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Partner selection in virtual enterprises: a multi-criteria decision support approach

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Partner selection in virtual enterprises (VE) can be viewed as a multi-criteria decision making problem that involves assessing trade-offs between conflicting tangible and intangible criteria. In general, this is a very complex problem due to the dynamic topology of the network, the large number of alternatives and the different types of criteria. In this paper we propose an exploratory process to help the decision-maker obtain knowledge about the network in order to identify the criteria and the companies that best suit the needs of each particular project. This process involves a multi-objective tabu search metaheuristic designed to find a good approximation of the Pareto front, and a fuzzy TOPSIS algorithm to rank the alternative VE configurations. In the exploratory phase we apply clustering analysis to confine the search according to the decision-maker beliefs, and case base reasoning, an artificial intelligence approach, to totally or partially construct VEs by reusing past experiences. Preliminary computational results clearly demonstrate the potential of the approach for practical application.

Keywords: virtual enterprises; cluster analysis; case base reasoning; multi-objective tabu search; TOPSIS

1. Introduction

A virtual enterprise (VE) can be defined as a temporary alliance of independent and geographically dispersed enterprises set up to share skills or core competencies and resources, in order to respond to business opportunities, with the cooperation among the enterprises being supported by computer networks (Camarinha-Matos and Afsarmanesh 2005).

In a virtual enterprise (VE), partner selection is a particularly difficult problem because of the short life-cycles of these organisations (temporary alliances) and because of the lack of formal mechanisms (contracts) to assure participants responsibility. According to Mowshowitz (1994), the functioning of virtual enterprises follows the switching principle since connections among members are switched on and off when needed. Reactivity and flexibility are the major benefits of this type of approach but, at the same time, the main problems of VE (Gunasekaran *et al.* 2008).

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The creation of a VE is usually triggered by a market opportunity, giving rise to a 'project' that is usually decomposable in relatively independent sub-projects or activities. The work needed to 'fulfil' a project involves a set of collaborative activities and the cooperation relationships established can be represented by an activity network.

In this setting, the evaluation and selection of the right partners is a crucial process. It is a difficult problem due to:

(1) The complex interactions/connections between the different entities (the design problems are known to involve multiple objectives and constraints);
(2) The highly dynamic supply chain (SC) network structure (resulting from the frequent changes in its composition and because the criteria for partner selection can be entirely different from one project to the next);
(3) The fact that the expression of the entities' preferences may be partially based on incomplete or non-available information.

The dynamic aspects of the SC network result from the willingness to be responsive to the needs of the market and at the same time to satisfy the various constraints of the network. To deal with this problem under a multi-criteria perspective, we allow several types of information (numerical, interval, qualitative and binary) in order to facilitate the expression of the stakeholders' preferences or assessments about the potential partners. This is an important requirement in practice as the multiplicity of factors considered when selecting partners for a business opportunity, such as cost, quality, trust and delivery time, cannot be expressed in the same measure or scale.

In general, the partner selection problem consists of exploring the available data in order to obtain a given classification, ranking or sorting of the candidates. The use of rankings to recommend candidates is very common (see, e.g., Büyüközkan *et al.* 2008), but according to Munda (2005) rankings are not always trustable, because the results obtained depend, for example, on the quality of the information available, on the set of criteria/indicators used to represent the reality, on the direction of each objective/indicator (maximising or minimising), on the relative importance of these indicators and on the ranking methods themselves. The quality and features of the whole process are very important to guarantee consistency between the adopted assumptions and the ranking obtained. In fact, the quality of the decisions depends crucially on the way the methodology handles the various dimensions (social, political, economical, technical, etc.) taken into account during the problem structuring stage. This is the reason why Roy (1996) claimed that what is really important is the decision process and not the final solution. In our opinion both are important, since the quality of the resulting virtual enterprise is somehow a consequence of the quality of the process.

One firm may be more effective, feel more secure or reliable when collaborating with a specific company or group of companies. Therefore the selection of partners is partially based on some non qualitative and even subjective information about the network and its members. In practice, it is often desirable that the companies that will perform a specific project are similar in some aspects (for example, in terms of organisational culture or IT usage) and complementary in others (for example, leadership skills, market knowledge or technological strengths). Therefore, we claim that decision support in this domain should combine a learning/exploratory process about the enterprise's relations with an algorithm that explores and ranks alternative VE configurations. However, knowledge acquisition can take a rather long time or can lead to significant errors arising from the incompleteness or vagueness of the data. In such situations and when historic data exists from previous collaboration experiences, it will surely be useful to analyse past successful similar partnerships to check if all or part of the partners are adequate to work together again in the new project. Carefully looking to the past will also avoid repeating mistakes in terms of VE formation and improve the knowledge about the network and its members.

Ha and Krishnan (2008) briefly survey several analytical methods used in the supplier selection process, as reported in the literature. Some of these approaches are more adequate for the pre-qualification of suitable suppliers (e.g., categorical methods, data envelopment analysis (DEA), cluster analysis, and case-based reasoning systems) and others for making the final partner choice (such as linear weighting, total cost of ownership, mathematical programming, statistical, and artificial intelligence-based models). Moreover, the authors believe that combining multiple techniques is in general more efficient for partner selection. In the literature, the most used approaches are combinations of analytical hierarchy process (AHP) with mathematical programming (Xia and Wu 2007), or multi-objective mathematical programming (Demirtas and Üstün 2008) with fuzzy theory (Cao and Zhou 2006), ant colony optimisation (Kang *et al.* 2007) or data envelopment analysis (Chen *et al.* 2007).

In this work the focus was rather in developing a flexible decision support approach to help the decision-maker (DM) during the partner selection process, including an exploratory phase that improves knowledge about the network, participants and criteria.

Our approach is based on a flexible hybrid algorithm that uses a multi-objective tabu search metaheuristic (MOTS) combined with the TOPSIS technique, in a fuzzy environment. This algorithm comprises three phases: exploration, searching and ranking.

The flexibility of the approach comes from the possibility of choosing different objectives and constraints for each project, from not having to weight criteria at the first steps of the method, and from the variety of possible variable types that the DMs can use to express their preferences. In previously published works, flexibility is small because the models are adjusted to a network with specific characteristics, e.g., operational costs (Ma *et al.* 2007) or risk factors (Li and Liao 2007). Moreover, when we look at other methodologies that have been applied to solve the partner selection problem, such as mathematical programming (Dotoli *et al.* 2006) or fuzzy mathematical programming (Araz *et al.* 2007), where the decision problem is formulated using mathematical expressions, flexibility is smaller because the decision environment can change significantly.

