representation supports composition constructs that are available in commonly used composition languages, such as BPEL4WS or OWL-S. Note that our representation is different from the most widely used tree-based representations in [38, 23, 117]. These differences are as follows.

1. *Start* and *End* are included in $\mathcal{T}$, as they are related to measuring the semantic matchmaking qualities regarding I_T and O_T.

2. $\mathcal{I}_C$, $\mathcal{O}_C$, $\mathcal{PI}_C$, QoS_C are attributes, defined as a tuple $(\mathcal{I}_C, \mathcal{O}_C, \mathcal{PI}_C, QoS_C)$ for any C_S in $\mathcal{T}$. These attributes must be updated after population initialisation and genetic operations described in Sect. 3.5.2.

3. $\mathcal{T}$ preserves all the semantic matchmaking information, which can be easily used for computing robust casual links.

To compute semantic matchmaking quality, we need to retrieve all the robust causal links on $\mathcal{T}$. This is performed by retrieving robust causal links for every sequential composition $C = \bullet(S, C')$. For example, in Fig 3.3, two robust causal links ($link_2 : S_1 \rightarrow S_2$ and $link_3 : S_1 \rightarrow S_3$) are retrieved from $C_1 = \bullet(S_1, C_{\parallel})$, because outputs $O_{S_1} = \{c, d, j\}$ match inputs $I_{C_{\parallel}} = \{c, h, d, f, g\}$.

3.5.2 GP-Based Algorithm

Now we present our GP-based approach for service composition, see Algorithm 3. To begin with the algorithm, we generate the initial population P_0, which is then evaluated using our comprehensive quality model. The iterative part of the algorithm comprises lines 3 to 7,

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which will be repeated until the maximum number of generations is reached or the best solution is found. During each iteration, we use tournament selection to select individuals, on which crossover and/or mutation are performed to evolve the polulation. These steps correspond to the standard GP steps [48] except for some particularities that will be discussed below.

ALGORITHM 3. GP-based algorithm for service composition.

Input : $T, \mathcal{SR}, \mathcal{O}$
Output: an optimal composition solution
1: Initialise population P_0 (using a 3-step method);
2: Evaluate each individual in population P_0 (using our comprehensive quality model);
3: **while** *max.populations or max.fitness not yet met* **do**
4:     Select the fittest individuals for evolution;
5:     Apply crossover and mutation to the selected individuals;
6:     Evaluate each new individual;
7:     Replace the individuals with the smallest fitness in the population by the new individuals;
8: Find the individual with the highest fitness in the final population;

Population initialisation. The initial population is created by generating a set of service compositions in form of DAGs, and then transforming them into their tree-like representations (*the individuals*). The initialisation is performed as follows:

STEP 1. Greedy search is performed to randomly generate a set of DAGs, each representing a (valid) service composition for the given composition task T. For this, a simple forward graph building algorithm is applied starting with the node *Start* and the inputs I_T of the composition task T. Details of this algorithm can be found in [62]. An example of a generated DAG is shown in Fig. 3.4 with seven robust casual links marked on.

STEP 2. The DAGs can be simplified by removing some redundant edges and service nodes. While this step is not compulsory, it can help to notably reduce the size of the DAG and, consequently, the corresponding tree-like representation.

STEP 3. We transform each DAG into its tree-like representation using an algorithm modified from [23] to satisfy the particular requirements of our proposed approach. For example, Fig. 3.3 shows an example of a tree-like individual corresponding to the DAG shown in Fig. 3.4.
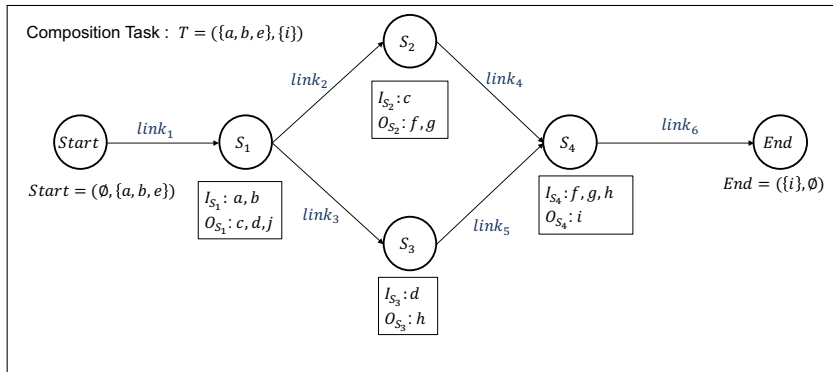

