Multi-Criteria Partner Selection in Virtual Organisations With Transportation Costs and Other Network Interdependencies*

Toni Jarimo
VTT Technical Research Centre of Finland
P.O. Box 1000, FIN-02044 VTT, Finland
E-mail: toni.jarimo@vtt.fi

Ahti Salo
Systems Analysis Laboratory
Helsinki University of Technology
P.O. Box 1100, FIN-02015 TKK, Finland
E-mail: ahti.salo@tkk.fi

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Abstract

In this paper we study how the selection of partners in a virtual organisation (VO) can be assisted through mixed integer linear programming (MILP) models. Additionally to fixed and variable costs, we present extensions that accommodate transportation costs, capacity risk-measures, and inter-organisational dependencies such as the success of past collaboration. Experiences from a real case study indicate that these models are helpful in VO decision making; computational experiments suggest that the models are tractable. In general, the MILP models are potentially applicable to a variety of portfolio selection problems.

Keywords: partner selection, multiple criteria, virtual organisation, mixed integer linear programming, portfolio selection

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1 Introduction

Collaborative networks are becoming more important in global and regional business, thanks to their ability to combine organisational competences. But when individual companies seek efficiency gains by focusing on their core competences while outsourcing non-core operations, the number and complexity of inter-firm transactions grows [1]. This calls for the development and deployment of decision support models that help companies in the management of such relationships. Towards this end, several researchers have introduced the idea of a 'club' that consists of a set of member-organisations with a mutually agreed cooperation structure for the creation of temporary networked project organisations called *virtual organisations* (VO) [2, 3, 4]. We call this club a *virtual organisation breeding environment* (VBE) [3], which is characterised by a common ICT infrastructure, strategy, and processes for agile VO creation, among others.

Specifically, we focus on the problem of selecting VO partners in a VBE. That is, when a VBE identifies a business opportunity, it must determine a 'good' VO configuration to meet an identified customer need. This is essentially an optimisation problem for which we develop a mixed integer linear programming (MILP) model in order to allocate work among potential VO partners, taking into account fixed and variable work costs, transportation costs, risks of capacity shortfall, and inter-organisational dependencies.

The explicit consideration of risks and inter-organisational dependencies, in particular, are novel features that are motivated by real problems, such as our case example on the selection of partners for the construction of a magnetic clutch prototype for lorries. Yet these features have not received earlier attention by way of formal modelling or practical application. The MILP models are potentially applicable also to other *portfolio selection* problems, where a subset of elements is to be chosen from a larger set with respect to multiple constraints and criteria [5, 6, 7].

The rest of this paper is structured as follows. Section 2 reviews earlier partner selection models. Section 3 develops the MILP model for VO partner selection. Section 4 presents a real-life case example and illustrates the use of our MILP model. Finally, Section 5 concludes with suggestions for further research.

2 Mathematical Methods for Partner Selection

Several authors have developed VO partner selection methods for minimising a single criterion, most notably the total life cycle costs defined in terms of production, operation, and transportation costs, for instance [8, 9, 10, 11]. However, many 'soft' factors—such as corporate culture and social relations—that influence the VO performance cannot be captured by pure cost models. This has motivated some authors to propose multi-criteria models for VO partner selection [12, 13, 14, 15].

Computational requirements have been curtailed by pre-screening the candidates. In the spirit of data envelopment analysis, Talluri et al. [16] calculate the input-output (I-O) ratio for partner candidates, with respect to multiple weighted inputs and outputs. They then solve a linear program to identify the *efficient* candidates, i.e. candidates with the highest I-O ratios for given weights. Candidates that are not efficient at any weights are excluded from the final integer goal programming model. Feng and Yamashiro [9] manually select partner candidates for a qualitative pre-qualification phase, based on the candidates' competences with regard to customer needs. In this phase, they first determine feasible partner combinations, which are then compared by solving a mixed-integer non-linear program.

Only few authors [16, 17] have paid attention to inter-organisational dependencies. These include considerations such as trust, cultural homogeneity, and success of past collaboration that may contribute to the expected success of the VO [18, 19]. Furthermore, the minimisation of risks due to capacity fluctuations and quality failures has received only little attention [20, 21, 22], although they are highly relevant to partner selection.

3 A Model of Collaboration

3.1 Parameters and Variables

We model VO partner selection as a work-allocation problem where $M = \{1, \ldots, m\}$ denotes the set of candidate partners in the VBE. At the outset, the VBE identifies a business opportunity which is to be addressed by carrying out a project for the Customer. The project tasks are denoted by $N = \{1, \ldots, n\}$ so that the workload w_j of $j \in N$ is measured in relevant units (e.g. person months). Table 1 summarises the relevant parameters and variables: here, the *continuous* x variables denote the allocation of work among candidates, while the *binary* y and z variables pertain to individual and multiple candidates, respectively.

PLEASE INSERT TABLE 1 ABOUT HERE

The parameters in our basic model are:

$C_{i,j}$ = distribution of the capacity (i.e. amount of work) that candidate i can perform on task j (e.g. person months),

$p_{i,j}$ = probabilities associated with the capacity distribution $C_{i,j}$,

$v_{i,j}$ = variable costs of candidate i working on task j (e.g. €/person month),

f_i = fixed cost of introducing candidate i into the VO,

$f_{i,j}$ = fixed cost of candidate i starting to work on task j.

