Minimum Cost Network Design in Strategic Alliances

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Abstract

Strategic alliances are established between firms to improve their competitiveness in markets and generally appear in the form of joint ventures. Such collaborative efforts require centralized planning, and the survival of the alliance largely depends on the success of joint planning processes. In this regard, we investigate the opportunities that centralized collaboration can offer to firms when designing their service networks. Apart from the classical fixed and variable costs associated with the network design, we also consider transaction costs induced by the formation of the alliance,

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which can broadly be defined as cost components related to the coordination and monitoring of the people, efforts and resources. We concentrate on bilateral alliances and develop alternative models for solving their associated network design problem. We also adopt a state-of-the-art heuristic to solve large-scale instances. Our findings confirm that accounting for the transaction cost in network design is vital for the alliance. These transaction costs can be high enough to even render the collaboration unattractive. Hence, careful data collection and model treatment are required before deciding whether to form an alliance.
Keywords: Network design, collaboration, strategic alliances, centralized planning, transaction costs

1. Introduction

The purpose of this paper is to investigate the opportunities that *strategic collaboration* can offer to firms when designing their service networks. Strategic alliances exist in sectors such as air, land or maritime transportation and logistics. An example in the airline industry is the recent Air Canada and Air China agreement on a joint venture to expand their collaboration opportunities and hence compete in the market more aggressively (Reuters, 2018).

1.1. Literature Review

The scientific literature on collaborative transportation planning generally approaches the network design problem at a tactical or operational level by considering exchanges of customer service requests between collaborators. In two recent surveys on collaborative transportation, Verdonck et al. (2013) and Gansterer and Hartl (2018) discussed order sharing and capacity sharing as two operational approaches in collaboration, in which planning decisions are taken in a centralized or decentralized fashion (Gansterer and Hartl, 2018; Agarwal and Ergun, 2008). In decentralized planning, the decisions are taken by the firms individually using pre-established mechanisms, which enable the collaborators to exchange orders or capacities. Agarwal and Ergun (2008) considered a collaborative multicommodity flow game at an operational level in which the collaborators own capacities on edges, and the capacity on a single edge can be shared by multiple players. Each player is assumed to make selfish routing decisions and shares its excess capacities with the other players for a predetermined fee. The paper designs a benefit sharing mechanism among the collaborators by determining capacity exchange costs using game theory. Houghtalen et al. (2011) handled capacity exchange costs in a decentralized decision making environment in air alliances, but assumed a different mechanism than that of Agarwal and Ergun (2008) in which the use of airplane capacity by other coalition members is acknowledged a priori and the capacities are reserved for them. In liner shipping, Agarwal and Ergun (2010) also considered decentralized planning, while side payments to carriers as an added incentive are included.

In the research area of collaborative network design problems, most papers apply methods from game theory for a fair allocation of benefits and to motivate the individual firms to participate in the coalition. For a survey on cost allocation methods in collaborative transportation, we refer the reader to Guajardo and Rönnqvist (2016). Centralized planning of a coalition of firms, on the other hand, is often assumed to be equivalent to a single firm making the planning with full information and full control of assets. Examples of centralized planning include freight carrier collaboration (Krajewska et al., 2008), in which the benefits obtained from managing distributions as a single body are allocated to the participants by making use of the Shapley value. Another example is shipper collaboration (Ergun et al., 2007b), where multiple shippers manage their distribution networks by minimizing their total delivery costs. In this context, Ergun et al. (2007b) introduced the lane covering problem (LCP), in which cycles covering a given set of separated lanes are constructed in order to minimize the cost of relocating vehicles by the carriers. Ergun et al. (2007a) developed optimization techniques for the LCP, while Özener and Ergun (2008) discussed cost allocation strategies among shippers for bundling their lanes to ensure a sustainable collaboration. Recently, Kuyzu (2017) developed a branch-and-price algorithm to solve an LCP variant. Özener et al. (2011) also considered the LCP but in a decentralized manner, where the shippers only exchange lanes for their own interests rather than for the benefit of the coalition. These applications are again all operational and consider the costs associated with managing the network, but not the setup costs for designing the network.

Network design is an umbrella term for several different problems such as service network design (Li et al., 2017), supply chain network design (Varsei and Polyakovskiy, 2017; Choi et al., 2001), humanitarian supply network design (Dufour et al., 2018; Charles et al., 2016), manufacturing network design (Shi and Gregory, 1998), facility network design (Robinson and Swink, 1995), refueling station network design (de Vries and Duijzer, 2017; Kuby and Lim, 2005) and fiber optical network design (Yazar et al., 2016) to name a few. The problem we consider in this paper is more general, and is in line with the definition of Gendron and Crainic (1994) and Croxton et al. (2007), where commodities flow between origin and destination pairs and a subset of arcs of a given graph are selected to minimize the total cost. In this framework, another conceptually related line of research to the network design problem at the strategic level is the hub location problem. In this problem, some nodes are identified as potential hub locations and higher volume of goods being transported between the hubs leads to reduced transportation costs due to economies of scale. In the hub location problem with fixed costs, both fixed and variable costs are included. Two surveys on the topic are those of Alumur and Kara (2008) and Campbell and O'Kelly (2012). The economies of scale between the hubs are generally modeled by multiplying the hub-to-hub flow with a fixed discount factor $\alpha < 1$. However, to the best of our knowledge, the idea of collaboration is not explicitly considered in the hub location literature.

1.2. The Nature of Strategic Alliances

In this study, we consider collaboration within a centralized planning setting. As in the previous studies, we assume full information sharing between collaborators but in contrast to existing works, we consider the problem at a *strategic* level. In other words, we can think of this collaboration as one of the extreme cases of horizontal cooperation, the *strategic alliance* among multiple firms, in which the firms decide to share their resources to undertake a mutually beneficial project (The Economist, 2009). We refer the reader to Cruijssen et al. (2007b) for a survey of opportunities of horizontal collaborations and to Tran and Haasis (2015) for brief review of liner shipping collaborations.

A strategic alliance is generally formed to enter a foreign market as a joint venture. A common strategy is adopted, and the resources and investment decisions are shared for gains by all the collaborators (The Economist, 2009). Hence, conceptually, the planning decisions are centralized. In the economic theory, it has long been acknowledged that such collaborations increase resource utility and, hence, increase productivity (Cruijssen et al., 2007a). However, besides its many advantages, collaboration among multiple decision making bodies such as firms or governments also entails transaction costs related to the coordination of people, efforts and resources (Dyer, 1997; Krueger and McGuire, 2005). The theory of transaction cost economics (TCE) deals with the behaviors of firms and their ruling structures. The main objective of TCE is to understand the dynamics that govern interfirm alliances and cooperation efforts. The transaction cost was initially recognized in early works on the theory of firms (Coase, 1937). It has since been formalized by Oliver Williamson (Williamson, 1979), a Nobel Prize laureate for his studies on transaction cost economics. He broadly defined the transaction costs as the *'comparative costs of planning, adapting, and monitoring task completion under alternative governance structures'* (Williamson, 2005). The transaction costs in strategic alliances are related to the frequency, intensity and complexity of tasks (Gulati and Singh, 1998; White and Siu-Yun Lui, 2005), as well as to the size of firms (Nooteboom, 1993) and the perceptions of equitable behavior (White and Siu-Yun Lui, 2005). A larger number of collaborating firms implies more transactions taking place and more complications due to additional planning, coordination and monitoring requirements. It is generally acknowledged that measuring the transaction costs is hard (Collins and Fabozzi, 1991). In the context of our study, we refer to transaction costs as *collaboration costs*, which are expressed as a function of the number of collaborators. We use the terms transaction cost and collaboration cost interchangeably.