Figure 3.4: Example of a DAG used for transferring it into tree-like representation

Crossover and Mutation. During the evolutionary process, the correctness of the representation is maintained by crossover and mutation.

A crossover operation exchanges a subtree of a selected individual (its attributes noted as $C_1(\mathcal{I}_{C_1}, \mathcal{O}_{C_1}, \mathcal{PI}_{C_1}, QoS_{C_1})$) with the subtree of another selected individual (its attributes noted as $C_2(\mathcal{I}_{C_2}, \mathcal{O}_{C_2}, \mathcal{PI}_{C_2}, QoS_{C_2})$) if they represent the same functionality (i.e. $\mathcal{I}_{C_1} = \mathcal{I}_{C_2}$ and $\mathcal{O}_{C_1} = \mathcal{O}_{C_2}$). That is, at the root nodes of both subtrees, we have identical inputs and identical outputs. A crossover operation is performed in two cases: crossover on two functional nodes or on two terminal nodes. We never exchange a functional node with an terminal node, since the two associated subtrees cannot be equivalent in this case. For example, *End* must appear in the subtree associated with any functional node, but not for any selected terminal node (atomic services).

A mutation operation replaces a subtree of the selected individual (its attributes noted as $C_1(\mathcal{I}_{C_1}, \mathcal{O}_{C_1}, \mathcal{PI}_{C_1}, QoS_{C_1})$) with a newly generated subtree satisfying the least required functionality. To do this, a subtree C_1 must be selected from the selected individual, and a new composition task $T = (\{\mathcal{PI}_{C_1}\}, \{\mathcal{O}_{C_1} \cap O_T\})$ or $T' = (\{\mathcal{PI}_{C_1}\}, \{\mathcal{O}_{C_1}\})$ is used to generate a tree in the same way as the 3-step method performed during the population initialisation. We utilise the available inputs and least required outputs for mutation, because it potentially bring more possibilities in generating more varieties of subtrees. The mutation is performed in two cases: mutation on a functional node with T or on a service node with T', two examples shown in Fig 3.5 (a) and (b). In Fig 3.5 (a), a functional node $C_{\parallel}$ is selected for mutation, the whole subtree is replaced with the generated subtree excluding its head (i.e., *Start* and its parent node ●). In Fig 3.5 (b), a atomic service S_1 is selected for mutation, the branch of the selected node (i.e., S_1 and its parent node ●) is replaced with the generated subtree excluding both its head (i.e., *Start* and its parent node ●) and its tail (i.e., *End*).

