Balancing between Local and Global Optimization of Web Services Composition by a Fuzzy Transactional-aware Approach

Fatma Rhimi[1,2], Saloua Ben Yahia[1] and Samir Ben Ahmed[1]
[1]*Université de Carthage, INSAT, LISI Laboratory, Tunis, Tunisia*
[2]*ESPRIT, School of Engineering, Tunis, Tunisia*

Keywords: Fuzzy Logic, Optimization, Quality of Service, Skyline, Transactional Selection.

Abstract: The tremendous growth in the amount of available web services due to the proliferation of paradigms such as Big Data and Cloud Computing has raised many challenges in service computing. When there are multiple web services that offer the same functionalities, we need to select the best one according to its non-functional criteria (e.g. response time, price, reliability) while guaranteeing a global optimization. Many approaches have been introduced to tackle this problem. However, most of them neglected users preferences, which can be very vague and imprecise, in the selection process. Besides, transactional properties that can insure a reliable achievement of the composition are rarely considered. This paper suggests a solution to this challenge by modelling users uncertain preferences with fuzzy sets. We then compute the set of Skyline services which are the best candidates in the search space with fuzzy dominance relationship and fuzzy similarity measures. Finally we inject transactional properties in order to guarantee a global optimization with a successful achievement of the composition process. Experimental evaluation demonstrates the effectiveness of the proposed concept and the efficiency of our implementation.

1 INTRODUCTION

Web Services are growing in popularity as an efficient solution to enhance the interoperability for machine-to-machine interaction among different applications and different platforms. This is why business structures are moving today towards the service-oriented architecture as web services seem to be the best solution to allow the exchanges between them. Service composition is a process that combines multiple atomic web services in order to create value-added web services. Hence, it is arising as an effective solution to deliver customized services to the different users.

Quality-of-Service (QoS) is widely employed to represent the non-functional characteristics of web services and has been considered as the key factor in service selection. QoS is defined as a set of properties including response time, throughput, availability, reputation, etc. However, today with the prevalence of paradigms such as Big Data, Cloud Computing and XAAS (everything as a service), the number of available web services had exploded. This is why it has become difficult to choose the best candidates that would insure an optimal composition. By optimal composition we mean a composition that corresponds the most to the functional and non-functional criteria provided by the user.

Skyline is a technique that comes as a solution that helps reducing the search space based on a dominance relationship to preselect the best services and prune the others. Intuitively, a skyline query selects the “best” or most “interesting” points with respect to all dimensions. Thus, it can be very effective for reducing the number of candidates and enhancing the optimization.

On another hand, transactional properties of web services are crucial to insure the coherence of the composition process. In fact, delivering reliable service composition is very important for the overall quality of the service. Invoking distant atomic web services which interoperate with each other can be affected by failures, throughput, availability etc. Hence, insuring a reliable service becomes as important as delivering a service which meets users functional and non-functional requirements.

In this study, we argue that users preferences as well as transactional behavior of services should be considered in the selection process. Thus, we

Rhimi, F., Yahia, S. and Ahmed, S.
Balancing between Local and Global Optimization of Web Services Composition by a Fuzzy Transactional-aware Approach.
DOI: 10.5220/0005941200750082
In *Proceedings of the 11th International Joint Conference on Software Technologies (ICSOFT 2016) - Volume 2: ICSOFT-PT*, pages 75-82
ISBN: 978-989-758-194-6
Copyright © 2016 by SCITEPRESS – Science and Technology Publications, Lda. All rights reserved

suggest an approach that will recommend to the user the appropriate service according to his preferences using fuzzy techniques. Then, we will inject transactional properties in order to insure the reliability of the delivered service.

