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MULTIPLE CRITERIA PARTNER SELECTION IN VIRTUAL ENTERPRISES

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A virtual enterprise (VE) is a temporary organization that pools member enterprises core competencies and exploits fast changing market opportunities Partner selection can be viewed as a multi-criteria decision making problem that involves assessing trade-offs between conflicting tangible and intangible criteria, and stating preferences based on incomplete or non-available information. In general, this is a very complex problem due to the large number of alternatives and criteria of different types. In this paper we propose an integrated approach to rank alternative VE configurations using an extension of the TOPSIS method for fuzzy data, improved through the use of a tabu search meta-heuristic. Preliminary computational results clearly demonstrate its potential for practical application.

1 INTRODUCTION

A virtual enterprise (VE) is 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, the cooperation among the enterprises being supported by computer networks (Camarinha-Matos and Afsarmanesh, 2003). 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. The cooperation relationship can be represented by an activity network, where the participation of each partner in the project can be viewed as a ring in the chain. The problem of partner selection also arises when the VE needs to be reorganized by adding/expelling some members or by re-assigning tasks or roles in order to better cope with new market circumstances. In this work, we study the partner selection problem under a multi-criteria perspective. First, we review the literature about partner selection methods in various research contexts such as supply chain design, agile manufacturing, network design, dynamic alliances, and innovation management, in order to investigate their applicability to the VE case. We then propose an integrated approach to rank alternative VE configurations using an extension of TOPSIS for fuzzy data, improved through the use of a tabu search metaheuristic. The VE configuration process is a difficult problem due to the complex interactions between the different entities and because the expression of their preferences may be based on incomplete or non-available information. 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. A tabu search meta-heuristic is used to compute and reduce the potential VE configurations and the TOPSIS method is then applied to rank those configurations. The remainder of the paper is organized as follows. In Section 2 the problem is described, in section 3 the literature on the domain is briefly surveyed, in Section 4 the method used to solve the problem is presented, in Section 5 an illustrative example is described and finally, in Section 6 some preliminary conclusions are presented.

2 PROBLEM DESCRIPTION

The VE formation process can be described as follows. 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 or DM). Companies and relationships are characterised by a set of *m* attributes, some assigned to the nodes and some assigned to the edges of the network. These attributes will express the criteria used for evaluating solutions (i.e. VE configurations). The first step in this modelling process is to carefully define what attributes are going to be considered in both subsets. The Decision Maker can give weights to the attributes according to his believes about their relative importance for the project under consideration. The network includes a set of *n* companies (nodes) connected with each other, capable of performing activities and of providing a finite amount of resources, available over specific intervals of time. We also assume that project *P* involves *k* activities that demand a specific amount *Q* of resources and have to be performed within a given interval of time *S*. These activities have a number of precedence relationships and therefore form an activity network. Then the partner selection problem consists in choosing the best group of companies to perform all *k* activities of project *P* taking into account a set of evaluation criteria based on the *m* attributes established for the network. The main constraints of the problem are *time windows* and the *minimum amount of resources* required.

Partner selection can be viewed as a multiple attribute decision making (MADM) problem (Li and Liao, 2004). In this problem, the alternatives correspond to groups of enterprises that have the resources and skills needed to carry out the project. Given the multi-criteria nature of the problem, there is generally no "optimal" alternative, and a good "trade-off" solution must therefore be identified. In the classic problem formulation (see Cao and Gao, 2006) the objective is to select the optimal combination of partner enterprises for all activities, in order to minimize the risk or the costs of the project. When partner selection is based on multiple criteria, the objective function (1) can be defined as the sum of the scores for the various criteria. The following variables and parameters are defined:

$$x_{ijt} = \begin{cases} 1 & \text{if activity i is contracted to candidate j for period t} \\ 0 & \text{otherwise} \end{cases}$$

M: set of criteria, $M=\{1, 2, \ldots, m\}$

l_{lj}: score (contribution) of criterion l for candidate j

d_i: processing time of activity i

S_i=[f_i; g_i]: time window (interval) to perform activity i
D: due time to perform the project
K: set of activities in the project, $K=\{1, 2, \ldots, k\}$
Q_i: quantity of resources needed to perform activity i
V_j =[u_j; s_j]: interval of time in which candidate j is available
R_j: capacity (available quantity of resources) of candidate j
W_i: set of candidates for performing activity i
B: maximum investment for the project (budget)
b_{ij}: cost of performing activity i by candidate j