Figure 3.5: Examples of two mutations on terminal and functional nodes
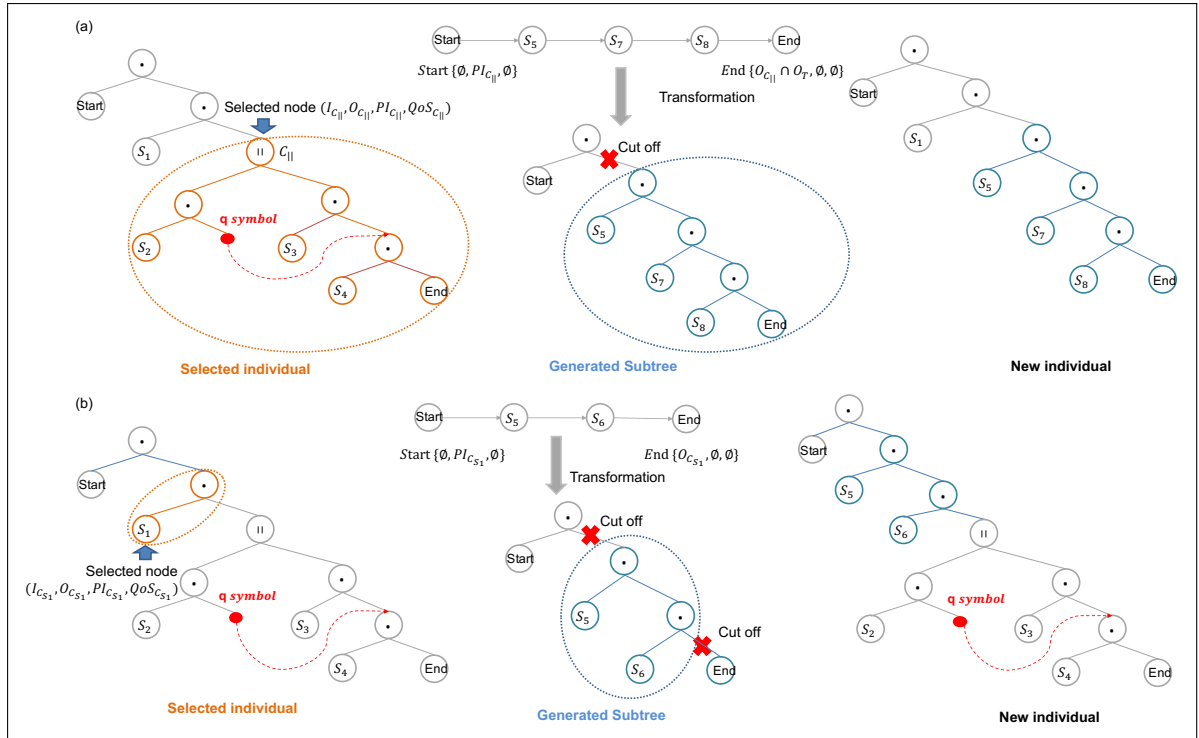
Note: The set of available nodes considered for crossover and mutation do not include *Start* and *End*, and their parent nodes, because these nodes remain the same for all individuals. In addition, the nodes selected for crossover and mutation must not break the functionality of q symbols. For example, in Fig. 3.3, both sequential composition C_2 and C_3

are not considered for crossover and mutation as they break the edge of q symbol, but the parallel composition $C_\parallel$ can be considered for genetic operations, as it may bring a new fully functional q symbol or a subtree without q symbol involved. The pointed subtree C_4 could also be selected for genetic operations.

3.6   Experiment Study for GP-based Approach

We have conducted experiments to evaluate our proposed approach. For our experiments we have used the benchmark datasets originating from OWLS-TC [49] , which have been extended with real-world QoS attributes and five composition tasks [62]. To explore the effectiveness and efficiency of our proposed GP-based approach, we compare it against one recent GP-based approach [62]. For that we have extended the later approach by our proposed comprehensive quality model, so that semantic matchmaking quality can be computed based on the parent-child relationship in the underlying tree representations.

To assure a fair comparison we have used exactly the same parameter settings as in [62]. In particular, the GP population size has been set to 200, the number of generations to 30, the reproduction rate to 0.1, the crossover rate to 0.8, and the mutation rate to 0.1. We have run every experiment with 30 independent repetitions. Without considering any users' true service composition preferences, the weights in fitness function in Eq. (3.3) have been are configured simply to balance semantic matchmaking quality and QoS. Particularly, w_1 and w_2 are both set to 0.25, while w_3, w_4, w_5, and w_6 are all set to 0.125. The parameter p of $type_{link}$ is set to 0.75 (*plugin* match) in accordance with the recommendation in [52].

Our experiments indicate that our method can work consistently well under valid weight settings and parameter p to be decided by users' preferences in practice.

