4.3
Networked partner selection with robust portfolio modeling

T. Jarimo, K. Korpiaho

This chapter illustrates the applicability of mathematical decision-analysis in VO partner selection. The approach allows for multiple criteria, which can also relate to inter-organizational issues such as collaboration history between partner candidates. Moreover, the approach is soft in the sense that it allows interval parameter data, instead of point estimates. Using the RPM method, Pareto-efficient VO configurations can be identified and the robustness of the candidates can be analyzed. The results suggest that the models are very useful in practical decision-making situations.

1. INTRODUCTION

For some time, competition has changed from the level of individual firms towards rivalry among company networks (Jarillo, 1988). Through networking, companies can focus on their niche core competences, which may contribute to increased global efficiency (Hamel and Prahalad, 1990). Networking, however, involves transaction costs, which partly result from partner search and selection (Williamson, 1975). Therefore, several methods have been proposed for the reduction of these costs. Most notably, multi-criteria approaches to partner selection have attracted the interest of researchers and practitioners in the field.

A Virtual Organization Breeding Environment (VBE) in particular is in good position for utilizing semi-automated approaches to support the partner selection in Virtual Organizations (VO). The repeated creation of VOs allows the collection of data on the VBE members. This data can be further used to evaluate the suitability of the candidates in specific VOs. (Camarinha-Matos and Afsarmanesh, 2003)

This chapter models the partner selection problem as a multi-objective binary program. In multi-criteria problems it is typically more beneficial to identify the set of Pareto-efficient solutions rather than a unique solution (Steuer, 1976). Here, we employ the Robust Portfolio Modeling (RPM, Liesiö et al. 2007) method for identifying the Pareto-efficient configurations of a partner selection case. The advantage of RPM is that the model parameters need not be point estimates, which in many cases is too restrictive. Instead, the model can contain interval values as input data. The modeling approach allows for candidate-specific criteria, as well as network criteria that need to be measured for the configuration as a whole.

The rest of this chapter is organized as follows. Section 2 reviews earlier soft methods for partner selection. Section 3 formulates a multi-criteria mathematical programming model, which is operationalized in the partner-selection case of Section 4. Section 5 discusses the approach and Section 6 concludes with topics for future research.

2. ROBUST METHODS FOR NETWORK FORMATION

In multi-criteria decision-making, the decision-maker (DM) can aggregate the different objectives, e.g., by way of a subjective *value function* which reflects his or her preferences for the relative importance of the selection criteria. This method is based on multi-attribute value theory (MAVT, Keeney and Raiffa, 1976). The value function is typically additive, and the preferences are captured through criteria weights, which can be elicited using systematic approaches, such as SMART (Edwards, 1977), SWING (von Winterfeldt and Edwards, 1986), SMARTS or SMARTER (Barron and Edwards, 1994). Another method, which has become popular among practitioners, is the *analytic hierarchy process* (AHP, Saaty, 1980). It relies on pairwise comparisons of the alternatives and selection criteria, but its theoretical foundations differ from that of MAVT (Dyer, 1990; Saaty, 2005).

A common case in decision-making is that no perfect information is available on the decision alternatives and/or the DM's preferences over the selection criteria. Therefore, several methods, based on MAVT or AHP, have been suggested to cope with imperfect information (Arbel, 1989; Mikhailov, 2000; Salo and Punkka, 2005). Using such methods can help evaluate the robustness of decisions under imperfect information, often referred to as *soft modeling*.

VO partner selection is essentially a multi-criteria decision-making problem which involves several factors, such as corporate culture and social relations (Meade et al., 1997). Moreover, perfect data on such factors is hardly ever available, thus VO partner selection has been the subject of some soft modeling techniques. Since partner selection itself is a precise problem, the ambiguity is usually related to the partner candidates' expected performance, or the preferences of the decision-maker. In many works, this ambiguity has been captured by fuzzy approaches.

One of the earliest soft partner selection studies is that of Mikhailov (2002), who develops a fuzzy programming method for incorporating uncertain attribute weights and candidate scores into the AHP framework. A somewhat different one-criterion model is that of Ip et al. (2003), who maximize the probability of success of a virtual enterprise. Because their model is neither linear nor convex, they develop a genetic algorithm for solving it. Li and Liao (2004), in turn, use trapezoidal fuzzy numbers to express parameters related to various kinds of risk factors that they use to analyze risks in dynamic alliances. Since risk factors are difficult to measure quantitatively, the fuzzy approach helps the DM compare the risks of different alliances. The decision support tool of Crispim and Sousa (2005) allows the DM to use interval and linguistic variables in describing the candidates' performance. Such variables are useful if no exact data on historical performance is available.

