

Combining Global Optimization with Local Selection for Efficient QoS-aware Service Composition

Mohammad Alrifai
L3S Research Center
University of Hannover
Germany
alrifai@L3S.de

Thomass Risse
L3S Research Center
University of Hannover
Germany
risse@L3S.de

ABSTRACT

The run-time binding of web services has been recently put forward in order to support rapid and dynamic web service compositions. With the growing number of alternative web services that provide the same functionality but differ in quality parameters, the service composition becomes a decision problem on which component services should be selected such that user's end-to-end QoS requirements (e.g. availability, response time) and preferences (e.g. price) are satisfied. Although very efficient, local selection strategy fails short in handling global QoS requirements. Solutions based on global optimization, on the other hand, can handle global constraints, but their poor performance renders them inappropriate for applications with dynamic and real-time requirements. In this paper we address this problem and propose a solution that combines global optimization with local selection techniques to benefit from the advantages of both worlds. The proposed solution consists of two steps: first, we use mixed integer programming (MIP) to find the optimal decomposition of global QoS constraints into local constraints. Second, we use distributed local selection to find the best web services that satisfy these local constraints. The results of experimental evaluation indicate that our approach significantly outperforms existing solutions in terms of computation time while achieving close-to-optimal results.

Categories and Subject Descriptors

H.3.5 [On-line Information Services]: Web-based services; H.3.4 [Systems and Software]: Distributed systems

General Terms

Management, Performance, Measurement

Keywords

Web Services, QoS, Optimization, Service Composition

1. INTRODUCTION

The service-oriented computing paradigm and its realization through standardized web service technologies provide a promising solution for the seamless integration of business applications to create new value-added services. Industrial

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practice witnesses a growing interest in the ad-hoc service composition in the areas of supply chain management, accounting, finances, eScience as well as in multimedia applications. With the growing number of alternative web services that provide the same functionality but differ in quality parameters, the composition problem becomes a decision problem on the selection of component services with regards to functional and non-functional requirements.

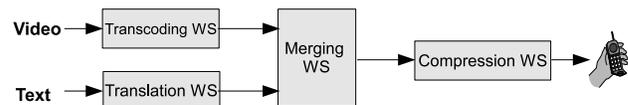


Figure 1: Web Service Composition Example

Consider for example the personalized multimedia delivery scenario (from [21]) in Figure 1. A smartphone user requests the latest news from a service provider. Available multimedia content includes a news ticker and topical videos available in MPEG 2 only. The news provider has no adaptation capabilities, so additional services are required to serve the user's request: a transcoding service for the multimedia content to fit the target format, a compression service to adapt the content to the wireless link, a text translation service for the ticker, and also a merging service to integrate the ticker with the video stream for the limited smartphone display. The user request can be associated with some end-to-end QoS requirements (like bandwidth, latency and price). The service composer has to ensure that the aggregated QoS values of the selected services match the user requirements at the start of the execution as well as during the execution. However, dynamic changes due to changes in the QoS requirements (e.g. the user switched to a network with lower bandwidth) or failure of some services (e.g. some of the selected services become unavailable) can occur at run-time. Therefore, a quick response to adaptation requests is important in such applications. The performance of the service selection middleware can have a great impact on the overall performance of the composition system.

Figure 2 gives a conceptual overview of the QoS-aware service composition problem. Given an abstract composition request, which can be stated in a workflow-like language (e.g. BPEL [19]), the discovery engine uses existing infrastructure (e.g. UDDI) to locate available web services for each task in the workflow using syntactic (and probably semantic) functional matching between the tasks and service descriptions. As a result, a list of candidate web services is obtained for each task. The goal of QoS-aware service selection middle-

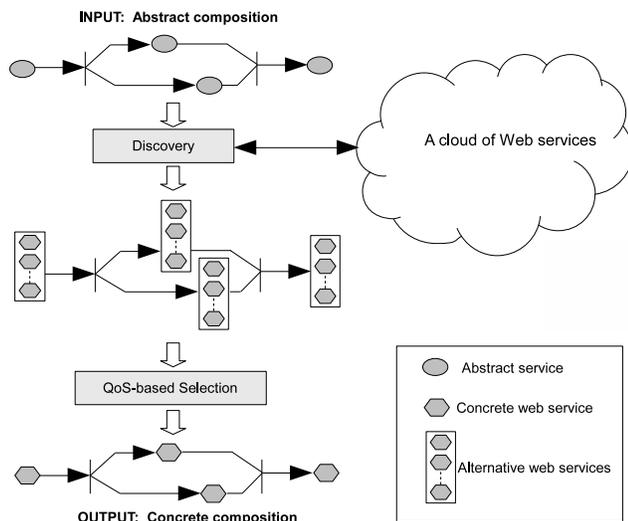


Figure 2: Conceptual Overview

ware is to select one component service from each list such that the aggregated QoS values satisfy the user's end-to-end QoS requirements. In service oriented environments, where deviations from the QoS estimates occur and decisions upon replacing some services has to be taken at run-time (e.g. in the multimedia application above), the efficiency of the applied selection mechanism becomes crucial. The focus of this paper is on the selection of web services based on their non-functional properties and the performance of the applied techniques.

Local Selection vs. Global Optimization

Two general approaches exist for the QoS-aware service composition: local selection and global optimization.

Local Selection: The local selection approach is especially useful for distributed environments where central QoS management is not desirable and groups of candidate web services are managed by distributed service brokers [8, 14]. The idea is to select one service from each group of service candidates independently on the other groups. Using a given utility function, the values of the different QoS criteria are mapped to a single utility value and the service with maximum utility value is selected. This approach is very efficient in terms of computation time as the time complexity of the local optimization approach is $O(l)$, where l is the number of service candidates in each group. Even if the approach is useful in decentralized environments, local selection strategy is not suitable for QoS-based service composition, with end-to-end constraints (e.g. maximum total price), since such global constraints cannot be verified locally.

