An Intelligent Decision Support System for IT Outsourcing

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Abstract. Outsourcing information technology (IT) is a major contemporary strategic decision. This paper proposes an intelligent decision support framework for effective IT outsourcing management. The proposed framework uses case-based reasoning as the main intelligent technique and integrates rule-base reasoning and compromise programming techniques in fuzzy environment for a real-time decision-making. While integrating different methodologies, our motaivation is to take the advantage of their strengths and cancel out each other's weaknesses. The framework potentially leads to more accurate, flexible and efficient retrieval of alternatives that are most similar and most useful to the current decision situation. Finally, a real-life case is given to validate the feasibility of the proposed framework.

1 Introduction

Throughout the past 25 years of rapid advances in information technology (IT), most businesses have realized the strategic role and competitive advantage IT can provide to an organization. Many companies see opportunity to cut IT costs while still maintaining the benefits of technology by downsizing the IT function and outsourcing it to firms that specialize in operating IT efficiently and reliably. Outsourcing IT can include mainframe and data centers, wide area networks, applications development and maintenance functions, end-user computing and business processing [10]. A decision to outsource is driven by numerous factors, from a desire for cost-cutting or managing legacy systems, to the desire to focus on the core business, enable rapid business change or expansion, or obtain strategic advantage by keeping up with ever changing technology [9, 16, 17, 27]. Two themes in the IT outsourcing research have attracted interest among the researchers: (1) the reasons for, the benefits and risks of outsourcing decision (make or buy), (2) the selection of a partner for the outsourcing relationship. This study focuses on the latter. Prior research discusses partner or supplier selection in various ways. The most common approaches and methods for supplier evaluation include different multi criteria decision-making (MCDM) methods such as analytic hierarchy process [14] and analytic network process [15], statistical techniques such as principal components analysis and factor analysis [4],

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data analysis techniques such as cluster analysis, discriminant analysis, data envelopment analysis [20] and simulation [24]. In this study, we develop an intelligent decision support (IDS) framework based on case-based reasoning (CBR) in fuzzy environment for effective IT supplier evaluation and selection. The proposed framework also integrates rule-base reasoning (RBR) and compromise programming techniques in fuzzy environment to deal with uncertain and imprecise decision situations. CBR is a good concept to transform the evaluation know-how from experts into a computer-assessment method to make the evaluation process more convenient and efficient [6]. It can capture all 'memory' of human being without losing them due to lapse of time and carelessness. Data processing procedure is the heart of CBR system, which guides the way to succession. Lack of a good information flow could let the system misunderstand how to store the cases and make use of them for decision-making [5]. In addition, CBR method alone in context-aware systems may not work as expected because it is highly possible to have a high number of items or variables to consider. That is, as the system becomes more realistic, the number of items, consequently the volume of the context tends to increase. Moreover, as the system increases the sensitivity, more contextual information can be newly involved. In that case, the number of criteria will exponentially increase, which will adversely affect system feasibility and hence performance. Thus, some supplemental methods to determine weights among the items need to be combined with the CBR method [7, 8]. For this reason, fuzzy logic and RBR concepts are merged into proposed CBR system. Fuzzy logic is a formal tool eminently suited for solving problems with imprecision inherent in empirical data [11]. RBR is a natural knowledge representation, in the form of 'If…Then.' structures [19]. It consists of an inference engine and assertion, which is employed for interpreting sets of facts and rules. In order to simultaneously improve searching speed and accuracy, we also integrate a particular multi criteria decision-making technique, more precisely compromise programming, with learning methodologies. Common tasks involved in these methodologies are considered and the manner of how to combine different techniques to build an IDS model is explored. The remainder of the paper is organized as follows. Section 2 describes the main points of the proposed IT outsourcing decision support model while Section 3 presents its implementation in a Turkish company. Concluding remarks are given in Section 4.