1.3. Problem Definition

To further elaborate on our problem, which we refer to as 'the collaborative strategic network design problem' (CSNDP), consider a graph representing a physical road network and a set of firms operating in this network, each of which needs to select a subset of the arcs of the graph to transport goods between multiple origin-destination (OD) pairs. In the classical network design problem, selecting an arc incurs a fixed cost and a variable cost associated with each unit of flow on the arc. In a non-collaborative scenario, the fixed costs are incurred by each firm separately.

Furthermore, since the quantities of goods being transported in a non-collaborative context are generally lower, the unit transportation costs are also higher. In the CSNDP, the level of integration among firms is strategic. Therefore, rather than sharing orders and capacities, we consider designing the networks in a centralized manner. In this regard, both fixed and variable costs are incurred by the central planning body, and cost reductions can be attained as a result of economies of scale. Specifically, we assume that there are alternative modes of transportation on the arcs, each with different fixed and unit transportation cost. Larger quantities of goods being transported may require a different mode of transportation, which in turn may change the fixed and variable costs associated with an arc. Beyond the fixed and variable costs, there also exists an additional cost component, referred to as the collaboration cost, associated with each arc of the graph. The collaboration cost is a function of the number of collaborating firms and may result from additional organizational needs by the collaboration (which require a one-time investment such as building new headquarters) to coordinate the operations, or it may be related to a one-time equipment purchase used by the collaborating firms. In summary, the CSNDP contains three cost components associated with each arc of the graph: a one-time fixed cost, a collaboration cost depending on the number of collaborators, and a variable cost affected by the volume of goods being transported.

1.4. Scientific Contribution and Organization of the Paper

The scientific contribution of this paper is fourfold. First, we introduce a new problem: the strategic collaborative network design problem. To the best of our knowledge, this is the first study to consider collaboration at a strategic level in network design. Second, we account for a critical cost component overlooked in the literature on strategic alliance formations: the collaboration cost. Third, we develop models and strengthening valid inequalities to solve this problem. Fourth, we customize an effective matheuristic algorithm capable of handling large-size instances. Through computational experiments, we demonstrate the importance of accounting for the cost of collaboration in network design, and the fact that this cost component may have profound impacts on the total costs that may hamper the benefits of collaboration and even render it unattractive.

The remainder of the paper is organized as follows: we introduce formulations and valid inequalities for the CSNDP in Section 2. The matheuristic is also presented in Section 2. We present the data, experimental results and discussions in Section 3. Finally, we present our conclusions in Section 4.

2. Problem Representation and Formulation

Consider a directed graph $G = (N, A)$ representing a physical road network with node and arc sets N and A, respectively. Let F be the set of firms operating in this network. A commodity k is defined as a triple $\langle o_k, d_k, W_k \rangle$, where o_k, d_k and W_k are the origin-destination pair and the demand quantity of commodity, respectively. Let K_f be the set of commodities of firm $f \in F$. In this regard, multiple modes of transportation (also called vehicles in the following) are available for each arc. The fuel consumption of a vehicle determines its efficiency and its associated transportation costs. Therefore, each mode of transportation has a different unit transportation cost and the total cost depends on the quantity of goods transported. Due to vehicle capacities and cost structures, the preferred mode of transportation depends on the total quantity of goods being transported on an arc. To account for the fact that different quantities of flow assigned to an arc may imply the use of different modes of transport, we consider that each arc $(i, j) \in A$ has $|S_{ij}|$ flow segments, where $S_{ij} = \{1, \ldots, |S_{ij}|\}$ represents the set of flow segments on arc $(i, j) \in A$. Each segment $s \in S_{ij}$ corresponds to a mode of transportation and can accommodate a flow range specified by a lower bound l_{ij}^s and an upper bound u_{ij}^s. Furthermore, each segment $s \in S_{ij}$ induces a fixed cost c_{ij}^s and a variable cost d_{ij}^s. Let b_{ij}^s be the breakpoint for segment $s \in S_{ij}$, which corresponds to its upper bound. We then have $l_{ij}^1 = 0$, $l_{ij}^s = b_{ij}^{s-1} = u_{ij}^{s-1}$ for $s = 2, \ldots, |S_{ij}|$ and $b_{ij}^{|S_{ij}|} = u_{ij}^{|S_{ij}|}$, where $u_{ij}^{|S_{ij}|}$ is also the capacity of arc (i, j). An example of a cost structure on arc (i, j) with three segments, showing the breakpoints and the fixed and variable costs, is depicted in Figure 1. The economies of scale, represented by the decreasing slope of the curve in Figure 1, lead to the fact that collaboration by multiple firms on an arc is always preferred over non-collaboration under concave cost structures and no collaboration cost. Furthermore, when firms collaborate, the fixed arc cost is paid only once for all firms, whereas in the non-collaborative scenario, each firm operating on the arc pays the fixed cost. The total cost accounted for in the CSNDP includes the collaboration cost, in addition to the fixed and variable costs depicted in Figure 1. When the collaboration cost is very high, the cost function may be non-concave, in which case collaboration on an arc could be disadvantageous for an individual firm. Nev-ertheless, empirical evidence shows that this is very unlikely and the collaboration cost is moderate (Lesmond et al., 1999). Furthermore, the collaboration decision is taken at the strategic level and no further decision is made at the tactical level. The model we develop below is used to minimize the cost of network design in strategic collaborations. An alternative model is developed and presented in the appendix, in which the collaboration decisions are taken at the tactical level (i.e., at the arc level). This paper focuses on strategic collaborations.

Let e_{ij}^m denote the collaboration cost on arc (i, j) for $m \geq 2$ firms collaborating on the arc. The variables used in the model are as follows:

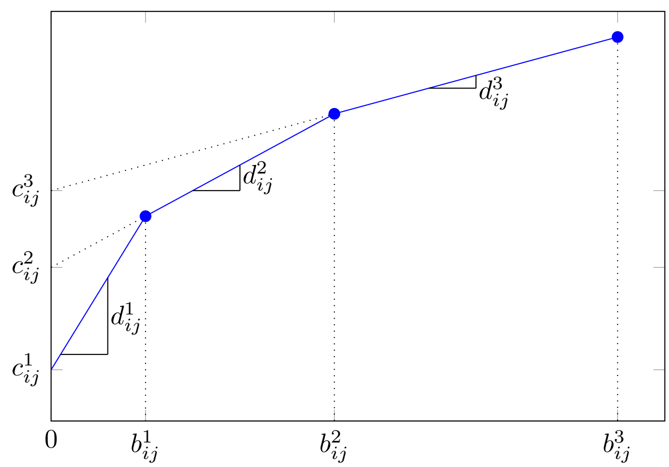

Figure 1: Example of a cost structure on arc (i, j) with three segments, showing the breakpoints and the fixed and variable costs.

x_{ij}^{kf} = fraction of commodity k of firm f transported on arc (i, j),

z_{ij}^{s} = total flow on arc (i, j) in segment $s \in S_{ij}$,

y_{ij}^{s} = 1 if total flow on arc (i, j) is within $(l_{ij}^s, u_{ij}^s]$ and 0 otherwise,

w_{ij}^{f} = 1 if firm f uses arc (i, j) and 0 otherwise,

t_{ij}^{m} = 1 if the number of collaborating firms on arc (i, j) is m and 0 otherwise.