Capacity information is given through discrete probability distributions so that $c^k_{i,j}$ denotes the kth element of $C_{i,j}$ and $p_{i,j}(k)$ is the corresponding probability. Without loss of generality, it can be assumed that the possible capacities are sorted in descending order so that $c^1_{i,j} = \max_k c^k_{i,j}$. Because the probabilities add up to one, the expected capacity that candidate i devotes to task j is

$$E[C_{i,j}] = \sum_k p_{i,j}(k) c^k_{i,j} \quad \forall\, i \in M,\ j \in N.$$

The decision variable is the work-allocation matrix $X_{m \times n}$ whose element $x_{i,j}$ denotes the amount of work on task j that is assigned to candidate i. The following auxiliary variables are helpful in model formulation. Let

$$y_i = \begin{cases} 0, & \text{if } x_{i,j} = 0\ \forall\, j \in N \\ 1, & \text{if } x_{i,j} > 0 \text{ for at least one } j \in N. \end{cases}$$

Thus, y_i is equal to one if candidate i performs some work in the project, and zero otherwise. Also, let

$$y_{i,j} = \begin{cases} 0, & \text{if } x_{i,j} = 0 \\ 1, & \text{if } x_{i,j} > 0. \end{cases}$$

The distinction between these variables is that y_i indicates whether or not candidate i is involved in the project, while $y_{i,j}$ indicates which tasks candidate i is involved in, if this should be the case. Thus, if $y_i = 0$ for some i, then $y_{i,j} = 0 \; \forall j$; and if $y_i = 1$ for some i, then $y_{i,j} = 1$ for at least one j.

3.2 Objective Function

Our basic model accounts for the candidates' variable and fixed costs through a single cost criterion

$$\min_{X,Y} Cost(X,Y) = \underbrace{\sum_{i=1}^{m} f_i y_i}_{\text{(I)}} + \underbrace{\sum_{j=1}^{n}\sum_{i=1}^{m}(v_{i,j}x_{i,j} + f_{i,j}y_{i,j})}_{\text{(II)}}, \tag{1}$$

where the work allocation matrix $X_{m\times n}$ contains the xs and the matrix $Y_{m\times(n+1)}$ contains the ys. In the objective function, the first term (I) captures fixed costs due to the introduction of partners, and the second term (II) covers fixed and variable costs due to the work that the partners perform on their respective tasks.

3.3 Constraints

Two types of constraints are needed to ensure the fulfilment of project requirements and the feasibility of the optimal solution. In order to satisfy project requirements, the workload of each task has to be completed, i.e.

$$\sum_{i=1}^{m} x_{i,j} \geq w_j \quad \forall\, j \in N. \tag{2}$$

The workload assigned to a candidate must not exceed maximum capacity

$$x_{i,j} \leq c_{i,j}^1 \quad \forall\, i \in M,\ j \in N.$$

Alternatively, the workload of the partner can be bounded by its expected capacity (i.e. $x_{i,j} \leq E[C_{i,j}]$), because it may not be able to devote its maximum capacity to the task. Finally, workloads must be non-negative:

$$x_{i,j} \geq 0 \quad \forall\, i \in M,\ j \in N.$$

To ensure feasibility, the binary y_is must satisfy the constraints:

$$y_i \geq \frac{\sum_{j \in N} x_{i,j}}{\sum_{j \in N} w_j} - \epsilon \qquad \text{and} \qquad y_i \leq \frac{\sum_{j \in N} x_{i,j}}{\sum_{j \in N} w_j} - \epsilon + 1 \qquad \forall\, i \in M. \tag{3}$$

The numerators denote the total amount of work that is allocated to candidate i while the denominator is the total workload of the project: thus, these quotients are equal to the proportion of the project's workload that is allocated to candidate i. Furthermore, ϵ corresponds to the proportion of the total workload that a candidate must exceed so as to be a relevant VO partner. Thus, $y_i = 1$ if at least $\epsilon \times 100$ percent of the project's workload is allocated to candidate i, and $y_i = 0$ otherwise.

In the first expression of (3), the denominator ensures that the right hand is less than one (if it were larger than one, the model would become infeasible because y_i is a zero-one variable). A similar argument holds for the denominator in the other inequality, too.

The following constraints ensure that the binary $y_{i,j}$s assume their correct values:

$$y_{i,j} \geq \frac{x_{i,j}}{c_{i,j}^1}, \quad \forall\, i \in M, j \in N \text{ s.t. } c_{i,j}^1 > 0.$$

That is, $y_{i,j} = 1$ if at least some work of task j is allocated to candidate i, and $y_{i,j} = 0$ otherwise. No upper constraint for $y_{i,j}$s is needed, because increases in these binary variables cause higher costs, wherefore $y_{i,j}$s remain at zero level whenever feasible. However, if one were to introduce an additional decision criterion such that the benefit increases when $y_{i,j} = 1$, an upper bound similar to that for y_is becomes necessary.