1.1 Contributions

This paper aims to present a new approach for web services selection which balances between local optimization by selecting services that correspond to the users preferences, and global optimization by respecting transactional properties. The first step is the computation of the set of Skyline services. Traditional Skyline computation methods rely on Pareto dominance relationship: a service p dominates another service q if p is at least as good as q in all the dimensions and strictly better in at least one dimension. Such strict dominance relationship suffers from looseness and does not accord an importance to the user's preferences. Besides, users behavior is subjective, vague and imprecise. We suggest a two steps approach:

- We will in first place select the services with the best matching degrees with the user's preferences based on fuzzy similarity measures.
- We will inject transactional properties in order to guarantee a reliable successful composite service.

Considering all this, our main contributions may be summarized in the following points:

- We will address the problem of computing service Skyline with a consideration of user's preferences by making use of fuzzy preference relationships rather than Pareto dominance relationships.
- We compute the matching degree between web services and users requirements using fuzzy similarity measures.
- We proceed to optimizing the overall composition using transactional properties of web services.
- We evaluate the efficiency and the effectiveness of the proposed method with a theoretical study and an experimental evaluation.

1.2 Outline

Section II presents the related work of this study .In section III we present the background of this work so we can advance the followed approach. Section IV will describe the different steps of the proposed approach. In Section V, we present the experimental evaluation of the approach. Finally, section VI will conclude the paper.

2 REALTED WORK

2.1 Web Services Composition and Skyline Computation

The problem of QoS-based web service selection and composition has received a lot of attention during the last years. Local selection methods using techniques such as Simple Additive Weighting (SAW) were conducted to select services that ensure an optimal composition. However, local selection could not satisfy global constraints on the composition as it treats each service class individually. Zeng et al., (2003) tackled this problem using a global planning composition based on mixed integer Programming technique for dynamic and quality-driven selection. However, the costs of this approach are exponential in a large space. Linear programming methods are very effective when the size of the problem is small, but suffer from poor scalability due to the exponential time complexity of the applied search algorithms. In their work, Alrifai and Risse (2009) proposed a hybrid selection approach that combines local selection with global selection by decomposing global constraints into local constraints in order to find close-to optimal solutions. Canfora (2005) proposed a genetic algorithm to the QoS-based composition. Genetic algorithms are based on the evolution theory and in opposition to linear programming algorithms, the input data doesn't need to be linear. Besides, genetic algorithms are related to the number of service classes and not to the number of candidate web services, so they are more effective in a large space context. However, linear programming is proved to be faster than genetic algorithms and is preferred hence in a small space. Yu and Keiw-Jay (2004) proposed heuristic algorithms that can come as an alternative to exact solutions. The authors modelled the problem as combinatorial problem and proposed a heuristic Branch and Bound algorithm (WS HEU) and a heuristic graph model (MCSP-K). The two algorithms are proved to be more efficient than exact algorithms. Ardagna and Pernici (2007) tried to overcome the shortcomings of both local and global service composition by proposing an approach that addresses optimization problems under severe QoS constraints.

Skyline is a mechanism that interferes as a filter in the search space that would select only the interesting points. Hence, by discarding all the irrelevant data points, the number of possible combinations would be dramatically reduced. The analysis of the Skyline was originally considered as a mathematical problem. It was then introduced in the first place in the field of database. Given a set of points in d-dimensional space, the Skyline is defined as the subset containing the points which are not dominated by another point. Paradigms like Block Nested Loops (BNL) and Divide to Conquer are among the first attempts to solve the computing of Skyline. BNL algorithm uses a nested loop to compare the points. Divide to Conquer algorithm recursively divides the whole space into small sets (regions), calculates the Skyline for each region separately, and merge them in the final Skyline. BNL has proposed the Sort Filter Skyline (SFS) algorithm, which adopts a pre-sorting to improve the efficiency. SFS has also been improved by linear Elimination Sort Skyline (LESS), which operates on a small set of best data objects to remove other objects in the original passage of the external sort. The index structures such as B-trees have also been utilized to improve the performance of analyzing the Skyline. Nearest Neighbour (NN) and Branch and Bound Skyline (BBS) are two representative algorithms that can progressively address the Skyline based on R-tree structure. In recent works, many researchers focused on computing skyline services in the context of service composition. However, the majority of these works relied on Pareto dominance relationship for this purpose Alrifai et al., (2010), Chen (2014), Abourezk and Idrissi (2014). Pareto dominance has the shortcoming of neglecting the smoothness and fuzziness of human preferences. Benouaret et al. (2011) addressed this problem with a fuzzy dominance relationship. Fuzzy logic was addressed in the optimization techniques for service composition in many contributions such as those of Almulla et al., (2010), Torres et al., (2011), Xuan and Tsuji (2008) and Wang (2006).

