Semantic Technology Recommendation Based on the Analytic Network Process

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***Abstract*—Semantic technologies have become widely adopted in recent years, and choosing the right technologies for the problems that users face is often a difficult task. This paper presents an application of the Analytic Network Process for the recommendation of semantic technologies, which is based on a quality model for semantic technologies. Instead of relying on expert-based comparisons of alternatives, the comparisons in our framework depend on real evaluation results. Furthermore, the recommendations in our framework derive from user quality requirements, which leads to better recommendations tailored to users' needs. This paper also presents an algorithm for pairwise comparisons, which is based on user quality requirements and evaluation results.**

I. Introduction

Semantic technologies provide new ways to express in machine processable formats knowledge and data that can be exploited by software, and we have seen an exponential growth of these technologies in recent years.

One of the characteristics of semantic technologies is the existence of several different types of technologies. It is often the case that when solving certain problems, users have to use various semantic technologies that belong to different types. In some cases, especially for less experienced users, selecting the right technologies for solving a problem can be a difficult task.

Multiple criteria decision making (MCDM) methods are widely accepted and have been used across various fields, including Software Engineering. These methods have also been successfully applied in software selection problems, which is regarded as an important and rather difficult problem, such as in the selection of ERP systems [1].

Different problems often require different system functionalities and one functionality might not be relevant for every problem. In MCDM recommendation frameworks, usually all functionalities are considered and, therefore, some functionalities that are not important for a problem are taken into account, which might lead to complexity and poor recommendations.

Furthermore, the comparison of alternatives is usually performed manually by a group of experts. In some cases, expert-based comparisons can be difficult because there are no experts that are familiar with every available alternative. Besides, the addition of new alternatives would require experts to perform additional comparisons.

Furthermore, expert-based comparisons are highly subjective and there are cases when we have objective evaluation results in which we can ground recommendations.

This paper presents an application of the Analytic Network Process (ANP) for the recommendation of semantic technologies. The recommendation framework is based on a quality model for semantic technologies, and the recommendations are based on user quality requirements.

The comparison of alternatives in our framework depends on real semantic technology evaluation results provided by the SEALS European project[1]. In this paper, we also present an algorithm for the comparison of alternatives, which uses those results together with user quality requirements.

The reminder of this paper is organized as follows. Section II presents the best-known MCDM methods. Section III gives an overview of the proposed recommendation framework, while Section IV describes the semantic technology quality model. Section V describes the ANP and, afterwards, an algorithm for pairwise comparisons based on quality requirements and evaluation results is presented in Section VI. Section VII presents in detail the ANP framework for the semantic technologies, while Section VIII gives an illustrative example. Finally, Section IX draws some conclusions and includes ideas for future work.

II. Related Work

When facing the complex decision of selecting the best solution between a group of alternatives that can be compared according to different conflicting criteria, decision makers use MCDM methods that help them to better structure the problem and make better decisions. In MCDM problems, alternatives represent concrete products, services or actions that will help in achieving a goal, while criteria represent the characteristics of the alternatives that are important for making a decision.

A large number of MCDM methods have been defined to date. However, no method is considered to be the best to be applied in every decision making problem [2]. Next, we describe the most relevant MCDM methods in the literature, and give examples of their use in the Software Engineering and in the semantic technology fields.

[1] http://www.seals-project.eu/

PROMETHEE methods [3] belong to a family of outranking methods which are based on preference analysis, and different PROMETHEE methods can be used depending on the goal to be achieved. Alternatives are compared using one of six types of preference functions for each criterion, and the results are synthesized into positive and negative outranking flows. The positive outranking flow of an alternative determines how much it dominates the others, while the negative outranking flow shows how much an alternative is dominated by the others; these positive and negative outranking flows can be synthesized into one final indicator.

One of the drawbacks of the PROMETHEE methods is that they do not include any particular procedure for the calculation of the importance (weights) of criteria [4], which is a key information needed for obtaining the outranking flows.

