Optimal Partner Selection in Virtual Organisations With Capacity Risk and Network Interdependencies*

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Abstract

In this paper, we consider how the selection of partners in a virtual organisation (VO) can be assisted through mixed integer linear programming (MILP) models, when the configuration of VOs is based on a virtual organisation breeding environment (VBE). Apart from our basic model – which focuses on the minimisation of fixed and variable costs – we present extensions that accommodate transportation costs, alternative measures for capacity risk, and inter-organisational dependencies due to an earlier collaboration history. A real case study and computational experiments suggest that our MILP models are tractable for problems of reasonable size and useful in VO decision making.

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

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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 as individual companies seek efficiency gains by focusing on their core competences while outsourcing non-core operations, the degree of inter-firm transactions grows considerably. This makes it imperative to manage network relations well, which in turn calls for the development and deployment of decision support models that assist companies in the management of these relations. [1, 2, 3]

The above trends have motivated extensive research into collaborative networks. Specifically, 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) [4, 5, 6]. Here, we adopt the terminology of Camarinha-Matos and Afsarmanesh [4], who call the club a *virtual organisation breeding environment* (VBE). The VBE structure is characterised by a common ICT infrastructure, strategy, and processes for agile VO creation, among others.

In this paper, we focus on the problem of selecting VO partners in a VBE. That is, when a VBE identifies a business opportunity, it has to determine a 'good' VO configuration for meeting the identified customer need; this is essentially an optimisation problem that can be formulated as a mixed integer linear programming (MILP) model. To support the VBE in solving it, we develop a model for allocating work among potential VO partners, taking into account fixed and variable work costs, transportation costs, risks of capacity shortfall, as well as 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 where partners were selected for the construction of a magnetic clutch prototype for lorries. This notwithstanding, these features have not yet received much attention by way of formal modelling or practical application [7, 8]. They can be operationalised through decision criteria in conjunction with goal-programming techniques [9] or additive value functions [10].

The rest of this paper is structured as follows. Section 2 reviews earlier models on partner selection. 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 Virtual Organisation Partner Selection

For some time, competition has changed from the level of individual firms towards rivalry among company networks [3]. Through networking, companies can focus on their niche core competences, which may contribute to increased global efficiency [11]. Networking, however, involves transaction costs [12] due to partner search and selection, among others [13], wherefore several methods have been proposed for the reduction of these costs.

Several authors have developed VO partner selection methods that minimise a single criterion, most notably the total costs over the VO's life cycle. Ko et al. [14], Ip et al. [15], and Wu and Su [16] present integer programming models to minimise total costs that consist of production, operation, and transportation costs, for instance. Ko et al. [14] and Ip et al. [15] solve their models with heuristic tabu search and the branch-and-bound algorithm, respectively, while Wu and Su [16] reformulate their model as a graph theoretic representation which is then solved with an approximation algorithm. Feng and Yamashiro [17] define a "comprehensive cost function" which is formed by adding costs due to processing activities, transportation, and earliness-and-tardiness. They then carry out a qualitative pre-qualification of candidate partners in order to reduce the size of the mixed integer non-linear program that must be solved. Ip et al. [18] present a somewhat different one-criterion model where the probability of success of a virtual enterprise is maximised. They also develop a genetic solution algorithm, because their model is neither linear nor convex.

Despite the importance of costs, VO partner selection is inherently a multi-criteria decision-making problem which involves several "soft" factors – such as corporate culture and social relations – that cannot be readily captured by pure cost models. Further to this realization, Meade et al. [19] introduce a framework for strategic alliance structuring where the criteria weights are determined by the Analytical Network Process (which extends the Analytic Hierarchy Process (AHP) [20] by permitting more complex criteria structures than plain hierarchies). Mikhailov [21] and Sha and Che [22] address multiple objectives with the AHP, while Boon and Sierksma [23] employ direct weighting of attributes. Furthermore, Mikhailov [21] develops a fuzzy programming method for incorporating uncertain attribute weights and candidate scores into the AHP framework. Boon and Sierksma [23] and Sha and Che [22] develop integer programming formulations and solve the resulting problems with standard optimisation approaches, such as branch-and-bound methods.