Our basic optimisation model can now be stated as

$$
\begin{aligned}
\min_{X,Y} \; Cost(X,Y) &= \sum_{i=1}^{m} f_i y_i + \sum_{j=1}^{n}\sum_{i=1}^{m}(v_{i,j}x_{i,j} + f_{i,j}y_{i,j}) \\
\text{s.t.} \quad \sum_{i=1}^{m} x_{i,j} &\geq w_j \quad \forall\, j \in N \\
x_{i,j} &\leq c^1_{i,j} \quad \forall\, i \in M,\; j \in N \\
y_i &\geq \frac{\sum_{j\in N} x_{i,j}}{\sum_{j\in N} w_j} - \epsilon \qquad \forall\, i \in M \\
y_i &\leq \frac{\sum_{j\in N} x_{i,j}}{\sum_{j\in N} w_j} - \epsilon + 1 \qquad \forall\, i \in M \\
y_{i,j} &\geq \frac{x_{i,j}}{c^1_{i,j}}, \quad \forall\, i \in M, j \in N \;\text{ s.t. }\; c^1_{i,j} > 0 \\
x_{i,j} &\geq 0 \quad \forall\, i \in M,\; j \in N \\
y_i &\in \{0,1\} \quad \forall\, i \in M \\
y_{i,j} &\in \{0,1\} \quad \forall\, i \in M,\; j \in N.
\end{aligned}
$$

3.4 Transportation Costs

Insights into the role of transportation costs can be gained from one of our case VBEs, the *CeBeNetwork GmbH* (http://www.cebenetwork.com), which is a 'strategic supplier' for *Airbus* with numerous projects in areas such as aerodynamics R&D, wind-tunnel testing, and IT systems development for aircrafts. An IT project, for instance, typically involves both software and hardware solutions. The development of software does not involve transportation needs, but hardware equipment must be transported from the manufacturing site of CeBeNetwork to the Airbus manufacturing site.

More generally, we consider a manufacturing VO where each partner supplies a specific component that is a part of the end-product. Whenever two or more components are assembled together, these components must be at the same site, which means that transportation costs are incurred unless all components are manufactured and assembled at the same site.

Transportation costs are driven mainly by two factors, 1) geographical distance and 2) volume and weight of the cargo. For instance, consider a project of three tasks such that the output of Task 1 must be made available at the same site where Task 3 is carried out and that the volume of this transportation is 5 units. This task sequence is illustrated through the simple network in Figure 1a. Because Task 2 does not have physical connection to Tasks 1 or 3, it is a disconnected node. For instance, Task 1 could correspond to the manufacturing of a microchip, which is assembled into the end-product in Task 3. Task 2, in turn, could represent software development for the end-product.

PLEASE INSERT FIGURE 1 ABOUT HERE

Assume that we have four partner candidates, between which the unit transportation costs are as shown in Figure 1b. Moreover, assume that Candidates 1 and 3 are capable of performing Task 1, while Task 3 can be performed by Candidates 1 and 4. Figure 1c integrates the information of Figures 1a and 1b, as well as information about which candidates can perform the corresponding tasks. Thus, depending on the work allocation of Tasks 1 and 3, the transportation costs are as shown in Figure 1c.

The above concepts can be formalised as follows. Let $r = (r', r'')$ denote a pair of tasks such that the (physical) output of task r' must be at the same location where task r'' is carried out (see Figure 1a). Let R denote the set of all such pairs. For each $(r', r'') \in R$, let $\delta_{r',r''}$ be the corresponding output volume of task r' (measured in a relevant unit, e.g. kg). For instance, in the example of Figure 1, R consists of only one pair, namely $(1, 3)$ with an output volume of $\delta_{1,3} = 5$.

The cost of transportation can be presented as a graph whose nodes correspond to the candidate partners and whose edges represent the unit transportation costs between adjacent nodes (see Figure 1b). Specifically, for candidates a and b, these unit costs are denoted by $t_{a,b}$. In Figure 1b, for instance, we have $t_{1,4} = 6$.

For each pair $(r', r'') \in R$, we have two sets of candidates, i.e. 1) those that are capable of performing task r' and 2) those that are capable of performing task r'' (see Figure 1c). These two sets are connected by edges between the candidates such that each edge represents the transportation cost from one candidate to another, in accordance with the relation (r', r''). For instance, if Candidate 1 were to perform Task 1 and Candidate 4 were to perform Task 4, the transportation costs would be $5 \times 6 = 30$, because $\delta_{1,3} = 5$ and $t_{1,4} = 6$.

Transportation costs can now be incorporated into our MILP model as follows. For any given pair of tasks $r = (r', r'')$, we define the binary variable $z^r_{a,b}$

$$z^r_{a,b} = \begin{cases} 0, \text{ if } y_{a,r'} = 0 \text{ or } y_{b,r''} = 0 \\ 1, \text{ if } y_{a,r'} = 1 \text{ and } y_{b,r''} = 1 \end{cases} \quad \forall\ r \in R,\ a, b \in M \text{ s.t. } c^1_{a,r'} \geq w_{r'} \text{ and } c^1_{b,r''} \geq w_{r''},$$

where this definition applies for all pairs of candidates (a, b) such that a is capable of performing task r' and b can perform task r''. Thus, $z^r_{a,b}$ is one if tasks r' and r'' are enabled by transportation between candidates a and b; otherwise $z^r_{a,b}$ is zero. In addition, the following constraints are needed:

$$z^r_{a,b} \leq \frac{y_{a,r'} + y_{b,r''}}{2} \quad \text{and} \quad z^r_{a,b} \geq y_{a,r'} + y_{b,r''} - 1.$$

The first of these constraints ensures that $z^r_{a,b}$ is zero if tasks r' and r'' are not allocated to candidates a and b, respectively. The second constraint ensures that $z^r_{a,b}$ is one if candidates a and b work on tasks r' and r'', respectively.