Another interesting feature of the developed optimisation approach is that it can be used as a black box based on a set of simple concepts (e.g., alternatives solutions are created by changing partners at a time). The user has just to specify the criteria (objectives, constraints and weights), to confine the search and, finally, to follow the obtained ranking. The major difficulty he/she has to face comes, in our opinion, from the demanding task of expressing preferences about the network members for each criterion. However, the use of a different type of variables can somehow simplify this task.

In general the DM has to define the weights of each criterion (see, e.g., Lin *et al.* 2007, Sari *et al.* 2007, Büyüközkan *et al.* 2008) as input data to the model, in a phase where not all relevant information is available or trustable. Moreover, the decision-maker's objectives and aspirations may change during the stage when the decision process is being structured. We believe that it is difficult for the DM, in this early phase where the solution space can be quite vast, to set weights on a realistic level and to understand the interdependencies among the objective functions. Different weights provide different

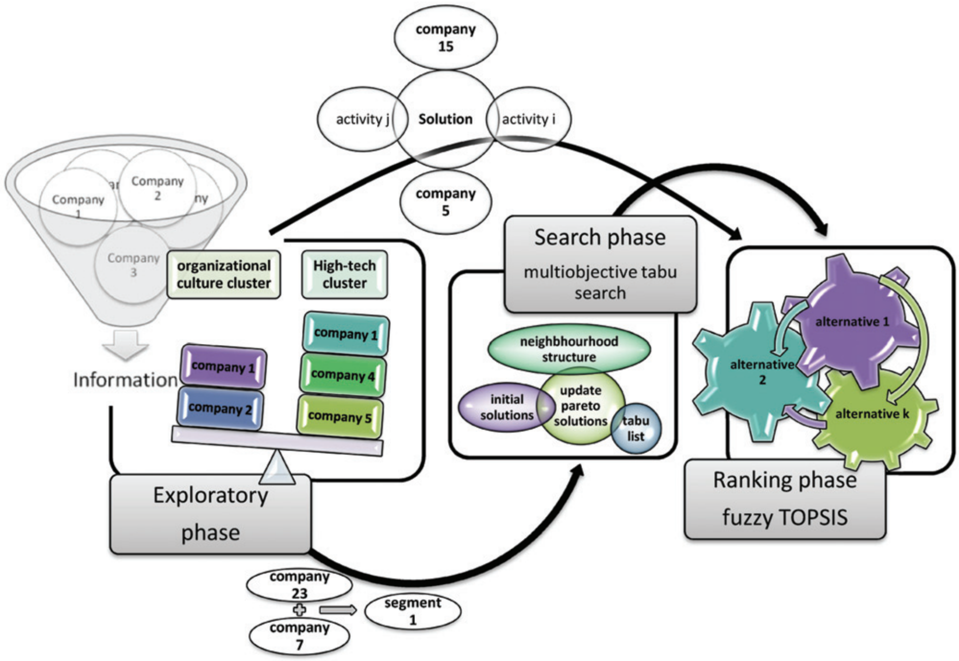

Figure 1. Phases of the algorithm.

solutions but the same solution can be generated by different weights, and this may be confusing to the DM.

Another difference to previous works results from the use of the concept of Pareto non-dominance with a directional search (a solution is Pareto optimal if there are no other feasible solutions with higher value of some objectives without a lower value in at least one other objective). This technique makes it possible to obtain a set of solutions that represent well the objectives without the need of explicitly assigning weights to the objective functions (aggregation scheme). The weights are only used at the final stage because we want the DMs to rank the criterion importance, using their expertise or experience, so that the final solutions are closer to their ideals.

The other key innovation of the methodology, when compared with the methods from the literature (see, e.g., Ma *et al.* (2007) for genetic algorithms, Ng (2008) for linear programming, Li and Liao (2007) for fuzzy theory) consists of the introduction of an exploratory phase with the aim of obtaining relevant information about the network, the criteria to be adopted, the project itself, and the decision-maker (DM). This information will be exploited in subsequent phases of the algorithm (Figure 1). This phase will help the DM during decision process structuring (in selecting the criteria defining constraints, choosing the constraints or the weights, etc.). For that purpose we suggest the use of cluster analysis, case base reasoning (CBR) and of a procedure to choose the criteria based on the correlation concept.

The remainder of the paper is organised as follows. In Section 2 the problem is presented; in Section 3 the exploratory phase is described; in Section 4 the algorithm used to identify and to rank the problem alternatives is presented; in Section 5 an illustrative example is described; and finally, in Section 6 some preliminary conclusions are presented.

2. Problem description

Assume a network A representing all potential partners (companies) and their relationships. A specific entity is responsible for the VE formation process (this entity is here referred to as the decision-maker – DM). Relationships are characterised by a set of attributes (possibly to be used as criteria in the evaluation process), some assigned to the nodes and some assigned to the edges of the network. In the node attributes we have the resource availability that will be assessed according to project constraints (e.g., time windows, minimum amount of resources required) and other company characteristics relevant to the decision process (e.g., the size or financial stability of firms).

We can consider *hard* or *soft* constraints, so that the process does not exclude too many potential candidates in the earliest phases of the selection process. For example, a good candidate that does not satisfy the time window constraints can still be eligible if there is margin to remake the scheduling of the activities. The edge attributes include variables that are related to the links or connections between pairs of companies (e.g., evaluation of past relationship experiences, distance, trust, price, etc....). Moreover we consider that the network is a directed graph because there is the possibility that, for example, the degree of trust between two firms is not reciprocal. We also assume the network to be a VBE, i.e., a stable association of organisations and their related supporting institutions with common operating principles and infrastructures in order to be prepared to collaborate in a potential VE (Camarinha-Matos and Afsarmanesh 2003). From the two sets of attributes (edge and node attributes) it is possible to capture the organisational characteristics (objectives) necessary to perform the project.

The companies in a network may be very different from each other, and each company is characterised by a set of attributes that can be rather large in number. Moreover, these companies may be organised in quite different networks, depending on the particular considered criteria or objectives collecting and handling the associated data may therefore be a complicated task and may require a considerable effort just in structuring the problem.