3. MATHEMATICAL MODEL OF PARTNER SELECTION

3.1 Decision Variables and Objective Function

The partner selection problem can be mathematically formulated as follows. Following commonly used notation (e.g. Liesiö et al. 2007), let there be m partner candidates $X = \{x^1, \dots, x^m\}$. From these candidates a configuration p is formulated by selecting partners into it. The x^j s are used as the decision variables, if $x^j \in p$ then $x^j = 1$, otherwise $x^j = 0$. Each candidate is evaluated with regard to the n decision criteria $i = 1, \dots, n$, and the resulting score vector for x^j is $v^j = [v_1^j, \dots, v_n^j]$. The relative importance of the decision criteria are captured through criteria weights $w_1, \dots, w_n$, which are non-negative and scaled to sum up to one. The value of a configuration p is the weighted sum of the scores

$$V(p) = \sum_{x^j \in p} \sum_{i=1}^{n} w_i v_i^j . \tag{1}$$

Usually, partners are selected with respect to specific competences or project tasks, to which the above scores typically connect.

3.2 Optional Constraints

Without any constraints, the objective function (1) could prefer selecting all the candidates. Thus, the following types of restrictions are common and can be modeled as linear inequalities (Stummer and Heidenberger, 2003).

Resource constraints: These are the most commonly used constraints. A candidate j consumes or produces different kinds of resources l denoted by r_l^j, which are positive for consumption and negative for production. The resource limit for resource l is c_l. The following linear inequality determines the feasible configurations:

$$\forall l: \qquad \sum_{x^j \in p} r_l^j \le c_l . \tag{2}$$

Positioning constraints: With these constraints we can ensure that at least or at most a certain number of partners from a subset $X' \subseteq X$ will be chosen to our configuration. If at most m' partners are wanted, we create a new positioning resource constraint $\hat{l}$ and set $r_{\hat{l}}^{j} = 1 \quad \forall x^{j} \in X'$ and $r_{\hat{l}}^{j} = 0$ for the rest. The following inequality ensures that at most m' partners from X' are chosen:

$$\sum_{x^{j} \in p} r_{\hat{l}}^{j} \leq m'. \tag{3}$$

In contrast, if we multiply both sides of the inequality (3) by -1 and keep the less than or equal sign as it is, the inequality ensures that at least m' partners are chosen from X'. Positioning constraints are used to ensure e.g. that at least one partner is selected for each required competence.

Logical constraints: As the name states, we use these constraints to build logical requirements to our configuration. If, for example, x^{k} can be selected only if at least m' partners from X' are selected, we create constraint $\tilde{l}$ and set $r_{\tilde{l}}^{j} = -1$ $\forall x^{j} \in X'$ and $r_{\tilde{l}}^{j} = 0$ to the rest, except $r_{\tilde{l}}^{k} = m'$. The following inequality ensures that x^{k} is in the configuration only if the requirement holds:

$$\sum_{x^{j} \in p} r_{\tilde{l}}^{j} \leq 0. \tag{4}$$

If at most m' candidates can be chosen, both sides of the inequality should be multiplied by -1 while the less than or equal sign remains as it is. If both of these inequalities are used at the same time either all the candidates in X' and x^{k} are chosen or none of them are chosen. The logical constraints can be used to ensure that x^{k} is chosen if exactly m' partners are chosen from X', but it is possible to choose less than m' partners from X'. These inequalities are used to model inter-organizational dependencies.

Threshold constraints: These constraints can be used as balancing constraints, to ensure certain performance levels or to reject otherwise high value configurations where too low performance on some criterion has been compensated by other criteria. If we require that the resulting configurations earn at least $h_{\bar{l}}$ points from the i th criterion, we create constraint $\bar{l}$ and set $r_{\bar{l}}^{j} = -v_{i}^{j} \quad \forall j$. The following inequality ensures that the required performance levels are reached:

$$\sum_{x^{j} \in p} r_{\bar{l}}^{j} \leq -h_{\bar{l}}. \tag{5}$$

The inter-organizational dependencies can be modeled into the selection problem with the help of logical constraints and dummy partners. For example, we gain synergy value $v^{\tilde{j}}$ if partners x^{k} and $x^{k'}$ are chosen to our configuration. We create a dummy partner $x^{\tilde{j}}$ and set its score vector to be $v^{\tilde{j}}$. In addition, we create new constraints $\tilde{l}$ and $\tilde{l}+1$ and set $r_{\tilde{l}}^{k} = r_{\tilde{l}}^{k'} = -1$, $r_{\tilde{l}}^{\tilde{j}} = 2$, $r_{\tilde{l}+1}^{k} = r_{\tilde{l}+1}^{k'} = 1$, $r_{\tilde{l}+1}^{\tilde{j}} = -2$ and $r_{\tilde{l}}^{j} = r_{\tilde{l}+1}^{j} = 0$ for all the other partners. The following inequalities ensure that the dummy partner $x^{\tilde{j}}$ is selected if and only if partners x^{k} and $x^{k'}$ are selected, too:

$$\begin{aligned} &\sum_{x^j \in p} r_{\tilde{l}}^{j} \leq 0 \\ &\sum_{x^j \in p} r_{\tilde{l}+1}^{j} \leq 1. \end{aligned} \tag{6}$$

Partner synergies are illustratively modeled through a network of project proposals. With ten candidates there can be at maximum 45 edges between the 10 vertices, thus to model this network with the help of dummy candidates and inequalities which we already used for synergy requires only at worst case 45 dummy candidates. Each edge defines one dummy candidate, which is chosen only when both its end-point vertices are chosen. The edges can be weighted with the scores of the dummy candidates.

Finally, some of the tasks can be more important to the completion of the project than the others. We can model this with additional criteria for all the tasks and by giving scores to candidates depending on how important they are to a certain task.

3.3 Solving the Partner Selection Model

In summary, the model (1)-(6) comprises a binary linear program (BP), where the binary x^{j}s are variables, the objective function is in (1), and the optional constraints are in (2)-(6). Linear models are favorable in that they can be readily solved using for instance Simplex (Dantzig, 1963) and Branch-and-Bound algorithms (Land and Doig, 1960), which solve the problem with exact parameter values.

The recently developed RPM method (Liesiö et al., 2007) is particularly suitable for solving multi-criteria portfolio-selection problems, where a subset of elements is to be chosen from a larger set, with respect to multiple criteria. The above partner selection model fits into this category. The advantage of RPM is that it allows interval-values for model parameters and criterion weights. Given the parameter space, the result of the RPM algorithm is the set of Pareto-efficient solutions, which offers good grounds for further analysis of the decision alternatives.

4. ILLUSTRATIVE CASE EXAMPLE

We applied the model to a partner selection case of Virtuelle Fabrik (http://www.vfeb.ch), which is an operative VBE located in Switzerland (Jarimo et al., 2006). The results suggest that relevant criteria can be taken into account and reasonable configurations are identified.

4.1 Project Description

The aim of the project was to construct a prototype magnetic clutch to be used in trucks. The project was broken down into nine tasks, which were 1) Grinding, 2) Gear milling, 3) Metal sheet forming, 4) Milling and turning of bigger parts, 5) Welding, 6) Bending of pipes, 7) Engineering, 8) Milling and turning of smaller parts, and 9) Project management. For each task, there were two to five partner candidates, some of which were candidates for several tasks (Table 1).

Table 1 – Tasks and partner candidates of the case project

Tasks	Candidates
Grinding	Sulzer AG, Brunner
Gear milling	Okey AG, Humbel
Metal sheet forming	Beni Butscher, Unima AG
Milling bigger parts	SMA, Knobel, OMB AG, SIG
Welding	Beni Burtscher, Amsonic
Bending of pipes	Fornara, SMA
Engineering	Schuler, AE&P AG, Schär Engineering
Milling smaller parts	Innotool, SIG, Wiftech, Bühler, Alwo AG
Project management	VF AG, Schär Engineering, AE&P AG, CCB

The partners were to be selected according to the following criteria: 1) Punctuality, 2) Partnership synergy, 3) Reliability, 4) Cost, and 5) Economical situation. The Customer of the project was a large German auto manufacturer, and a very important reference to Virtuelle Fabrik. The project had a tight schedule and the Customer's top priority was to finish the project in time. Thus, punctuality and reliability were the most important criteria in partner selection. Moreover, it was assumed that a successful collaboration history contributes to finishing the project in time. The Cost and Economical situation do not directly influence the schedule of the project, therefore they were less important. However, this only means that in the additive model the weights of the less important criteria do not exceed those with higher importance – Costs and Economical situation are not ignored. In general, the criteria need to be selected and weighted case-specifically; in another case for instance Costs or some completely new criteria could be the most important ones (Baldo et al., 2007).