We now present a formulation for CSNDP, which we refer to as F1.

$$\text{(F1) minimize} \sum_{(i,j)\in A} \sum_{s\in S_{ij}} (c_{ij}^s y_{ij}^s + d_{ij}^s z_{ij}^s) + \sum_{(i,j)\in A} \sum_{m=2}^{|F|} e_{ij}^m t_{ij}^m \tag{1}$$

subject to

$$\sum_{j:(i,j)\in A} x_{ij}^{kf} - \sum_{j:(j,i)\in A} x_{ji}^{kf} = \begin{cases} 1 & \text{if } i = o_k \\ -1 & \text{if } i = d_k \\ 0 & \text{otherwise} \end{cases} \qquad i \in N, f \in F, k \in K_f \qquad (2)$$

$$\sum_{s\in S_{ij}} z_{ij}^s = \sum_{f\in F} \sum_{k\in K_f} W^k x_{ij}^{kf} \qquad (i,j) \in A \qquad (3)$$

$$l_{ij}^s y_{ij}^s \leq z_{ij}^s \leq u_{ij}^s y_{ij}^s \qquad (i,j) \in A, s \in S_{ij} \qquad (4)$$

$$\sum_{s\in S_{ij}} y_{ij}^s \leq 1 \qquad (i,j) \in A \qquad (5)$$

$$\sum_{k\in K_f} x_{ij}^{kf} \leq |K_f| w_{ij}^f \qquad (i,j) \in A, f \in F \qquad (6)$$

$$\sum_{f\in F} w_{ij}^f = \sum_{m=1}^{|F|} m t_{ij}^m \qquad (i,j) \in A \qquad (7)$$

$$\sum_{m=1}^{|F|} t_{ij}^m \leq 1 \qquad (i,j) \in A \qquad (8)$$

$$x_{ij}^{kf}, z_{ij}^s \geq 0 \qquad (i,j) \in A, f \in F, k \in K_f \qquad (9)$$

$$t_{ij}^m, w_{ij}^f, y_{ij}^s \in \{0,1\} \qquad (i,j) \in A, f \in F, s \in S_{ij}, m = 1, \ldots, |F|. \qquad (10)$$

The objective function minimizes the sum of fixed, variable and collaboration costs. Constraints (2) are the flow balance equations. Through Constraints (3), (4) and (5), we determine the segment into which the total flow on arc (i,j) falls, which in turn determines the corresponding fixed cost incurred. In the case of no flow, no fixed cost is incurred. In order to count the number of firms collaborating on each arc, we use w_{ij}^f and t_{ij}^m variables. If there exists a firm using an arc, then the corresponding w_{ij}^f variable is forced to one by Constraints (6). The relationship between w_{ij}^f and t_{ij}^m variables is enforced by Constraints (7) and Constraints (8). Constraints (9) and

(10) define the domains of the variables. Note that the t_{ij}^m variables allow us to model any collaborative cost function depending on the number of collaborators.

2.1. Valid Inequalities

We now present a set of inequalities valid for formulation F1. The valid inequalities

$$x_{ij}^{kf} \leq \sum_{s \in S} y_{ij}^s \qquad (i,j) \in A, f \in F, k \in K_f \tag{11}$$

imply that if any firm transports a commodity on an arc, then one of the segments must be selected on this arc.

The disaggregated version of Constraints (6) results in the valid inequalities

$$x_{ij}^{kf} \leq w_{ij}^f \qquad (i,j) \in A, f \in F, k \in K_f, \tag{12}$$

which imply that if a firm transports a commodity on a given arc, then the corresponding indicator variable w_{ij}^f must be equal to one.

The valid inequalities

$$\sum_{s \in S} y_{ij}^s \leq \sum_{f \in F} w_{ij}^f \qquad (i,j) \in A \tag{13}$$

imply that if the flow on arc (i, j) belongs to segment s then at least one firm uses the arc. The final set of valid equalities

$$\sum_{s \in S} y_{ij}^s = \sum_{m=1}^{|F|} t_{ij}^m \qquad (i,j) \in A \tag{14}$$

means that a segment on an arc is used if and only if the arc is used by at least one firm.

2.2. The Special Case of Bilateral Alliances

In the case of two firms, i.e. $|F| = 2$, formulation F1 can be simplified. In particular, the t_{ij}^m variables are no longer needed since the collaboration cost is only incurred when both companies collaborate on the arc. This can be modeled by means of w_{ij}^f variables. For this special case, let variable r_{ij} be the collaboration cost on arc $(i,j) \in A$. We refer to the following model as F2:

$$\text{(F2) minimize} \sum_{(i,j)\in A} \sum_{s\in S_{ij}} (c_{ij}^s y_{ij}^s + d_{ij}^s z_{ij}^s) + \sum_{(i,j)\in A} r_{ij} \tag{15}$$

subject to

$$(2), (3), (4), (5), (6) \tag{16}$$

$$(\sum_{f\in F} w_{ij}^f - 1) e_{ij}^2 \leq r_{ij} \qquad (i,j) \in A \tag{17}$$

$$x_{ij}^{kf}, z_{ij}^s, r_{ij} \geq 0 \qquad (i,j) \in A, f \in F, k \in K_f \tag{18}$$

$$w_{ij}^f, y_{ij}^s \in \{0,1\} \qquad (i,j) \in A, f \in F, s \in S_{ij}, m = 1, \ldots, |F|. \tag{19}$$

Constraints (17) force variable r_{ij} to be at least e_{ij}^2 if both w_{ij}^1 and w_{ij}^2 equal 1. Note that valid inequalities (11), (12) and (13) are also valid for F2.

Proposition 1. *F2 is a valid reformulation of F1.*

Proof. In a network with two firms, constraints (7) state that $\sum_{f\in F} w_{ij}^f = t_{ij}^1 + 2t_{ij}^2$ for all $(i,j) \in A$. Then, constraints (8) imply that $\sum_{f\in F} w_{ij}^f \leq 1 + t_{ij}^2$. Defining $r_{ij} = e_{ij}^2 t_{ij}^2$ and replacing in the previous inequality yields $\sum_{f\in F} w_{ij}^f - 1 \leq r_{ij}/e_{ij}^2$, which is the same inequality as (17). Thus, we replace constraints (7) by (17) to obtain a new formulation. This allows us to remove t^1_{ij} from the formulation without loss of generality, since it only appears in (9). The new formulation corresponds to F2. □

As we will see in the computational study section, the solution performances of these two models are quite different, particularly when F1 is strengthened using (14), which is not valid for F2.