Then, the problem can be modelled as follows:

$$\text{Max } \sum_{l}^{L}\sum_{i}^{k}\sum_{j}^{w_i} l_{li}x_{ijt}, \qquad \forall t \in T \tag{1}$$

$$\text{s.t.} \qquad \sum_{i}^{k}\sum_{j}^{w_i}\sum_{t}^{d_i} x_{ijt}b_{ij} \leq B \tag{2}$$

$$\sum_{t}^{d_i}\sum_{j}^{w_i} x_{ijt}(f_i + d_i) \leq \sum_{t}^{d_k}\sum_{j}^{w_k} x_{kjt}f_k, \qquad \forall i,k \in K \tag{3}$$

$$d \leq D, \quad \text{with} \quad d = max\{\sum_{j}^{w_i}\sum_{t}^{d_i}\left(f_i + d_{ij}\right) \times x_{ijt}\} \tag{4}$$

$$\sum_{j}^{w_i}\sum_{t}^{d_i} x_{ijt} = 1, \qquad \forall i \in K \tag{5}$$

$$u_j \leq g_i - d_i, \qquad \forall i \in K, \quad \forall j \in W_i \tag{6}$$

$$s_j \geq f_i + d_i, \qquad \forall i \in K, \quad \forall j \in W_i \tag{7}$$

Constraint (2) states that the sum of costs is not larger than the global budget for the project. Constraints (3) impose the precedence relationships between the activities. Constraint (4) ensures that the project is completed no later than the project deadline. Constraints (5) impose that for any given activity, only one candidate (or group of enterprises working as an individual element) can be selected. Finally constraints (6) and (7) ensure that the interval of time when the resources of candidate j are available fits the "time window" for activity i. Other constraints related to third party logistics (3PL) might be included but, as an alternative, these aspects can be covered by the objective function through the attributes considered by the decision maker. In this work, we start by identifying potential non-dominate VE configurations, and accordingly we explicitly consider multiple objectives:

$$\text{Max } z_1 = \sum_{i}^{k}\sum_{j}^{w_i} l_{li}x_{ijt}, \qquad \forall t \in T \;\; and \;\; m = 1 \tag{8}$$

…

$$\text{Max } z_m = \sum_{i}^{k}\sum_{j}^{w_i} l_{li}x_{ijt}, \qquad \forall t \in T \;\; and \;\; m = M \tag{9}$$

3 LITERATURE REVIEW

A review of the literature about partner selection methods in various research contexts (such as supply chain design, agile manufacturing, network design, dynamic alliances, and innovation management) has been performed in order to investigate the distinct approaches used to tackle this problem. We have concentrated this survey on research based on mathematical or quantitative decision-making approaches published in the last years (since 2001), and have grouped those approaches according to the methodology adopted. The survey included 41 papers covering quite different perspectives. Three classification criteria have been adopted for categorising the reviewed articles: Research context (Virtual enterprise/dynamic alliance, manufacturing, and supply chain/network; Methods used to solve the problem (almost all the research papers we found use hybrid algorithms), and Criteria/factors on which the partner selection is based. From the 41 papers reviewed, we can summarise our findings as follows.