Data concerning Punctuality, Reliability, and Economical situation consisted of Virtuelle Fabrik's managerial assessment of the candidates' performance, evaluated on a 1-6 scale. No exact estimates were required, but instead the score could be an interval within the 1-6 scale. The costs were given as the total price in Euros for performing the task for which the candidate is attached. Partnership synergy was modeled through a network that described the candidates' collaboration history (Figure 1).

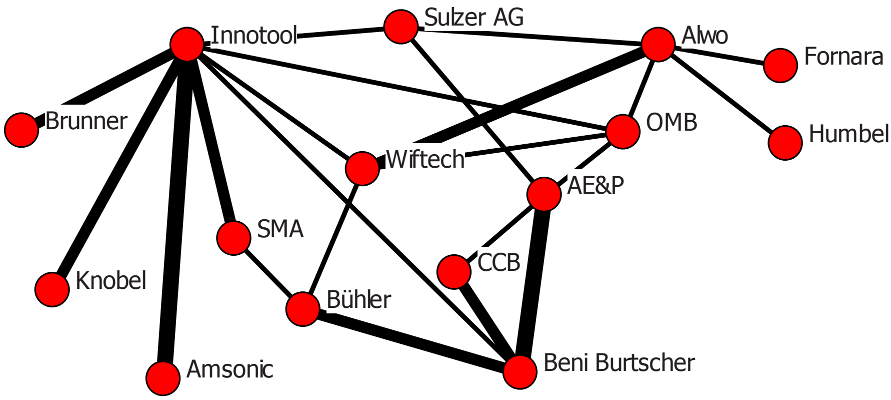

Figure 1 – Intensity of past collaboration between the partner candidates

In Figure 1 each circle represents a partner candidate of the case and the links between the candidates represent the number of past joint projects; a thicker line between two candidates represents a greater number of joint projects in the past. Also here, the score related to links need not be exact; intervals are allowed. Candidates that had no earlier collaboration with the others are excluded from the figure.

4.2 Case Analysis

With this data, the problem is that of selecting a good partner for each task, with respect to minimizing Cost and maximizing Punctuality, Partnership synergy, Reliability, and Economical situation. This can be modeled as a multi-criteria binary programming problem as described above. Using the novel RPM-algorithm (Liesiö et al. 2007) developed for this kind of selection problems, the model was solved as follows.

First, we defined that Punctuality, Partnership synergy, and Reliability are more important than Cost and Economical situation. The minimum weight of a criterion was 0.1. Solving the problem with this information resulted in 129 various Pareto-efficient configurations, which is too much to consider for a DM.

Second, we made our preference information more accurate by raising Punctuality and Reliability to be the most important criteria, leaving Partnership synergy as the second important and Cost and Economical situation as the least important ones. This increase of information reduced the number of Pareto-efficient configurations to 109, which is still too much.

Finally, we defined that the weights of Punctuality and Reliability are close to each other, which results in configurations with good scores in both of the most important criteria. Consequently, six Pareto-efficient configurations remained, listed in Table 2. It is worth noting that making the information more accurate reduces the set of Pareto-efficient configurations so that the DM can finally end up with a manageable number of solutions.

Table 2 – Performance of six Pareto-efficient configurations

Configuration	Punctuality	Reliability	Partnership synergy	Economical situation	Cost (€)
#74	48	52	29	45	123710
#76	48	52	28	45	123010
#80	48	52	27	47	126270
#73	46	53	29	44	123110
#75	46	53	28	44	122410
#79	46	53	27	46	125670

With a closer look at Table 2, the most interesting one is Configuration #74, which has the highest scores on Punctuality and Partnership synergy, and the second highest score on Reliability. It is also estimated as one of the least expensive configurations.

An interesting measure for the robustness of the partner candidates is the percentage of Pareto-efficient configurations in which the candidates are involved. Table 3 shows these robustness scores for those candidates that are involved in at least one Pareto-efficient configuration. Candidates with a score of 100 are robust choices within the parameter space, irrespective of the relative importance of the selection criteria.