Global Optimization: The global optimization approach was recently put forward as a solution to the QoS-aware service composition problem [24, 25, 5, 6]. This approach aims at solving the problem on the composite service level. The aggregated QoS values of all possible service combinations are computed, and the service combination that maximizes the aggregated

utility value, while satisfying global constraints is selected. The global selection problem can be modeled as a *Multi-Choice Multidimensional Knapsack problem* (MMKP), which is known to be NP-hard in the strong sense [20]. Consequently, it can be expected that an optimal solution may not be found in a reasonable amount of time [16]. The exponential time complexity of the proposed solutions [24, 25, 5, 6] is only acceptable if the number of service candidates is very limited. Already in larger enterprises and even more in open service infrastructures with a few thousands of services the response time for a service composition request could already be out of the real-time requirements.

Contribution of the Paper

Since the QoS requirements (e.g. response times, throughput or availability) are only approximate, we argue that finding a "reasonable" set of services that avoid obvious violations of constraints at acceptable costs is more important than finding "the optimal" set of services with a very high cost. In addition, we advocate that the selection of component services should be carried out in a distributed fashion, which fits well to the open web service environment, where central management is not feasible.

The contribution of this paper can be stated as follows:

- A *distributed QoS computation model for web services*. Unlike existing solutions that model the QoS-aware service composition problem as a conventional global optimization problem, we exploit the special structure of the web service composition problem to reduce the cost of QoS optimization. The QoS optimization in our model is carried out by a set of distributed service brokers. The idea is to decompose QoS global constraints into a set of local constraints that will serve as a conservative upper/lower bounds, such that the satisfaction of local constraints by a local service broker guarantees the satisfaction of the global constraints.
- An *efficient QoS-aware service selection approach*. We propose an efficient and scalable mechanism for selecting web services for a given composition request from a collection of service candidates, such that the fulfillment of user's end-to-end QoS requirements and preferences can be ensured. By combining global optimization with local selection our approach is able to efficiently solve the selection problem in a distributed manner. Experimental evaluations show that our hybrid approach is able to reach close-to-optimal results much faster than existing 'pure' global optimization approaches.

The rest of the papers is organized as follows. In the next section we discuss related work. Section 3 introduces the system model and gives a problem statement. Our approach for efficient and distributed QoS-aware service selection is presented in Section 4. Performance analysis and experimental evaluations for comparing our solution against existing solutions are presented in Section 5. Finally, Section 6 gives conclusions and an outlook on possible continuations of our work.

2. RELATED WORK

The requirements for composition of web services can be stated in a workflow language such as Business Process Execution Language (BPEL) [19]. In [26, 9] ontology-based representations for describing QoS properties and requests were proposed to support semantic and dynamic QoS-based discovery of web services. Quality of service management has been widely discussed in the area of middleware systems [7, 11, 12, 13]. Most of these works focus on QoS specification and management. Recently, the QoS-based web service selection and composition in service-oriented applications has gained the attention of many researchers [24, 25, 5, 6, 15, 23]. In [15] the authors propose an extensible QoS computation model that supports open and fair management of QoS data. The problem of QoS-based composition is not addressed by this work. The work of Zeng et al. [24, 25] focuses on dynamic and quality-driven selection of services. The authors use global planning to find the best service components for the composition. They use (mixed) linear programming techniques [18] to find the optimal selection of component services. Similar to this approach Ardagna et al. [5, 6] extends the linear programming model to include local constraints. Linear programming methods are very effective when the size of the problem is small. However, these methods suffer from poor scalability due to the exponential time complexity of the applied search algorithms [16]. In [23] the authors propose heuristic algorithms that can be used to find a near-to-optimal solution more efficiently than exact solutions. The authors propose two models for the QoS-based service composition problem: 1) a combinatorial model and 2) a graph model. A heuristic algorithm is introduced for each model. The time complexity of the heuristic algorithm for the combinatorial model (WS_HEU) is polynomial, whereas the complexity of the heuristic algorithm for the graph model (MCSP-K) is exponential. Despite the significant improvement of these algorithms compared to exact solutions, both algorithms do not scale with respect to an increasing number of web services and remain out of the real-time requirements. Any distributed implementation of these algorithms would raise a very high communication cost. The WS_HEU for example, is an improvement of the original heuristic algorithm for solving general *Multi-Choice Multi-dimensional Knapsack* problems named M-HEU [1]. The WS_HEU algorithm starts with a pre-processing step for finding an initial feasible solution, i.e. a service combination that satisfies all constraints but not necessarily is the best solution. A post-processing step improves the total utility value of the solution with one upgrade followed by one or more downgrades of one of the selected component services. Applying this algorithm in a distributed setting where the QoS data of the different service classes is managed by distributed service brokers would raise very high communication cost among these brokers to find the best composition. In this paper, we propose a heuristic algorithm that solves the composition problem more efficiently and fits well to the distributed environment of web services.

3. SYSTEM MODEL

In our model we assume that we have a universe of web services \mathbb{S} which is defined as a union of *abstract service classes*. Each abstract service class $S_j \in \mathbb{S}$ (e.g. flight booking services) is used to describe a set of functionally-

equivalent web services (e.g. Lufthansa and Qantas flight booking web services). In this paper we assume that information about service classes is managed by a set of service brokers as described in [15, 14]. Web services can join and leave service classes at any time by means of a subscription mechanism.

3.1 Abstract vs. Concrete Composite Services

As shown in Figure 2 we distinguish in the composition process between the following two concepts:

- An abstract composite service, which can be defined as an abstract representation of a composition request $CS_{abstract} = \{S_1, \dots, S_n\}$. $CS_{abstract}$ refers to the required service classes (e.g. flight booking) without referring to any concrete web service (e.g. Lufthansa flight booking web service).
- A concrete composite service, which can be defined as an instantiation of an abstract composite service. This can be obtained by binding each abstract service class in $CS_{abstract}$ to a concrete web service s_j , such that $s_j \in S_j$. We use CS to denote a concrete composite service.