2.3. Matheuristic Based on Iterative Linear Programming

Network design problems are notoriously hard to solve. Different exact solution techniques have been implemented based on reformulations, Benders decomposition and Lagrangian relaxation (Gendron, 2011). Heuristics have also been developed for large-scale instances. One such recently developed heuristic is based on ideas from iterative linear programming (ILP) (Gendron et al., 2018), in which a restricted model and a linear relaxation are iteratively solved to find promising solutions. The ILP heuristic is reported to obtain solutions that compare favorably with most state-of-the-art heuristics on benchmark instances. In this section, we tailor the ILP to solve our problem and extend it.

Let $\mathcal{P}$ and $\mathcal{Q}$ be two models. In the initialization of the algorithm, $\mathcal{P}$ equals either F1 or F2 and $\mathcal{Q}$ equals $\mathcal{P}$. A first step is to solve the linear programming (LP) relaxation of $\mathcal{Q}$, which we refer to as $\overline{\mathcal{Q}}$. In this LP relaxation, possibly many binary variables naturally assume integral values. The idea of ILP is to fix those variables at their values in the LP relaxation and solve a restricted integer programming (IP) model. Let A^0 and A^1 be the sets of binary variables that are at their lower and upper bounds, respectively, in the LP relaxation. The restricted IP model is referred to as $\mathcal{P}(A^0, A^1)$ and is solved in a time limit of $\mathbf{T}$, which can possibly provide an optimal solution of $\mathcal{P}$ when the assignment of variables in A^0, A^1 matches their optimal values. The algorithm iterates between solving $\overline{\mathcal{Q}}$ and $\mathcal{P}(A^0, A^1)$ for a time limit of T_{max}. In their application, Gendron et al. (2018) only have design variables in a classical network design problem, which correspond to arc selection decisions. They are the fixed variables when solving the restricted problem. In our application, on the other hand, we have the design variables for firms (w_{ij}^f), segment variables (y_{ij}^s) and collaboration variables (t_{ij}^m), which are all binary. Fixing all binary variables quickly renders the problem infeasible. Therefore, we customize the ILP algorithm to fit our model by only fixing the design variables for firms. Next, we append the following logic-based cut to $\mathcal{Q}$ to exclude the considered solution:

$$\sum_{f \in F} \sum_{(i,j) \in A^0} w_{ij}^f + \sum_{f \in F} \sum_{(i,j) \in A^1} (1 - w_{ij}^f) \geq 1. \tag{20}$$

We update the best solution v^* by comparing it to the objective function value of the restricted problem, $v(\mathcal{P}(A^0, A^1))$. The algorithm continues for T_{max} seconds. The pseudo-code is presented in Algorithm 1, which we refer to as ILP Heuristic-1 (ILPH-1).

Algorithm 1: ILP Heuristic-1

Function ILPH-1($\mathcal{P}, T, T_{max}$);
$\mathcal{Q} \leftarrow \mathcal{P}, v^* \leftarrow \infty$;
repeat
  if $\overline{\mathcal{Q}}$ *(the LP relaxation of $\mathcal{Q}$) is infeasible* **then break**;
  Solve $\overline{\mathcal{Q}}$ to obtain A^0 and A^1;
  Solve $\mathcal{P}(A^0, A^1)$ using time limit $\mathbf{T}$;
  if $v^* > v(\mathcal{P}(A^0, A^1))$ **then** $v^* = v(\mathcal{P}(A^0, A^1))$;
  Update $\mathcal{Q}$ by appending cut (20);
until `CPUTIME()` $> T_{max}$;

In order to possibly improve the results, we modified the ILPH-1 Algorithm as follows. In large-scale problem instances, the restricted problem $\mathcal{P}(A^0, A^1)$ may not provide a feasible solution within the time limit. For this reason, the first modification is in line 6. We impose both a time limit and the condition that a feasible solution is obtained. We implement this in CPLEX by *MIPInfoCallback*, which is called prior to solving each node in the branch-and-cut search. In order to present the second modification, we first introduce $\hat{\mathcal{Q}}$ to be the root node relaxation of model Q. The main difference between the LP relaxation and the root node relaxation is that the $\hat{\mathcal{Q}}$ formulation is strengthened at the root node by adding various cuts by CPLEX. Therefore, the optimality gap as well as the solution quality can improve. In the second modification, we alter line 5 of Algorithm 1 as "Solve $\hat{\mathcal{Q}}$ to obtain A^0 and A^1". We refer to the heuristic we obtain after these two modifications as *ILPH-2*, which is shown in Algorithm 2. To implement, we customized CPLEX to solve the model in a single branch-and-bound tree in order to solve the root node relaxation only once and not at every iteration. In particular, we build a tree in which every node has a single child and the corresponding branching cut is the logic-based cut (20). Therefore, at every node of the tree, we reoptimize the ILP after appending the new cut. This not only allows us to use CPLEX generated cuts, but also it helps its heuristic algorithms to generate feasible solutions. When creating the child node in a *BranchCallback*, we also solve the restricted ILP to generate a solution.

Algorithm 2: ILP Heuristic-2

1 **Function** ILPH-2($\mathcal{P}, T, T_{max}$);
2 $\mathcal{Q} \leftarrow \mathcal{P}, v^* \leftarrow \infty$;
3 **repeat**
4   **if** $\hat{\mathcal{Q}}$ *(the root-node relaxation of* $\mathcal{Q}$*) is infeasible* **then break**;
5   Solve $\hat{\mathcal{Q}}$ to obtain A^0 and A^1;
6   Solve $\mathcal{P}(A^0, A^1)$ until a feasible solution is found **and** a time **T** is reached;
7   **if** $v^* > v(\mathcal{P}(A^0, A^1))$ **then** $v^* = v(\mathcal{P}(A^0, A^1))$;
8   Update $\mathcal{Q}$ by appending cut (20);
9 **until** `CPUTIME()` $> T_{max}$;

3. Experimental Study

In this section, we introduce the datasets and we test the performances of the models and the valid inequalities presented in the preceding section. We also investigate the cost differences between scenarios in which the firms prefer to collaborate and those in which the firms do not collaborate. We then discuss the results and the impacts of different parameters on the costs.

3.1. Testbed

The Canad instances (Frangioni, 2012), which have been used extensively in the network design literature (Crainic et al., 2001; Hewitt et al., 2010; Gendron and Larose, 2014; Chouman et al., 2016), are our main source of data. We note that these instances were generated assuming only a single firm. The properties of 'r01-r09 networks' in the Canad instances are summarized in Table 1. There are nine settings for varying fixed costs and capacities for each of these networks, totaling 81 instances. Nine of these instances are infeasible for the classical network design problem (Chouman et al., 2016). While some of these instances may be feasible for particular settings in our experimental design, they are still infeasible for others and thus we choose to exclude them from our experiments. Therefore we consider 72 instances from the R dataset. We also consider 'C' and 'C+' networks and their properties are shown in Tables 2 and 3, respectively. There are 43 networks, all of which are feasible for the non-collaborative case. They are the most difficult C and C+ instances (Gendron et al., 2018). The 'F/V' column in Tables 2 and 3 indicates whether the emphasis is on (F)ixed or (V)ariable costs and the 'T/L' column indicates whether the capacities are (T)ight or (L)oose.