3.6.1   Comparison against a previous GP-based approach

Table 3.4 shows the fitness values obtained by the two GP-based approaches. To compare the results, an independent-samples T-test over 30 runs has been conducted. The results show that our GP-based approach outperforms the previous GP-based approach [62] in finding more optimized composition solutions for Tasks 3 and 4. (Note: the P-values are lower than 0.0001). For Tasks 1, 2 and 5, both approaches achieve the same fitness. Therefore, the overall effectiveness of our proposed approach is considered to be better.

Table 3.4: Mean fitness values for our approach in comparison to [62]
(Note: the higher the fitness the better)

Task	Our GP-based approach	Ma et al. approach [62]
OWL-S TC1	0.923793 ± 0.000000	0.923793 ± 0.000000
OWL-S TC2	0.933026 ± 0.000000	0.933026 ± 0.000000
OWL-S TC3	$0.870251 \pm 0.000000 \uparrow$	0.832306 ± 0.008241
OWL-S TC4	$0.798137 \pm 0.007412 \uparrow$	0.760146 ± 0.005044
OWL-S TC5	0.832998 ± 0.000000	0.832998 ± 0.000000

Table 3.5 shows the execution times observed for the two GP-based approaches. Again an independent-samples T-test over 30 runs has been conducted. For Tasks 1 and 2 both approaches need about the same time, while for Tasks 3,4, and 5 our approach needs slightly more time. (Note: the P-values are lower than 0.0001). However, even in the worst case it exceeds [62] by no more than 1 second, which is acceptable for most real-word scenarios. Hence, in terms of efficiency our approach is comparable to [62].

Table 3.5: Mean execution time (in ms) for our approach in comparison to [62]
(Note: the shorter the time the better)

Task	Our GP-based approach	Ma et al. approach [62]
OWL-S TC1	7396.366667 ± 772.408168	7310.866667 ±952.701775
OWL-S TC2	2956.133333 ± 761.350965	3036.966667 ± 777.121101
OWL-S TC3	1057.266667 ± 174.405183	763.800000 ± 221.241232 ↓
OWL-S TC4	4479.466667 ± 519.767172	3068.800000 ± 472.013106 ↓
OWL-S TC5	6276.533333 ± 1075.102328	5030.200000 ± 991.863812 ↓

The experiments confirm that there is a trade-off between fitness and execution time in GP-based service composition. It can be argued that our proposed approach achieves a better balance as the computed solutions observe a significantly higher fitness while there is a moderate increase in execution time compared to [62].