3.2 QoS Criteria

In our study we consider quantitative non-functional properties of web services, which can be used to describe the quality criteria of a web service [24, 15]. These can include generic QoS attributes like response time, availability, price, reputation etc, as well as domain-specific QoS attributes like bandwidth for multimedia web services as long as these attributes can be quantified and represented by real numbers. We use the vector $Q_s = \{q_1(s), \dots, q_r(s)\}$ to represent the QoS attributes of service s , where the function $q_i(s)$ determines the value of the i -th quality attribute of s . The values of these QoS attributes can be either collected from service providers directly (e.g. price), recorded from previous execution monitoring (e.g. response time) or from user feedbacks (e.g. reputation) [15]. The set of QoS attributes can be divided into two subsets: positive and negative QoS attributes. The values of positive attributes need to be maximized (e.g. throughput and availability), whereas the values of negative attributes need to be minimized (e.g. price and response time). For the sake of simplicity, in this paper we consider only negative attributes (positive attributes can be easily transformed into negative attributes by multiplying their values by -1).

3.3 QoS Computation of Composite Services

The QoS value of a composite service is decided by the QoS values of its component services as well as the composition model used (e.g. sequential, parallel, conditional and/or loops). In this paper, we focus on the sequential composition model. Other models may be reduced or transformed to the sequential model. Techniques for handling multiple execution paths and unfolding loops from [10], can be used for this purpose.

The QoS vector for a composite service CS is defined as $Q_{CS} = \{q'_1(CS), \dots, q'_r(CS)\}$. $q'_i(CS)$ represents the estimated value of the i -th QoS attribute of CS and can be aggregated from the expected QoS values of its component

services. In our model we consider three types of QoS aggregation functions: 1) summation, 2) multiplication and 3) minimum relation. Table 1 shows examples of these aggregation functions.

Aggregation type	Examples	Function
Summation	Response time	$q'(CS) = \sum_{j=1}^n q(s_j)$
	Price	
	Reputation	$q'(CS) = 1/n \sum_{j=1}^n q(s_j)$
Multiplication	Availability	$q'(CS) = \prod_{j=1}^n q(s_j)$
	Reliability	
Minimum	Throughput	$q'(CS) = \min_{j=1}^n q(s_j)$

Table 1: Examples of QoS aggregation functions

3.4 Global QoS Constraints

Global QoS constraints represent user's end-to-end QoS requirements. These can be expressed in terms of upper (and/or lower) bounds for the aggregated values of the different QoS criteria. As mentioned earlier, we only consider negative QoS criteria. Therefore in our model we only have upper bound constraints.

Definition 1. (Feasible Selection) Let $CS_{abstract}$ be a given composition request and $C' = \{c'_1, \dots, c'_m\}$, $0 \leq m \leq r$, be a vector of global QoS constraints on $CS_{abstract}$. Let CS be an instantiation of $CS_{abstract}$, in which a concrete web service is selected for each service class. We consider CS a feasible selection iff $q'(CS) \leq c'$, $\forall c'_k \in C'$, i.e. all global constraints are satisfied.

3.5 Utility Function

In order to evaluate the multi-dimensional quality of a given web service a utility function is used. The function maps the quality vector Q_s into a single real value, to enable sorting and ranking of service candidates. In this paper we use a Multiple Attribute Decision Making approach for the utility function: i.e. the *Simple Additive Weighting (SAW)* technique [22]. The utility computation involves scaling the QoS attributes' values to allow a uniform measurement of the multi-dimensional service qualities independent of their units and ranges. The scaling process is then followed by a weighting process for representing user priorities and preferences. In the scaling process each QoS attribute value is transformed into a value between 0 and 1, by comparing it with the minimum and maximum possible value according to the available QoS information of service candidates. For a composite service $CS = \{S_1, \dots, S_n\}$, the aggregated QoS values are compared with minimum and maximum possible aggregated values. The minimum (or maximum) possible aggregated values can be easily estimated by aggregating the minimum (or maximum) value of each service class in CS . For example, the maximum execution price of CS can be computed by summing up the execution price of the most expensive service candidate in each service class in CS . Formally, the minimum and maximum aggregated values of the

k -th QoS attribute of CS are computed as follows:

$$Qmin'(k) = \sum_{j=1}^n Qmin(j, k) \quad (1)$$

$$Qmax'(k) = \sum_{j=1}^n Qmax(j, k)$$

with

$$Qmin(j, k) = \min_{s_{ji} \in S_j} q_k(s_{ji}) \quad (2)$$

$$Qmax(j, k) = \max_{s_{ji} \in S_j} q_k(s_{ji})$$

where $Qmin(j, k)$ is the minimum value (e.g. minimum price) and $Qmax(j, k)$ is the maximum value (e.g. maximum price) that can be expected for service class S_j according to the available information about service candidates of this class.

Now the utility of a component web service $s \in S_j$ is computed as

$$U(s) = \sum_{k=1}^r \frac{Qmax(j, k) - q_k(s)}{Qmax(j, k) - Qmin(j, k)} \cdot w_k \quad (3)$$

and the overall utility of a composite service is computed as

$$U'(CS) = \sum_{k=1}^r \frac{Qmax'(k) - q'_k(CS)}{Qmax'(k) - Qmin'(k)} \cdot w_k \quad (4)$$

with $w_k \in \mathbb{R}_0^+$ and $\sum_{k=1}^r w_k = 1$ being the weight of q'_k to represent user's priorities.

Definition 2. (Optimal Selection) The optimal selection for a given web service composition request $CS_{abstract}$ and a given vector of global QoS constraints $C' = \{c'_1, \dots, c'_m\}$, $0 \leq m \leq r$, is a feasible selection (according to Definition 1) with the maximum overall utility value U' .