The Analytic Hierarchy Process (AHP) [5] is a well-known method developed by Thomas L. Saaty. It requires the formulation of the decision problem into a hierarchical structure of goal, criteria, and alternatives.

The key concept in the AHP is a pairwise comparison, which is used to determine the importance of the criteria, as well as to compare the alternatives according to each criterion. Saaty also provides a scale for pairwise comparisons, which consists of natural numbers ranging from 1 (equal importance) to 9 (extreme importance). If number x is assigned when comparing alternative a to b, then a reciprocal value ($1/x$) is assigned when comparing alternative b to a. Furthermore, Saaty developed a method for verifying the consistency of pairwise comparisons, which is regarded as the main advantage of the AHP [6].

The Analytic Network Process (ANP) [7] is another method developed by Saaty, which is a generalization of the AHP where the decision problem is formulated as a network of criteria and alternatives. The main difference between the ANP and the AHP is that the ANP is designed for those problems in which the criteria in the decision process depend on each other.

In recent years, we have seen applications of the PROMETHEE methods in Software Engineering, for example, in the selection of web services [8], [9]. The AHP has been adopted in many different fields because of its simplicity and ease of use, and it is described in the literature as one of the most widely used MCDM methods [10]. In the Software Engineering field, the AHP has been frequently used for software selection problems [11]. The ANP has also been applied successfully in various problems, including Software Engineering ones, such as the selection of ERP systems [12] and of web services [13].

In the semantic technology field, we have only found one example of applying MCDM methods. In her work, Mochól developed an AHP-based framework for manual and (semi-) automatic selection of ontology matching approaches [14].

Mochól's work is focused only on one specific type of semantic technologies, i.e., ontology matching tools, while in our case multiple types of technologies are taken into account simultaneously.

III. Overview of the Recommendation Framework

This section presents the overview of the software recommendation framework. Following a typical MCDM framework, alternatives would be a set of software products to be compared according to different software quality characteristics (i.e., criteria). Then, the output would be a ranking of alternatives.

Next, we present the differences of our framework (depicted in Fig. 1) compared to such typical approach.

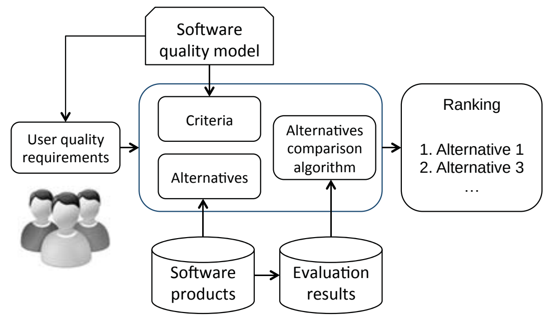

Fig. 1: Overview of the recommendation framework.

- *Software quality model.* When using a MCDM method in a software recommendation process, the criteria usually are software quality characteristics. Therefore, software quality models are a good starting point for the recommendation problem.

  In those cases where there are many dependencies among quality characteristics, which is usual in Software Engineering and in our case, it is recommended to adopt the ANP, to take advantage of these dependencies.
- *User quality requirements.* Usually, criteria that are taken into account in MCDM problems cover all the quality characteristics defined. In our case, solving a problem does not require every characteristic and, therefore, the criteria to take into account consist only of those specified by the user.
- *Alternatives.* In our framework, recommendation covers not one type of software product, but different types of products. User requirements can be satisfied either by a single product or by a combination of them. Therefore, an alternative consists of a combination of software products that together cover a set of common functionalities.
- *Comparison algorithm.* The comparison of alternatives is in most cases performed manually based on subjective opinions made by experts. In our case, the task of comparing the alternatives by experts is difficult because there are no experts with expertise in every software product type. Therefore, in order to overcome this problem and to enable the automatic comparisons, we propose an automated comparison algorithm that is based on evaluation results and user quality requirements.
- *Evaluation results.* For the previously mentioned algorithm a set of evaluation results for the different types of software products is needed. In our case, we use a

corpus of semantic technology evaluation results that have been produced in the SEALS project. These results cover five types of semantic technologies (ontology engineering tools, ontology matching tools, reasoning systems, semantic web services, and semantic search tools), which have been evaluated according to different characteristics (scalability, conformance, interoperability, accuracy, etc.).