2 The Proposed IT Outsourcing Decision Support System

2.1 The Proposed Framework and Utilized Techniques

In the IT outsourcing decision support system, the description of previous IT outsourcing evaluation and selection processes and results, serves as the central link of decision support for the decision maker. The framework is constructed to assist IT customers on formulating IT outsourcing decisions involves three main sub-systems. Thus, customers define their service and strategic preferences through a hybrid CBR, RBR and fuzzy compromise programming approach. The IDS system's initial input is the IT service request of customer. It aims to eliminate the unnecessary data, which is not valuable for the given request. The usefulness of data is defined by its similarities to the customer requirements. Thus, our framework primarily requires that the customer defines the degree of importance of the strategic level evaluation criteria. This is the distinguishing part of our model, since many CBR and RBR applications [5, 7] require case features in this stage of the decision-making problem instead of customer preferences. The importance weights of the strategic level criteria are evaluated by the customer and then carried as input to the first rule-based sub-system. This sub-system enables an initial elimination of the cases in the case base regarding their similarities to the requested case considering their strategic ratings.

In a second elimination, the customer's IT service specifications, namely the requested case features are considered. In a similar fashion, the remaining cases in the case base are reexamined to remove the ones that are irrelevant. For instance, this second rule-based sub-system prevents dealing with mainframe service cases when the customer looks for an IT management and support service.

The final assignment before entering to the CBR cycle is the determination of importance of IT business service levels, which will be the input of the CBR sub-system. The first stage of the CBR cycle is the representation of the cases and, the next stage involves the measurement of similarities between the requested (new) case and each case already in the case base. Our framework makes use of the fuzzy compromise programming approach to calculate these similarities. The case(s) with the minimum distance value is (are) the most similar case(s) to the new case; therefore recently proposed solutions can be applied to the new problem. The CBR cycle ends with the adaptation of this case, if confirmed, into the case base.

Before giving the evaluation criteria of the proposed framework, techniques used in IDS system are briefly presented in the following sub-sections.

2.1.1 Rule-Based Reasoning (RBR) and Case-Based Reasoning (CBR)

RBR and CBR are two of the problem solving methodologies of Artificial Intelligence (AI). CBR, rooted in early 1980s, provides a theoretical basis and application method for human analogy, with many distinguishing features from other major AI methods. The main characteristic is that CBR enables to make use of the specific knowledge by remembering a previous similar situation and by reusing information and knowledge of that situation. It is an alternative approach to RBR where the knowledge is expressed with the rules. On contrary, major AI techniques rely solely on general knowledge of a problem domain or they establish generalized relationships between problem descriptors and conclusions [1]. As a result, CBR is recommended to developers trying to reduce the knowledge acquisition task, avoid repeating mistakes, learn over time, and maybe most significantly reason with incomplete or imprecise data [21]. It is difficult to assume that CBR is a concept completely different from RBR. In fact, some researchers present CBR as a specific type of RBR [5], while others define RBR as an alternative to CBR [18]. RBR represents knowledge using "If-Then" rules. This characteristic of RBR systems renders them poor at dealing with vague nature inherent in the IT service provider selection. The most significant difference between the CBR and RBR processes is their performance in learning duration curve. Since in CBR, the decisions are made according to previous cases, the system requires an amount of time for accumulating a sufficient number of cases. However, the performance of the RBR is always the same, as the decisions are made concerning only the predetermined rules [5]. The initial step of a CBR system is the representation of cases. A case should contain the composition of the problem, its solution and the outcome; namely both the content and the context. The case is a data format containing words, numbers and symbols to represent solutions and a state of affairs [8]. The cases are stored in a case base and each case is represented with a set of attributes for an effective storage during matching process. Another advantage of using discrete and standard attributes is that they preclude the subjectivity when defining a case. These attribute values are useful during the case retrieval stage when analyzing the similarities between the new case and the old ones. Among the steps of the CBR cycle, case retrieval is the key challenge, since a CBR system is not a valuable methodology without effective case retrieval. The similarity measure used to quantify the degree of resemblance between a pair of cases plays a very important role in case retrieval. Hence, CBR systems are sometimes called similarity searching systems [18]. In this study we propose to use the compromise programming technique as a distance-based approach for similarity identification.