2.2 Transactional-aware Service Selection

Due to the characteristics of web services including loosely coupled and heterogeneous nature, insuring a reliable execution of services becomes very challenging. Liu et al., (2006) proposed rules for ensuring transactional services in parallel and sequential compositions. Hadded, Manoeuvrier and Rukoz proposed in their leading study (2010) an algorithm combining QoS optimal web services selection with transactional constraints to generate transactional composite services. Bhiri et al., (2006) proposed an algorithm to check the validity of a composition according to the set of acceptable termination states of a transactional composite web service.

2.3 Fuzzy Similarity Measures

Fuzzy sets were introduced by Lotfi Zadeh (1965) as an extension of the classical notion of sets.

Fuzzy similarity measures are measures used to compute the degree of similarity between two fuzzy sets. The concept of similarity is interpreted in different ways depending on the context. The interpretation of similarity in everyday language is “having characteristics in common”. This interpretation of similarity differs from the one we use. We define similarity between fuzzy sets as the degree to which the fuzzy sets are equal. This definition is related to the concepts represented by the fuzzy sets. Fuzzy sets are considered similar if they are defined by overlapping membership functions that assign approximately the same values of membership to the elements in their universe of discourse. Their similarity is the degree to which they can be considered as equal.

3 DESCRIPTION OF THE PROPOSED APPROACH

In this work, in order to tackle the different challenges of service selection, we propose a system composed by mainly five steps as shown in Fig.1:

- First of all, users requirements on functional criteria and non functional criteria are collected. An initial set containing the deployed services that offer the required functionality with the required Quality of Service is given.
- We compute the Skyline services of our search space using fuzzy dominance relationship.
- We refine the output by determining the set of services that correspond the most to the user's preferences using Fuzzy Similarity Measures.
- Finally, we will select from the top-K services for each service class, the services that will guarantee a coherent execution according to transactional properties.

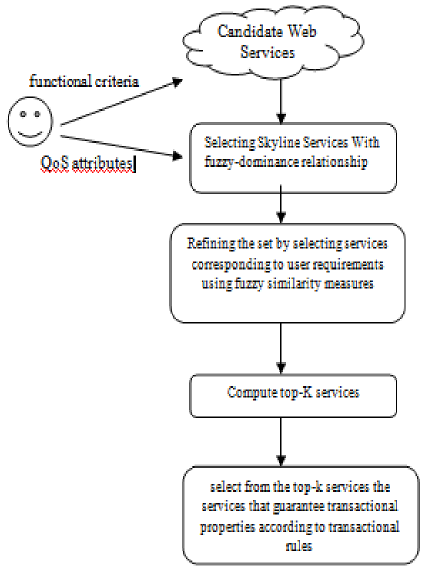

Figure 1: System Architecture.

3.1 Computing Service Skyline

The first step in our proposed approach is computing the set of skyline points from the search space. This step will enormously reduce the candidate services as it will select only the non-dominated services. Skyline can be formally defined as follows:

Given a set of points S in a space with D dimensions, Skyline points are the points who are not dominated by any other point in the search space according to those dimensions. A definition of the dominance concept is then crucial to the understanding of the skyline concept.