Fischer et al. [7] account for inter-organisational dependencies among a group of organisations in their model. They formulate their optimisation problem in VO selection as that of finding the maximum weight path from a source to a drain in a digraph, and solve this problem with an Ant Colony Optimisation algorithm. Fischer et al. [7] aggregate multiple criteria into a one-dimensional objective function with the AHP. The goal-programming model of Talluri et al. [24], in turn, seeks to minimise 1) costs, 2) distances, and 3) inception time, and to maximise 4) cultural compatibility. The number of candidates – and thus the size of the model – is reduced by excluding inefficient candidates to ensure computational tractability.

These developments notwithstanding, several topics of considerable practical relevance have received little attention. First, hardly any multi-criteria models have dealt with inter-organisational dependencies – including considerations such as inter-organisational trust, cultural homogeneity, and success of past collaboration – which contribute to the expected success of future collaboration

[4, 25, 26, 27]. Because these criteria need to be applied to a group of organisations (as opposed to a single organisation), the resulting models tend to become more complex [7]. Second, few studies have addressed the issue of risk management in partner selection, even though the minimisation of risks due to capacity fluctuations and quality failures, for instance, are highly relevant.

In this setting, we develop novel models which account for inter-organisational dependencies and capacity risks through additional selection criteria. With the help of these models, the decision maker (DM) can identify configurations that are Pareto-efficient in the sense that there are no other configurations which would perform at least equally well on all selection criteria and strictly better on at least one criterion [28].

Another departure from earlier models is that the amount of work that is allocated to partners can be a continuous quantity. This is motivated by two practical reasons. First, partners are rarely selected according to the final project description: rather, at the outset of the VO creation process, the project description is tentative so that it may be viable to allocate work on some tasks to several partners. Second, during the VO creation, the project description and the proposed work allocation are iteratively refined until the project is finally started. These phenomena can be better addressed by using continuous work-allocation variables rather than discrete "machine-job" variables.

3 A Model of Collaboration

VO partner selection can be treated as a work-allocation problem. In Sections 3.1-3.3, we formulate our basic mixed integer linear programming (MILP) model. In Sections 3.4-3.6, this model is augmented by considering transportation costs, risk metrics, and inter-organisational dependencies. Section 3.7 discusses the treatment of multiple criteria, and finally Section 3.8 presents additional features, such as overwork pricing and capacity transfer.

3.1 Parameters and Variables

Let $M = \{1, \dots, m\}$ denote 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 $N = \{1, \dots, n\}$, and task $j \in N$ involves a workload w_j which is measured in relevant units (e.g. person months). Table 1 summarises all relevant parameters and variables. Here, *continuous* x's denote the work allocation of individual candidates, *binary* y's pertain to individual candidates, and *binary* z's relate to multiple partner candidates.

PLEASE INSERT TABLE 1 ABOUT HERE

In the basic model, the following parameters are collected from the candidates and relevant data bases:

$C_{i,j}$ = 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. In what follows, $c_{i,j}^k$ 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 $c_{i,j}^k$s are sorted in descending order so that $c_{i,j}^1 = \max_k c_{i,j}^k$. The probabilities sum up to one, i.e., $\sum_k p_{i,j}(k) = 1$. Thus, the expected capacity that candidate i devotes to task j is

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

The decision variable is the work-allocation matrix $X_{m\times n}$ where the element $x_{i,j}$ denotes the amount of work that candidate i performs on task j. The following auxiliary variables based on x's are defined to facilitate the 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 and only if candidate i performs some work in the project, and zero otherwise. Also, let

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

That is, $y_{i,j}$ indicates whether or not some work on task j is allocated to candidate i. The distinction between y_i and $y_{i,j}$ is that the former tells whether candidate i is involved in the project at all, whereas the latter indicates, in case $y_i = 1$, which tasks i is involved in. Thus, if $y_i = 0$ for some i, then $y_{i,j} = 0\ \forall\ j$. Again, if $y_i = 1$ for some i, then $y_{i,j} = 1$ for at least one j.

3.2 Objective Function

Our basic model has a single cost criterion which accounts for the candidates' variable and fixed costs, i.e.,

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

where the work allocation matrix $X_{m\times n}$ contains x's and the matrix $Y_{m\times(n+1)}$ contains the y's. In the objective function, the first term (I) is the sum of fixed costs due to the addition of partners to the VO, while the second term (II) covers the fixed and variable costs due to the work that the partners perform on their respective tasks. This function is flexible in that some costs can be ignored if they are irrelevant.