3. Exploratory phase

The exploratory process works as an initial phase in the whole decision support process. This phase allows the DM to test various scenarios for which the companies are grouped in different ways and/or the criteria are verified in terms of reliability and importance. It also explores, with historic data, previous VE formations, trying to identify the most similar ones in order to reuse the information (e.g., what companies belong to the VE, or what performance indicators values determine the success of the VE).

In this work we use cluster analysis and CBR to obtain a better knowledge of the network, in a way that is different from those proposed in the supply chain literature, where these techniques are used separately and only to reduce the problem dimension (see, e.g., Hong *et al.* 2005, Luu *et al.* 2006, Sarkar and Mohapatra 2006, Bottani and Rizzi 2008). As another possibility, with this additional knowledge we can create or forbid some alternatives (potential groups of firms that have the resources and skills needed to carry out the project), create 'segments' (i.e., groups of two or three companies that work very well together) or confine the search to a given cluster of companies.

A VE comprises cooperation at several levels, such as R&D, production, marketing or distribution. These different perspectives can, for example, lead us to choose as partners, companies belonging to the same cluster (e.g., group of companies with similar (high) technical skills), or to choose companies belonging to different clusters, according to the activity to be allocated (e.g., for activities related to distribution choose the best companies in the cluster where companies are strong at this function). In spite of the additional computational effort required by this interactive learning process when compared with a free search (which may be significant if the network size and/or the number of criteria considered is high), the proposed approach has as an additional advantage the possibility of identifying different solutions, closer to the DM ideals.

3.1 *Criteria selection – dimensions*

In this work we have assumed the existence of certain 'dimensions' defined as a set of attributes (or criteria) as a way to obtain a simpler representation of all characteristics of the network. Attribute selection becomes an important issue in the VE configuration process as it involves the determination of the attributes that are relevant to explain the data, and conversely of those attributes that are redundant or provide little information. This process of identifying the attributes that are relevant for decision-making often provides valuable structural information and is therefore important in its own right. Moreover, if we consider the dynamic nature of the network, we can easily conclude that relevant attributes for one project may be inappropriate for another. It should also be noticed that only some of the available criteria are useful to characterise the enterprise for each dimension (e.g., financial stability), so one key task of the DM is to carefully define what those criteria are (e.g., ROE, debt/assets, cash flow, etc.). Moreover, such criteria need to be statistically analysed before they can be considered suitable for inclusion in the model. For example, it would be inadequate to consider criteria that are highly correlated.

3.1.1 *Criteria correlation*

A sound decision analysis naturally requires the use of criteria that are independent from each other. However, it is often found that the adopted criteria are highly correlated, thus suggesting that some of them may be redundant and that it would be sufficient to consider a smaller number of criteria. For example, price/cost may be influenced by the quality of products. Correlated criteria introduce redundancy and double counting, and generate inconsistent results. For this reason, prior to any aggregation, the criteria should be tested in terms of correlation.

According to Jenkins and Anderson (2003), this question is even more critical in the cases where the evaluation of each criterion is partially or completely subjective, because the DM may easily double count the same aspect or attribute, or even consider it with different importance. Our problem consists of classifying and evaluating the various potential partners and therefore the information we obtain is often partially or completely subjective. In this way, the identification of the interdependence between different criteria is critical and will allow the DM to replace those criteria that are highly correlated by others not accounted before or omitted, with a small loss of information. Methods from multivariate statistics such as 'principal components' and 'factor analysis' are not applicable because they simply form linear combinations of the original variables and do not allow the existence of qualitative information.

To find possible correlations among criteria we calculate correlation coefficients, even if this procedure requires that all criteria are expressed in similar comparable scales. For that purpose we use the formulas of the variance and the correlation for fuzzy sets, as introduced by Chiang and Lin (2000). Consider the fuzzy set $A \rightarrow (\mu_A(x_1), \mu_A(x_2), \ldots, \mu_A(x_i))$ that corresponds to the grades of the membership's functions of A. Then the average and variance membership grades of the membership function of A, defined on X, (x_1, x_2, $\ldots$, x_n – set of original data (number, linguistic, binary) with size n), can be written as:

$$S_A^2 = \frac{\sum_{i=1}^{n} (\mu_A(x_i) - \bar{\mu}_A)^2}{n-1} \tag{1}$$

$$\bar{\mu}_A = \frac{\sum_{i=1}^{n} (\mu_A(x_i))}{n}, \tag{2}$$

and the correlation coefficient, $r_{A,B}$, between the fuzzy sets A and B as:

$$r_{A,B} = \frac{\sum_{i=1}^{n} (\mu_A(x_i) - \bar{\mu}_A)(\mu_B(x_i) - \bar{\mu}_B)/(n-1)}{S_A \times S_B}. \tag{3}$$

After the coefficients are calculated the DM should decide whether to exclude the criteria that are highly correlated, to change the associated weights, or to replace some of them. It should be noticed that the number of observations used in the calculation does not influence the value of the coefficient $r_{A,B}$ but does affect the accuracy of the relationship between criteria.

3.2 *Clustering*

Cluster analysis (CA) is a popular data mining technique (see, e.g., Olafsson *et al.* 2008) that involves the partitioning of a set of objects into a set of mutually exclusive subsets such that the similarity between the observations within each subset (i.e., cluster) is high, while the similarity between the observations from the different clusters is low. In our case, this technique is useful to determine clusters of companies according to specific dimensions.

Clustering may be categorised in various ways such as hierarchical or partitional, deterministic or probabilistic, hard or fuzzy. The general approaches to clustering are: hierarchical clustering and partitional clustering (e.g., Samoilenko and Osei-Bryson 2008). Hierarchical clustering forms clusters through the agglomerative or the divisive methods. The agglomerative method initially assumes that each data point is its own cluster, and with each step of the clustering process, these clusters are combined to form larger clusters, which may themselves be combined to form a single cluster. The divisive method, on the other hand, starts with one single cluster containing all data points, and divides it into smaller dissimilar clusters. In partitional clustering, k-means clustering requires the number of resulting clusters k, to be specified *a-priori*. Thus, k-means clustering will produce k different clusters of greatest possible dissimilarity. In our work, since we want to explore the data and we do not know the number of clusters in advance, we have used hierarchical clustering through an agglomerative method. In this way, we start with as many clusters as companies, and iteratively the 'closest' companies are aggregated in the same cluster. Here, the closest companies are those that present the short Euclidean distance for each criterion considered. Afterwards, centroids for each new cluster are determined. The centroid of a cluster is the average point in the multidimensional space defined by the criteria, i.e., the cluster's centre of gravity.