Pareto Dominance

Definition

Given d the number of dimensions in the space and s_i , s_j two web services in the space, we say that s_i dominates s_j denoted by $s_i \prec s_j$ *iff* s_i is at least as good as s_j in all the dimensions and strictly better in at least one dimension.

Illustrative Example

Let's consider the common example in the literature that selects the set of interesting hotels in a reservation service represented in Fig.2. The hotels are represented by two criteria: their prices and their distances from the beach. It is obvious that a hotel with a low price and a small distance from the beach is preferred in this case. According to this, the Skyline points are a, l and m as they are the only points that are not dominated by any other point in the search space.

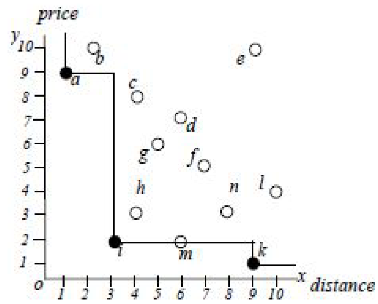

Figure 2: Example of Skyline Set.

Fuzzy Dominance

Given two points in a space with d dimensions, we can define the dominance relationship as follows:

$$\deg_{\mu_{\varepsilon,\lambda}}(s_i \prec s_j) = \frac{\sum_{m=1}^{d}(\mu_{\varepsilon,\lambda}(q_m(s_i), q_m(s_j))}{d} \quad (1)$$

With:

d : The space dimensions (i.e. the QoS attributes in our context)

s_i , s_j : two points in the search space

$q_m(s_i), q_m(s_j)$: The values of the m^{th} attribute for s_i and s_j respectively.

$\mu_{\varepsilon,\lambda}$: A fuzzy membership function that is defined as follows:

$$\mu_{\varepsilon,\lambda}(x,y) = \begin{cases} 0 \text{ if x-y} \le \varepsilon \\ 1 \text{ if x-y} \ge \lambda+\varepsilon \\ \frac{x-y-\varepsilon}{\lambda} \; otherwise \end{cases} \quad (2)$$

With $\varepsilon \ge 0$, $\lambda > 0$.

In this paper, we will compute Skyline services with fuzzy dominance relationship by the Fuzzy Branch and Bround Algorithm proposed in Rhimi, Ben Yahia and Ben Ahmed approach (2015). The proposed algorithm is a two-phase algorithm. The first phase consists in transforming the data points of the search space into a consistent fuzzy model. Branch and Bound Skyline is an algorithm suggested by Papadias (2003) based on R-Tree structure known for its efficiency and effectiveness in large spaces. It is widely used to reduce the search space. The second step is determining the Skyline points with a Branch and Bound algorithm according to the fuzzy dominance relationship.

3.2 Computing Similarity between Users Preferences and Services using Fuzzy Similarity Measures

In our work, we chose to model user's preferences with fuzzy sets as they are highly appropriated for expressing vagueness and smoothness in human linguistic terms. In fuzzy set and possibility framework, similarity of items is computed based on the membership functions of the fuzzy sets associated to the item features. Many Fuzzy Similarity Measures were introduced in literature Wu Zhang and Lu (2014), Zenebe and Norcio (2010). In our study, for services I_j and I_k, the following similarity measures between I_j and I_k denoted by $S(I_k, I_j)$ and are defined as:

$$S\ (I_k, I_j) = \frac{\sum_i \min(\mu_i(I_k), \mu_i(I_j))}{\sum_i \max(\mu_i(I_k), \mu_i(I_j))} \tag{3}$$

$$S\ (I_k, I_j) = \frac{\sum_i \mu_i(I_k) * \mu_i(I_j)}{\sqrt{(\sum_i (\mu_i(I_k))^2)}\sqrt{(\sum_i (\mu_i(I_j))^2)}} \tag{4}$$

$$S\ (I_k, I_j) = \frac{\sqrt{\sum_i (\mu_i(I_k) - \mu_i(I_j))^2}}{Max_i\{\mu_i(I_k), \mu_i(I_j)\}} \tag{5}$$

$$S(I_k, I_j) = 1 - \frac{2}{\sum_i (2*\mu_i(I_k) - 1)^2 + \sum_i (2*\mu_i(I_j) - 1)^2} * \sum_i (\mu_i(I_k) - \mu_i(I_j))^2 \tag{6}$$