Since the arc capacities provided in the dataset are assumed to be for a single firm, we multiply them by the number of firms in order to ensure the feasibility

Table 1: R class of networks in Canad instances

name	# nodes	# arcs	# commodities
r01	10	35	10
r02	10	35	25
r03	10	35	50
r04	10	60	10
r05	10	60	25
r06	10	60	50
r07	10	82	10
r08	10	83	25
r09	10	83	50

of the collaborative scenarios. We use these arc capacities in both collaborative and non-collaborative scenarios for fair comparisons of either scenario type. Let $\mathcal{C}_{ij}$, $\mathcal{D}_{ij}$ and $\mathcal{U}_{ij}$ be the fixed cost, variable cost and capacity of arc (i, j) provided in the dataset. These fixed and variable cost values are assumed to be the values for the first segment in our study. We assume a concave cost structure similar to that of Figure 1, since increasing quantities of commodities being transported imply decreasing variable costs. Let S be the number of segments, which we take as three. To generate the breakpoints of the segments and the fixed, variable and collaboration costs for each segment, we follow the same method as in Croxton et al. (2007) and Gendron and Gouveia (2016). By assumption, the capacity of arc (i, j) is equal to $|F|\mathcal{U}_{ij}$ and we set $b^0_{ij} = 0$ and $b^s_{ij} = \frac{s^2}{S^2}|F|\mathcal{U}_{ij}$ for $1 \leq s \leq S$. With this breakpoint assignment, we ensure that the segment lengths increase for increasing s as it is typical of transportation costs (Balakrishnan and Graves, 1989; Croxton et al., 2007). Inspired by the hub location literature, we assume a fixed discount factor α for the variable costs and let $d^1_{ij} = \mathcal{D}_{ij}$ and $d^s_{ij} = \alpha d^{s-1}_{ij}$ for $s \geq 2$. Once the variable costs and the breakpoints have been generated, the fixed costs can be determined as $c^1_{ij} = \mathcal{C}_{ij}$ and $c^s_{ij} = c^{s-1}_{ij} + b^{s-1}_{ij}(d^{s-1}_{ij} - d^s_{ij})$ for $2 \leq s \leq S$. The collaboration cost of a

Table 2: C class of networks in Canad instances

name	# nodes	# arcs	# commodities	F/V	T/L
c33	20	230	40	V	L
c35	20	230	40	V	T
c36	20	230	40	F	T
c37	20	230	200	V	L
c38	20	230	200	F	L
c39	20	230	200	V	T
c40	20	230	200	F	T
c41	20	300	40	V	L
c42	20	300	40	F	L
c43	20	300	40	V	T
c44	20	300	40	F	T
c45	20	300	200	V	L
c46	20	300	200	F	L
c47	20	300	200	V	T
c48	20	300	200	F	T
c49	30	520	100	V	L
c50	30	520	100	F	L
c51	30	520	100	V	T
c52	30	520	100	F	T
c53	30	520	400	V	L
c54	30	520	400	F	L
c55	30	520	400	V	T
c56	30	520	400	F	T
c57	30	700	100	V	L
c58	30	700	100	F	L
c59	30	700	100	V	T
c60	30	700	100	F	T
c61	30	700	400	V	L
c62	30	700	400	F	L
c63	30	700	400	V	T
c64	30	700	400	F	T

Table 3: C+ class of networks in Canad instances

name	# nodes	# arcs	# commodities	F/V	T/L
C+1	25	100	10	F	L
C+2	25	100	10	F	T
C+3	25	100	10	V	L
C+4	25	100	30	F	L
C+5	25	100	30	F	T
C+6	25	100	30	V	T
C+7	100	400	10	F	L
C+8	100	400	10	F	T
C+9	100	400	10	V	L
C+10	100	400	30	F	L
C+11	100	400	30	F	T
C+12	100	400	30	V	T

given number of firms is taken as a multiple of the fixed cost of the last segment on the arc, $e_{ij}^m = \frac{m}{|F|}\ \beta\ c_{ij}^S$ for $m \geq 2$, where $\beta \geq 0$ is a parameter, which we refer to as the *collaboration constant*. Note that $\beta = 0$ implies an absolute minimum cost for the firms, and the problem then boils down to a single body designing the network with full control of the assets and without any collaboration costs.

Since there are multiple firms in the alliance, their commodities can overlap. To measure the level of similarity between two firms and to investigate their impacts on the results, we introduce a *'similarity index'* (sIndex) of a firm, say Firm 1, with respect to another firm, Firm 2, defined as the percentage of the commodities that are common to both firms with respect to the number of Firm 1 commodities. For example, if Firm 1 has six commodities 1,...,6 and Firm 2 also has six commodities 4,...,9, then three (4, 5 and 6) are common to both firms. This implies that the sIndex of Firm 1 with respect to Firm 2 is equal to $3/6 = 0.5$. That is, 50% of Firm 1's commodities are the same as those of Firm 2. Therefore, using the same logic, the sIndex of Firm 2 with respect to Firm 1 is also $3/6 = 0.5$. sIndex = 1.0

implies a full overlap of commodities while sIndex = 0.0 implies that the firms share no commodities. In our computational experiments, we consider two firms in the alliance, three segments for the cost function of each arc in the network. Table 4 shows our design for sIndex $\in \{0.0, 0.5, 1.0\}$ for the 10, 25, 30, 40, 50, 100, 200 and 400 commodities considered in Tables 1 and 3. In our design, both firms have an equal number of commodities.

Table 4: Similarity index between two firms for different numbers of commodities

		Firm 1 commodities		Firm 2 commodities		
Commodities	sIndex	from	to	from	to	Common commodities
10	0.0	1	5	6	10	–
10	0.5	1	6	4	9	4–6
10	1.0	1	10	1	10	1–10
25	0.0	1	12	13	24	–
25	0.5	1	16	9	24	9–6
25	1.0	1	24	1	24	1–24
30	0.0	1	15	16	30	–
30	0.5	1	20	11	30	11–20
30	1.0	1	30	1	30	1–30
40	0.0	1	20	21	40	–
40	0.5	1	24	13	37	13–24
40	1.0	1	40	1	40	1–40
50	0.0	1	25	26	50	–
50	0.5	1	32	17	49	17–32
50	1.0	1	50	1	50	1–50
100	0.0	1	50	51	100	–
100	0.5	1	64	33	97	33–64
100	1.0	1	100	1	100	1–100
200	0.0	1	100	101	200	–
200	0.5	1	128	65	193	65–128
200	1.0	1	200	1	200	1–200
400	0.0	1	200	201	400	–
400	0.5	1	266	134	399	134–266
400	1.0	1	400	1	400	1–400