The total transportation costs can now be written as

$$Cost^{\text{TRANS}} = \sum_{r \in R} \delta_{r',r''} t_{a,b} z^r_{a,b}.$$

The above cost function is linear, thus the objective function (1) remains linear even when transportation costs are accounted for.

3.5 Capacity Risks

Risk management is vital due to the possibly adverse impact of uncertainties in the partners' individual or collaborative behaviour. Hallikas et al. [23] suggest that there are two main sources of uncertainties, namely *customer demand* and *customer delivery*, i.e. supply. Because the VO partner selection process is triggered by a business opportunity—or *realised* demand—demand risks are here not very relevant, because there are usually no risks with customer payments (excluding force majeure events such as bankruptcy). In our case, we therefore focus on capacity fluctuations that call for the reconfiguration of the VO.

In Section 3.1, we modelled capacities through discrete probability distributions. Several reasons suggest that this level of accuracy is often sufficient. First, small capacity fluctuations do not usually matter, because organisations can adapt themselves to them; this means that the DM is interested in large fluctuations that may call for the reconfiguration of the VO. Second, in the *ex ante* assessment of large fluctuations, the DM may have to accept rough risk estimates [23], which are often best approximated by a discrete distribution.

Among alternative measures for the management of capacity risks, we give precedence to *expected downside risk* (EDR) [24]. EDR can be interpreted as the expected shortfall from a given target value (i.e. the amount of work that is allocated to a partner). It is therefore more meaningful than variance-based measures which indicate 'risk' whenever there are capacity uncertainties, although the DM is not faced with risks when the available capacity exceeds the required level. EDR also belongs to the family of mean-risk dominance models and shares their desirable properties [6, 25].

In our model, the EDR of Candidate i's work allocation on task j is

$$\rho_{i,j}^{\mathrm{EDR}} = \sum_{\substack{k \\ c_{i,j}^k < x_{i,j}}} p_{i,j}(k)(x_{i,j} - c_{i,j}^k).$$

That is, $\rho_{i,j}^{\mathrm{EDR}}$ is the expected downside difference between the amount of work on task j that is allocated to Candidate i, on one hand, and i's capacity on this task, on the other hand. The summation is taken over the events $c_{i,j}^k$ that result in capacity shortfall, subject to the allocation of workload $x_{i,j}$.

In order to incorporate EDR into our model, let $c_{i,j}^{k+} \geq 0$ and $c_{i,j}^{k-} \geq 0$, denote the positive and negative difference of $c_{i,j}^{k} - x_{i,j}$ for any given $c_{i,j}^{k} \in C_{i,j}$. The correct values of $c_{i,j}^{k+}$ and $c_{i,j}^{k-}$ can be ensured through constraints

$$x_{i,j} - c_{i,j}^{k-} + c_{i,j}^{k+} = c_{i,j}^{k} \quad \forall\, i \in M,\ j \in N,\ c_{i,j}^{k} \in C_{i,j}.$$

The formula for EDR becomes

$$\rho_{i,j}^{\mathrm{EDR}} = \sum_{k} p_{i,j}(k) c_{i,j}^{k-},$$

where the summation is taken over the probability distribution $p_{i,j}(k)$. However, only capacity realisations below the target level contribute to the risk measure, because $c_{i,j}^{k-}$s are equal to zero otherwise. The total EDR of a VO configuration can thus be expressed as the sum $\sum_i \sum_j \rho_{i,j}^{\mathrm{EDR}}$.

EDR-based risk management can be captured by our MILP model either through goal programming (e.g. through linear constraints such as $\rho_{i,j}^{\mathrm{EDR}} \leq \mathrm{EDR}_{\max}$) or by aggregating risks and costs through a value function. Both approaches require parameter estimates, either in terms of accepted risk-levels $(\mathrm{EDR}_{\max})$ or through the explication of tradeoffs between cost and capacity risk. Furthermore, if the project has tasks whose completion is crucial to the completion of several other tasks, these tasks can be weighted more heavily in the model formulation: for example, one can associate lower accepted risk-levels or higher cost-of-risk with critical tasks.

3.6 Inter-organisational Dependencies

The collaborating entities can be individual workers, intra-organisational teams, business units, or distinct companies, among others. The adequate level of analysing collaboration depends on the case at hand: in partner selection, for instance, it is unrealistic to estimate the transaction costs that are likely to arise during the entire VO life-cycle; it is therefore more practical to study non-monetary indicators that influence the size of transaction costs over the VO life-cycle. One such indicator—which can be measured relatively easily—is the number of past collaboration activities among partner candidates. It is reasonable to assume that the more intensely the companies have collaborated earlier, the better they know each other's ways of action, which reduces the transaction costs of collaboration. In contrast, examples of measurable indicators that may result in *increased* transaction costs include geographical distance and linguistic difference. We refer to these and related indicators as *network preparedness criteria*.