Where $\mu_i(I_k)$ and $\mu_i(I_j)$ are respectively the fuzzy membership degrees of the ith QoS attribute of services I_k and I_j. These fuzzy set based similarity measures are: fuzzy set theoretic in (3), cosine in (4), proximity in (5), and correlation-like in (6).

The outcome of this step is a set of services that correspond the most to the user's constraints.

3.3 Transactional-aware Selection

In this section we will no more consider individual service classes. We will look at the whole service composition and try to insure a global optimal service selection.The description of the behavior of a web service composition is how atomic web services can be realized in terms of interactions with each other. In a composition where several WS components interact, unexpected behavior of a component WS can not only lead to failure but also can bring negative impact on all participants of the composition. The execution of a composite web service therefore requires transactional properties so that the overall coherence is insured. Based on the transactional properties and transactional rules of web services that have been defined in Hadded et al., (2010), we adopt the following definitions:

A web service is said to be retriable and we note it 'r' if it is sure to complete after a finite number of activations. It is said to be compensatable and we note it 'c' if it offers compensation policies to semantically undo its effects. Finally it is said to be pivot and we note it 'p' if once it successfully completes, its effects remain and cannot be semantically undone.

Now, we give the generalization of these properties for a composite web service (CWS) as defined by the authors.

A CWS is atomic if once all its component WSs complete successfully, their effect remains forever and cannot be semantically undone. Besides, if one component WS does not complete successfully, then all previously successful component WSs have to be compensated. we will note 'a' an atomic CWS . A CWS is compensatable and we note it 'c' if all its component WSs are compensatable.. An atomic or a compensatable CWS is retriable 'r' if all its components are retriable.

Finally, we define a Transactional Composite Web Service as a CWS whose transactional behavioral property is in {a, ar, c, cr.}

Hence, in order to insure a transactional Composite Web Service, the following rules should be considered in the selection process:

- A 'p' or 'a' WS can only be sequentially composed with a 'pr', 'ar', or 'cr' WS and can only be executed in parallel with a 'cr' WS.
- A 'pr' or 'ar' WS can only be executed in sequential or

in parallel with a 'pr', 'ar', or 'cr' WS.

- A 'c' WS can be sequentially composed with any transactional WS but can only be executed in parallel with a 'c' or 'cr' WS.
- A 'cr' WS can be executed in sequential or in parallel with any transactional WS.

In our approach, rules for insuring a successful termination of web services will be injected in the selection algorithm after the initial phases of local user-based optimization. Depending on the transactional properties of the WS we will select the candidates that insure a successful termination of the composition according to the rules. For sake of simplicity we will only consider a sequential workflow for our algorithm. We will let the parallel workflow for future work.

The description of the selection approach is given in algorithm 2.

Algorithm 2: TPAC (Transactional Preference- Aware Composition).

```
   Input:
   - Lists of top-k ranked concrete services
for each abstract service class computed by
Algorithm 2.
   -  composition workflow
   Begin
   // IAC: initial abstract class
   1. Select the first element of the list
of IAC
   2. found=0; i=0;
   4. For all the AC in the workflow:
   5.  If ( current WS  is  'p')
     6.  While (list_ next_ AC not empty and
found==0)
         7.if (element i of list is 'p' or
'a')
            8.  found=1;
         9.  Else  if ( current WS  is  'pr'
or 'ar')
              10.  While (list_ next_ AC and
found==0)
                  11.  if (element i of list
is 'pr' or 'ar' or 'cr')
                       12.  found=1;
                  13. Else  if ( current WS
is  'cr' or 'c')
                       14.Select  the  first
element of list_ next_ AC
   // can be composed in sequence with any
transactional WS
   15. END TPAC.
```

4 EXPERIMENTAL EVALUATION

4.1 Dataset and Experimental Setup

In our experiments, we adopt a real-world Web service dataset: WSDream dataset which is designed for QoS prediction approaches for Web service recommendation and adopted in many papers such as the works Zheng et al., (2014) (http://wsdream.github.io/dataset/wsrec_dataset1).