3.3 Constraints

The two types of constraints in the optimisation problem ensure that all project demands are met, and that the optimal solution is feasible.

Starting with project constraints, the workload of each task has to be completed, i.e.,

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

Furthermore, the workload that is allocated to a candidate must not exceed its maximum capacity:

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

Because the partner may not be able to devote its maximum capacity to the task, a less risky approach is to constrain the workload by the partner's expected capacity so that $x_{i,j} \leq E[C_{i,j}]$ (we shall address capacity risks at greater length in Section 3.5). Finally, workloads must be non-negative:

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

Continuing with feasibility constraints, correct values for binary y_is are ensured by the constraints:

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

Here, 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 the proportion of the projects' workload that is allocated to candidate i. Furthermore, ϵ corresponds to the proportion of the total workload that a candidate has to exceed in order to be considered a relevant VO partner. In consequence, $y_i = 1$ if at least $\epsilon \times 100$ percent of the projects' workload is allocated to candidate i, and $y_i = 0$ otherwise. In the first expression of (3), the denominator is needed to keep the right hand side below one. Otherwise, if the right hand side increased above one, the model would become infeasible because y_i is a zero-one variable. Similarly, in the latter expression, the denominator is needed to push the right hand side below one if not enough work is allocated to candidate i.

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

$$y_{i,j} \geq \frac{x_{i,j}}{c^1_{i,j}}, \quad \forall\, i \in M, j \in N \ \text{ s.t. } \ c^1_{i,j} > 0. \tag{4}$$

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 increasing these binary variables from zero to one results in higher total costs, meaning that the $y_{i,j}$s remain at zero level if this is feasible. If one introduces additional decision criteria such that the benefit increases when $y_{i,j} = 1$, then an upper bound similar to that for y_is becomes necessary.

In summary, our basic optimisation model can now be stated as

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

3.4 Transportation Costs

We begin our discussion of transportation costs with the following example of an existing VBE, presented by the *CeBeNetwork GmbH* (http://www.cebenetwork.com). CeBeNetwork 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. For instance, an IT project 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.

In general terms, we consider a manufacturing VO where each partner supplies a specific component which is part of the end-product. At each point of the manufacturing process where two or more components are assembled together, these components must be at the same site. In consequence, the components must be transported to the assembly site if the assembly does not take place at the same site where the components are manufactured.

Transportation costs are caused mainly by two factors, 1) geographical distance and 2) volume and weight of the cargo. For instance, it may be possible to compensate the cheaper labour costs of a far-away manufacturing site by the lower transportation costs from a near-by site. Thus, the operational costs discussed in Section 3.2 must be augmented by considering transportation costs, too. This can be achieved only by explicating the sequence of tasks that are involved in the assembly of the physical product.

For instance, consider a project of three tasks. Assume that output of Task 1 must be made available to the same site where Task 3 is carried out and that the volume of this transportation is 5 units. The corresponding task sequence can be illustrated with the simple network of Figure 1a. Because Task 2 does not have physical connection to Tasks 1 or 3, it is shown as 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, we 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 one pair only, namely $(1, 3)$, with the volume of $\delta_{1,3} = 5$.

The unit 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., (i) those that are capable of performing task r' and (ii) 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, in our example, 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:

$$z_{a,b}^{r} \leq \frac{y_{a,r'} + y_{b,r''}}{2} \quad \text{and} \quad z_{a,b}^{r} \geq y_{a,r'} + y_{b,r''} - 1. \tag{5}$$

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

The total transportation costs can now be written as

$$Cost^{\mathrm{TRANS}} = \sum_{r \in R} \delta_{r',r''} t_{a,b} z_{a,b}^{r}.$$

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

Under normal conditions, we can assume that infrastructure is reliable and therefore a transportation partner is available. However, if selecting the right transportation partner is crucial to the success of the project, then each $r \in R$ can be associated with a new task of the project. Thus, the selection of partners for these tasks is done similarly to other tasks. In this way, the DM can also cater for possible risks related to transportation, as shown in the following section.