However, finding the optimal composition requires enumerating all possible combinations of service candidates. For a composition request with n service classes and l service candidate per class, there are l^n possible combinations to be examined. Performing exhaustive search can be very expensive in terms of computation time and, therefore, inappropriate for run-time service selection in applications with many services and dynamic needs.

3.6 Problem Statement

The problem of finding the best service composition without enumerating all possible combinations is considered as an optimization problem, in which the overall utility value has to be maximized while satisfying all global constraints. Formally, the optimization problem we are addressing can be stated as follows:

For a given composition request $CS_{abstract} = \{S_1, \dots, S_n\}$ and a given set of m global QoS constraints $C' = \{c'_1, \dots, c'_m\}$, find an implementation $CS = \{s_1, \dots, s_n\}$ by binding each S_j to a concrete service $s_j \in S_j$ such that:

1. The overall utility $U'(CS)$ is maximized, and
2. The aggregated QoS satisfy: $q'_k(CS) \leq c'_k, \forall c'_k \in C'$

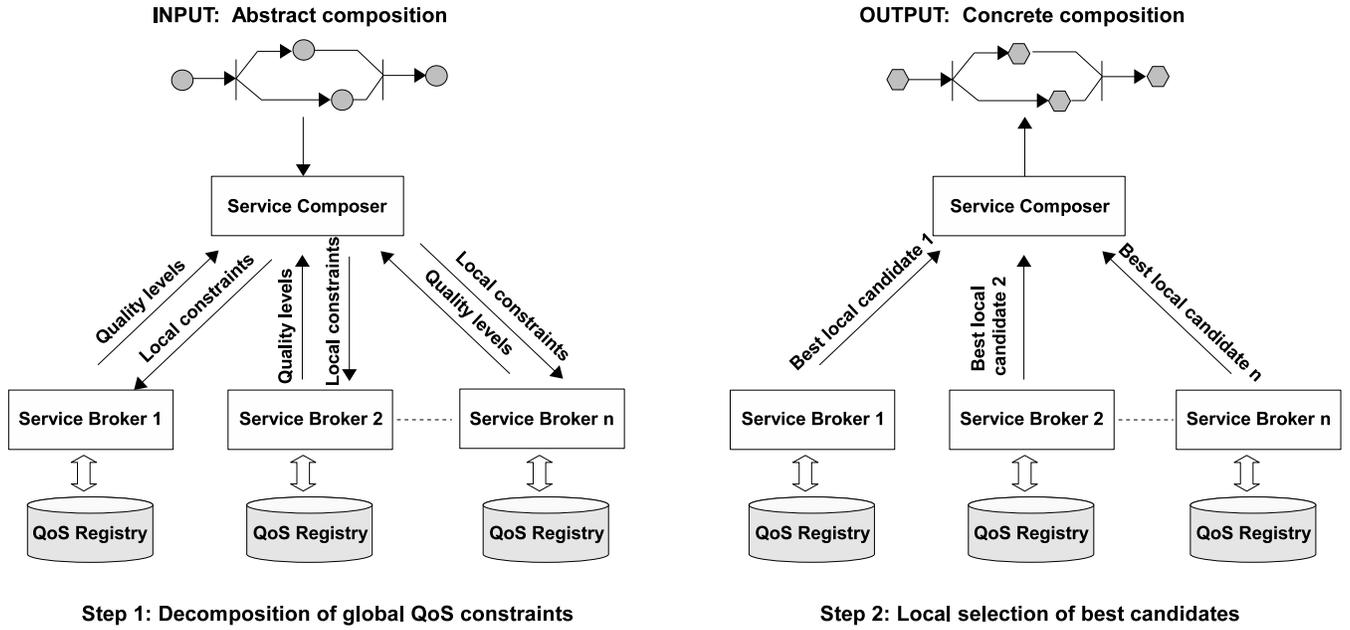


Figure 3: Distributed QoS-aware Service Selection

4. QOS-AWARE SERVICE COMPOSITION

The use of mixed integer programming [18] to solve the QoS-aware service composition problem has been recently proposed by several researchers [24, 25, 5, 6]. Binary decision variables are used in the model to represent the service candidates. A service candidate s_{ij} is selected in the optimal composition if its corresponding variable x_{ij} is set to 1 in the solution of the model and discarded otherwise. By re-writing (4) to include the decision variables, the problem of solving the model can be formulated as a maximization problem of the overall utility value given by

$$\sum_{k=1}^r \frac{Qmax'(k) - \sum_{j=1}^n \sum_{i=1}^l q_k(s_{ji}) \cdot x_{ji}}{Qmax'(k) - Qmin'(k)} \cdot w_k \quad (5)$$

subject to the global QoS constraints

$$\sum_{j=1}^n \sum_{i=1}^l q_k(s_{ji}) \cdot x_{ji} \leq c'_k, 1 \leq k \leq m \cdot w_k \quad (6)$$

while satisfying the allocation constraints on the decision variables as

$$\sum_{i=1}^l x_{ji} = 1, 1 \leq j \leq n. \quad (7)$$

Because the number of variables in this model depends on the number of service candidates (number of variables = $n \cdot l$), this MIP model may not be solved satisfactorily, except for small instances. Another disadvantage of this approach is that it requires that the QoS data of available web services be imported from the service broker into the MIP model of the service composer, which raises high communication.

To cope with these limitations, we divide the QoS-aware service composition problem into two sub-problems that can be solved more efficiently in two subsequent phases. Figure 3 gives an overview on our approach. In the first phase, the

service composer decomposes each global QoS constraints into local constraints on the component services level and sends these constraints to the involved service brokers. These constraints also include user's preferences, which are expressed in terms of weights of the QoS attributes. In the second phase, each service broker performs local selection to find the best component services that satisfy these local constraints. The two phases of our approach are described in the next subsections in more details.