The dataset contains QoS records of service invocations on 5825 Web services from 339 service users, which are transformed into two user-service matrices: a response-time user-item matrix and a throughput user-item matrix. For studying the prediction accuracy, we divide the dataset into two parts, one part as training set and the other part as testing set. In order to carry the predictions, we randomly remove entries from the training user-item matrices. Different methods are employed for predicting the QoS values of the removed entries. The original values of the removed entries are used as the expected values to study the prediction accuracy. Each experiment is evaluated by 10 times 10-fold cross validation. The 339 service users are divided into two groups: 300 randomly selected training users and the rest as test users. In 10-fold cross validation, the training users are randomly partitioned into 10 subsets. The process is repeated 10 times to predict the missing QoS values of test users based on QoS values of the corresponding training users. For studying the time execution, we suggest a scenario of a sequential workflow with eight service classes, but we vary the number of services and the transactional properties of the web services. We measure the average execution time required to solve the composition problem of twenty executions.

4.2 Evaluation Metrics

The following metrics have been used in this study:

Statistical Accuracy Metric

We use Mean Absolute Error (MAE) metric to measure the prediction quality of our method with the different fuzzy similarity measures. MAE is defined as the deviation of recommendations from their true user specified values and given by:

$$\sum_{i=1}^{n} \frac{|p_i - q_i|}{n} \tag{7}$$

p_i being the predicted rating of the service, q_i the actual rating of the service and n the number of predicted ratings.

Recall, Precision and F1 Metrics

Recall is defined as the fraction of preferred items that are recommended. Precision is defined as the fraction of recommended items preferred by the user. The F1-measure, which combines precision and recall, is the harmonic mean of precision and recall.

In this experiment, a preferred rating threshold is predefined. The preferred services are the services in the test set whose actual ratings are greater than the preferred rating threshold. The recommended services are the services whose predicted ratings are greater than the preferred rating threshold. The recall, precision and F1 are defined as follows.

$$precision = \frac{|preferred \cap recommended|}{recommended}$$

$$recall = \frac{|preferred \cap recommended|}{preferred}$$

$$F1 = \frac{2 * recall * precision}{recall + precision}$$

4.3 Experimental Evaluation

Effect of Varying Fuzzy Similarity Measures on Prediction Accuracy:

We propose to study the effect of the similarity measure on prediction accuracy. For this purpose, we will compare the precision, recall, F1 and MAE of our approach when using fuzzy set theoretic, cosine, proximity and correlation-like measures.

Figures 3 and 4 show that for precision and recall, correlation-like method has the highest prediction accuracy. However Fig. 6 show that it has a high MAE. Proximity and cosine have stable results for all metrics, but cosine has the lowest MAE which proves its efficiency.

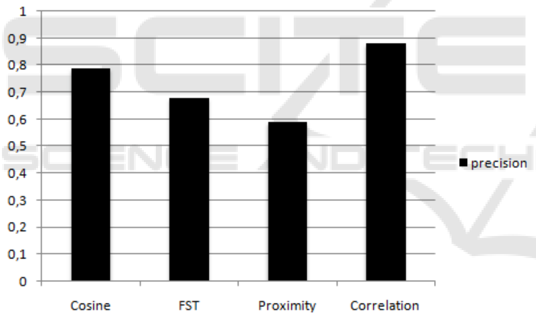

Figure 3: Precision of the different similarity measures.