The network preparedness criteria differ from traditional selection criteria (e.g. cost or quality) in that their measurement involves two or more companies (one cannot measure 'geographical distance' for a single company). Arguably, the measurement of such inter-organisational performance is easier within a VBE than in a totally 'open universe' of organisations. This is because the VBE members collaborate repeatedly, which permits the collection of data about inter-organisational performance [3].

The following formulation shows how inter-organisational dependencies are incorporated into our model, using collaboration history as an example of network preparedness criteria. For instance, Figure 2 illustrates the collaboration history of four fictitious companies. Here, Companies 2 and 3 have collaborated in one past project, and Companies 3 and 4 have collaborated in two earlier projects. Company 1 has no earlier collaboration with others.

PLEASE INSERT FIGURE 2 ABOUT HERE

Let $z_{a,b} \in \{0, 1\}$ be a binary variable which indicates whether or not a particular *pair* of candidates is selected into the VO. Formally, we let

$$z_{a,b} = \begin{cases} 0, & \text{if } y_a = 0 \text{ or } y_b = 0 \\ 1, & \text{if } y_a = 1 \text{ and } y_b = 1. \end{cases}$$

In other words, $z_{a,b}$ is one if some work is allocated to both candidates a and b, and zero if work is allocated to neither candidate or only to one of them. Hence, $z_{a,b}$ shows whether a *pair* of organisations is selected into the VO. This enables objective functions that account for inter-organisational dependencies, of which the collaboration history in Figure 2 is but one example.

For z, we need the constraints

$$z_{a,b} \leq \frac{y_a + y_b}{2} \quad \text{and} \quad z_{a,b} \geq y_a + y_b - 1 \quad \forall \{a, b\} \subset M,$$

The former constraint ensures that $z_{a,b}$ is strictly less than one if either y_a or y_b is zero. The latter one that $z_{a,b}$ is one if both y_a and y_b are equal to one.

We next define a quantitative measure for collaboration history. First, let $e_{a,b}$ denote the number of earlier collaboration activities between companies a and b, and let $e_{\max}$ be the maximum number of earlier collaboration activities of a single candidate. For instance, in Figure 2, we have $e_{2,3} = 1$, $e_{3,4} = 2$, and $e_{\max} = 3$, which is due to Candidate 3.

When the VBE has a documented collaboration history, the following linear measure can be used to approximate the benefits of earlier collaboration

$$\gamma^{\text{LIN}}(Y, Z) = \sum_{i \in M} e_{\max} y_i - \sum_{\substack{a,b \in M \\ a<b}} e_{a,b} z_{a,b}. \tag{4}$$

Here, Z is the $m \times m$ matrix of zs. The first sum in γ^{LIN} increases by $e_{\max}$ whenever the number of partners in the VO configuration grows by one, while the second subtracts the number of earlier collaboration activities of the new partner. Hence, γ^{LIN} increases whenever a new partner is added into the configuration, unless this new partner has $e_{\max}$ collaboration activities with the partners that are already part of the configuration. If the DM prefers a small number of partners and an active collaboration history, then a configuration with a small γ^{LIN} is preferred to one with a large γ^{LIN}.

The network preparedness criteria can be incorporated into our MILP model through the introduction of a suitable cost function or the adoption of a multi-criteria approach. In practise, the multi-criteria approach is likely to be dominant, since measuring inter-organisational dependencies in monetary terms may be difficult. For instance, the collaboration measure γ^{LIN} can be employed as a new criterion, apart from costs and risks.

3.7 Multi-criteria Analysis

Our optimisation framework has three types of selection criteria for the VO configuration: 1) total costs, 2) capacity risks, and 3) collaboration strength. These measures are not commensurate, wherefore they need to be considered explicitly.

First, the DM can employ *goal-programming*. Here, one of the objectives is typically optimised while other objectives are required to perform at some satisfactory level. Implicitly, we have already done this when requiring that the task workloads much be fulfilled (see 2): that is, the completion of the project is so important that no tradeoffs against other criteria are allowed. If all target levels can not be reached simultaneously, the DM may wish to minimise the total deviation from target levels. [26]

Second, the DM can aggregate the different objectives through a *value function* which reflects his or her preferences for the relative importance of the selection criteria [27]. These preferences can be captured by eliciting criteria weights with methods such as SMART [28], SWING [29], SMARTS or SMARTER [30]. In the value function framework, the value of a VO configuration to the DM is the weighted sum of scores on each criterion. Because the resulting *additive value function* is linear in scores, it can be readily maximised in the MILP framework.

4 Case Study: Magnetic Clutch Prototype for Lorries

We illustrate the use of the model with a partner-selection example of an existing VBE, the *Virtuelle Fabrik AG* (http://www.vfeb.ch). This VBE operates in North-Eastern Switzerland and offers the services of some 70 companies in the field of machinery manufacture. Recently, it has carried out projects for car and energy industries, for instance.