4.1 Decomposition of Global QoS Constraints

To ensure the fulfillment of global QoS constraints in a service composition problem without enumerating all possible combinations of component web service, we decompose each QoS global constraint c' into a set of n local constraints c_1, \dots, c_n (n is the number of abstract service classes in the composition request). The local constraints serve as a conservative upper bounds, such that the satisfaction of local constraints guarantees the satisfaction of global constraints.

A naive decomposition algorithm would be to divide each global constraint c' into n equal local constraints such that: $c_j = c'/n, 1 \leq j \leq n$. However, as different service classes can have different QoS value ranges, a more sophisticated decomposition algorithm is required. Furthermore, in order to avoid discarding any service candidates that might be part of a feasible composition, the decomposition algorithm needs to ensure that the local constraints are relaxed as much as possible while meeting global constraints. We solve this problem by modeling the QoS constraint decomposition problem as an optimization problem. The goal of this optimization problem is to find a set of local constraints for each service class that cover as many as possible service candidates, while their aggregation does not violate any of the global constraints. To this end, we divide the quality range of each QoS attribute into a set of discrete quality values, which we call *quality levels*. We then map each global

QoS constraint into a set of these quality levels, which will be used as local constraints by the local service selection algorithm. For example, given a set of candidate web services and their execution prices, we create a list of price levels for that service class (the following subsection describes how levels are determined). The global constraint on total execution price is then mapped to the price levels of service classes. We use mixed integer program (MIP) [18] solving techniques to find the best mapping of global constraints to local quality levels. Unlike the MIP model in [24, 25, 5, 6], our MIP model has much less number of variables (i.e. the quality levels instead of actual service candidates) and can be, therefore, solved much faster.

4.1.1 Determining Quality Levels

Quality levels are initialized for each service class S_j by dividing the value ranges of each QoS attribute q_k into a set of d discrete quality values as depicted in figure 4

$$Qmin(j, k) \leq q_{jk}^1 \leq \dots \leq q_{jk}^d \leq Qmax(j, k).$$

The quality levels are determined such that they represent the data collection of each service class. We first divide the range of attribute values into d sub-ranges. From each sub-range we randomly select one sample value. The more frequent a given value is, the higher the probability that it is selected as a quality level. We then assign each quality level q_{jk}^z a value p_{jk}^z between 0 and 1, which estimates the benefit of using this quality level as a local constraint. This value is determined as follows. First, we compute $h(q_{jk}^z)$, i.e. the number of candidate services that would qualify if this level was used as local constraint. Second, we calculate the utility value of each service candidate in the service class using the utility function (3) and determine $u(q_{jk}^z)$, i.e. the highest utility value that can be obtained by considering these qualified services. Finally, p_{jk}^z can be calculated as

$$p_{jk}^z = \frac{h(q_{jk}^z)}{l} \cdot \frac{u(q_{jk}^z)}{u_{max}} \quad (8)$$

where l is the total number of service candidates of service class S_j , and u_{max} is the highest utility value that can be obtained for this class by considering all service candidates. The value p_{jk}^z indicates how many web services would qualify if the z -th level was used as local constraint for the k -th QoS attribute in service class S_j , and estimates the highest obtainable utility value for that class.

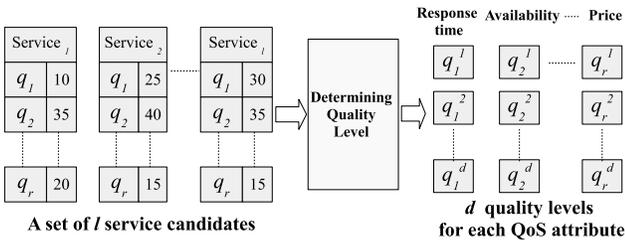


Figure 4: Quality Level Selection

4.1.2 Formulating the MIP Model

We use MIP model to find the best decomposition of QoS constraints into local constraints. Therefore, we use a binary decision variable x_{jk}^z for each local quality level q_{jk}^z such that

$x_{jk}^z = 1$ if q_{jk}^z is selected as a local constraint for the QoS attribute q_k at the service class S_j , and $x_{jk}^z = 0$ otherwise.

Therefore, we use the following allocation constraints in the model:

$$\forall j, \forall k : \sum_{z=1}^d x_{jk}^z = 1, 1 \leq j \leq n, 1 \leq k \leq m \quad (9)$$

Note that the total number of variables in the model equals to $n \cdot m \cdot d$, i.e. it is independent of the number of service candidates. If the number of quality levels d satisfies $m \cdot d \leq l$ we can ensure that the size of our MIP model is smaller than the size of the model used in [24, 25, 5, 6] (where the number of decision variables is $n \cdot l$), thus can be solved much faster.

The objective function of our MIP model is to maximize the p value (as defined in 8) of the selected local constraints to minimize the number of discarded feasible selections. Therefore, the objective function can be expressed as follows:

$$\text{maximize } \prod_{j=1}^n \prod_{k=1}^m p_{jk}^z, 1 \leq z \leq d \quad (10)$$

We use the logarithmic function to linearize (10) in order to be able to use it in the MIP model:

$$\text{maximize } \sum_{j=1}^n \sum_{k=1}^m \sum_{z=1}^d \ln(p_{jk}^z) * x_{jk}^z \quad (11)$$

The selection of the local constraints must ensure that global constraints are still satisfied. Therefore, we add the following set of constraints to the model:

$$\forall k : \sum_{j=1}^n \sum_{z=1}^d q_{jk}^z \cdot x_{jk}^z \leq c'_k, 1 \leq k \leq m \quad (12)$$

By solving this model using any MIP solver methods, we get a set of local quality levels. These quality levels are then sent to the distributed set of involved service brokers to perform local selection.