3.2. Computational Results

We test the performance of the models and the valid inequalities using the R dataset. We have implemented our models using Java and CPLEX 12.8.0.0. All experiments were conducted on a cluster of 27 machines each having two Intel(R) Xeon(R) X5675 3.07 GHz processors running on Linux. Each machine has 12 cores and each experiment was run using a single thread. A three-hour time limit was set. For performance testing, we take sIndex = 0, α=0.7 and β=0.1. The results are shown in Table 5. The first column indicates the implementation number. The second column shows which model is used, while the following three columns show the setting for the valid inequalities. Since inequalities (13) and (14) have sizes equal to the number of arcs, they are added a priori to the model. However, inequalities (11) and (12) are very numerous and therefore only the violated ones are added at the root node of the branch-and-bound tree in a branch-and-cut (B&C) framework. The column labeled '(11)–(12)' indicates whether these inequalities are added. The remaining set of columns show the results. The number of feasible and optimal solutions are shown in columns 6 and 7, respectively. The feasible instances are those that could not be solved to optimality within the time limit, but for which a feasible solution was obtained. The average optimality gap for the feasible instances is reported in column 8. The average solution time of all instances in seconds is shown in column 9. The linear programming (LP) relaxations of the models are reported in column 10. We also report the root node gaps after CPLEX cuts are added in the rightmost column.

The computational results in implementations 1$-$4 show that the valid inequalities (13) and (14) are very effective in accelerating the solution process of the F1 model. The second and fourth implementations are more than 50% faster than their counterparts, i.e., the first and the third implementations, respectively. Furthermore,

Table 5: Computational results of the models and the valid inequalities

Experimental settings					#	#	Opt.gap	Solution	Avg LP	Avg root
#	Model	(13)	(14)	(11)–(12)	Feasible	Optimal	(%)	time (s)	relaxation (%)	node gap (%)
1	F1	–	–	–	2	70	0.60	671.19	37.41	4.66
2	F1	+	+	–	–	72	0.00	322.36	36.77	2.40
3	F1	–	–	+	2	70	0.60	668.40	37.41	4.66
4	F1	+	+	+	–	72	0.00	320.81	36.77	2.40
5	F2	–	–	–	1	71	0.83	422.60	37.16	4.70
6	F2	+	N/A	–	2	70	0.36	590.46	37.16	4.70
7	F2	–	–	+	1	71	0.81	429.70	37.16	4.70
8	F2	+	N/A	+	2	70	0.36	588.44	37.16	4.70

all instances could be solved with valid inequalities (13) and (14) whereas this is not the case in the first and third implementations without these valid inequalities. We do not observe similar strong results for the valid inequalities (11)–(12). The solution times change insignificantly between the first and third implementations, and likewise between the second and fourth implementations. An important observation concerns the quality of the cuts added by CPLEX. Even though the LP relaxations of the models are quite weak, the gaps are significantly reduced at the root node by CPLEX cuts.

Looking at the fifth implementation in Table 5, we observe that the plain F2 model without any valid inequalities has an average runtime of 422.60 seconds, which is 248.59 seconds faster than the first implementation. The fifth implementation can also solve an extra instance to optimality. The valid inequalities do not provide an advantage for the F2 model. In contrast, adding valid inequalities (13) worsens the run times. Hence, observing the advantages that the valid inequalities (13) and (14) provide for the F1, we use F1 model with valid inequalities (13)–(14), i.e., the second implementation, for the rest of the experiments.

The above models failed to solve C and C+ instances and terminated with a large gap or could not even solve the root node relaxation. Therefore, we will test the ILPH-1 and ILPH-2 heuristics in the second part of the computational study. In our implementation, we set a time limit of one hour, similar to Gendron et al. (2018). To implement ILPH-1, we use CPLEX as our solver with the default settings. As in Gendron et al. (2018), the time limit for the restricted IP is 300 seconds.

ILPH-1 and ILPH-2 solved 88.22% and 70.32% of the R instances to optimality. The average optimality gaps are 0.12% and 0.26%, respectively. Since we have obtained very small gaps in both implementations, we tested both in the 43 most difficult C and C+ networks. For each network, there are 27 different configurations for sIndex, α and β, totaling 1161 instances. The results are shown in Table 6. The first column lists the four cases: the objective function values of the two heuristics are the same (ILPH-1 = ILPH-2), ILPH-2 performs better (ILPH-1 > ILPH-2), ILPH-1 performs better (ILPH-1 < ILPH-2), and both heuristics fail to generate a feasible solution (Undecided). The second column shows the number of instances in each case and the third column reports the average difference between the objective functions of the two heuristics with respect to the smallest of the two. In 40% of the instances, ILPH-2 performed better providing 9.13% improved solution on average than ILPH-1. In 27% of the instances ILPH-1 performed better, but the improvement is not as high as that of ILPH-2.

Table 6: ILPH-1 and ILPH-2 Heuristics Comparison

Obj.Fn. comparison	# Instances	Diff (%)
ILPH-1 = ILPH-2	154	0.00
ILPH-1 > ILPH-2	466	9.13
ILPH-1 < ILPH-2	313	2.23
Undecided	228	N/A

3.3. Results and Discussions

Here, we investigate the impact of the similarity index (sIndex), the variable cost discount factor (α) and the collaboration constant (β) on the cost of the network design in bilateral alliances. In our experimental design, we have sIndex $\in \{0, 0.5, 1.0\}$, $\alpha \in \{0.25, 0.50, 0.75\}$ and $\beta \in \{0.0, 0.1, 0.5\}$ for each instance. We also determine the network design cost when the firms do not collaborate, and indicate it as NC (not collaborating) in our results.

The number of commodities is different for each sIndex (Table 4). In order to make a fair comparison between results, the costs are reported as a percentage of the minimum cost of all instances for a given sIndex, which is achieved when $\beta = 0$ and $\alpha = 0.25$. In other words, we take a base value and report the cost changes as percentage with respect to this base value. Table 7 reports the average network design costs as percentages. The reference cells with the base values (at $\beta = 0$ and $\alpha = 0.25$) are highlighted in bold and are indicated as 0%. The largest cost increase is when the firms collaborate with high collaboration costs ($\beta = 0.5$) and with a discount factor $\alpha = 0.75$. The relative increase is 75%, 84% and 107% with respect to the base cases with sIndex equaling 0.0, 0.5 and 1.0, respectively. The NC scenarios result in cost increases ranging from 16% to 77% with respect to the base cases. The cost increase in any NC scenario is always between those of the $\beta = 0.1$ and $\beta = 0.5$ scenarios.