IV. Quality Model For Semantic Technologies

In the Software Engineering field, software quality models provide a common framework for software quality specification and evaluation by specifying a consistent terminology for software quality and by providing guidance for its measurement.

Quality models consist of a hierarchy of quality characteristics, which are further decomposed into sub-characteristics. For every quality sub-characteristic, a quality measure or a set of quality measures is defined, which are used for measuring and provide insight of the particular sub-characteristic.

In the case of the AHP, which requires a hierarchical structure in the model, hierarchical quality models (e.g., ISO 9126 [15] or SQuaRE [16]) are very convenient, and different authors have used quality models based on the ISO 9126 together with the AHP [17], [18], [19].

In the semantic technology domain, a quality model for semantic technologies has been proposed [20], which extends the ISO 9126 quality model. The quality model describes 14 quality characteristics and sub-characteristics, and 55 quality measures. Furthermore, for every quality measure, a formula for its calculation is defined [21]; these formulas formally specify the dependencies between measures.

V. Analytic Network Process

The inputs in the ANP are the different alternatives and the set of criteria used to compare them, and the output is a ranking of the alternatives with respect to the criteria.

The ANP consists of several consecutive steps [7]:

1) The first step of a decision process is to define a model of a problem, and it is often referred as the most important step [22]. In the ANP, the model consists of a network of elements (criteria and alternatives) and of the dependencies between them. Elements are organized into clusters, and dependencies between clusters are also defined; these dependencies are deduced based on the existing dependencies between elements.
2) For the defined network, a supermatrix is formulated. The rows and columns of the supermatrix are related to the elements in the network, and are grouped into the corresponding clusters. This way, a supermatrix consists of several sub-matrices, each related to two clusters in the network. The entries of the supermatrix represent the influence priorities of one element over another, e.g., the entry in the *i*-th row and the *j*-th column represents the importance of the *i*-th element over the *j*-th element.
3) The influence priorities are calculated with pairwise comparisons, similarly as in the AHP. For every column in the supermatrix, a pairwise comparison is performed for every cluster in a row separately, and it includes only the elements that influence the one related to the observed column. The standard Saaty's scale for the pairwise comparisons [5] is used, and the eigenvector of the comparison is calculated. The results from the eigenvector are then inserted into the corresponding positions of a column in the supermatrix. If two elements are not connected, a zero is entered.
   In the ANP, criteria are also compared with respect to each alternative. In the pairwise comparisons, every criteria that contributes to a certain alternative is compared to determine the level of contribution to that alternative. The results are then entered as the corresponding elements in the supermatrix. This step is particularly significant when observing the influence of criteria on a single alternative.
4) As the supermatrix has to be stochastic (i.e., the sum in every column has to be one), it has to be weighted. This is done by determining the importance of each block of clusters in the supermatrix in a set of pairwise comparisons performed similarly to the previous step. Then, each entry in the supermatrix is multiplied with the importance of the block the entry belongs to.
5) The next step is the convergence of the weighted supermatrix. The weighted supermatrix is put to a power of an increasing number, until the limit supermatrix is obtained, i.e., that in which the values in every column are equal.
6) The ranking of the alternatives is obtained from the limit supermatrix. The value in every row that corresponds to an alternative represents the result for that alternative in the decision process, which is used to determine the order of alternatives. A higher value denotes a better result, and is used for sorting the alternatives from best to worst.

VI. Alternatives Comparison Algorithm

As presented in Section V, in the third step of the ANP alternatives are compared with respect to each criterion. In this section we present an algorithm for the automatic comparison of alternatives, which is based on the standard 1-9 Saaty's comparison scale.