- Around 74% of the papers were published in the last two and a half years.
- In terms of research context, around 50% of the papers are on virtual enterprises, 25% on manufacturing, and around 25% on supply chains. Although there is a large number of papers published in this last area (supply chain, network design), many of them have not been considered in the survey because they do not tackle partner selection as an isolate problem, but try rather to optimize or create a chain/network configuration considering questions such as localization, inventory management and/or transportation.
- Although around 90% of the papers describe hybrid methodologies, the quantitative approaches to partner selection can be grouped into three main categories: optimization models (exact and heuristic algorithms) – 56%; multi-criteria decision aiding (such as AHP, MAUT, fuzzy set theory) - 32%; and other methods such as simulation or clustering - 12%. Genetic algorithms are very popular within heuristic approaches (85%), and only 2 in 13 articles use tabu search as an alternative method. The "main" algorithm is often combined with contributions from fuzzy set theory. In MADM, the combination of fuzzy numbers with AHP is the most frequent.
- Criteria may be grouped into two main classes: a) risk (e.g. political stability, economy status of the region, financial health, market fluctuations, competency), costs and time factors (around 46%); and b) other attributes (such as trust, technology level, capacity resources, organization structure, financial status, past performance, quality, etc.). In this last group: a) around 54% use quantitative information expressed by numbers, percentages or performance indices; b) around 27% use numerical scales; c) around 9% use fuzzy numbers to deal with the vagueness of the DM preferences; and d) around 9% use linguistic terms to facilitate the expression of DM preferences.

From this survey[1], it is also possible to draw some useful indications about the main research trends for partner selection in a virtual enterprise context, namely: an enormous concern about optimising the solution, i.e. to select the right partner; need to obtain complete and diversified information (multiple attributes) about each potential partner; subjectivity in the data; need to facilitate the expression of the decision maker's assessments about the potential partners; concern with dynamic aspects (e.g. time).

4 DEVELOPED APPROACH

The classic model based on risk and cost factors is a 0-1 integer programming with nonlinear objective and several inequality and equality constraints (Cao and Gao, 2006). Due to the complexity and the nonlinearity of the model, it cannot be efficiently solved by conventional methods. With exact algorithms it is in general impossible, for large problems, to obtain a satisfactory solution in a reasonable computational time. Metaheuristics assume therefore an important role in solving this kind of problems.

4.1 Metaheuristics

Metaheuristics are approximate methods designed to solve hard combinatorial optimisation problems (Reeves, 1993). In this work, we have implemented a TS metaheuristic (see e.g. Glover and Laguna 1997). The main components of TS are: the objective function, the initial (starting) solution, the neighbourhood structure and the tabu list.

We are basically looking for a set of nondominated alternative solutions. A solution (i.e. a potential VE configuration) is represented by a set of companies in the network, associated to the different project activities, along with the corresponding attribute values. In implementation terms, the set of initial solutions is generated through the following simple process: create a *table of enterprises, activities and constraints* (e.g. capacities). A given activity may be performed by a group of enterprises if, for example, separately they do not have enough resources. In this case, the group of enterprises is added to the network as a single unit and the attribute values associated to this unit result from the attribute values of the different enterprises. Following, by scanning that table, a candidate solution (set of enterprises) is created that optimizes each criterion separately considered. This means that this initial set is composed by as many solutions as criteria.

A multi-start improvement strategy was adopted, with these starting solutions. The improvement of a solution is then done by local search, with a neighbourhood structure that consists in swapping, for each activity, an enterprise in the current solution with an enterprise outside the solution (from the *table of enterprises*). The activities are explored by the order they have been defined in the project. In this way, the search starts by attempting to bring into the solution an alternative enterprise that can do the first activity. If this replacement leads to a non-dominated alternative, this new set of enterprises is saved in the *table of alternatives*. 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 utilization of the enterprises 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., non-dominated alternative) during a constant number ξ of consecutive iterations. The search only accepts feasible solutions. An intensification strategy is adopted after a given number of consecutive dominated solutions is found and consists of re-starting the procedure with one of the non-dominated start solutions kept.

Algorithm

Generate initial solutions $X=\{1,\ldots,i\}$

Randomly choose one solution from the set of initial solutions, as current solution $X^*=X_i$

Initialise tabu-list

Set aspiration criterion (neighbour solution dominates current solution)

While stopping criterion not met

Generate n neighbours of X_i

Choose Y the best neighbour of X_i, that is not in the tabu-list or that satisfies the aspiration criterion

If f(Y) is better than f(X*)