The capacity utilization in the optimal solutions is an important performance indicator measuring efficiency. It is the percentage of the capacity used in the final solution, calculated as $\sum_{f \in F, k \in K_f} x_{ij}^{kf} / u_{ij}^{|S_{ij}|}$ for an arc $(i, j) \in A$ with a non-zero flow. The average capacity utilization percentage in the optimal solutions per similarity index, α and β parameters is shown in Table 8. The average utilization increases

Table 7: Network design costs as percentages of the base values per similarity index, which is achieved when $\beta = 0$ and $\alpha = 0.25$. The reference cells are highlighted in bold.

sIndex	β	α		
		0.25	0.50	0.75
0.0	0	**0%**	22%	49%
	0.1	7%	30%	56%
	0.5	28%	50%	75%
	NC	18%	41%	68%
0.5	0	**0%**	26%	55%
	0.1	8%	33%	62%
	0.5	31%	57%	84%
	NC	16%	40%	68%
1.0	0	**0%**	35%	74%
	0.1	8%	44%	81%
	0.5	34%	71%	107%
	NC	19%	45%	77%

from 64.07% on average in the NC scenarios to 71.06% on average in collaborative scenarios. Increasing sIndex and decreasing α imply higher capacity utilization. The highest capacity utilization is 78%, which is achieved when sIndex = 1.0 and $\beta = 0$, i.e., when the firms have the same OD pairs and the collaboration comes at no cost.

To isolate and investigate the individual impact of α and β on the total cost, we change the basis with respect to which we reference the results in Table 7. Table 9 shows the percentage changes by referencing to the minimum cost for each sIndex and β in order to understand the impact of α constant on the design cost. The average increase in cost when $\alpha = 0.5$ with respect to the $\alpha = 0.25$ case is 22.3%, 25.2% and 33.6% for sIndex = 0, 0.5 and 1.0, respectively, which is shown in Figure 2. When $\alpha = 0.75$, then the average increase is 48.6%, 53.5% and 69.5% for sIndex = 0, 0.5 and 1.0, respectively. The cost increase is more pronounced for larger sIndex values both when $\alpha = 0.5$ and when $\alpha = 0.75$. This result is observed because larger

Table 8: Capacity utilization percentages in the optimal solutions per similarity index, α and β parameters.

sIndex	β	α		
		0.25	0.50	0.75
0	0	73%	68%	63%
	0.1	71%	67%	63%
	0.5	68%	65%	62%
	NC	63%	59%	55%
0.5	0	73%	71%	67%
	0.1	74%	72%	67%
	0.5	72%	69%	66%
	NC	67%	64%	59%
1.0	0	78%	76%	72%
	0.1	78%	76%	73%
	0.5	77%	76%	74%
	NC	72%	68%	64%

sIndex values imply that the firms have more common OD pairs and therefore the fixed cost is less dominant in the total cost with respect to the case with smaller sIndex values. In other words, the dominant cost component is the variable cost for larger sIndex values. Therefore, a change in the variable cost discount factor α implies a larger change in the cost for greater sIndex values. In Table 9, we also observe that, when sIndex =1.0, the cost increase is smaller in NC rows than the cost increase when the firms collaborate. For instance, the cost increase is 58% in the NC case when sIndex =1.0 and $\alpha = 0.75$ whereas the increase is 72%, 73% and 74% for $\beta = 0.5$, 0.1 and 0.0, respectively. In the NC case, both firms need to incur the fixed cost of a selected arc when they design their networks individually. Since the fixed costs are more dominant than the variable costs, an increase in the α discount factor has less impact on the total cost.

Finally, Table 10 shows the percentage increase with respect to the minimum

Table 9: Network design costs as percentages of the base values per similarity index and β parameter, which is achieved when $\alpha = 0.25$. The reference cells are highlighted in bold.

sIndex	β	α		
		0.25	0.50	0.75
0.0	0	**0%**	22%	49%
	0.1	**0%**	22%	48%
	0.5	**0%**	22%	47%
	NC	**0%**	23%	50%
0.5	0	**0%**	26%	55%
	0.1	**0%**	26%	54%
	0.5	**0%**	26%	53%
	NC	**0%**	24%	52%
1.0	0	**0%**	35%	74%
	0.1	**0%**	36%	73%
	0.5	**0%**	37%	72%
	NC	**0%**	26%	58%

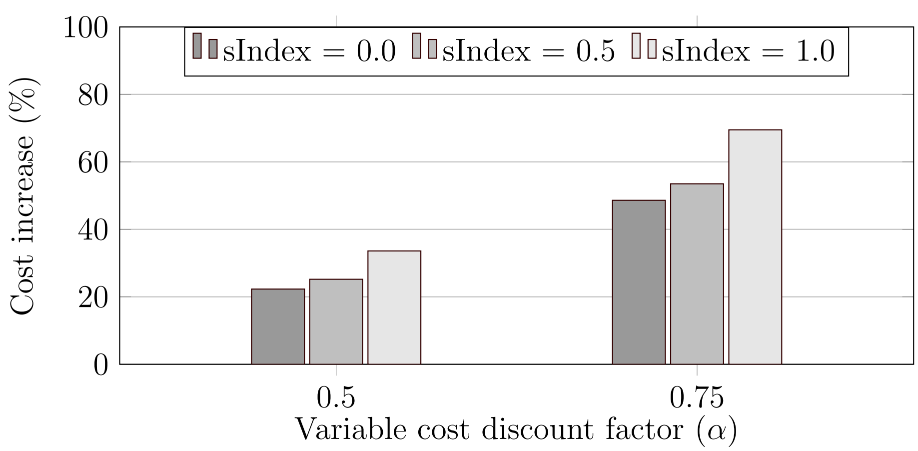

Figure 2: Cost increase as percentage of the cost in the base case

cost for each sIndex and α, in order to understand the impact of β on the design cost. The $\beta = 0$ case gives the minimum cost that firms can achieve when designing their network, in which no collaboration costs are incurred. The largest cost increase occurs when $\beta = 0.5$. For $\beta = 0.1$, the cost increase is between 7% and 9%; for $\beta = 0.5$, the increase is between 26% to 36%; and for the NC case, the cost increase is between 4% and 19%. We note that when $\beta \geq 0.5$, the average cost exceeds that of the NC case and collaboration is more expensive than when each firm designs its networks individually. Therefore, it is advantageous to collaborate provided that the collaboration costs are not unreasonably high. For this reason, the collaboration cost needs to be carefully determined and taken into account in the strategic alliance.

A bar chart representation of the same results is presented in Figure 3. In terms of change with respect to sIndex, we observe a decreasing trend in the NC case as sIndex increases, whereas we observe an increasing trend when the collaboration cost is at the high setting ($\beta = 0.5$). Larger sIndex values imply more OD pairs being common in both firms. Therefore, the firms can increase the amount of flow on arcs and gain cost reductions. This would intuitively imply that the higher the sIndex value, the more savings these firms can achieve. However, the cost for the $\beta = 0.5$ case counterintuitively increases by increasing sIndex. The main reason is the high collaboration costs being paid. It is at such a high level that firms use an arc and bear the associated high collaboration costs to minimize their total cost. Even though we can explain the reason for such an occurrence, it is never wise to collaborate under such high collaboration costs since the total costs are higher than the non-collaboration costs.