3.5 Capacity Risks

Risk management is vital due to the possibly adverse impact of uncertainties in the partners' individual or collaborative behaviour [29]. Hallikas et al. [30] 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 largely beyond the scope of this paper. In our case it is meaningful to consider risks through fluctuations in capacity, where risks are realised through the costs of the reconfiguration of the VO. The reason for this is that project finance, i.e. payment from customer, is normally risk-free, excluding force majeure reasons such as customer's bankrupt.

In Section 3.1, capacities were specified as 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 such fluctuations; thus, the DM is interested in large fluctuations that may call for the reconfiguration of the VO. Second, the *ex ante* assessment of minor fluctuations is difficult, which means that the DM may have to accept rough risk estimates [30]. A discrete distribution is sufficient for this purpose.

The management of capacity risks calls for a risk measure. Among alternative measures, *expected downside risk* (EDR), introduced by Eppen et al. [31] for capacity-risk management, is suitable for our purposes, largely because it can be interpreted as the expected shortfall from the given target value (in our case the allocated work). Recently, EDR has also been adopted in the context of investment portfolio optimisation [32]. This measure belongs to the family of mean-risk dominance models [31, 33] which are discussed at some length in Gustafsson and Salo [32].

Arguably, it is more meaningful to measure capacity risk as the expected shortfall from a target value or – more specifically in our case – the allocated workload than as variance. This is because variance-based measures indicate 'risk' whenever there are capacity uncertainties; yet, if the capacity varies well above the required level, the DM is not faced with risks. Thus, variance-based risk measures would be misleading.

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 value of 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 those events $c_{i,j}^k$ that would 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 with 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 $\sum_i \sum_j \rho_{i,j}^{\mathrm{EDR}}$.

Risk management based on EDR 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 through a value function that relates risks to costs. These 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. From the dynamic perspective, if the project involves tasks whose completion is crucial to the completion of several other tasks, such 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, for instance. The level at which collaboration is analysed depends on the case at hand. Nevertheless, work performed in collaboration causes transaction costs that would not exist if one entity performed the job. At the partner selection phase of VO creation it is unrealistic to estimate the transaction costs that arise during the VO life-cycle. Therefore, it is 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 between partner candidates. It is reasonable to assume that the more 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 *increase* transaction costs are geographical distance and linguistic difference. When used as partner selection criteria in VO configuration, we refer to these 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 (i.e., one cannot measure 'geographical distance' for a single company). The traditional selection criteria are usually applicable to a single company [34]. The measurement of inter-organisational performance is more viable in the management of a VBE than in an "open universe" of organisations. This is because the VBE members collaborate repeatedly, which permits the collection of data about inter-organisational performance [4]. Thus, considerations such as trust, success of past collaboration, and congruence between organisational culture and objectives can be employed as potentially useful criteria for VO partner selection in a VBE.

The following formulation shows how inter-organisational dependencies are incorporated into our model, using collaboration history as an instance of network preparedness criteria. Network relations are commonly described through graphs where edges represent interrelationships between organisational pairs [35]. 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 any of the others.

PLEASE INSERT FIGURE 2 ABOUT HERE

In order to incorporate inter-organisational dependencies into our model, we define a binary variable $z_{a,b} \in \{0, 1\}$ 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 one of them. This variable permits the modelling of bilateral relations, of which the collaboration history in Figure 2 is but one example.

For z, we need the following constraints:

$$z_{a,b} \leq \frac{y_a + y_b}{2} \quad \text{and} \quad z_{a,b} \geq y_a + y_b - 1 \quad \forall \{a, b\} \subset M, \tag{6}$$

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

Next, we define a measure for using collaboration history as a selection criterion. 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 that one partner candidate has. For instance, considering 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 represent the benefits that accrue from earlier collaboration:

$$\gamma^{\text{LIN}}(Y, Z) = \sum_{i \in M} e_{\max} y_i - \sum_{\substack{a,b \in M \\ a<b}} e_{a,b} z_{a,b}. \tag{7}$$

Here, Z is the $m \times m$ matrix of zs. The first sum-term of γ^{LIN} increases by $e_{\max}$ whenever the number of partners in the VO configuration is increased by one. The second sum-term, in turn, subtracts from this the number of earlier collaboration activities the new partner has. 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. Assuming 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}.