4.2 Local Selection

After decomposing global QoS constraints into local ones, the second step of our solution is to perform local selection for each service class independently. Upon the receipt of local constraints and user' preferences from the service composer, each service broker performs the local selection and returns the best web service candidate to the service composer. The received local constraints are used as upper bounds for the QoS values of component services. Web services that violate these upper bounds are skipped from the selection. A list of qualified services is created and sorted by their utility values.

The use of (3) for this purpose is not appropriate for the following reason. This utility function compares the distance $Qmax(j, k) - q_k(s_{ji})$ between the quality value of a service candidate s_{ji} and the local maximum value in its class S_j with the distance $Qmax(j, k) - Qmin(j, k)$ between the local minimum and maximum values. This scaling approach can be biased by local properties leading to local optima instead of global optima. Therefore, we compare the distance $Qmax(j, k) - q_k(s_{ji})$ with the distance

between the maximum and minimum overall quality values: $Qmax'(k) - Qmin'(k)$. This scaling method ensures that the evaluation of service candidates is globally valid, which is important for guiding local selection in order to avoid local optimums. The scaling process is then followed by a weighting process for representing user's over the different QoS attributes. We compute the utility $U(s_{ji})$ of the i -th service candidate in class S_j as

$$U(s_{ji}) = \sum_{k=1}^r \frac{Qmax(j,k) - q_k(s_{ji})}{Qmax'(k) - Qmin'(k)} \cdot w_k \quad (13)$$

with $w_k \in \mathbb{R}_0^+$ and $\sum_{k=1}^r w_k = 1$ being the weight of q_k to represent user's priorities.

5. PERFORMANCE STUDY

The aim of this evaluation is to validate our hypothesis that our approach achieves close-to-optimal results with a much lower computation time compared to "pure" global optimization approach as proposed by [15, 25, 6]. In the following we use the label "hybrid" to refer to our solution and the label "global" to refer to the "pure" global optimization approach.

5.1 Performance Analysis

The scalability of QoS-based service composition systems is affected by the time complexity of the applied algorithm. There are three factors that determine the size of the composition problem: the number of required service classes n , the number of service candidates per class l , which we assume to be equal for all classes, and the number of global QoS constraints m . As the problem can be modeled as a Multi-Choice Multidimensional Knapsack problem (MMKP), which is known to be NP-hard [20], the time complexity of any exact solution is expected to be exponential. Existing global optimization solutions model the service selection problem as a standard mixed integer program (MIP). The worst case time complexity of MIP solvers using the simplex method is an exponential function $O(2^{n \cdot l})$ [16], which restricts the applicability of these solutions to small size composition problems, where the number of service candidates l is very limited. Returning back to the given service composition scenario in section 1, already with a few hundreds of web service candidates that provide the same functionality (e.g. transcoding web services), the response time of this approach to QoS-optimized service selection (or replacement) requests can be out of the run-time requirements.

In our Hybrid approach, we use mixed integer programming to solve part of the problem, namely, the decomposition of the global QoS constraints into local ones. The actual selection of services, however, is done using distributed local selection strategy, which is very efficient and scalable. The local utility computation for service candidates has a linear complexity with respect to the number of service candidates, i.e. $O(l)$. As service brokers can perform the local selection in parallel, the total time complexity of this step is not affected by the number of service classes, hence, the complexity of the second step remains $O(l)$.

The time complexity of our approach is dominated by the time complexity of the constraint decomposition part. The number of decision variables in our MIP model is $n \cdot m \cdot d$, where n is the number of service classes, m is the number of global QoS constraints and d is the number of quality

levels. Consequently, the time complexity of our approach is independent on the number of available web services, which makes it more scalable than existing solutions that rely on "pure" global optimization. By selecting a low number of quality levels d with $1 < d \ll \frac{l}{m}$ we ensure that the size of the MIP is much smaller compared to the MIP model used in the global optimization approaches in [15, 25, 6].

5.2 Experimental Evaluation

We have conducted extensive simulations to evaluate the performance of the proposed QoS-aware service selection approach, which we describe in this section.

Evaluation Methodology

We have created several test cases of the QoS-based service composition problem. Each test case consists of a service composition request with n service classes, l service candidates per class and m global QoS constraints. By varying these numbers we created a collection of test cases, where each unique combination of these parameters represents one test case. We first solved each test case using the global optimization approach to find the optimal selection of component services that satisfy all global QoS constraints, while maximizing the overall utility value. We recorded the required computation time t_{global} and the obtained utility value u_{global} by this method for each test case. We then provided the same test cases to our hybrid service selection method and compared its computation time t_{hybrid} and the aggregated utility value of the returned selection u_{hybrid} with t_{global} and u_{global} for the same test case respectively. In order to study the effect of the chosen number of quality levels in the hybrid approach, we solved each test case several times with different number of quality levels. The number of quality levels in this experiment was set to 10, 20, 30, 40 and 50 levels.

The Dataset

In our evaluation we experimented with two QoS datasets. The first dataset is the QWS real dataset from [2, 3, 4]. This dataset includes measurements of 9 QoS attributes for 2500 real web services. Table 2 lists the QoS attributes in this dataset and gives a brief description of each attribute. The dataset was measured using commercial benchmark tools for

Table 2: QoS attributes in the QWS dataset

QoS attribute	Description	Units Of Measurement
Response Time	Time taken to send a request and receive a response	millisecond
Availability	Number of successful invocations/total invocations	percent
Throughput	Total number of invocations for a given period of time	invocations / second
Likelihood of success	Number of response/number of request messages	percent
Reliability	Ratio of the number of error messages to total messages	percent
Compliance	To which extent a WSDL document follows the WSDL spec.	percent
Best Practices	To which extent a web service follows the Web Services Interoperability (WS-I) Basic Profile	percent
Latency	Time the server takes to process a given request	millisecond
Documentation	Measure of documentation (i.e. description tags) in WSDL	percent