Table 10: Network design costs as percentages of the base values per similarity index and α parameter, which is achieved when $\beta = 0$. The reference cells are highlighted in bold.

sIndex	β	α		
		0.25	0.50	0.75
0.0	0	**0%**	**0%**	**0%**
	0.1	7%	8%	7%
	0.5	28%	28%	26%
	NC	18%	19%	19%
0.5	0	**0%**	**0%**	**0%**
	0.1	8%	8%	7%
	0.5	31%	32%	29%
	NC	16%	14%	13%
1.0	0	**0%**	**0%**	**0%**
	0.1	8%	9%	8%
	0.5	34%	36%	33%
	NC	19%	10%	4%

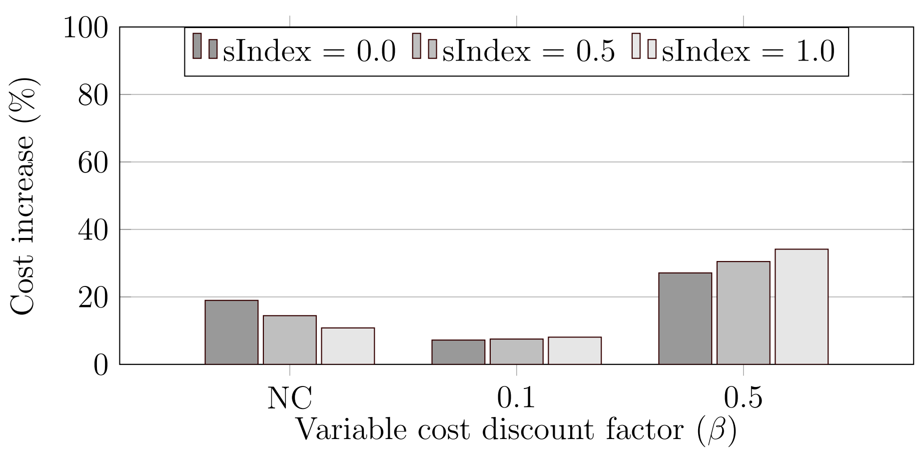

Figure 3: Bar chart representation of results in Table 10 displaying the network design cost increase with respect to $\beta = 0$ case.

4. Conclusions

It is vital for the survival of the alliances to carefully plan their operations and accurately determine their costs. In a centralized planning environment with collaboration, the fixed and variable costs are often accounted for when designing networks. In our study, we have argued that considering these two cost components is necessary but not sufficient. We have taken into account the collaboration cost, have introduced the network design problem for strategic alliances and have developed models to solve it. Significant gains can be attained by collaborating, but these gains may be hampered by the costs associated with collaboration. Even further, this cost component may be high enough to dominate the total cost and hence render the collaboration unattractive. Hence, a careful data collection and model treatment is required before deciding to form an alliance.

Appendix

In this appendix, we present a model that makes collaboration decisions at the tactical (i.e., arc) level. In this model, we represent collaborations by subsets of the firms on each arc. A subset with a single firm in it represents non-collaboration. If a firm transports any amount on an arc (i, j), it is required to be in one of these subsets. The variables used in the model are as follows:

x_{ij}^{kf} = fraction of commodity k of firm f transported on arc (i, j),

$q_{ij,\Lambda}$ = 1 if the firms in set $\Lambda \subset F$ are collaborating on arc (i, j) and not collaborating with any firm in $F \setminus \Lambda$ and 0 otherwise,

$z_{ij,\Lambda}^{s}$ = total flow of firms in set $\Lambda \subset F$ on arc (i, j) in segment $s \in S_{ij}$ if $q_{ij,\Lambda} = 1$ and 0 otherwise, $y_{ij,\Lambda}^{s}$ = 1 if total flow of of firms in set $\Lambda \subset F$ on arc (i, j) is within $(l_{ij}^{s}, u_{ij}^{s}]$ and 0 otherwise, We now present a formulation, which we refer to as F3.

$$\text{(F3) minimize} \sum_{\Lambda \subset F} \sum_{(i,j) \in A} \sum_{s \in S_{ij}} (c^s_{ij} y^s_{ij,\Lambda} + d^s_{ij} z^s_{ij,\Lambda}) + \sum_{\Lambda \subset F : |\Lambda| \neq 1} \sum_{(i,j) \in A} e^{|\Lambda|}_{ij} q_{ij,\Lambda} \tag{21}$$

subject to

$$\sum_{j:(i,j) \in A} x^{kf}_{ij} - \sum_{j:(j,i) \in A} x^{kf}_{ji} = \begin{cases} 1 \text{ if } i = o_k - 1 \\ \text{if } i = d_k \\ 0 \quad \text{otherwise} \end{cases} \qquad i \in N, f \in F, k \in K_f \tag{22}$$

$$\sum_{\Lambda \subset F} \sum_{s \in S_{ij}} z^s_{ij,\Lambda} = \sum_{f \in F} \sum_{k \in K_f} W^k x^{kf}_{ij} \qquad (i, j) \in A \tag{23}$$

$$l^s_{ij} y^s_{ij,\Lambda} \leq z^s_{ij,\Lambda} \leq u^s_{ij} y^s_{ij,\Lambda} \qquad (i, j) \in A, s \in S_{ij} \tag{24}$$

$$\sum_{\Lambda \subset F} \sum_{s \in S_{ij}} y^s_{ij,\Lambda} \leq 1 \qquad (i, j) \in A \tag{25}$$

$$\sum_{s \in S_{ij}} z^s_{ij,\Lambda} \leq \sum_{f \in \Lambda} \sum_{k \in K_f} W^k q_{ij,\Lambda} \qquad (i, j) \in A, \Lambda \subset F \tag{26}$$

$$\sum_{\Lambda \subset F : f \in \Lambda} q_{ij,\Lambda} \leq 1 \qquad (i, j) \in A, f \in F \tag{27}$$

$$x^{kf}_{ij} \leq \sum_{\Lambda \subset F : f \in \Lambda} q_{ij,\Lambda} \qquad (i, j) \in A, f \in F, k \in K_f \tag{28}$$

$$x^{kf}_{ij}, z^s_{ij,\Lambda} \geq 0 \qquad (i, j) \in A, f \in F, k \in K_f \tag{29}$$

$$q_{ij,\Lambda}, y^s_{ij,\Lambda} \in \{0, 1\} \qquad (i, j) \in A, s \in S_{ij}, \Lambda \subset F. \tag{30}$$

The objective function minimizes the sum of fixed, variable and collaboration costs. Constraints (22) are the flow balance equations. Through Constraints (23),(24) and (25), we determine the segment into which the total flow on arc (i, j) falls, which in turn determines the corresponding fixed cost incurred. In the case of no flow, no fixed cost is incurred. In order to determine which firms collaborate on each arc, we use $q_{ij,\Lambda}$ variables. Constraints (26) ensure the relationship between segment variables $z^s_{ij,\Lambda}$ and $q_{ij,\Lambda}$ variables. If some firms in Λ collaborates on arc (i, j), then they can have positive flow on this arc. Constraints (27) guarantee that a firm can only participate in a single collaboration or can be non-collaborating. The subsets of F also includes sets with a single firm, which represent the non-collaborating firms. Constraints (28) forces a firm to necessarily participate in a collaboration or be a non-collaborating firm. Constraints (29) and (30) define the domains of the variables. Note that due to the exponential number of subsets of the firms set, the model is naturally limited to only a few collaborating firms.

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