3.6.2 Further Discussion

For Tasks 3 and 4, the optimized composition solutions obtained by the two approaches are shown in Fig. 3.6(a) and Fig. 3.6(b), respectively. The functional and nonfunctional descriptions of all services involved in these solutions are listed in Fig. 3.6(c).
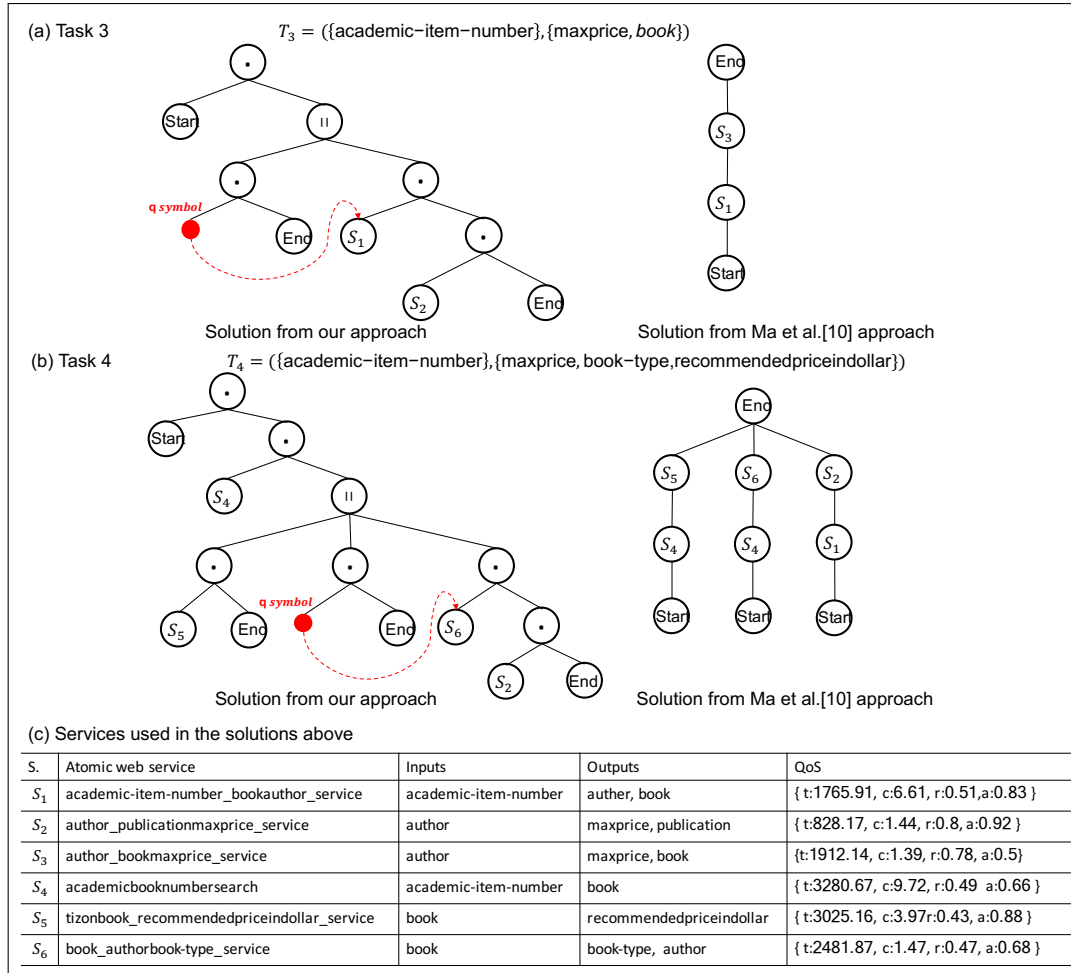

Figure 3.6: Example of best solutions using the two GP-based approaches

For Task 3 the composition task is $T_3 = (\{academic\text{-}item\text{-}number\}, \{book, maxprice\})$. The

best composition solutions obtained by the two approaches are different, see Fig. 3.6. Both solutions have the same semantic matchmaking quality as the matchmaking type of all links is *exact* match. However, both solutions differ in their QoS. This is due to the different services that are involved: S_2 versus S_3. The QoS of S_2 is much better that of S_3. Consequently, the best composition solution obtained by our approach has higher fitness according to our quality model. It is interesting to observe that the best composition solution obtained by our approach for Task 3 can be evolved from the best composition solution in [62] just by a single mutation on S_3 using available inputs.

For Task 4 the composition task is $T_4 = (\{academic\text{-}item\text{-}number\}, \{maxprice, book-type, recommendedpriceindollar\})$. The best solutions obtained by the two approaches are also different, see Fig. 3.6. Note that solution generated by our approach is composed of four atomic services (S_4, S_5, S_6 and S_2) while the solution generated by approach [62] is composed of five atomic services (S_4, S_5, S_6, S_1 and S_2). Both solutions have the same semantic matchmaking quality as the matchmaking type of all links is *exact* match. However, the overall QoS of our approach is better. This is due to the additional S_1 in their approach, which has a significant negative impact on QoS.

We observe from above examples that our approach is able to produce better solutions because our proposed representation keeps available inputs and least required outputs of each node on the tree which unlocks more opportunities for mutation and crossover rather than restricting them to the previously used inputs and ouputs only.