In general, the main use of collaboration data is to help determine which subsets of a VBE have higher expected collaboration strength, in view of the earlier track record of more or less successful collaboration activities. This and other network preparedness criteria (e.g., geographical distance) can be incorporated into our MILP model with the z variables.

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. We have proposed a linear measure for each objective; but since these measures are not commensurate, the DM needs to consider these multiple objectives explicitly.

First, the DM can employ *goal-programming*. Here, one of the objectives is typically optimised while the 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, then the DM may wish to minimise the total deviation from target levels. [9]

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 [10]. These preferences can be captured by eliciting criteria weights with methods such as SMART [36], SWING [37], SMARTS or SMARTER [38]. The properties of these methods have been examined in several empirical studies [39, 40, 41, 42]. 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.

We find that goal programming techniques are suitable for networks whose management is largely based on performance measurement. This is because these techniques help managers set aspiration levels for different performance indicators. Value functions, in turn, may be suitable for networks that favour group decision-making. With the above weight-elicitation techniques, groups can generate weights that illustrate the relative importance of different criteria. For instance, SMARTS and SMARTER can be used even with little experience of weight elicitation, whereas SMART, SWING, and direct weighting are suggested for more experienced decision makers. Networks using value functions can also adjust criteria weights through learning from past decisions.

3.8 Additional Features

The MILP model can be extended through modifications from problems such as capital budgeting, job-shop scheduling, and portfolio selection, which all have connections to our partner selection model [9]. For instance, *Common capacity* between several tasks can be captured through an additional constraint such as $x_{i,a} + x_{i,b} \leq c_{i,ab}$. *Cardinality constraints* on the number of organisations that may take part in performing some task can be modelled through binary variables: for instance, if task j denotes project management activities that must be performed by a single organisation, we add the constraint $\sum_i y_{i,j} = 1$.

Overwork pricing is captured with a new variable $x^+_{i,j}$ which denotes work in excess of the capacity $c^1_{i,j}$. The capacity constraint now consists of two equalities, $x_{i,j} - x^+_{i,j} \leq c^1_{i,j}$ and $x^+_{i,j} \leq c^{1+}_{i,j}$, of which the latter one puts an upper bound for the amount of overwork. The cost function takes an additional term $v^+_{i,j} x^+_{i,j}$, where $v^+_{i,j}$ is the marginal variable cost of overwork.

Capacity transfer between the members of the VBE can be modelled with the variable $\Delta^j_{a,b}$, which denotes the transfer of capacity from a to b in relation to task j. Moreover, every $c^k_{a,j}$ in the constraints must be replaced by $c^k_{a,j} - \Delta^j_{a,b}$, and every $c^k_{b,j}$ by $c^k_{b,j} + \Delta^j_{a,b}$. The possibility of capacity transfers opens up exciting possibilities for hedging against capacity risk by using *capacity option-contracts* [43]. If a VBE member sells a capacity option, the owner of the option has the right but not the obligation to use the capacity of that member. The price of using the capacity is agreed in the option contract. Using capacity options, a VO manager has a portfolio of VO partners for his/her project, augmented by substitute companies (i.e. the subjects of the option contracts) if an initially selected VO partner cannot manage its workload.

Additional selection criteria which pertain to a single partner can be captured using the binary y_i variables; these criteria may cover aspects such as quality of outputs or financial status of the partner (for a list of 183 evaluation attributes, see[44]). For instance, if q_i denotes the quality level of candidate i, the quality of a VO configuration can be approximated by the sum $\sum_i q_i y_i$. Furthermore, additional criteria that rely on the comparison of two partners can be captured by introducing binary variables, analogously to consideration of the collaboration history in Section 3.6.

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). The VBE operates in North-Eastern Switzerland, offering the services of some 70 companies in the field of machinery manufacture. Recently, they have had projects for instance for car and energy industries.

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 presented by the current model. The following describes the use of our 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. Moreover, the tasks needed 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, so that there were 21 partner candidates altogether. The candidates were chosen on the basis of their competences and availability during the project.

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 in this case the least important criterion.