2.1.2 Compromise Programming

Initially proposed by Zeleny [28], compromise programming is a distance-based MCDM approach and it is viewed as an effort to approach or emulate the ideal solution as closely as possible. It defines a metric as the distance of the alternatives from an ideal solution, where each alternative under consideration reaches its optimum value. Consequently, a rational decision maker should select the alternatives that are closer to the defined ideal solution than those that are farther. Recently, a compromise ranking method (known as VIKOR) is introduced as one applicable technique to implement within MCDM [23]. VIKOR method provides a maximum group utility for the majority and a minimum of an individual regret for the opponent. It introduces the multi-criteria ranking index based on the particular measure of closeness to the ideal solution. The details of this method can be found in [23, 26]. Within the VIKOR method, the distance is formulated as below

$$S_j = \sum_{i=1}^{n} w_i \left(f_i^+ - f_{ij}\right) \Big/ \left(f_i^+ - f_i^-\right), \tag{1}$$

$$R_j = \max_i \left[w_i \left(f_i^+ - f_{ij}\right) \Big/ \left(f_i^+ - f_i^-\right) \right], \tag{2}$$

$$Q_j = v\left(S_j - S^+\right) \Big/ \left(S^- - S^+\right) + (1-v)\left(R_j - R^+\right) \Big/ \left(R^- - R^+\right) \tag{3}$$

with $S^+ = \min_j S_j$, $S^- = \max_j S_j$, $R^+ = \min_j R_j$, $R^- = \max_j R_j$. Here, w_i are the associated weights of each of the objectives i; f_{ij} is the objective value of the jth alternative in ith objective; f_i^+ and f_i^- are the best and worst possible solution of the alternatives in the objective space; S_j and R_j values represent the average and the worst group scores for alternative j respectively. Finally, v is the weight of the decision-making strategy "the majority of criteria" (or "the maximum group utility"). The compromise Q_j can be selected with "voting by majority" ($v > 0.5$), with "consensus" ($v = 0.5$), or with "veto" ($v < 0.5$). Incorporating fuzzy arithmetic within the general framework of composite programming necessitates the use of fuzzy numbers for the ideal and anti-ideal points, as well as, to the outcomes of the objective functions. Consequently, the equations 1-3 are written as follows,

$$\tilde{S}_j = \sum_{i=1}^{n} \tilde{w}_i \left(\tilde{f}_i^+ - \tilde{f}_{ij}\right) \Big/ \left(\tilde{f}_i^+ - \tilde{f}_i^-\right), \tag{4}$$

$$\tilde{R}_j = \max_i \left[\tilde{w}_i \left(\tilde{f}_i^+ - \tilde{f}_{ij}\right) \Big/ \left(\tilde{f}_i^+ - \tilde{f}_i^-\right) \right], \tag{5}$$

$$Q_j = v\left(\tilde{S}_j - \tilde{S}^+\right) \Big/ \left(\tilde{S}^- - \tilde{S}^+\right) + (1-v)\left(\tilde{R}_j - \tilde{R}^+\right) \Big/ \left(\tilde{R}^- - \tilde{R}^+\right). \tag{6}$$

In our case, we try to find the alternative with the minimum distance to the ideal point, thus, we will choose the smallest Q_j value among the ones obtained by equation 6. The fuzzy subtractions used in this formula are calculated using the distance formulation proposed in [3].

2.2 IT Supplier Evaluation Criteria

A set of evaluation criteria has to be defined in advance to determine the IT service provider who offers the best all-around package of products and services for the customer. Traditionally suppliers focused on a technical output evaluation, in terms of quality, delivery speed and reliability, price offered, but when the relationship becomes closer and longer, the number of selection criteria increase, and suppliers are selected on their global performances. Global evaluations range from total costs analysis to the consideration of supplier's capacity, their future service capability or the closeness of the relation and continuous improvement capabilities. In strategic evaluations technological, financial and organisational capabilities are considered together with technological and strategic coherence [2, 12, 13, 22, 25].

Based on these emphasized different factors, two groups of evaluation criteria are determined and used in our proposed framework. The first group focuses on the strategic aspects of the IT service provider companies and identifies them as follows [25]: financial stability, successful track record, similar size, comparable culture, similar values and goals, and fit to develop a sustainable relationship. The second group of evaluation criteria is developed to measure important aspects of the supplier's business in five main groups: technical expertise, performance, quality, total cost and intangibles. By using these two groups of criteria, we created an IT service provider evaluation system as explained in detail in the case study.

3 A Case Study

The XYZ Company is a part of an important group in Turkey, which consists of 14 companies, each spread over some sectors. In 2005, the board of directors decided that the companies should outsource their IT service needs to reap various benefits, from cost savings to increased flexibility, and from improved quality of services to better access to state-of-the-art technology. For this reason, a prototype tool is developed to solve the IT outsourcing decision problem of this company. We proposed to establish a common knowledge base, which will benefit from the past experiences of each company. Such a knowledge base would provide companies the information necessary when signing contracts with IT firms.