X*=Y

Update tabu-list

Return X*

4.2 Multi-attribute decision-making

Multi-attribute decision-making (MADM) is the general process of evaluating and selecting alternative options, characterized by multiple, usually conflicting, attributes or criteria. Many multi-attribute decision-making methods have been proposed in the literature (MAUT, SAW, AHP, TOPSIS, ELECTRE, PROMETHEE, …). TOPSIS (a technique for ordering preferences by similarity to an ideal solution), one of known classical MADM methods, first developed by Hwang and Yoon (1981), 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. TOPSIS is very easy to implement but assumes the satisfaction of the following requirements: a previous assignment of weights to the attributes by the DM, and a fixed, pre-defined number of alternatives. (Shih et al., 2004). In real-world decision problems we have to handle information that is uncertain, incomplete and/or missing (Li and Lao, 2007). Furthermore, there are many decision situations in which 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. In these situations an “approximate value” may be acceptable and so the use of a qualitative approach is appropriate (Herrera et al., 2004). “Linguistic variables” will represent qualitative aspects, with values that are not numbers but words or sentences in a natural language, thus making it easier to express preferences. *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 = {s_0 = very low; s_1 = low; s_2 = medium; s_3 = high; s_4 = very high}, in which $s_a < s_b$ if a < b. The semantics of the elements in the term set (the meaning of each term set) is given by fuzzy numbers defined on the [0, 1] interval and described by membership functions. For the same attribute, the cardinality of S may vary depending on the DM’s knowledge about the enterprises under analysis (it may be more detailed in some cases or vaguer in others). Since, fuzziness is inherent to most decision making processes when linguistic variables are used to describe qualitative data, we will use an extension of the TOPSIS procedure for fuzzy data (see e.g. Jahanshahloo et al. 2006). This procedure has the following steps:1. Identify the evaluation criteria; 2. Generate the alternatives; 3. Evaluate alternatives in terms of the criteria (i.e. compute the fuzzy values of the criterion functions); 4. Identify the weights of the criteria; 5. Construct the fuzzy decision matrix; 6. Compute the normalized fuzzy decision matrix; 7. Construct the weighted normalized fuzzy decision matrix; 8. Identify a fuzzy positive ideal solution and a fuzzy negative ideal solution; 9. Compute the distance between each alternative *i* and the fuzzy positive ideal solution (eq. 10, 11); 10. Compute the "closeness coefficient" to determine the ranking order of all alternatives (eq. 12)

$$\tilde{d}_i^{+} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_{ij}^{+}) \,, \qquad i = 1, \ldots, m \tag{10}$$

$$\tilde{d}_i^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_{ij}^{-}) \,, \qquad i = 1, \ldots, m \tag{11}$$

where $\tilde{v}_{ij}^{+}$ = (1, 1, 1) is the fuzzy positive ideal solution and $\tilde{v}_{ij}^{+}$ = (0, 0, 0) is the fuzzy negative ideal solution for each criterion (benefit or cost criterion).

$$\tilde{R}_i = \tilde{d}_i^{-} / (\tilde{d}_i^{+} + \tilde{d}_i^{-}) \,, \qquad i = 1, \ldots, m \tag{12}$$

4.2.1 Differences to the standard procedure

To construct the fuzzy decision matrix we first need to transform the numerical values, interval values and linguistic terms into fuzzy sets (see Herrera et al., 2004) by using equation (11). Due to the incommensurability among attributes, to do this transformation we previously need to normalize the values of the attributes (thus not requiring to do step #6 above). Each solution involves a given number of enterprises for the same project activities, and to evaluate that solution we take the values of each attribute considered for each enterprise separately. To avoid the loss of information caused by the aggregation of values we consider some artificial attributes that characterize the solution itself. In this way, for a given project with *k* activities and a network of enterprises characterized by *m* attributes, the solution includes the enterprises that will perform the *k* activities ($m \times k$ attributes). Following this principle we do not need to perform any aggregation and we keep all the information of all enterprises in the solution.