Each partner candidate was given a probability distribution for finishing the tasks in time based on historical performance. The probabilities associated with the capacity distributions were the only parameters that had to be estimated. Data on the candidates' collaboration history was readily available (see Figure 3), and candidates' costs for finishing the tasks were known. Altogether, 288 parameter values were estimated or acquired from databases and bids from partner candidates.

Explaining the model to the DM, data gathering, parameter estimation, and the interpretation of the results took about one day in total. This, however, does not include the planning of the project, which is beyond the scope of partner selection. The DM was already familiar with the concepts of this paper since Virtuelle Fabrik has been a partner in our ECOLEAD research project (http://www.ecolead.org), which probably expedited the process. The required time can be reduced further by systemising the data gathering and parameter estimation.

PLEASE INSERT FIGURE 3 ABOUT HERE

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 decision criteria that are relevant to the evaluation of alternative VO configurations.

In the analysis of this case, six Pareto-efficient configurations were identified using our optimisation framework implemented in Java. The calculations were carried out with the lp_solve software (available at http://groups.yahoo.com/group/lp_solve/). Finding one Pareto-efficient configuration takes a few seconds on a normal PC (1.2 GHz Intel processor with 1 GB of RAM). Table 2 presents the performance of these configurations on the three selection criteria. The configurations have been sorted first by risk, second by collaboration, and third by cost, which was also the relative importance of the selection criteria. Hence, Configuration 1 would best reflect the DM's preferences.

PLEASE INSERT TABLE 2 ABOUT HERE

The risk-measure used was the EDR, where a smaller score is preferred to a greater one, zero being the theoretically best. The collaboration-score is calculated using the γ^{LIN}-measure (7) that accounts for 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.

In Table 3 we have made a sensitivity analysis on the partner 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 [45].

PLEASE INSERT TABLE 3 ABOUT HERE

The manager of Virtuelle Fabrik was particularly satisfied with the model's capability to highlight inter-organisational dependencies; for a DM, it is difficult to intuitively see synergies of different VO configurations. Moreover, scoring methods that evaluate partner candidates individually cannot either account for inter-organisational dependencies.

5 Conclusions and Further Research

In this paper, we have developed multi-criteria optimisation models for the VO partner-selection problem in a VBE. Our models allow the DM to apply several selection criteria to the analysis of alternative configurations either by using goal programming techniques or additive value functions (see, e.g., [10]). These models extend earlier research also by considering the risks of individual VO failures and inter-organisational dependencies (say, due to the earlier collaboration history). Computationally, our models are tractable in problems of reasonable size, and enable the development of decision support systems that assist the DM in assessing alternative VO configurations. Such support systems can be highly useful when the DM seeks to identify Pareto-efficient VO configurations, even through the actual selection of VO partners is unlikely to be fully relegated to an optimisation model.

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. Thus, the VBE can consider even additional selection criteria in VO configuration in order to account for aspects such as earlier collaboration history, degree of mutual trust, or similarity of ICT infrastructures [4]. Numerical parameter estimates on these aspects can be 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 and deployment of MILP models.

Experiences from our case study with a real VBE suggests that the formulation and solution of proposed models can be quite helpful in partner selection. This is, in part, due to their ability to capture inter-organisational dependencies that can be difficult to address without explicit decision support. Another domain with considerable potential for the use of models consists of problems where the VBEs carry out repeatedly one-off projects with high uncertainties (say, due to factors such as technological success).

This research suggests several topics for further research. First, the identification of substitute partners for hedging against capacity risk can be of considerable value, and could be implemented through capacity option-contracts; in effect, although capacity option contracts have been studied in supply chains [46], 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 the relevant model parameters (e.g. characteristics of candidate partners, DM's preferences for the evaluation criteria), preference programming methods [47] that deal with incomplete information explicitly may be useful in VO creation, too. Third, efficient algorithms and heuristic approximative approaches for finding the set of Pareto-efficient VO configurations may be needed. Here, the recently developed Robust Portfolio Modelling method is one promising approach [45].