The inputs of the algorithm are a threshold value t, extracted from the user quality requirements, and evaluation results for the two alternatives, a_1 with the result v_1, and a_2 with the result v_2. The output is a natural number on Saaty's scale, which tells to which degree one alternative is preferable over the other.

There are several cases, with respect to the four types of scale [23] for a quality measure:

- *Nominal scale.* Nominal scale is a type of scale in which results are descriptive labels with no significance of order. We distinguish two possible cases, depending on whether the evaluation result meets the threshold:
  - If only one result is equal to the threshold, e.g., v_1, when comparing a_1 to a_2 a value of 9 (extreme importance) is assigned and, according to the pairwise

comparison rule, a value of 1/9 is assigned when comparing a_2 to a_1.
  - If both results meet the threshold or none of them does, both alternatives are of equal importance. Therefore, a value of 1 is assigned in both comparisons.
- *Ordinal, interval or ratio scale.* Ordinal scale is a type of scale in which results are also descriptive labels, but with significance of order. In interval and ratio scales the results are numerical values and the difference between two results can be calculated. This leads to the following possible cases:
  - If v_1 is equal or better than the threshold, while v_2 is worse, a value of 9 is assigned when comparing a_1 to a_2, and a value of 1/9 when comparing a_2 to a_1.
  - If both alternatives are worse or better than the threshold, they are of equal importance with respect to the requirement. However, they are still compared, and a value of 5 (strong importance) is assigned when comparing the better alternative to the worst. Similarly as in previous cases, a value of 1/5 is assigned when comparing the worse alternative to the better.
  - If both results are equal, a value of 1 is assigned in both comparisons.

  In the ordinal, interval, and ratio scales, when comparing two values, the nature of the criterion determines which result is better. Two possible cases exist: higher-best scale, in which the higher value denotes a better result, and lower-best scale, in which the lower value denotes a better result.

VII. The ANP for Semantic Technologies

In this chapter we describe the particularities of the ANP with respect to the semantic technology domain.

A. ANP Network for Semantic Technologies

The quality model for semantic technologies provides a good starting point in defining the ANP network. In several consecutive steps, we transformed the quality model into the network:

1) Every quality measure from the quality model becomes an element of the network.
2) As every quality measure is used for measuring a sub-characteristic, the network elements are grouped into clusters, each containing those measures that are related to a certain sub-characteristic.
3) Based on the formulas for obtaining the quality measures, defined in the quality model, the dependencies between the measures are deduced. Every two dependent elements are then connected with an arc; the element where the arc begins depends on the element where the arc ends.
4) Based on the dependencies between elements, dependencies between clusters are defined in such a way that two dependent elements imply a dependence between their clusters.

Due to space reasons, we cannot present the whole network. Therefore, on Fig. 2 we present only one part of the network where seven quality measures are grouped into four clusters; dependencies between measures are represented with arcs.

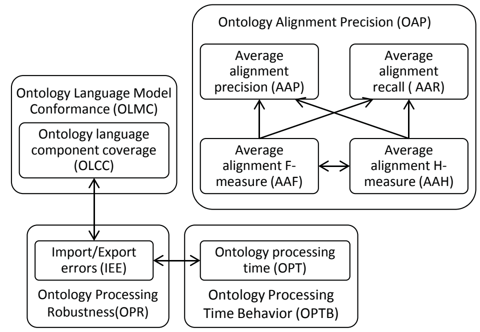

Fig. 2: Part of the semantic technology ANP network.

The network in this case consists only of quality characteristics (criteria), and alternatives are not included. The reason for this is that recommendations are based on user quality requirements, and alternatives are formed and inserted into the network only after the quality requirements are specified.

B. Supermatrix

Based on the previously defined network, a supermatrix was constructed. It consists of several sub-matrices where every sub-matrix is related to two clusters of the network, one at the left of the matrix and one at the top.