3.7 Summary for GP-based Approach

In this work, we introduces a novel GP-based approach to comprehensive quality-aware semantic web service composition. In particular, a tree-like representation is proposed to direct cope with the evaluation of semantic matchmaking quality. Meanwhile, crossover and mutation methods are proposed to maintain the correctness of individuals. The experiment shows that our proposed approach could effectively produce better solutions in both semantic matchmaking quality and QoS than the existing approach.

3.8 Conclusion

In the preliminary work, we propose and formalize a novel and effective comprehensive quality model for simultaneously optimize QoS and quality of semantic matchmaking. Apart from that, two novel and effective EC-based methods are proposed for comprehensive quality-aware semantic web service composition. In particular, indirect and direct representations are designed for studying their effectiveness and efficiency along with novel EC-based methods. Overall experimental studies show both two methods reach good performances comparing to existing works. We also find that our PSO-based approach utilizing an indirect representation outperforms our GP-based approach utilizing a direct representation for finding more effective solutions. These findings motivate us to work on a more effective indirect presentation along with PSO-based memetic method.

Chapter 4

Proposed Contributions and Project Plan

In the previous chapter, some preliminary works have been done to investigate the performances of direct representation and indirect representation on the proposed PSO-based approach and GP-based approach respectively. We have shown that those two approaches outperform some recent existing EC-based approaches using our proposed comprehensive quality evaluation model. To conduct a further research on the remaining subjectives for objective one and the rest three objectives outlined in the proposal, we present the proposed contribution, project plan, timeline and thesis outlines in this chapter.

4.1 Proposed Contributions

This thesis will contribute to the field of semantic web service composition by considering several key composition problems simultaneously, and to the field of Evolutionary Computation techniques by proposing more novel representation and genetic operators. The proposed contributions of this project are listed below:

1. Develop a new fully automated semantic web service composition approach for simultaneously optimizing the quality of semantic matchmaking and QoS. We expect that more effective and efficient methods for handling a novel combinatorial optimization problem for semantic web service composition, which is done by relying on effective representations, a comprehensive quality model and a motivated EC-based method with local search or AI planning techniques.

2. Develop EMO-based approach to effectively and efficiently explore the Pareto front of comprehensive quality-aware service composition. Meanwhile, conditional constraints on SLA and customized matchmaking level is expected to effectively and efficiently handled. Apart from that, posteriori preference articulation techniques for user preference on comprehensive quality is also expected to reach the most preferred Pareto solutions. Each of these achievements is not considered in any past research.

3. Develop an EC-based approaches for dynamic web service composition problem. We expect these approaches effectively and efficiently handle composition environment changes. In particular, the changes of QoS, Ontology and service repository (i.e., service failure and new service registration). These changes are not fully studied in the past, and this problem be firstly solved using motivated EC-based techniques.

Table 4.1: The milestones of PhD project plan.

Phase	Description	Duration (months)
1	Reviewing literature, developing initial EC-based composition approach, and writing the proposal	9 (Complete)
2	Develop hybrid approaches to comprehensive quality-aware automated web service composition	6 (In progress)
3	Develop multi-objective approaches to optimize the comprehensive quality for fully automated service composition	7
4	Develop hybrid techniques to support dynamic semantic web service composition effectively	8
5	Develop hybrid approaches for semantic web service compositions based on preconditions and effects	3
6	Writing the thesis	6

4. Develop EC-based approaches to a more complex and realistic semantic web service composition based on not only inputs and outputs, but preconditions and postconditions. We expected a general mechanism is developed for supporting all the service composition constructs considering preconditions and effects. Those occasionally considered precondition and effects are neither fully studied for supporting all the composition constructs, nor employed in a fully automated approach.

4.2 Overview of Project Plan

Six milestones for PhD project are defined in the initial research plan shown in Table 4.1. The first phase of this plan has been completed, which comprising of literature view, two initial works on comprehensive quality-aware semantic web service composition and a research proposal writing. The second phase is related to the first objective of this proposal and is currently in progress and covered in Chapter 3 of the proposal. The remaining phases are expected to be completed as planned.

