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A multi-objective optimization model for designing resilient supply chain networks

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ABSTRACT

Supply chains evolve over time: they expand via planned construction and/or corporate mergers and acquisitions, and contract due to required facility closures, partnership terminations, and/or other cost-cutting decisions. In addition, businesses also operate in an uncertain world wherein network and other design decisions must be made despite the reality of unforeseen future events that can and often do disrupt or damage corporate supply chains. We present a multi-objective network design model and accompanying optimization-based decision support methodology for supply chain architects. Our methodology helps to evaluate the trade-off between total network cost minimization and maximizing overall supply chain network connectivity. Decision makers can evaluate a collection of solutions with different cost and connectivity values using our methodology and choose the network configuration that best serves the needs of their organization. Though our multi-objective network design model is applicable for individual companies looking to expand or contract their internal supply chains, we demonstrate our model's efficacy through the lens of a practically-motivated corporate merger and acquisition activity.

1. Introduction

Companies around the globe regularly experience unforeseen events, both internal and external to their organization, that can (and often do) adversely impact their supply chains. These events, such as material supply shortages, customer demand changes, and natural disasters, often result in supply chain network design changes, such as supply chain expansion via planned construction and/or corporate mergers and acquisitions, and supply chain contraction due to facility closures, partnership terminations, and/or other cost-cutting decisions. In this paper, we present a multi-objective, optimization-based network design methodology to help supply chain architects improve the effectiveness of their supply chain networks. Our methodology effectively evaluates the trade-off between two conflicting objective functions of interest: minimizing total supply chain costs and maximizing overall supply chain network connectivity.

A clear application of network design arises in building an effective supply chain. Traditionally, this line of research has focused on cost-efficient designs; however, increased globalization and diminishing profit margins (Christopher and Holweg, 2011), among other factors, are driving modern supply chains to focus on consistently and quickly providing consumers with quality products. This, in turn, has resulted in a recent research trend of considering non-cost-related metrics in supply chain design (Brewer and Speh, 2000; Bullinger et al., 2002; Gunasekaran et al., 2004; Gunasekaran et al., 2001; Kleijnen and Smits, 2003; Lai et al., 2002; Schmitt and Singh, 2012).

Specifically, many researchers are now focused on designing supply chains that can effectively operate in the presence of external (e.g., supply shortages or demand fluctuations) and/or internal disruptions (e.g., a strike at a facility). This is becoming increasingly necessary, as a relatively small disruption can have a significant impact on the overall performance of the supply chain (Chopra and Sodhi, 2004). The literature on managing risk in supply chains is vast. As a starting point, we refer the reader to (Fahimnia et al., 2015; Heckmann et al., 2015; Ho et al., 2015; Snyder et al., 2016) as they are excellent review papers on the subject area and can provide for a broader background on this subject.

A supply chain is termed *robust* when it can withstand the adverse impacts of a disruption (Klibi et al., 2010; Tang, 2006). Further, supply chains capable of recovering quickly from disruptions are commonly

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characterized as being resilient (Bhamra et al., 2011; Christopher and Peck, 2004; Ponomarov and Holcomb, 2009; Ratick et al., 2008), although these two terms are oftentimes used interchangeably. In their 2010 review, Klibi et al. (2010) point both to supplier and shipping option redundancy as typical features of robust supply chains. Carvalho et al. (2012) show via simulation how the existence of these features can effectively mitigate disruptions. Further, Tang (2006), in citing both natural disasters and business structure-related issues as sources of potential disruption, confirms the desirability of these features and suggests that multiple transportation modes are also desirable to promote supply chain robustness. Kamalahmadi and Mellat-Parast (2017) analyze how inventory and supplier redundancy can increase a supply chain's resilience. Researchers have examined specific strategies for improving supply chain robustness and/or resilience by mitigating disruption risks in agricultural (Behzadi et al., 2017; Vlajic et al., 2012), automotive (Simchi-Levi et al., 2015; Thun and Hoenig, 2011), retail (Oke and Gopalakrishnan, 2009), medical (Fahimnia et al., 2017), electronics manufacturing (Aalaei and Davoudpour, 2017), and petrochemical (Vugrin et al., 2011) industries, amongst others.

Supply chain resilience has been, and continues to be, studied from several viewpoints in the literature (see, e.g., (Azevedo et al., 2008; Iakovou et al., 2007; Kim et al., 2015; Rice and Caniato, 2003)). Ratick et al. (2008) took a geographic view of supply chain resilience when determining the locations of backup facilities. Looking to diminish the impact of potential natural disasters, the authors suggest that a greater distance between facilities would lessen the impact if an area were to be hit by an earthquake, hurricane, or similar phenomenon. Their optimization model utilizes a set covering technique in minimizing the number of facilities needed to cover an area adequately. Similarly, Craighead et al. (2007) assert that the severity of supply chain disruptions can be mitigated by appropriate design characteristics, including network density, network complexity, and the node criticality of the network. Their work is extended by Falasca et al. (2008) and Adenso-Diaz et al. (2012) who quantify the relationships between design characteristics and the associated resiliency of the resulting supply chain. Networks developed with different objectives are submitted to simulation scenarios in order to determine the measure of resiliency produced by varying approaches to design.