3.3 *Case-base reasoning*

Case-based reasoning (CBR) is an artificial intelligence (AI) learning technique that has recently drawn the attention of many researchers (Chang *et al.* 2008). It enables the use of specific knowledge by remembering a previous similar situation and by reusing information and knowledge from that situation. CBR is recommended for reducing the knowledge acquisition effort, for avoiding the repetition of mistakes, for improving learning over time, and for handling situations with incomplete or imprecise data (Fernandez-Riverola *et al.* 2007). A CBR system analyses a new problem situation and, by using indexing algorithms, it retrieves previously stored cases together with their solutions by matching them against the new problem situation. It then provides a solution to the new problem following four cyclical processes: retrieving, adapting and reusing knowledge stored in the form of cases in the case base (Aamodt and Plaza 1994), revising the solution, and retaining the learned case. Among the several referred tasks, retrieving the most similar case(s) is the first and most crucial step and involves evaluating the degrees of similarity between any two cases being compared. The approach commonly used to assess similarity is the 'distance function'.

In our work the CBR procedure is used to retrieve candidate companies that, in past projects, have performed the activities included in the current project. These companies are used to create alternative non-dominated solutions that will be explored in the multi-attribute phase, and/or to create 'segments' (which are incomplete solutions composed of some companies/activities that in the past had a good, successful partnership experience) to be used in the multi-objective phase. To match the query case, we compare old projects with the new one, in order to find identical activities. If all activities are equal (independently of the activity order or precedence in the past) we may have immediately found an alternative solution for the current project, if the so-called 'hard constraints' are respected. Otherwise, we use the list of companies that had performed the activities to create as many as possible new alternative solutions through an enumerating algorithm. This algorithm follows a permutation scheme to create feasible potential solutions from the detected companies. Moreover, the list of companies is complemented with *similar* companies (i.e., with companies having similar attribute values) that have not yet performed the activities in question. This similarity is measured through a Euclidian distance formula, since we use fuzzy sets to express the attribute values. Therefore, for any two fuzzy sets $A, B \in \mathrm{FS}(X)$, with membership functions μ and ν, respectively, we use the following normalised Euclidean distance (see Balopoulos *et al.* 2007):

$$d_{nE}(\mu, \nu) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mu(x_i) - \nu(x_i))^2}. \tag{4}$$

To complete this process it is necessary to update the case-base data. Since this step is useful to perform a pre-qualification, we only consider successful cases. However, key performance indicators like profit, delivery of the product on time, etc., could be used when the case is saved, in order to keep a complete historic data. In that situation during '*Step 0. Establishment of case-base*' described below, the indicators and bound values must be identified. This must also be done in '*Step 1. Retrieve cases*' where those indicators must be used by the matching method in order to retrieve just suitable cases.

The CBR search algorithm proposed is described below.

Step 0: Establishment of case-base: a case-base is a structure where the cases are stored. A case-base contains problems and solutions that can be used to derive a solution for a new situation.

- Identify the partner selection features (criteria);
- Identify the activities used in previous projects (resources);
- Store previous cases in the case-base.

Step 1: Retrieve cases: cases in the case-base are retrieved using the matching method.

Step 1.1: Development of a matching method for case retrieval: a matching method is developed to search the case-base and find the most similar one to the new case situation. In our study it consists of verifying if activities are the same, i.e., use the same resources.

- Matching the activities between older projects and the present project (new problem);
- List the most similar projects:
  - If there is an older project(s) that is identical to the new project, save its related information;
  - If not: create a list of companies that had been performing the activities presented in the new project case.

Step 2: Solution adaptation.

Through an enumerating algorithm create/adapte/reuse as many solutions as possible from the list of companies:

- If any project activity is still empty then:
  Through the use of a similarity measure complete the solution with companies that had not been used in the past, but have similar attribute values and capacity to perform the activities presented in the new project case
- Create segments of companies that are saved to posterior use by metaheuristics

Step 3: Save the adopted solution.

The adopted solution is confirmed in terms of feasibility and then exported/retained to the case-base for future use.

4. Multiple criteria approach

Multiple criteria decision making (MCDM) has been one of the fastest growing areas of operational research, as it is often realised that many real problems can be better modelled by explicitly considering several (conflicting) criteria. The main goal of MCDM is to assist a DM to choose, rank, or sort alternatives within a finite set according to two or more criteria (Roy 1996). Criteria can be used to denote both objectives and attributes. Often the terms MCDM, multiple attribute decision making (MADM), and multiple objective decision making (MODM) are confused or used with the same meaning. MADM studies problems where the decision space is discrete, i.e., these problems have a limited number of alternative solutions. The typical problem is associated with assessment and selection. In a general way, it can be said that MADM selects the best alternative among a finite number of choices, unlike MODM where the best alternative is designed with multiple objectives based on continuous decision variables subject to constraints (Hwang and Yoon 1981).

In this work we study the 'partner selection problem' under a multi-criteria perspective, i.e., with objectives and attributes. Given the multi-criteria nature of the problem, there is generally no 'optimal' alternative, and a good 'trade-off' solution must therefore be identified. We are here considering a 'design' problem (MODM perspective), usually characterised by an 'explosive', combinatorial number of alternatives, as well as multiple conflicting objectives – such problems are denoted as multi-objective combinatorial optimisation (MOCO) problems. Here, the main practical issue is that the solution space is huge and therefore the set of feasible solutions cannot be enumerated.

Real-life MOCO problems in network design are typically of a large size, with a particularly large solution space, exact optimisation approaches being therefore impossible to use (Ölçer 2008). More specifically, the partner selection problem cannot be solved exactly due to its high computational complexity (see Wang *et al.* 2001), and we have therefore to consider approximate methods like multi-objective metaheuristics. These methods generate solutions of reasonably good quality in a reasonable amount of time independently of the mathematical structure of the problem. We have therefore developed a metaheuristic approach based on multi-objective tabu search (TS) to hopefully find out a representative set of Pareto-optimal solutions.

After the Pareto front is found, i.e., a set of potentially interesting solutions are available, one of these solutions has to be chosen for implementation. In this phase partner selection is viewed as a MADM problem (Li and Liao 2007) and the main question is how to rank/order alternatives (which one is better or the best). To assess the alternatives and choose the best one amongst them some kind of judgment is needed (the DM expressed preferences).