Our approach is slightly different from those in the literature because we do not use fuzzy numbers in the fuzzy decision matrix. Instead we use fuzzy sets since we want to give more autonomy (through the use of different and more extensive cardinality ranges in linguistic attributes) to the DM. A fuzzy subset of a set *S* is a mapping from *S* into [0, 1], where the value of the mapping for an element of *S* represents the `degree of membership' or `membership value' of the element in the fuzzy subset. So instead of using distance formulas for fuzzy numbers (see Li and Yang 2004) we have to use distance formulas for membership functions (see Balopoulos et al. 2007). For any two fuzzy sets $A, B \in FS(X)$, with membership functions μ and ν, respectively, we use the following normalized euclidean distance:

$$d_{nE}(\mu, \nu) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\mu(x_i) - \nu(x_i))^2} \tag{13}$$

5 ILLUSTRATIVE EXAMPLE

Assume we would like to form a VE to perform two projects decomposed in 6 activities each (Table 1).

Table 1: Projects data

Project 1						Project 2					
Activities (code)	Precedent activities	Duration	Earliest start time	Latest finish time	Quantity of resources	Activities (code)	Precedent activities	Duration	Earliest start time	Latest finish time	Quantity of resources
7	-	36	64	217	400	4	-	99	131	274	362
8	-	62	147	241	604	2	-	56	180	218	206
3	-	67	188	350	528	9	-	30	102	338	135
5	7	16	217	281	275	6	4	41	274	361	116
4	8	25	241	274	368	9	2	32	218	358	282
8	5	43	281	365	304	8	4	44	274	339	221

Suppose a network where 10 different activities can be performed, and composed by 100 enterprises characterized by: enterprise code; activity; interval time about availability of resources; capacity; plus 8 evaluation attributes (Table 2). The attribute type may be: linguistic, numerical and interval. We may want to maximize the attribute (benefit attributes) or minimize it (cost attributes). If the attribute is linguistic, the scale cardinality has to be defined. Figures have been randomly generated. For the linguistic variables we have assumed triangular membership functions with three possible cardinalities of 3,5 or 7, with the following term sets: {none, more or less, perfect}, {none, low, more or less, high, perfect}, {none, very low, low, more or less, high, very high, perfect}. The duration are randomly defined in the correspondent intervals: activities [30, 100], the *earliest start time* [0, 365 - duration], the *latest finish time* [earliest start time, 365], the *quantity of resources* [100, 1000].

Table 2: Description of attributes

Attributes	***c1***	***c2***	***c3***	***c4***	***c5***	***c6***	***c7***	***c8***
Type (N - numerical; I - interval; L – linguistic)	L	N	I	I	L	N	N	L
max (+) / min (-)	+	+	-	-	+	+	-	+
cardinality (for linguistic)	7	-	-	-	3	-	-	7
weight(%)	20	23	2	7	19	13	13	2

By applying the Tabu Search procedure we have obtained 20 non-dominated alternatives shown in Table 3. Each row contains the VE composition for the project activities (i.e. the companies assigned to the activities). E.g. solution VE1 for project 1 includes companies 21, 81, 14, 31, 24 and 81, respectively for activities 1, 2, 3, 4, 5 and 6.

Table 3: Non-dominated alternatives

Project 1 (*Activities*)							Project 2 (*Activities*)						
	1	***2***	***3***	***4***	***5***	***6***		***1***	***2***	***3***	***4***	***5***	***6***
VE1	21	81	14	31	24	81	VE1	24	59	27	76	27	81
VE2	35	22	41	79	75	22	VE2	75	59	27	4	27	22
VE3	21	97	14	26	75	97	VE3	75	59	109	86	109	97
VE4	21	81	14	13	102	81	VE4	77	36	25	51	25	81
VE5	74	44	30	55	12	44	VE5	12	2	25	76	25	44
VE6	74	44	48	55	57	44	VE6	57	2	110	34	110	44

VE7	42	44	41	79	39	44	VE7	39	98	27	56	27	44
VE8	83	3	30	79	65	3	VE8	65	2	109	51	109	3
VE9	100	97	48	90	104	97	VE9	108	98	110	99	110	97
VE10	35	44	41	79	39	44	VE10	105	98	27	56	27	44
VE11	35	44	41	79	24	44	VE11	105	2	27	56	27	44
VE12	21	44	41	79	24	44	VE12	24	2	27	76	27	44
VE13	74	44	41	79	24	44	VE13	24	2	27	76	27	22
VE14	74	81	30	79	24	44	VE14	24	36	27	76	27	22
VE15	74	3	30	79	24	44	VE15	24	59	27	76	27	22
VE16	74	3	30	79	57	44	VE16	24	2	27	76	27	22
VE17	74	81	30	79	57	22	VE17	24	36	27	76	27	22
VE18	74	3	30	79	57	22	VE18	24	59	27	76	27	22
VE19	74	94	30	79	57	22	VE19	24	2	27	76	27	22
VE20	74	6	30	79	57	22	VE20	24	36	27	76	27	22

By applying the fuzzy TOPSIS approach, we have obtained the ranking of the non-dominated alternatives set shown in table 4.