4.3 Project Timeline

Table 4.2 provide an estimated timeline comprising of the minor goals and milestones, which is expected to serve as a guide and be completed through the PhD project.

4.4 Thesis Outline

The following is an outline of the PhD thesis, in which Chapter 6 may be replaced by Chapter 7 since it is an optimal objective.

- *Chapter 1: Introduction*
  This chapter covers a problem statement, motivations, research goals, contributions, and organization of the thesis.

- *Chapter 2: Literature Review*
  This chapter initially provides some fundamental concepts for demonstrating the background of service composition. Followed, a comprehensive understanding and analyzing of existing work on the web service composition. In particular, four research directions for web service composition are investigated: single-objective approach,

Table 4.2: Project timeline for the remaining 24 months.

		Time in Months											
Phase	Task	2	4	6	8	10	12	14	16	18	20	22	24
n/a	Updating the literature review	x	x	x	x	x	x	x	x	x	x	x	x
2	Developing indirect representation utilize in a hyper-heuristics methods	x	x										
3	Investigating unconstrained MO optimization for semantic quality-aware service composition		x	x									
3	Improving performance of MO approach by integrating other techniques			x	x								
3	Extending MO approach to handle constraints on SLA and semantic matchmaking level				x	x							
3	Extending MO approach to integrate user preferences					x	x						
4	Develop EC-based approach to handle changes in QoS and Ontology						x	x					
4	Develop EC-based approach to handle service failure and new service registration							x	x				
5	Develop EC-based approach to handle preconditions and effects.								x	x			
6	Writing the first thesis draft										x	x	
6	Editing the final draft											x	x

multi-objective approach, dynamic service composition and semantic web service composition. However, these techniques are mainly focused on EC-based approaches

- *Chapter 3: EC-based Approaches to Comprehensive Quality-Aware Web Service Composition*
  This chapter will introduce new and effective approaches that combine EC-based techniques and other searching methods. These approaches are developed to effective and efficient handle comprehensive quality-aware fully automated semantic service composition problems. Apart from that, the performance of different direct/indirect representations is also investigated here.

- *Chapter 4: EMO-based Approaches to Comprehensive Quality-Aware Semantic Service Composition*
  This chapter will demonstrate our fully automated multi-objective approaches, which optimizes every quality criteria of comprehensive quality for semantic web service composition. Constraints on SLA and customized matchmaking levels are also considered in the multi-objective approaches. Apart from that, user preferences are integrated into multi-Objective approaches to effectively and efficiently reach the most preferred Pareto solutions.

- *Chapter 5: EC-based Approaches to Support Dynamic Semantic Web Service Composition*
  This chapter will discuss effective and efficient EC-based methods for handling dynamic service composition problems regarding the changes in QoS and Ontology and service repository (i.e., service failure new service registration). Those approaches are compared with existing dynamic service composition approaches, which do not utilize EC-based techniques.

- *Chapter 6: EC-based Approaches for Semantic Web Service Compositions Based on Preconditions and Effects*
  This chapter will discuss semantic service composition problems. We firstly introduce a proposed matchmaking mechanism for preconditions and effects, which fully support different composition constructs, such as sequence, parallel, loop and choice. These problems will be fully automated solved by EC-based methods focusing on improving their effectiveness and efficiency.

- *Chapter 7: Conclusions and Future Work*
  This chapter concludes all the contributions made by our proposed approaches in each objective. In addition, the limitations are also pointed along with the future research directions.

4.5 Resources Required

4.5.1 Computing Resources

This research mainly utilises an experimental approach. Due to the high computation of the experiment execution, ECS Grid computing facilities is required to complete these experiments.

4.5.2 Library Resources

The related literature of this research can be found online using the resources provided by Victoria University of Wellington. Apart from that, useful textbook and lecture notes can be also found in university's library.

4.5.3 Conference Travel Grants

Publications to relevant venues in this field are expected throughout this project, therefore travel grants from Victoria University of Wellington are required for key conferences.

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