There are cases where the attributes cannot be assessed precisely in a quantitative form, due to their particular nature (e.g., trust) or because either information is unavailable or the cost of their computation is too high. 'Linguistic variables' may then be an acceptable choice (Herrera *et al.* 2004).

In these 'linguistic variables' values are not numbers but words or sentences in a natural language. The linguistic term set, usually called S, comprises a set of linguistic values that are generally ordered and uniformly distributed. For example, a set S of five terms could be defined as follows: $S = \{s0 = \text{very low}; s1 = \text{low}; s2 = \text{medium}; s3 = \text{high}; s4 = \text{very high}\}$, in which $sa < sb$ if $a < b$. The semantics of the elements in the term set (the meaning of each term) is given by fuzzy numbers defined on the [0, 1] interval and described by membership functions.

In general, partner selection approaches do not use mixed types of variables, rather applying a single type of variables: only fuzzy numbers (e.g., Cao and Zhou 2006), or linguist terms (e.g., Lin *et al.* 2007), or numbers, indexes and ratios (e.g., Sari *et al.* 2007). In cases where an attempt to use quantitative and qualitative information together was made, approaches are usually rather inflexible, requiring for example the fixation of the scale cardinality (e.g., $\# = 9$ scale or a five-point like scale (Araz *et al.* 2007)). In this work we allow several types of information (numerical, interval, qualitative and binary) and for the same attribute, the cardinality of S may vary depending on the DM's knowledge about the companies under analysis (that knowledge can be more detailed in some cases or vaguer in others). We will use a fuzzy TOPSIS technique to rank the Pareto solutions.

4.1 *Multi-objective tabu search*

In the real world, optimisation problems often involve several conflicting objectives, therefore being impossible to find a solution where all the objectives are at their individual optimum. The best trade-offs among the objectives can be defined in terms of Pareto optimality. A solution is Pareto optimal if there are no feasible solutions that would increase some objectives without causing a simultaneous decrease in at least one other objective. All these Pareto optimal solutions form the so-called Pareto front.

Quite often, in practice, the multiple objectives are aggregated into one single objective function (Berkoune and Mesghouni 2008). Optimisation is then conducted with one objective, and the result is strongly dependent on how the objectives are aggregated (for example, through the use of scalar functions (Zhang and Li 2007)). Different weights provide different solutions but the same solution can be generated by different weights, possibly confusing the DM.

In this work, we have implemented a tabu search (TS) metaheuristic (see, e.g., Glover and Laguna 1997) with multi-objective functions, without any aggregation scheme, because we believe that in this phase where the solution space can be quite vast (the number of alternatives tending to infinity), it may be quite difficult for the DM to set weights on a realistic level and understand the interdependencies among the objective functions. This phase is critical because the MADM methods cannot be directly applied to assess a large number of alternatives, since they tend to generate inconsistencies (Zanakis *et al.* 1998).

The main components of a TS algorithm are: the objective function, the initial (starting) solution, the neighbourhood structure and the tabu list. In implementation terms, for our problem, the set of initial solutions is generated through the following simple process: create a *table of enterprises*, *activities and constraints* (e.g., capacities). Then, by scanning that table, a candidate solution (set of enterprises) is created that optimises each criterion separately considered. This means that this initial set is composed by as many solutions as criteria.

The improvement of a solution is then done by local search, based on swapping, for each activity, a company or a segment previously formed (group of companies, see Section 3.3) in the current solution, with a company outside the solution (from the *table of enterprises*). The search accepts infeasible solutions and uses the concept of directional search (Alves and Climaco 2004) without reference points (desirable values for each objective function). Instead, we use two matrices, one for constraints and another for objectives. They are similar to a tabu list, with the exception that we wish to force, and not to forbid, the search to be performed in a given direction.

The algorithm starts to explore all objective functions and only chooses a specific objective function f_1, to be improved, when it notices that f_1 has not been improved for a given number of iterations. If this is the case, in the next iteration the search will make use of just one objective. The same scheme is applied to the constraints, i.e., in cases where the search has been performed in infeasible regions of the solution space for too long, in the next iteration the algorithm only accepts feasible solutions respecting to the constraint with higher infeasibility.

This is done in order to obtain a dispersed set of Pareto solutions along the front, and because of the possible highly constrained nature of the problem, allowing the exploration of promising feasible and infeasible regions to identify a final, feasible optimal, or near optimal solution. In implementation terms, we use two parameters, one for the objectives and another for the constraints that are activated when an objective has not been improved in the last iterations and/or the solutions obtained are infeasible.

The activities are explored in the order they have been defined in the project. In this way, the search starts by attempting to bring into the solution an alternative company that can do the first activity or segment provided by CBR procedure, eventually prioritised by a given criterion (constraint or objective). If this replacement leads to a non-dominated alternative, and the current solution is feasible, the set of Pareto solution candidates is updated. Then, this process is repeated with the other activities. The best solution found is kept as the new 'current solution' since the strategy used in the neighbourhood search is the 'best improvement'. Two tabu lists are used: the first forbids the utilisation of the combination companies/activity recently chosen, and the second forbids the choice of the last activity selected. The tabu tenure of the first tabu list is determined randomly from a given interval (in our case, [number of nodes/10; number of nodes/2]). This exploration of the neighbourhood is repeated until the search cannot reach any alternative solution (i.e., a non-dominated solution) during a given number ξ of consecutive iterations.

4.2 *Multi-attribute decision-making*

Fuzziness is inherent to most decision making processes when linguistic variables are used to describe qualitative data. In this context, we have used an extension of the TOPSIS procedure for fuzzy data (see, e.g., Jahanshahloo *et al.* 2006) to rank the Pareto solutions obtained by the MODM procedure. TOPSIS (a technique for ordering preferences by similarity to an ideal solution) is one classical MADM method, developed by Hwang and Yoon (1981). It is based on the idea that the chosen alternative should be as 'close' as possible to the 'positive ideal solution' and, on the other hand, as 'far' as possible from the 'negative ideal solution'. In our approach some features have been added to the standard procedure, namely:

- The use of fuzzy sets to express the data, providing more autonomy to the DM (through the use of different and more extensive cardinality ranges in linguistic attributes). Since the transformation of the different types of variables considered (numerical, interval values and linguistic terms) into fuzzy sets requires a normalisation of the attribute values, the positive and negative ideals will be $(1, 1, 1, \ldots, \#)$ and $(0, 0, 0, \ldots, \#)$ respectively.
- The use of artificial attributes to avoid aggregation (and loss) of information. In this way, for a given project, with I activities and a network of enterprises characterised by M attributes, the solution will include the enterprises that will perform the I activities ($M \times I$ attributes).