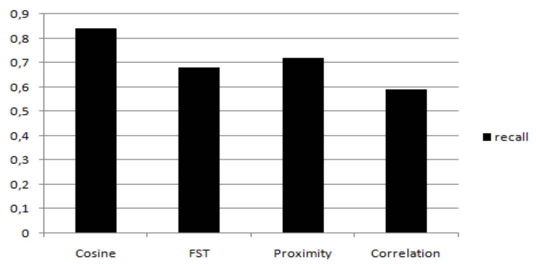

Figure 4: Recall of the different similarity measures.

Effect of Varying Number of Services Per Class on Time Execution:

We notice that the computation cost increases when the number of candidate services increases which can be explained by the number of possible combinations. However, we notice that time execution is still reasonable as there are different steps to reduce the number of possible candidates.

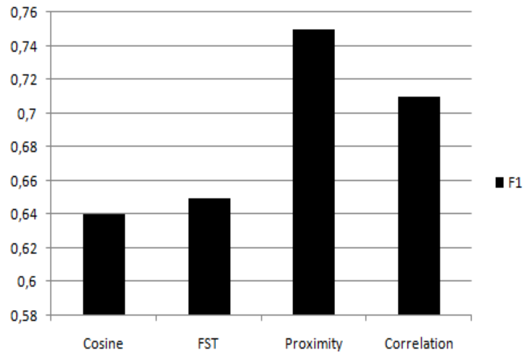

Figure 5: F1 of the different similarity measures.

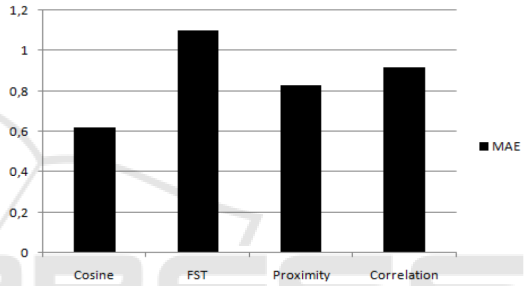

Figure 6: MAE of the different similarity measures.

Thus, it is clear that the utilization of user's preferences for pruning the services in the search space eases time-consumption during the generation of match results in the injection of transactional properties.

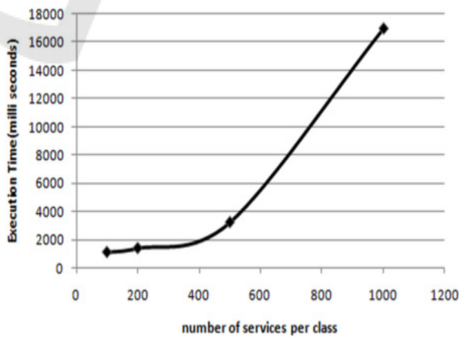

Figure 7: Execution time varying number of services.

5 CONCLUSIONS

In this paper, we proposed a new method for combining local and global web services optimization. Local optimization is given by including users preferences in the selection process. In fact, we suggest an approach that firstly computes the set of Skyline services using fuzzy dominance relationships. Then we refine the result according to the user's expressed preferences. Our approach first computes the similarity between the skyline services and the user request with fuzzy similarity measures.

Finally, global optimization represented in our study by successful termination of the composition is injected. We make sure that in the selection process, only candidates that guarantee transactional properties of web services are chosen. The results showed improvements in accuracy. We also proved that the approach is not time-consuming as many steps are used to prune that candidates.

In future work, we will study the injection of transactional properties in a parallel workflow with all possible combinations. We will also try to include global constraints on the QoS in order to insure global optimization from another perspective.

REFERENCES

Abourezk,M., A. Idrissi. "Introduction of an outranking method in the Cloud computing research and Selection System based on the Skyline", *IEEE Eighth International Conference on Research Challenges in Information Science*, 2014, pp. 1-12.

Almulla, M., K. Almatori and H. Yahyaou, "A QoS-Based Fuzzy Model for Ranking Real World Web Services. Web Services" 2011 *IEEE International Conference on Web Services*, 2011, .pp. 203 – 210.