Table 3 – Sensitivity analysis on the efficient partner candidates

Task	Candidates and their robustness scores			
Grinding	Sulzer	67	Brunner	33
Gear milling	Humbel	50	Okey AG	50
Metal sheet forming	Beni Burtscher	100		
Milling bigger parts	Knobel	100		
Welding	Beni Burtscher	100		
Bending of pipes	SMA	100		
Engineering	AE & P AG	100		
Milling smaller parts	Innotool	67	Bühler	33
Project management	AE & P AG	100		

Selecting the candidates that have the highest robustness scores leads to Configurations #73 (Gear milling: Okey AG) or #74 (Gear milling: Humbel). Configuration #73 outperforms #74 in terms of Reliability and Cost, but has lower scores with respect to other criteria. Neither Okey AG nor Humbel had earlier collaboration with the other partners of Configurations #73 and #74, thus these configurations have the same score on Partnership synergy. In conclusion, through the score table together with robustness analysis we have come up with two interesting configurations, namely #73 and #74, on which the decision-maker can focus in further analysis and negotiations.

5. DISCUSSION

The multi-criteria approach has several advantages:

- The methods are theoretically sound, relying on multi-attribute value theory and mathematical optimization. This facilitates for instance efficient identification of Pareto-efficient configurations and flexibility in that additional linear constraints and objectives can be formulated.
- No point estimates on parameter values of criterion weights are required. Instead, interval values can be given as input, which is practically favorable. For a decision maker it may be difficult or overly expensive to collect exact information. Therefore, the softness of the model indeed contributes to the practicality of the approach.
- The robustness of the partner candidates can be analyzed easily. Calculating the percentage of Pareto-efficient configurations in which each partner candidate is involved divides the candidates in three categories: 1) candidates that are selected in each Pareto-efficient configuration, 2) candidates that are selected in at least one Pareto-efficient configuration, and 3) candidates that are not selected in any of the Pareto-efficient configurations. Category 1) candidates are the most robust choices, since they are selected irrespective of the uncertainty in parameter values or the relative importance of the selection criteria.

We model partner selection as a centralized decision-making problem. This is reasonable if one entity is fully responsible for selecting the network partners. In the above Virtuelle Fabrik case the customer wanted that the broker company takes responsibility of the project, hence it was natural that the broker selected the partners unilaterally. Indeed, centralized decision making typically fits cases that involve a hierarchical topology.

However, there are situations where the decision-making is in fact decentralized. This is the case if the partner candidates themselves decide with whom to collaborate. An example of a decentralized partner selection process is the formation of inter-organizational research projects. In this case, the formation of the final consortium is a multi-party negotiation process between research teams at universities, research institutes, and companies.

Another decentralized partner selection case could be that of selecting a new partner into the VO, whereby the original partners may be willing to influence the selection process. For such cases the candidates that were not originally selected but who were part of some Pareto-efficient configurations provide a good starting point for searching. The use of decision-support tools increases transparency in group decision-making, too.

A prerequisite for the use of decision support tools in partner selection is the availability of data for parameter estimation. The long-term VBE cooperation structure supports parameter estimation because it enables the collection of longitudinal performance data. Moreover, longitudinal data helps VBE management in identifying trends for instance in individual members' performance.

6. CONCLUSIONS AND FURTHER CHALLENGES

This chapter illustrated the use of multi-criteria mathematical programming methods for robust partner selection in collaborative networks. The objective of the model is to match the core competencies of partner candidates with the requirements of a project and thereby select the optimal VO to serve the customer. The analysis and the realistic case study suggest that the methods are both theoretically sound and practically useful.

Solving the models with RPM allows the decision makers to give interval parameter-estimates. The more imprecise the information the larger is the set of Pareto-efficient solutions. Thus, the decision maker can gradually increase the accuracy of the parameter estimates until a manageable number of Pareto-efficient solutions remains. From the remaining set, the decision maker can select the most preferred configuration and make possible manual modifications to it.

The models are potentially useful in cases where one decision maker selects network partners. Such cases occur in a VBE that repeatedly creates VOs whenever there is potential for value creation through collaboration. Customers often wish that only a single partner – the broker – is responsible for the operations of the VO. It is therefore natural that the broker has the control over the VO and partner selection. In group decision-making, the models can improve the common understanding of the case at hand and increase transparency of the decision criteria and their assessment.

Topics for future research are manifold. First, our optimization model could be improved by several features. These include for instance dynamic decision-making and uncertainties, interdependent risks, hedging against capacity risk, etc. Second, the effect of incentives, e.g. profit sharing rules, on VO creation should be studied. Third, VBE member performance measurement models are needed in order to most efficiently use operative models. For instance, our model raises the need to measure factors related to cooperative efficiency.

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