5. Illustrative example

Consider a network where 12 different activities that require 10 different resources can be performed, and formed by 100 candidates (companies) characterised by 20 criteria

Table 1. Criteria characteristics.

Criteria	Type	Edge attribute	Cardinality (for linguistic)	Organisational culture	Competencies
c1	linguistic	yes	5	–	–
c2	linguistic	yes	7	–	–
c3	linguistic	no	7	√	–
c4	number	no	–	–	–
c5	number	no	–	√	–
c6	percentage	yes	–	–	√
c7	linguistic	yes	5	–	–
c8	linguistic	no	5	√	–
c9	percentage	no	–	–	–
c10	binary	no	–	–	–
c11	linguistic	yes	7	–	√
c12	number	no	–	√	–
c13	number	no	–	–	√
c14	linguistic	no	5	√	–
c15	linguistic	yes	3	–	–
c16	number	no	–	–	√
c17	binary	no	–	–	–
c18	linguistic	no	7	–	√
c19	binary	yes	–	–	–
c20	linguistic	yes	7	–	–

Notes:
c3: attitude toward uncertainty/risk = {extremely adverse, very adverse, adverse, neutral, keen, very keen, totally keen};
c5: power distance (# of hierarchical levels from top to bottom of organisation);
c6: market entrance capability;
c8: individualism vs collectivism = {very individualist, individualist, neutral, collectivist, very collectivist};
c11: managerial skills = {extremely bad, very bad, bad, neutral, good, very good, excellent};
c12: age of the organisation (years);
c13: productivity;
c14: masculinity vs femininity = {very masculine, masculine, neutral, feminine, very feminine};
c16: cost (per unit);
c18: technical expertise = {extremely bad, very bad, bad, neutral, good, very good, excellent}.
Criteria expressed by numbers assume values between 1 and10, except c12 where we admit values between 1 and 20.

(12 nodes criteria and eight edge criteria) expressed in four different types of information: numerical, percentage, binary and linguistic (Table 1).

Some attributes are chosen to define clusters of candidates according to several dimensions such as organisational culture, management capability, financial stability or market knowledge. It is reasonable to assume that the group of companies that will perform the project will match better together if they have similar cultures, even if we do not have preferences for a specific culture. On the other hand, the enterprise may have a better performance if, with respect to other characteristics (e.g., leadership, managerial competencies), companies are complementary.

Suppose we would like to set up a VE to perform a given project composed of six activities (Figure 2). Assume that in this project we consider five criteria (Table 2) – for illustration purposes these criteria have been randomly chosen from all criteria presented

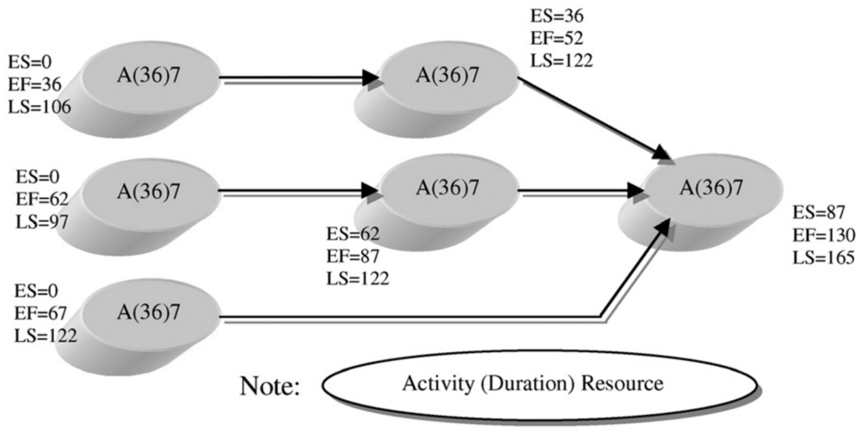

Figure 2. Project data in operational sequence graphs.

Table 2. Objectives, weights and constraints.

Objectives	c5	c6	c2	c18	c8
Type	number	percentage	linguistic	linguistic	linguistic
Edge attribute	no	yes	yes	no	no
Max (+)/min (−)	−	+	−	+	+
Weight (%)	14	23	6	30	27
Constraints	c12	c11	c14	c17	c16
Type	number	linguistic	linguistic	binary	number
Edge attribute	no	yes	no	no	no
Inequality	≥	≥	≥	=	≤
B side	6	good	neutral	1	7
Type	hard	soft	hard	hard	soft

Notes:
c2: quality of the product = {extremely bad, very bad, bad, neutral, good, very good, excellent};
c5: power distance (# of hierarchical levels from top to bottom of organisation);
c6: market entrance capability;
c8: individualism vs collectivism = {very individualist, individualist, neutral, collectivist, very collectivist};
c11 managerial skills = {extremely bad, very bad, bad, neutral, good, very good, excellent};
c12 production capacity;
c14 masculinity vs femininity = {very masculine, masculine, neutral, feminine, very feminine};
c16 cost (per unit);
c17 information and communication technology resources;
c18 technical expertise = {extremely bad, very bad, bad, neutral, good, very good, excellent}.
Criteria expressed by numbers assume values between 1 and 10.

in Table 2, and they have been assigned weights according to the DM preferences. Assume also that there are five constraints, also randomly chosen from all the criteria. These constraints are divided into hard and soft constraints (Section 2). When the constraints are related to an edge criterion, we consider the following rule: a company satisfies the constraint if 75% of the connections (edges that lead to the company) achieve the constraint boundary.