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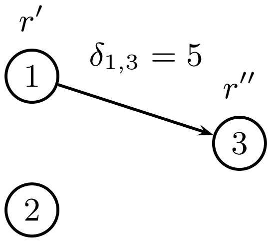
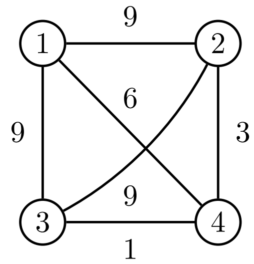
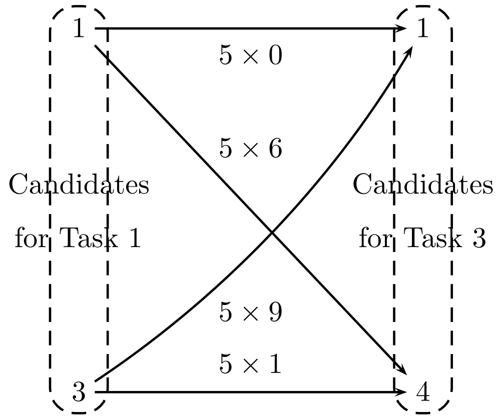
Figure 1



a) Task Sequence for Assembly



b) Unit Transportation Costs between Candidates



c) Costs of Possible Transportation Routes

Figure 2

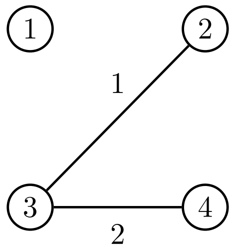
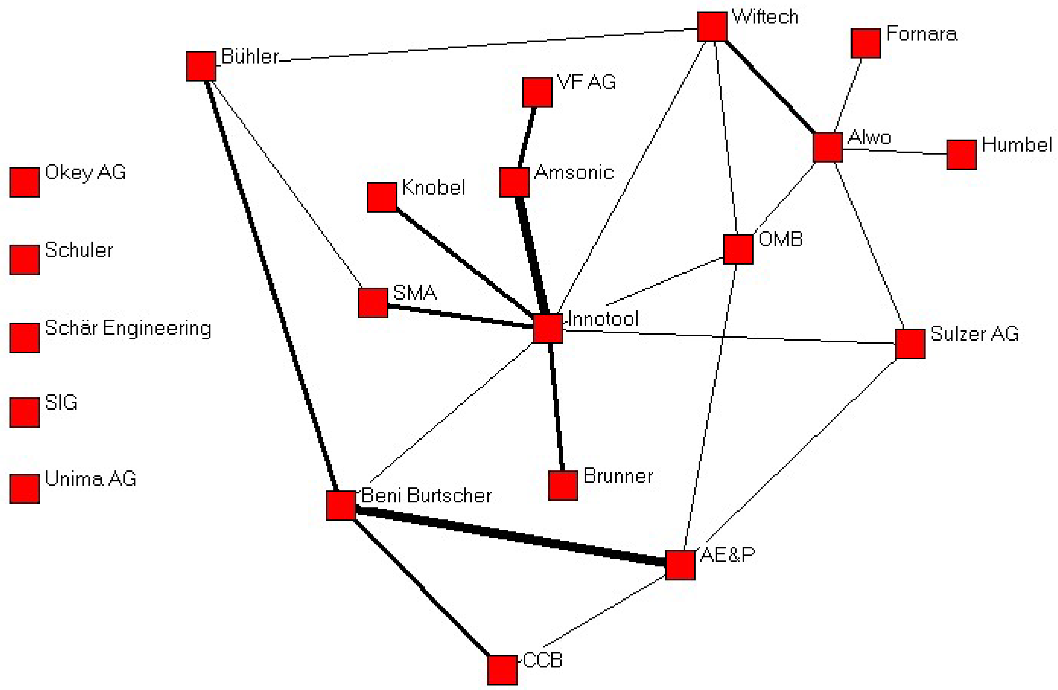


Figure 3



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

Legends for Figures

Figure 1: An Example of Transportation Parameters

Figure 2: An Example of Candidates' Collaboration History

Figure 3: Collaboration history of some members of Virtuelle Fabrik (line thickness corresponds to intensity)

Table 1: Parameters and Variables

Parameters	Definition
$C_{i,j}$	distribution for candidate i's capacity on task j
$c_{i,j}^k$	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 $c_{i,j}^k$
$t_{a,b}$	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''
$\rho_{i,j}^{\mathrm{RISK}}$	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
$z_{a,b}^r$	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		