4.1 Project Description

We applied our MILP model to a real-life case of Virtuelle Fabrik, where partners were to be selected for a project ordered by a large German car manufacturer. The aim of the project was to devise and construct a prototype magnetic clutch to be used in lorries. We performed the case study in close collaboration with the manager of Virtuelle Fabrik, who also contributed by suggesting many of the features that are contained in our model. Here, we illustrate the model with real data.

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. These tasks had to follow a tight schedule set by the end customer. For each task, there were two to five partner candidates, some of which were candidates for several tasks. The total number of candidates was 21. They were chosen on the basis of their competences and availability.

There were three selection criteria in the following order of declining priority: 1) minimise delay risks, 2) maximise earlier collaboration, and 3) minimise costs. The project had a tight schedule, thus minimisation of risks was most important. Moreover, successful collaboration history was expected to contribute to finishing the project in time. Costs were the least important criterion.

Each partner candidate was given a probability distribution for finishing the tasks in time based on historical performance. Only the probabilities associated with the capacity distributions had to be estimated, because the candidates' costs for finishing the tasks were known and data on the candidates' collaboration history was readily available (see Figure 3). In Figure 3, each square 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. Candidates that have had no earlier collaboration with other candidates are not connected (i.e. Okey AG, Schuler, Schär Engineering, SIG, and Unima AG). Out of the 288 parameters that were estimated or taken from databases, 210 pertained to the collaboration history of Figure 3: with 21 candidates there are maximum $(21^2 - 21)/2 = 210$ links between the candidates. However, only 23 of these were non-zero, representing the 23 links of the network. Costs and capacity distributions were described by 26 and 52 parameter values, respectively.

PLEASE INSERT FIGURE 3 ABOUT HERE

One full workday was needed to explain the model to the DM, gather data, estimate parameters, and interpret the results. The DM was already familiar with the concepts since Virtuelle Fabrik has been a partner in the ECOLEAD research project (http://www.ecolead.org), which expedited the process. The required time can be reduced further by systemising the activities of data gathering and parameter estimation.

4.2 Partner Selection

The problem was to select a good VO configuration for the project, subject to the above information on the project and candidate partners. This problem was essentially that of allocating the task workloads to partners, in recognition of their capacities and the relevant evaluation criteria.

In our case study there were six Pareto-efficient configurations. Table 2 presents the performance of these configurations in view of the three selection criteria. The configurations have been sorted in the decreasing importance of these criteria (risk, collaboration, cost). Hence, Configuration 1 would best reflect the DM's preferences.

PLEASE INSERT TABLE 2 ABOUT HERE

The risk-measure used was the expected downside risk (EDR), meaning that smaller scores indicate lower risks. The collaboration-score is calculated using the γ^{LIN}-measure (4) that accounts for the earlier collaboration as well as for the total number of partners in a configuration. Also here a smaller score is preferred. Cost is the expected total cost in Euros, based on the candidates' prices.

Table 3 gives a sensitivity analysis on the candidates. The score after each candidate represents the percentage of Pareto-efficient configurations in which the work of the corresponding task has been allocated to the candidate. This score can be interpreted as a measure of robustness in the sense that a partner with a high score is a good choice despite the relative importance of the selection criteria [7].

PLEASE INSERT TABLE 3 ABOUT HERE

4.3 Computational Tractability

Finding one Pareto-efficient configuration in the above case takes a few seconds on a normal PC (1.2 GHz processor with 1 GB of RAM), with a Java implementation (http://java.sun.com) using the lp_solve library (http://groups.yahoo.com/group/lp_solve/). However, since lp_solve does not exploit specific integer programming algorithms, such as Branch-and-cut, many commercial solvers would be considerably faster [31].

The computational complexity of a MILP model increases with the number of integer variables (Table 4): for instance, in a case with 10 tasks and 10 different partner candidates for each task (i.e. 100 candidates altogether), the maximum number of binary variables is 6050. MILP models of that size are readily solved with up-to-date software. Moreover, the maximum number involves interdependencies between each task and each partner, which is not the case in practise: e.g. the average degree of a node in the Virtuelle Fabrik collaboration graph (Figure 3) is $2 \times 23/21 = 2.19$. The average of, say four links from 100 partner candidates yields 1300 integer variables in total, which is considerably less than the maximum 6050. Hence, realistic problems with hundreds of partner candidates are accurately solvable.

PLEASE INSERT TABLE 4 ABOUT HERE

4.4 Managerial and Practical Implications

The manager of Virtuelle Fabrik was particularly satisfied with the model's capability of highlighting inter-organisational dependencies: for him, it was difficult to intuitively see the synergies of different VO configurations. In addition to the case-study with Virtuelle Fabrik, a workshop was arranged in Brussels on May 7, 2007. In this workshop, the representatives of four network partners of the ECOLEAD project evaluated the usefulness of our partner selection models, using the above Virtuelle

Fabrik case as a demonstrator. The four networks were CeBeNetwork, IECOS (http://www.iecos.com), ISOIN (http://www.isoin.net), and Swiss Microtech (http://www.swissmicrotech.ch). The users compared the Virtuelle Fabrik case with the conditions of their own networks and shared their comments with the researchers.