For every column in a supermatrix, influence priorities for the criteria were calculated in pairwise comparisons. This task, unlike the comparison of alternatives, was performed by a team of experts in semantic technologies. Every two elements in two rows within a certain cluster that have influence on an element in a column are compared in a pairwise comparison with the following question: "given an element in the column, which of the two elements in the rows has more influence?".

Table I shows an example of a pairwise comparison in which the priorities of measures with respect to *Average alignment F-measure* are calculated. We can see from the network (Fig. 2) that *Average alignment F-measure* depends on *Average alignment H-measure*, *Average alignment precision*, and *Average alignment recall*. Therefore, those three measures are compared in the pairwise comparison to determine their importance. For example, the *Average alignment precision* has a strong plus over the *Average alignment H-measure*, which implies the value 6 in their comparison.

Column *Importance* gives the overall importance for each measure. This comparison suggests that, e.g., *Average alignment precision* influences *Average alignment F-measure* with 0.462 degree of importance.

TABLE I: Pairwise comparisons of measures with respect to Average alignment F-measure.

AAF	AAP	AAR	AAH	Importance
AAP	1	1	6	0.462
AAR	1	1	6	0.462
AAH	1/6	1/6	1	0.076

Using the method provided by Saaty, we verified the consistency of every pairwise comparison in our supermatrix. The method is based on the calculation of the consistency ratio, whose value is limited to 0.1, and which is satisfied in all the pairwise comparisons performed.

Table II presents the part of the supermatrix that is related to the part of the network presented on Fig. 2. The priorities in the supermatrix were obtained through pairwise comparisons performed by experts, and we can see that the values obtained in Table I are inserted into the appropriate positions as a sub column in the supermatrix (column AAF).

TABLE II: Part of the supermatrix.

	OLCC	**IEE**	**OPT**	**AAP**	**AAR**	**AAF**	**AAH**
OLCC	0	1	0	0	0	0	0
IEE	1	0	1	0	0	0	0
OPT	0	1	0	0	0	0	0
AAP	0	0	0	0	0	0.462	0.462
AAR	0	0	0	0	0	0.462	0.462
AAF	0	0	0	0	0	0	0.076
AAH	0	0	0	0	0	0.076	0

The influence priorities of the clusters (i.e., of each block in a supermatrix) are calculated in an analogue way as the influences of their elements. Table III shows the priorities for the previously-presented part of the network.

TABLE III: Cluster priorities.

	OLMC	**OPR**	**OPTB**	**OAP**
OLMC	0	0.15	0	0
OPR	1	0.204	1	0
OPTB	0	0	0	0
OAP	0	0	0	1

VIII. Illustrative Example

In this section, we describe an example of using the proposed recommendation framework. In it, we assume that a user needs to modify existing ontologies (i.e., semantic models) and then match their concepts to other ontologies. For this task, two types of tools are needed, ontology engineering and ontology matching tools.

Table IV shows the user quality requirements in terms of a quality measure and a threshold, as well as the tools that at least cover one requirement; T1 and T2 are ontology engineering tools and T3 and T4 are ontology matching tools. The set of alternatives will consist of the four combinations of tools that cover every user quality requirement: T1+T3 (A1), T1+T4 (A2), T2+T3 (A3), and T2+T4 (A4).

TABLE IV: User requirements and alternatives.

Requirements		**Scale type**	**Tools**			
Quality measure	**Threshold**	**Higher/Lower best**	**T1**	**T2**	**T3**	**T4**
OLCC	80	Higher	85	70	/	/
IEE	3	Lower	5	2	/	/
AAF	0.75	Higher	/	/	0.8	0.74

The network related to this problem is that presented on Fig. 2, with the addition of one cluster related to all four identified alternatives. The part of the supermatrix related to the criteria is that of Table II, while the supermatrix of the complete problem is shown in Table V.

The values in the alternatives cluster of the supermatrix are obtained from the evaluation results; using the comparison algorithm presented in Section VI alternatives are compared according to each of the criteria from the user requirements.