3.1 Case Representation

Case representation and organization is the key part of a CBR and RBR system in each stage of the methodology. A case includes not only the concrete features such as its category, its region or its duration but also strategic and business related features. Each case should be defined in respect to three main categories of features:

- *General case features:* Main service category, Sub service category, Service scale, Technical capacity, Price, Duration, Personal qualification, Region.
- *Strategic case features:* Similar values and goals, Similar size, Financial stability, Comparable structure, Successful track record, Fit to develop a sustainable relationship.
- *IT business case features:* Technical expertise, Performance, Total cost, Quality, Intangibles.

3.2 Identification of Strategic Evaluation Criteria and Case Features

In the following part of the section, we have chosen an illustrative example to clearly show the application of the model with the developed tool. The tool is made as user-friendly as possible, to facilitate its use to personnel from different backgrounds. Figure 1 depicts the initial front end where the customer is expected to give his/her IT service requests' importance degree. At this point, we assume that the decision makers (customers in our case) use linguistic terms in the following set to express the importance of criteria: W = {Absolutely Important, Very Strongly Important, Strongly Important, Moderately Important, Important}. These weights are then quantified with fuzzy numbers.

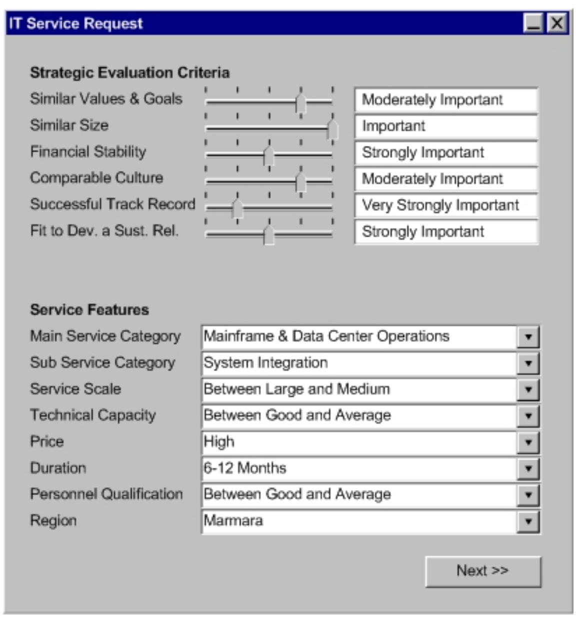

Fig. 1. The first user interface of the developed decision support tool

As an illustrative case, we have chosen a system integration service request for mainframe and data center operations of a high price and between large and medium scale, with between good and average personnel qualification and technical capacity, whose duration is between six-twelve months in the region Marmara. Besides for this service, the successful track record is defined as very strongly important, the financial stability and the development of a sustainable relationship is defined as strongly important, having comparable culture and similar values and goals as moderately important, while being similar size with the outsourcing company as important.

3.3 Case Retrieval in RBR

The interviews performed with several company experts have directed us to integrate a rule-based elimination stage in respect to strategic criteria; since the majority of the experts have stated that the strategic criteria are the most significant indicators in the selection process. The criteria values evaluated in the previous stage are utilized to compose the first rule:

If ((*OldCase*(*i*)..*SimilarValuesGoalsValue* < *Moderately important*) *and*
(*OldCase*(*i*).*SimilarSize* < *Important*) *and*
(*OldCase*(*i*).*FinancialStabilityValue* < *Strong important*) *and*
(*OldCase*(*i*).*ComparableCultureValue* < *Moderately important*) *and*
(*OldCase*(*i*).*SuccessfulTrackRecordValue* < *Very strongly important*) *and*
(*OldCase*(*i*).*FitToDevelopRelationshipsValue* < *Strongly important*))
Then Disregard (*NewCase*)

For the second rule-base sub-system, the cases are again eliminated, but this time in a more strict way according to their features. The second rule written for the illustrative example is