First, the following summarises the functionalities the users appreciate in the models:

- Objective comparison of the partner candidates' capabilities and performance with respect to multiple criteria was deemed useful. Since partner selection is a daily process for network managers, they appreciated the possibility of quick comparisons of the expected performance of alternative VO configurations.
- Systematic use of historical performance data in partner selection was considered to improve the expected performance of VOs. In particular, the ability to account for the references about past collaboration was seen useful.
- The users saw that the models would reduce subjective assessment and the risk of forgetting small or new VBE members that have only a few references in collaborative projects but high potential.

Second, according to the users, the models could be further improved as follows:

- Many of the users would like to see the models operationalised into software tools with graphic web interface. They also wish to further customise the models for their networks and integrate them with other management systems.
- The users would like to see how different *projects* are related to each other, in terms of e.g. common partners and risks. This would facilitate holistic project portfolio and resource management for the VBE.
- The networks would need a web questionnaire for VBE members to gather the input for databases. The databases need to be comprehensive enough to facilitate the use of the models.

The above encouraging comments from the end-user community reflect the practical relevance of the models.

5 Conclusions and Further Research

The models developed in this paper extend earlier research through the consideration of multiple criteria, risks of individual VO failures and inter-organisational dependencies. These extensions enable the development of decision support systems that help the DM assess alternative VO configurations: indeed, experiences from our case study with a real VBE suggest that such systems can be very useful when the DM seeks to identify Pareto-efficient VO configurations.

Because the VBE supports the creation of VOs from a relatively stable set of members, it is in a good position to collect data on its members. Numerical parameter estimates can be typically obtained by using accumulated databases, by soliciting expert opinions, or by collecting bids from candidate partners. However, if the VBE has not been able to collect performance data from its members, the availability of parameter estimates may limit possibilities for the development of MILP optimisation models.

Our MILP models are relevant for a broad range of problems where a subset of candidates must be selected from a large set in view of multiple constraints and criteria. Such portfolio selection problems are common in the management of project, patent, and product portfolios, to name but some examples. These MILP models are also flexible in that constraints or objective functions can be readily modified. Computationally, they are tractable in problems with hundreds of partner candidates.

This research suggests topics for further research. First, the identification of substitute partners for hedging against capacity risk through capacity option-contracts can be of considerable value: indeed, although capacity option contracts have been studied in supply chains [32], they have received little attention in the context of temporary virtual organisations. Second, because it may be difficult or prohibitively expensive to acquire complete information about all relevant model parameters (e.g. characteristics of candidate partners, DM's preferences for the evaluation criteria), preference programming methods [33] that deal with incomplete information may be useful in VO creation, too.

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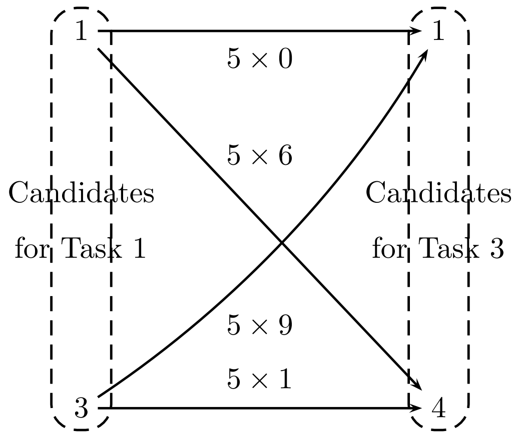
Figure 1

a) Task Sequence for Assembly   b) Unit Transportation Costs between Candidates



c) Costs of Possible Transportation Routes

Figure 2

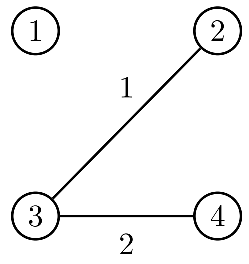
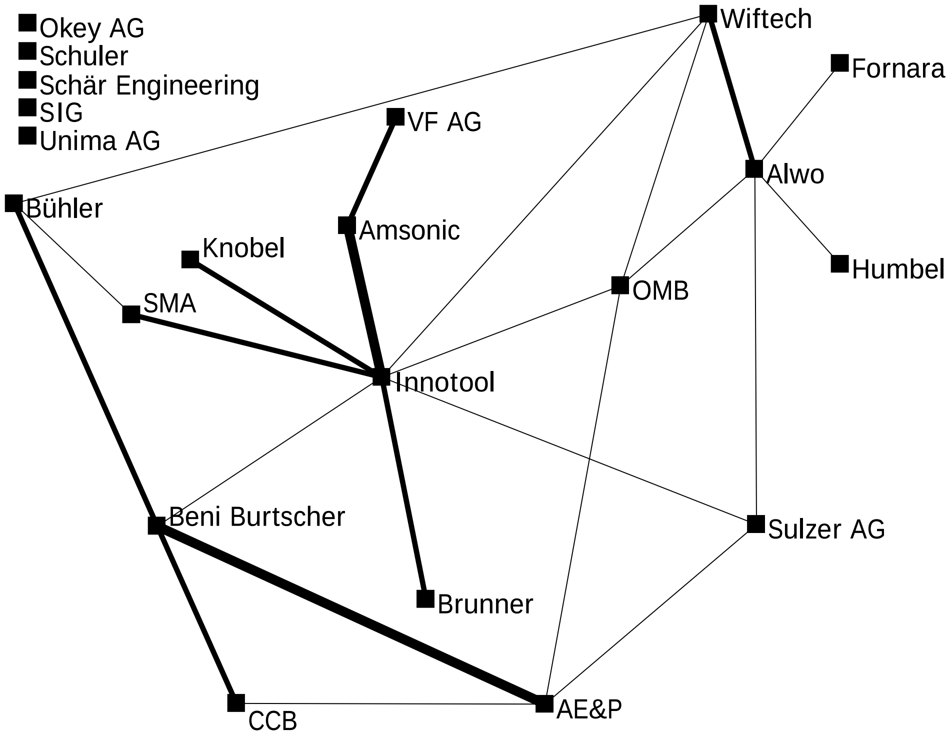