For example, the comparison of alternatives according to *Ontology language component coverage* is shown in Table VI. A1 satisfies the requirement, while A3 does not and, hence, a value of 9 (extreme importance) is assigned when comparing A1 to A3. The overall importance of the alternatives according to the observed criteria is shown in the *Importance* column, and is entered in the corresponding column of the supermatrix.

TABLE VI: Alternatives comparisons with respect to OLCC.

OLCC	A1	A2	A3	A4	Importance
A1	1	1	9	9	0.45
A2	1	1	9	9	0.45
A3	1/9	1/9	1	1	0.05
A4	1/9	1/9	1	1	0.05

The weighted supermatrix is obtained by multiplying each element in the supermatrix with the importance of the cluster, after which a limit supermatrix is obtained. Every column in the limit supermatrix has the same values, which are shown in the *Limit supermatrix* column in Table V.

From the limit supermatrix, we can observe that the best alternative is A3 (with 0.074 score) and A1 (with 0.064) comes after. Both alternatives satisfy two requirements, and A3 is better with respect to *Import/Export errors (IEE)*, while A1 is better with respect to *Ontology language component coverage (OLCC)*; both are equal with respect to the *Average alignment F-measure*. However, since *Import/Export errors* is a characteristic more important than *Ontology language component coverage* ($0.346 > 0.184$) because of the dependencies in the network, A3 has a higher score.

Alternatives A4 and A2 satisfy only one requirement; therefore they are ranked as third and fourth respectively, where A4 is ranked better because it satisfies a characteristic that is more important (*Import/Export errors*).

IX. Conclusions And Future Work

This paper has presented a semantic technology recommendation framework, which is based on the Analytic Network Process. To apply the ANP to the semantic technology domain, we have defined the ANP network, which is based on a quality model for semantic technologies.

Having a quality model makes the definition of the network a straightforward task. Furthermore, the semantic technology quality model is a basis for the specification of quality requirements, and helps users to tailor the recommendation process to their needs.

This paper also describes an algorithm for the automatic comparison of alternatives in the ANP, and also in the AHP.

TABLE V: Supermatrix for the example.

	OLCC	**IEE**	**OPT**	**AAP**	**AAR**	**AAF**	**AAH**	**A1**	**A2**	**A3**	**A4**	**Limit supermatrix**
OLCC	0	1	0	0	0	0	0	1	1	1	1	0.184
IEE	1	0	1	0	0	0	0	1	1	1	1	0.346
OPT	0	1	0	0	0	0	0	0	0	0	0	0.12
AAP	0	0	0	0	0	0.462	0.462	0	0	0	0	0.017
AAR	0	0	0	0	0	0.462	0.462	0	0	0	0	0.17
AAF	0	0	0	0	0	0	0.076	1	1	1	1	0.064
AAH	0	0	0	0	0	0.076	0	0	0	0	0	0.002
A1	0.45	0.05	0	0	0	0.45	0	0	0	0	0	0.064
A2	0.45	0.05	0	0	0	0.05	0	0	0	0	0	0.05
A3	0.05	0.45	0	0	0	0.45	0	0	0	0	0	0.074
A4	0.05	0.45	0	0	0	0.05	0	0	0	0	0	0.060

This algorithm is domain independent and can be used in other scenarios in which evaluation results are available.

The comparison of alternatives in our framework is based on real evaluation results. New results and alternatives can be easily included in the framework, without the long process of expert-based comparisons required by the ANP.

Evaluation results are currently available only for individual tools. A future line of work is to specify new evaluations and obtain results for combinations of tools, i.e., for whole alternatives.

In the interval and ratio scales, the distance of the evaluation results form a threshold can be precisely calculated. Therefore, the alternatives comparison algorithm can be improved to take into account those distances.

The network and the supermatrix in our framework are made by experts in the semantic technology field. However, we plan to perform a validation with a broader group of experts and, in case of changes, to provide a way of easily updating the network and the supermatrix.

Future work also includes the implementation of the proposed framework in a web application. This will give users an easy access to a system that will help them in choosing the best semantic tools for solving the particular problems they face.

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