Table 4: Closeness coefficients/Ranking of the alternatives

Project 1					Project 2				
Rank		$\tilde{d}_i^+$	$\tilde{d}_i^-$	$\tilde{R}_i$	Rank		$\tilde{d}_i^+$	$\tilde{d}_i^-$	$\tilde{R}_i$
1	VE16	308.615	188.746	0,057634	1	VE6	867.903	513.326	0,055843
2	VE6	308.508	188.321	0,057531	2	VE2	868.596	510.457	0,055506
3	VE20	308,63	188.368	0,057523	3	VE3	868.094	50.667	0,055147
4	VE13	308,68	187.654	0,057309	4	VE10	868.516	505.683	0,05502
5	VE18	308.636	187.623	0,057307	5	VE20	868.311	504.037	0,054863
6	VE7	308.671	187.493	0,057264	6	VE11	868.499	503.047	0,05475
7	VE5	308.634	186.476	0,056977	7	VE18	868.379	497.232	0,054159
8	VE15	308.659	185.693	0,056747	8	VE16	868.353	496.773	0,054113
9	VE10	308.766	18.493	0,056509	9	VE7	868.606	490.278	0,053429
10	VE11	308.748	18.477	0,056466	10	VE13	868.591	487.449	0,053138
11	VE2	308.831	184.436	0,056355	11	VE5	868.544	486.387	0,053031
12	VE19	308.743	176.865	0,054182	12	VE15	868.501	485.601	0,052952
13	VE17	308.809	175.964	0,053909	13	VE9	868.304	485.115	0,052913
14	VE14	308.832	173.938	0,053318	14	VE17	868.615	482.308	0,052605
15	VE3	308.695	173.427	0,053192	15	VE19	868.585	476.417	0,051998
16	VE9	308,72	170.573	0,052359	16	VE8	868.701	470.816	0,051411
17	VE8	308.849	168.091	0,051616	17	VE14	868.737	470.453	0,051372
18	VE12	308.925	166.468	0,051131	18	VE12	868.925	455.494	0,049809
19	VE4	309.147	147.143	0,045434	19	VE4	869.238	436.086	0,047772
20	VE1	309.091	145.427	0,044936	20	VE1	869.303	407.918	0,044822

6 CONCLUSIONS

The selection of partners is a critical issue in the formation of a virtual enterprise, the basic problem consisting in choosing the entities to be involved in an emergent business opportunity, according to their attributes and interactions. The work presented in this paper is in line with the key trends we have identified in a comprehensive literature survey, by namely considering: a) multiple attributes to describe/structure the decision problem; b) different types of "variables" in order to facilitate the expression of the preferences of the decision-maker; c) the subjectivity of information that leads to the use of a "fuzzy" approach; d) an optimization perspective through the use of metaheuristics; and e) the dynamic aspects occurring when various projects take place simultaneously. In this paper we have presented a formal description for the selection partner problem, consisting in a mathematical formulation based on a multi-attribute perspective. The developed approach can be viewed as a 2-phase algorithm where we first determine a set of potential VE configurations, and then generate a ranking list of potential VEs through the use of a fuzzy TOPSIS based procedure. This efficient quantitative tool seems to provide an adequate support to simulate different alternatives in VE formation or reorganization (through the introduction of different attributes or values/perceptions about the characteristics of the enterprises). Therefore, the final decision is taken by the decision maker. As future work we intend to improve the algorithm to cope with situations where the product is not known or structured in advance.

[1] The complete survey will be presented in a paper to be soon submitted for publication in an international journal.

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