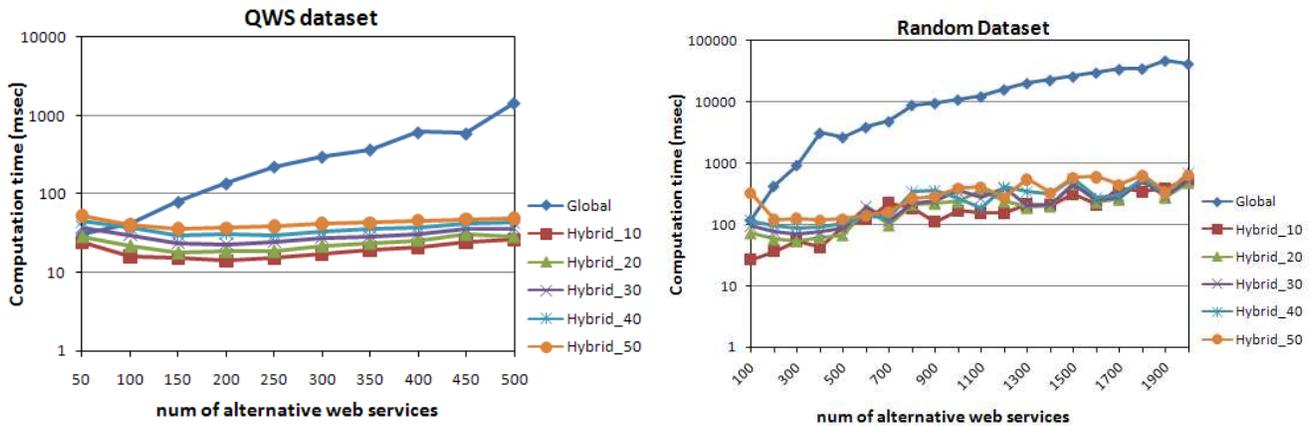


Figure 5: Performance comparison w.r.t. the number of web service candidates

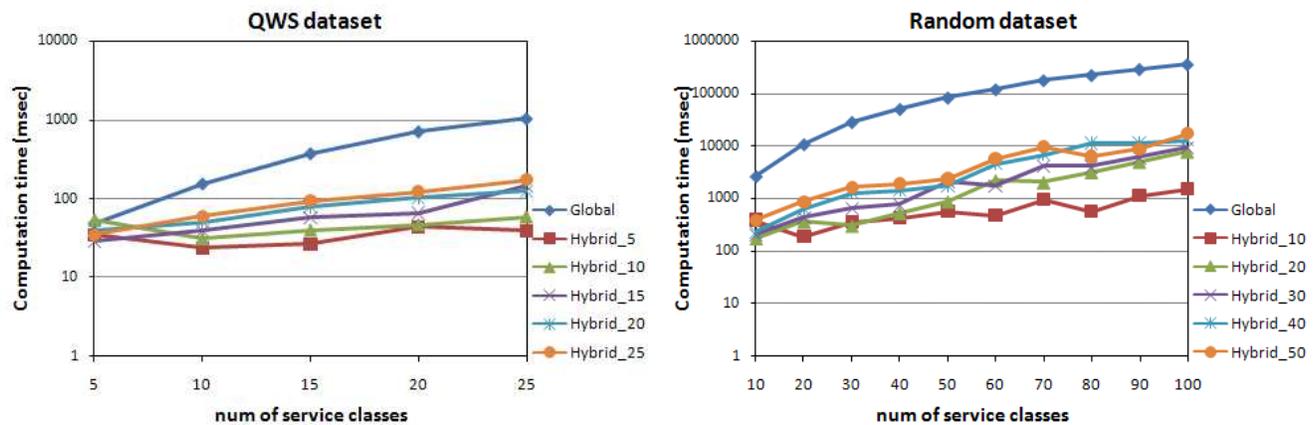


Figure 6: Performance comparison w.r.t. the number of web service classes

web services, which were located using public sources on the Web, including UDDI registries, search engines and service portals. For more details about this dataset we refer the reader to [3, 4].

In order to make sure that the results of our experiments are not biased by the used QWS dataset, we experimented with a second dataset. The second dataset was created by assigning arbitrary QoS values to 20000 artificial web services. The QoS values were normally distributed in the range between 1 and 100.

Experiment Settings

We used the open source (Mixed Integer Programming) Lp-Solve system *lpsolve* version 5.5 [17] for solving the MIP model in both approaches. The experiments were conducted on a HP ProLiant DL380 G3 machine with 2 Intel Xeon 2.80GHz processors and 6 GB RAM. The machine is running under Linux (CentOS release 5) and Java 1.6.

Performance Results

In Figure 5 we compare the performance of our hybrid approach and the global optimization approach with respect to the number of service candidates. The graphs show the measured computation times t_{global} and t_{hybrid} for each test case. The number of service candidates per class l varies from 50 to 500 for the QWS dataset and from 100 to 2000

services per class. In this experiment, the number of service classes n is fixed to 5 for the QWS dataset and to 10 classes for the random dataset in all test cases. The number of QoS constraints in all these test cases was fixed to 3 constraints.

The results indicate that the hybrid approach significantly outperforms the global approach for both datasets. By increasing the number of service candidates, the required computation time of the hybrid approach increases very slowly compared to the global approach, which makes our solution more scalable.

The results also show that increasing the number of quality levels in the hybrid approach increases the computation time. We also notice that with small number of service candidates, increasing the number of quality levels “more than necessary” (i.e. to 50 quality levels in this case) can lead to longer computation time than in the global approach. This is an expected behavior as we already discussed in Section 5.1. According to our analysis, the number of quality levels d must be less than l/m . In the aforementioned situation this was not the case (in the random dataset for example, $d = 50$, whereas $l/m = 33.3$).