Figure 3


Okey AG
Schuler
Schär Engineering
SIG
Unima AG
Wiftech
Fornara
VF AG
Alwo
Bühler
Knobel
Amsonic
Humbel
OMB
SMA
Innotool
Beni Burtscher
Sulzer AG
Brunner
AE&P
CCB

Legends for Figures

Figure 1: An Example of Transportation Parameters

Figure 2: An Example of Candidates' Collaboration History

Figure 3: Intensity of past collaboration between the partner candidates of Virtuelle Fabrik

Table 1: Parameters and Variables

Parameters	Definition
$C_{i,j}$	distribution for candidate i's capacity on task j
$c^k_{i,j}$	kth element of $C_{i,j}$
$e_{a,b}$	intensity of earlier collaboration between candidates a and b
f_i	fixed cost of candidate i's work on the project
$f_{i,j}$	fixed cost of candidate i's work on task j of the project
i	index for candidates
j	index for project's tasks
k	index for the candidates' capacity distributions
m	number of candidates
n	number of tasks in the project
$p_{i,j}(k)$	probability that candidate i's realised capacity on task j is $c^k_{i,j}$
$t_{a,b}$	unit transportation cost between candidates a and b
$v_{i,j}$	variable cost of candidate i's work on task j
w_j	workload of task j
$\delta_{r',r''}$	quantity of transportation required between tasks r' and r''
$\rho^{\mathrm{RISK}}_{i,j}$	capacity risk of i's work on task j, using risk measure RISK
Variables	
$x_{i,j}$	candidate i's work allocation on task j
y_i	takes value one if i is selected into the VO; zero otherwise
$y_{i,j}$	takes value one if i performs work on task j; zero otherwise
$z_{a,b}$	takes value one if both candidates a and b are selected into the VO; zero otherwise
$z^r_{a,b}$	takes value one if candidates a and b perform tasks r' and r'', respectively, and transportation is required between tasks r' and r''; zero otherwise

Table 2: Performance of six Pareto-efficient configurations on three selection criteria

Task \ Configuration	1	2	3	4	5	6
Bending of pipes	SMA	SMA	SMA	SMA	SMA	SMA
Engineering	Schuler	Schär Engineering	Schär Engineering	AE&P	AE&P	AE&P
Gear milling	Okey AG	Okey AG	Okey AG	Okey AG	Okey AG	Okey AG
Grinding	Brunner	Brunner	Brunner	Brunner	Brunner	Brunner
Metal sheet forming	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher
Milling bigger parts	SMA	SMA	SMA	SMA	OMB	SMA
Milling smaller parts	Innotool	Innotool	Innotool	Innotool	Innotool	Innotool
Project management	VF AG	Schär Engineering	VF AG	AE&P	AE&P	VF AG
Welding	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher	Beni Burtscher
Performance (all criteria to be minimised):						
Risk	0.25	0.75	0.75	1.25	1.25	1.75
Collaboration	86	73	83	70	94	81
Cost	131312	132116	123215	124005	121934	122057

Table 3: Sensitivity Analysis

Task	Robustness of Partner Candidates		
Bending of pipes	SMA: 100		
Engineering	AE&P: 50	Schär Engineering: 33	Schuler:17
Gear milling	Okey AG: 100		
Grinding	Brunner: 100		
Metal sheet forming	Beni Burtscher: 100		
Milling of bigger parts	SMA: 83	OMB: 17	
Milling smaller parts	Innotool: 100		
Project management	VF AG: 50	AE&P: 33	Schär Engineering: 17
Welding	Beni Burtscher: 100		

Table 4: Upper Bounds for the Number of Binary Variables in the Model (n=number of tasks, m'=number of candidates per task)

Variable	# Variables	Note
y_i	$m' \times n$	One per each candidate
$y_{i,j}$	$m' \times n$	One per each candidate
$z^r_{a,b}$	$m'^2(n-1)$	Number of edges in a complete bipartite graph (m'^2) for each transportation requirement ($n-1$).
$z_{a,b}$	$\frac{1}{2}m' \times n(m' \times n - 1)$	Number of edges in a complete graph of $m' \times n$ nodes
Total	$\frac{3}{2}m' \times n + \frac{1}{2}(m' \times n)^2 + m'^2(n-1)$	