If ((*OldCase*(*i*).*MainCategory* ≠ *Mainframe & Data Center Operations*) *and*
(*OldCase*(*i*).*SubCategory* ≠ *System Integration*) *and*
(*OldCase*(*i*).*Scale* ≠ *Between Large and Medium*) *and*
(*OldCase*(*i*).*TechnicalCapacity* ≠ *Between Good and Average*) *and*
(*OldCase*(*i*).*Price* ≠ *High*) *and*
(*OldCase*(*i*).*Duration* ≠ (6-12 *months*)) *and*
(*OldCase*(*i*).*PersonnelQualification* ≠ *Between Good and Average*) *and*
(*OldCase*(*i*).*Region* ≠ *Marmara*))
Then Disregard (*NewCase*);

3.4 Case Retrieval in CBR

The intelligent decision support tool, developed using SWI Prolog environment, enabled to diminish the search space to find the matching cases by means of these two consequent RBR sub-systems. In the next stage, namely the CBR sub-system, the customer is expected to determine the performance values that s/he required. Hence, the next sub-system illustrated in Figure 2 demands from the customer the degree of importance and the ratings of each IT business evaluation criterion.

In the example, the customer have stated that when deciding on a IT service, the technical expertise is strongly important, the performance and the intangible factors are moderately important, the total cost is very strongly important and the quality of the service is strongly important for her/him. These evaluations enable the tool to calculate the importance weights of each IT business criteria as given in Table 1.

Table 1. The importance weights of IT business criteria

	Linguistic assessment	Logistics business criteria weights
Technical Expertise	Strongly important	(0.122, 0.219, 0.409)
Performance	Moderately important	(0.098, 0.188, 0.364)
Total cost	Very strongly important	(0.146, 0.250, 0.409)
Quality	Strongly important	(0.122, 0.219, 0.409)
Intangibles	Moderately important	(0.098, 0.188, 0.364)

Following the weighting of the business criteria, the customer is expected to evaluate the performance of these criteria. For our example, these values are determined as, total cost should be in very strong level, technical expertise and intangibles should be in strong level, the quality should be in average level and the performance should be in sufficient level. This is the ideal solution for the MCDM. The aim of the CBR sub-system is to find the most similar cases to this ideal solution using the importance weights when measuring the distance.

In the last part, the intelligent decision support tool measures similarities using the fuzzy compromise programming and it gives a performance value to each one of the cases. Figure 2 shows the most similar cases, in other words the cases with the lowest

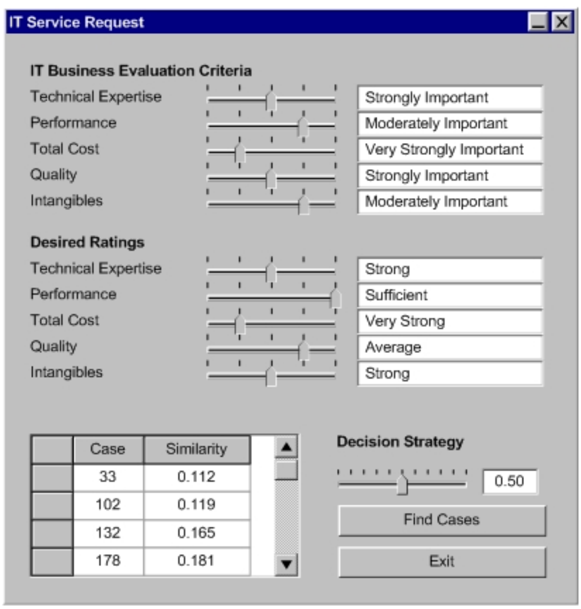

Fig. 2. The second user interface of the decision support tool

distances from the desired (ideal) case. In our application, the case # 33 is lowest value, which implies the highest similarity.

4 Conclusions

This paper proposes an IDS model for an effective IT supplier evaluation and selection. The proposed framework use CBR as the main intelligent technique and integrated RBR and fuzzy compromise programming techniques for real-time decision-making involving uncertain and imprecise decision situations. The details of the methodology are given within an application of IT outsourcing supplier selection for a Turkish company. In conclusion, the results and benefits of the proposed framework can be summarized as follows: faster reaction to a change in the IT activity requests and in the importance degrees of supplier evaluation criteria, a decrease in the decision-making time in IT outsourcing, the right choice of suppliers and the retention of supplier intelligence in IT outsourcing management. Further development of the framework in the connection of other AI techniques (such as neural network) to become a hybrid AI approach is worthwhile direction in this field.

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