In the experiment shown in Figure 6 we study the performance of both approaches with respect to the number of service classes n in the composition. The number of service classes varies from 5 to 25 for the QWS dataset and from 10 to 100 classes for the random dataset. The number of

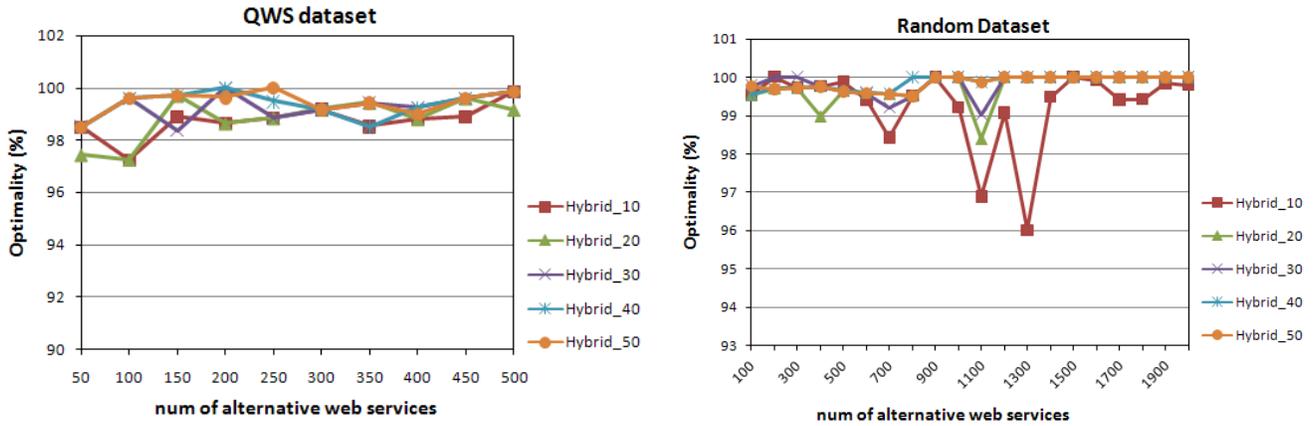


Figure 7: Optimality w.r.t. the number of web service candidates

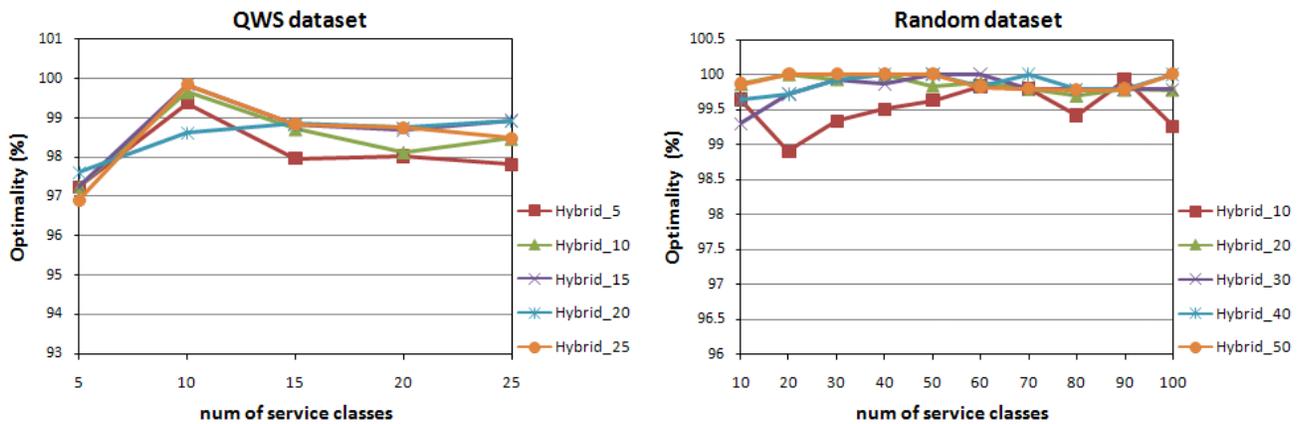


Figure 8: Optimality w.r.t. the number of web service classes

service candidates per class l in this experiment is fixed to 100 for the QWS dataset and to 500 for the random dataset. The results of this experiment show that our approach still outperforms the global approach in all test cases.

Optimality

As our hybrid solution is an approximate solution, we have evaluated the quality of the results obtained by our solution by comparing it with the optimal results obtained by the global optimization approach. We compute the optimality of the results of the hybrid approach by comparing the overall utility value (u_{hybrid}) of the selected services to the overall utility value (u_{global}) of the optimal selection obtained by the global approach, i.e.:

$$optimality = u_{hybrid}/u_{global}$$

Figure 7 shows the achieved optimality in several test cases with different number of service candidates, while Figure 8 shows the achieved optimality in several test cases with a varying number of service classes. The results indicate that the hybrid approach was able to achieve above 96% optimality in average. The results also show that in average, increasing the chosen number of quality levels improves the achieved optimality. This improvement does not come without cost as we can see from Figures 5 and 6. There

is a trade-off between optimality and performance. Nevertheless, in average, the hybrid approach is able to reach a close-to-optimal results with very low cost.

6. CONCLUSION AND FUTURE WORK

In this paper we presented an efficient heuristic for the QoS-based service composition, which is known to be NP-hard. We combine global optimization with local selection methods to benefit from the advantaged of both worlds. Our proposed method allows to dramatically reduce the (worst case) efforts compared to existing solutions. Our evaluations show a significant improvement in terms of computational time, while achieving close to optimal results. This is especially useful for applications with dynamic changes and real-time requirements. In the current approach the number of service levels is fixed and need to be defined beforehand. Currently we are studying the impact of the applied method as well as the number of the selected quality levels on the performance and quality of the obtained results. We also aim at developing a self-adaptive approach, which optimizes itself by determining the best number of quality levels at run-time based on the available QoS information. A protocol for coordinating the distributed service brokers, which are involved in a QoS optimization process, is also part of our future work.

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