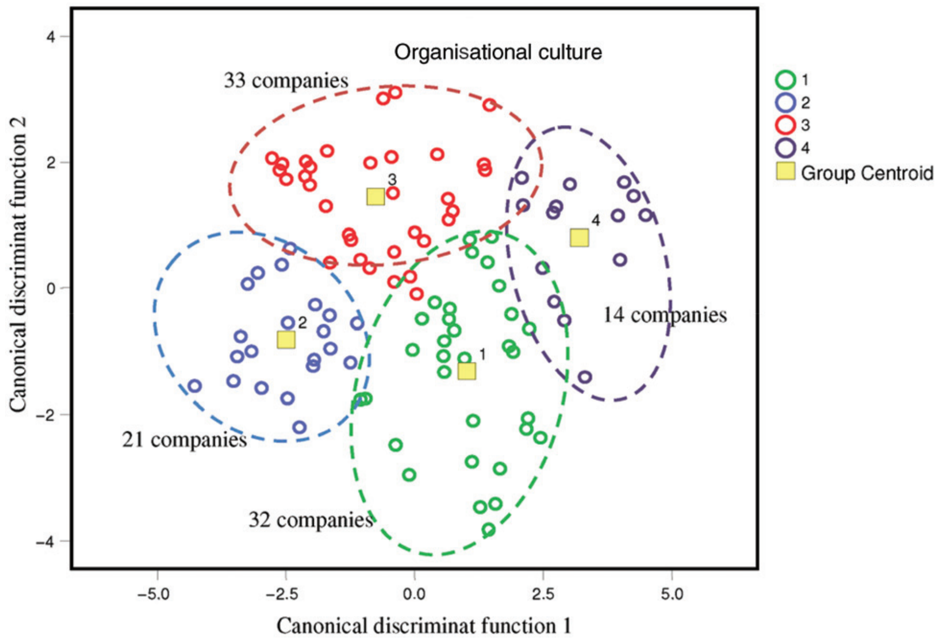

Figure 3. Clusters formation of organisational culture.

Assume also that the historic data comprises 10 projects with the same characteristics (i.e., decomposed in six activities each one, characterised by 20 criteria, etc. ...).

Figures have been randomly generated and the algorithm was implemented in C++ with the use of the SPSS software to perform cluster analysis.

In this example, the DM will first calculate the correlation between criteria in order to check if the chosen criteria have to be changed (Table 3). In our example the criteria selected do not present significant interdependences, however if the objective set comprises one more criteria C_4 (number of partnership experiences) with positive correlation (0.359; we consider that correlations of less than 0.30 indicate little if any relationship between the variables) to C_8 (individualism vs collectivism) it will be necessary to adjust the weights to not double count similar aspects, or exclude one of them from the objective set. We have decided to exclude C_4 since it is a binary variable, and so conveying less information than C_8, a linguistic variable, due to similar reasons the criterion C7 was excluded while we maintained C2.

Next we assume that the DM wants to partition the companies into groups with similar organisational cultures. Taking, for example, variables based on the framework proposed by Hofstede (2003) to define organisational culture (attitude toward uncertainty/risk, masculinity[1] vs femininity[2], individualism vs collectivism, small[3] vs large[4] power distance) and the age of the organisation, we have obtained the clusters presented in Figure 3 and in Table 4.

It is critical that the DM is able to 'describe' each cluster in a clear way, in order to verify if the results are valid: cluster 1 includes companies which are neutral towards uncertainty/risk, have on average six hierarchical levels, have a individualist culture, are relatively old (approximately 15 years on average) and are neutral in relation to masculinity/femininity. The same kind of analysis must be performed regarding the other clusters.

Table 3. Correlation coefficients.

	Objectives				
Criteria	c2	c5	c6	c8	c18
1	0.017	0.009	0.137	0.038	0.035
2	1.000	0.007	0.118	0.033	0.036
3	−0.015	0.003	−0.002	0.032	0.019
4	0.030	0.034	0.054	0.359	0.042
5	0.007	1.000	−0.003	0.043	0.082
6	0.118	−0.003	1.000	0.002	0.014
7	0.330	0.032	0.196	0.005	0.020
8	0.033	0.043	0.002	1.000	0.009
9	−0.005	0.086	0.040	0.008	0.076
10	−0.076	−0.010	−0.087	−0.003	0.012
11	0.324	0.023	0.161	0.006	0.023
12	0.004	0.040	0.108	−0.001	0.039
13	0.017	0.093	−0.031	0.006	0.070
14	0.015	0.053	0.037	0.031	0.001
15	0.212	0.057	0.116	0.003	0.060
16	−0.020	0.047	−0.038	0.014	0.040
17	−0.076	−0.010	−0.087	−0.003	0.012
18	0.036	0.082	0.014	0.009	1.000
19	−0.117	−0.047	−0.098	−0.007	−0.009
20	0.251	0.054	0.161	0.003	0.006

Note: shading, correlations coefficients higher than 0.03.

Table 4. Clusters data of organisational culture.

	Cluster			
Criterion	1	2	3	4
Attitude toward uncertainty/risk	neutral	neutral	keen	keen
Power distance	6	6	2	2
Individualism vs collectivism	individualist	neutral	collectivist	neutral
Age of the organisation (years)	14.69	17.57	6.76	5
Masculinity vs femininity	neutral	feminine	neutral	masculine

Notes:
1. attitude toward uncertainty/risk = {extremely adverse, very adverse, adverse, neutral, keen, very keen, totally keen};
2. power distance = {9, 8, 7, 6, 5, 4, 3, 2, 1};
3. individualism vs collectivism = {very individualist, individualist, neutral, collectivist, very collectivist};
4. masculinity vs femininity = {very masculine, masculine, neutral, feminine, very feminine}.

Assuming the DM wants to check if the suggested companies significantly differ, when the whole network is taken into consideration against the network formed from cluster 1, both situations are maintained in the future steps of the algorithm.

By applying the CBR procedure we first try to find identical projects (i.e., projects that require the same resources). In our example not one was found. Then the CBR procedure tries to find segments (Table 5) and, by the enumeration algorithm, to create

Table 5. Alternative solutions and segments obtained from CBR procedure.

Resource Activity	7 A	8 B	3 C	5 D	4 E	8 F
	Companies from historic data used to create solutions					
	10	6	15	16	1	6
	33	12	61	31	2	12
	51	83	78		8	83
	97	94	91		50	94
					89	
Enumeration solutions sample						
solution 1	10	94	15	31	1	94
solution 2	10	83	61	16	2	94
solution 3	10	83	61	16	2	83
solution 4	10	83	61	16	2	12
solution 5	10	83	61	16	2	6
solution 6	10	83	61	16	8	94
solution 7	10	83	61	16	8	83
...	...	...	...	...	...	...
Segments from historic data used by multi-objective tabu search						
segment 1	27				1	
segment 2		4			55	
segment 3		79			55	
segment 4		83	15		22	
segment 5		23	15		22	
segment 6		4	61		55	
segment 7		31	61		55	
segment 8	10	94	78	16		
segment 9	51	94	78	16		
segment 10	10			38		
segment 11	10			40		
segment 12	27		91			
segment 13	10	6	47	73	89	
segment 14	10	59	47	73	89	

feasible non-dominated solutions. We found 67 feasible non-dominated solutions from 2560 possible permutation solutions and from these, 32 solutions involve companies from cluster 1.