Alrifai, M. and T. Risse, 2009. Combining global optimization with local selection for efficient qos-aware service composition. In *International World Wide Web Conference*.881–890.

Alrifai, M., D. Skoutas, and T. Risse," Selecting skyline services for qos-based web service composition" in *Proceedings of the International World Wide Web Conference*, 2010, pp. 11-20.

Ardagna, D., B.Pernici, 2007.Adaptive Service Composition in Flexible Processes. *IEEE Trans. Software Eng.* 369-384.

Benouaret, K., D. Benslimane, A. Hadjali, "On the Use of Fuzzy Dominance for Computing Service Skyline Based on QoS", In *the 9th International Conference on Web Services (IEEE ICWS 2011)*, 2011, pp.540-547.

Bhiri, S., O.Perrin and C.Gaudart, "Transactional Patterns for Reliable Web Services Compositions" in *Proceedings of the 6th International Conference on Web Engineering*, 2006, pp. 137-144.

Canfora,G., 2005.An approach for QoS-aware service composition based on genetic algorithms. *Proceedings of the 2005 Conference on Genetic and Evolutionary Computation*. 1069-1075.

Chen, L., "Ensuring reliability and qos optimizing for web service composition", *Computational Intelligence and Security Conference*, 2014, pp. 510-513, 2014.

Haddad,J. E., M. Manoeuvrier and M.Rukoz, "TQoS:Transactional and QoS-aware selection algorithm for automatic Web service composition", *IEEE Transaction on Service Computing*, vol. 3, pp. 73-85, 2010.

Liu,A., L.Huang and Q.Li, "QoS-Aware Web Services Composition Using Transactional Composition Operator" in *Proceedings of Web-Age Information Management Conference*, 2006, pp. 217-228.

Papadias,D., Y. Tao, G. Fu, "Progressive Skyline computation in database systems", *Journal ACM*.

Rhimi, F., S. Ben Yahia and S. Ben Ahmed, " Novel Approach for Computing Skyline Services with Fuzzy Consistent Model for QoS- based Service Composition", *International Joint Conference on Software Technologies*, 2015, pp. 135-143.

Torres, R., H. Astudillo, R. Salas, "Self-Adaptive Fuzzy QoS-Driven Web Service Discovery", *IEEE International Conference on Services Computing*, 2011, pp. 64–71.

Wang, P., K.M. Chao, C.C. Lo, C.L. Huang and Y. Li, "A Fuzzy Model for Selection of QoS-Aware Web Services", *IEEE International Conference on e-Business Engineering*, 2006, pp. 585-593.

Wu, D., G.Zhang, and J.Lu, "A Fuzzy Preference Tree-Based Recommender System for Personalized Business to Business E-Services", *IEEE Transactions on Fuzzy Systems*, Vol.23, pp. 29-43, 2014.

Xuan, V. and H. Tsuji, "QoS Based Ranking for Web Services: Fuzzy Approaches", *In the 4th International Conference on Next Generation Web Services Practices*, 2008, pp. 77 – 82.

Yu, T. and L.Kwei-Jay,Service selection algorithms for Services web withend-to-end QoS constraints, 2004. *Lin e-Commerce Technology Proceedings IEEE International Conference*.129 – 136.

Zadeh, L. A.. "Fuzzy sets". *Information and Control*, vol. 8, pp. 338-353, 1965.

Zenebe, A. and A.F.Norcio," Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems", *Fuzzy Sets and Systems*, vol. 161, pp. 3044-3063, 2010.

Zeng, L., B. Benatallah, M. Dumas, J. Kalagnanam, and Q. Sheng, 2003. Quality-driven Web Service Composition. In *WWW* 411-421.

Zheng, Z., Y.Zhang, and M.R. Lyu, "Investigating QoS of Real-World Web Services", *IEEE Transactions on Services Computing*, vol.7, pp.32-39, 2014.