Concerning the improvement phase, the algorithm computed 14 non-dominated alternatives from cluster 1 (a smaller network with similar companies according to the criteria considered), and 80 when the initial network was considered (Table 6). In this table, each row contains the VE composition for the project activities (i.e., the companies assigned to the activities). For example, solution VE_1 includes companies 96, 85, 9, 16, 25 and 85, respectively for activities 1, 2, 3, 4, 5 and 6.

Once the inputs have been 'fuzzified', according to their own membership function and linguistic variables terms set, we have obtained the ranking of the non-dominated alternatives set shown in Table 7, through the computation of the distances between each alternative and the fuzzy positive ideal, as well as the 'closeness coefficients'.

Table 6. Non-dominated alternatives.

Resource Activity	7 A	8 B	3 C	5 D	4 E	8 F
Alternatives	Non-dominated solutions for cluster 1					
1	96	85	9	16	25	85
2	27	23	9	16	1	23
3	27	3	9	16	1	3
4	27	23	9	16	1	23
5	96	85	78	16	89	85
6	96	85	9	16	89	85
7	96	85	9	16	1	85
8	96	85	36	38	25	85
9	96	85	36	16	25	85
10	96	85	9	16	35	85
11	96	85	36	38	1	85
12	96	85	36	16	1	85
13	96	85	36	38	35	85
14	96	85	36	16	35	85
	Non-dominated solutions for entire network					
1	96	85	9	77	25	85
2	10	6	9	16	1	6
3	10	4	9	16	1	4
4	10	6	9	62	17	6
5	97	85	78	77	89	85
6	10	6	9	62	1	6
7	10	6	36	32	28	6
8	10	6	9	32	28	6
9	10	6	9	77	28	6
10	10	6	9	77	35	6
11	10	6	26	16	35	6
12	10	6	26	16	1	6
13	10	6	9	77	17	6
14	10	6	26	16	17	6
15	10	6	9	16	54	6
16	10	6	9	62	54	6
...	...	...	...	...	...	...

This table shows the solutions, their position in the ranking, and the procedure that has discovered/built such coalition of companies.

Analysing the results obtained, we should suggest VE_{16}, as being clearly better (0.200753) than VE_{67}, in the second position (with 0.178098) for the entire network, or VE_4 followed by VE_6 for a cluster network.

6. Conclusions

The problem of selecting partners for a virtual enterprise consists of choosing the entities to be involved in an emergent business opportunity, according to their

Table 7. Closeness coefficients/ranking of the alternatives.

Cluster 1						Project activities					
Rank	$\tilde{d}_i^+$	$\tilde{d}_i^-$	$\tilde{R}_i$	VE	Algorithm	A	B	C	D	E	F
1	8.01248	1.90556	0.19213	4	TS	27	23	9	16	1	23
2	8.13789	1.77051	0.178688	6	TS	10	6	9	62	1	6
3	8.13789	1.77051	0.178688	9	TS	10	6	26	16	28	6
4	8.1137	1.75816	0.178098	67	CBR	51	83	91	16	50	6
5	8.1137	1.75816	0.178098	59	CBR	51	83	91	16	89	83
6	8.13445	1.75654	0.17759	13	TS	10	6	9	77	17	6
7	8.13445	1.75654	0.17759	14	TS	33	6	78	16	89	83
8	8.10675	1.72919	0.175804	22	CBR	33	83	78	16	89	94
9	8.10675	1.72919	0.175804	24	CBR	51	6	78	16	89	94
10	8.10606	1.72629	0.175573	11	CBR	33	12	91	16	89	94

Entire network						Project activities					
Rank	$\tilde{d}_i^+$	$\tilde{d}_i^-$	$\tilde{R}_i$	VE	Algorithm	A	B	C	D	E	F
1	8.04265	2.02013	0.200753	16	TS	10	6	9	16	35	6
2	8.1137	1.75816	0.178098	67	CBR	51	83	91	16	50	6
3	8.1137	1.75816	0.178098	59	CBR	51	83	91	16	89	83
4	8.10675	1.72919	0.175804	12	TS	10	6	26	16	1	6
5	8.10675	1.72919	0.175804	24	CBR	51	6	78	16	89	94
6	8.10606	1.72629	0.175573	11	CBR	33	12	91	16	89	94
7	8.10606	1.72629	0.175573	58	TS	33	6	78	16	89	83
8	8.10478	1.72086	0.17514	18	TS	10	6	36	77	35	6
9	8.10478	1.72086	0.17514	71	TS	10	6	26	62	54	6
10	8.10283	1.71259	0.174479	40	CBR	51	83	91	16	89	12

attributes and interactions. This paper has tried to emphasise the need to obtain relevant knowledge about the network before starting to search the best partner candidates. This exploratory phase is done by looking at past experiences, as a way to reuse information about successful past partnerships, and by approximating/confining the search to the ideals of the decision-maker (DM).

The approach developed in this work can be viewed as the basis for an easy to configure and use, flexible decision support system, designed around three phases: (1) cluster analysis and CBR is used to identify the information to be applied in subsequent phases; (2) a multi-objective metaheuristic is used to compute a representative set of non-dominated solutions; (3) the TOPSIS technique is applied to perform a ranking of the alternative solutions. This approach creates a quite general and flexible research framework, which can be used to analyse numerous partner selection scenarios. The DM can naturally and easily change the objectives and constraints of the project in order to obtain a satisfactory solution, and can use a mix of variable types to express his/her preferences. Another relevant feature of this approach is that the optimisation algorithm can be used as a black box; the user is just required to help structuring the decision process (by specifying objectives, constraints and weights), to confine the search, and to choose an alternative taking into account the suggested ranking. However, there are still some considerable difficulties in requiring the user to express his/her preferences, in terms of various criteria, about what may be a rather large number of network members. Using different types of variables (as done in our approach) may however somehow simplify this task. The final decision is always taken by the decision-maker.

Notes

1. Based on traditional male values (e.g., competitiveness, assertiveness, ambition).
2. Based on traditional female values (e.g., relationships orientated).
3. People relate to one another as equals regardless of formal positions.
4. There is a formal hierarchy accepted by all.

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