Given the complexities associated with designing an effective supply chain, "supply chain design" optimization models have been developed for the purpose of recommending a design on the basis of some criteria. In his summary review, Shen (2007) presents several variations of the general multi-echelon supply chain design problem. These problems can include intricacies such as inventory positioning, routing decisions, make-versus-buy decisions, and quality issues, and can even be extended to multiple commodities. Capacity levels are often assumed to be either infinite or static, although Amiri (2006) addresses the case where multiple choices of capacities are available for storage at distribution centers within a supply chain. Melo et al. (2009) and Hinojosa et al. (2008) both allow for facilities to both *open and close* within the scope of their multi-period network models. Reliability metrics have been developed (Miao et al., 2009; Thomas, 2002) and applied within the context of mathematical optimization (Berman et al., 2009; Cardoso et al., 2015; Cui et al., 2010; Daskin et al., 2005; Meena and Sarmah, 2013; Sawik, 2013; Snyder and Daskin, 2005, 2007) to design disruption-tolerant supply chains.

One commonality among these supply chain design models is their focus on a single objective, whereas our model considers two: a network connectivity objective (which serves to facilitate robust solutions) and a cost objective. Network connectivity is, on its own, well-studied within the context of network design. The *survivable network design* problem, as summarized in the survey paper (Kerivin and Mahjoub, 2005a), seeks to design a minimum cost network that ensures each pair of nodes is connected by a certain number of arc-disjoint paths. Variants of this problem have received significant attention from the optimization community (Bienstock and Muratore, 2000; Kerivin and Mahjoub, 2005b; Magnanti and Raghavan, 2005) over the last few decades. To our knowledge, however, there is no existing research that examines the tradeoff between network connectivity with both strategic and operational costs.

Our contributions are as follows: We model, for the first time in the literature, the problem of supply chain network design under cost and network connectivity objectives. We formulate a novel deterministic multi-objective optimization model to construct a minimum cost network that hedges against disruption, providing decision makers the flexibility to prioritize network resiliency over price, or vice versa. From an application perspective, we implement the model by examining the post-acquisition, physical reorganization of supply chains, a topic that has received little attention in the literature, by applying the model to data representing the scenario in which one food processing company is considering redesigning their supply chain after acquiring another company's assets. The remainder of the paper is organized as follows: We define our model and solution approach in the following section, followed by (in Section 3) an illustrative example and (in Section 4) a case study that applies our model to a problem instance constructed utilizing data from a multi-billion dollar food processing company. Section 5 concludes.

2. Deterministic optimization model

The proposed model designs a multi-commodity supply chain network by optimizing with respect to two objectives: cost and demand-weighted connectivity. Specifically, the model determines (i) production capacities for each commodity's supply nodes, (ii) flow capacities for each arc in the network, and (iii) an operational plan that determines production quantities and locations as well as flow routing for each commodity. Costs are associated with both the network design decisions (expanding production and flow capacities) and the operational-level production quantity and flow-routing decisions. Decisions (i) and (ii), respectively, can be specified to incorporate opening new (or closing existing) production facilities or distribution channels. These decisions yield the supply chain network's topology, which in turn determines each commodity's vulnerability to disruptions. In order to incorporate vulnerability into the model, we optimize with respect to *demand-weighted connectivity*—that is, the sum (weighted by each commodity's demand) of the minimum number of facility disruptions/closures that would be required to disconnect a commodity's demand node from all of its supply nodes. By using a multi-objective approach, we can generate the tradeoff curve between the two competing objectives, enabling decision makers the flexibility of choosing a Pareto optimal solution based upon their preferences.

2.1. Notation and model formulation

Consider a directed network $G = (N, E)$ with commodity set P. The node set N contains the subsets D_p and $S_p \subseteq N \backslash D_p$, which are the demand nodes and supply nodes of product p, respectively. Let $\mathrm{RS}(i)$ denote the set of all nodes with outgoing arcs ending at node i (i.e., $\mathrm{RS}(i) = \{j \in N | (j, i) \in E\}$), and let $\mathrm{FS}(i)$ denote the set of all nodes with incoming arcs emanating from node i (i.e., $\mathrm{FS}(i) = \{j \in N | (i, j) \in E\}$).

Network design decisions are incorporated for each product/supply pair via the incorporation of binary decision variable z_{ip}, which equals 1 if the production capacity for product $p \in P$ at node $i \in S_p$ is set to a pre-defined *high* level, $r^+_{ip} > 0$; otherwise, $z_{ip} = 0$, indicating the production capacity is set to r^-_{ip} (where $r^-_{ip} < r^+_{ip}$). We refer to r^-_{ip} as the *low* level. Thus, the production capacity at node i is discrete and can be either r^-_{ip} or r^+_{ip}. If $z_{ip} = 1$, a cost of g_{ip} is incurred. Note that this cost can be interpreted as either (i) an additional investment required to increase the production capacity from its current level, r^-_{ip}, to r^+_{ip} or (ii) savings realized via decreasing the production capacity from its current level r^+_{ip}, to r^-_{ip}. Thus, via appropriately defining r^-_{ip}, r^+_{ip}, and g_{ip}, the model can allow for the possibility of expanding or reducing an existing production operation. Likewise, by defining $r_{ip}^- = 0$, we incorporate the possibility of adding a new (or canceling an existing) production operation.

In similar fashion to the node-level design decisions described above, binary decision variables y_{ij} are incorporated to model whether the flow capacity of arc $(i, j) \in E$ is set to (the high level) u_{ij}^+ or (the low level) u_{ij}^-, where $0 \le u_{ij}^- < u_{ij}^+$. Hence, the flow capacity of arc (i, j) is discrete and can be either u_{ij}^- or u_{ij}^+. If the capacity of arc $(i, j) \in E$ is set to the high level, a cost of f_{ij} is incurred. For simplicity of exposition, we have not introduced specific notation to impose flow capacities (and associated network design decisions) on the nodes; however, this can be incorporated within the stated model via a well-known node-splitting transformation, as described in (Ahuja et al., 1993).

Associated with each assignment of binary values to the z- and y-variables is a network topology: Let $S_p(z) \equiv \{i \in S_p: r_{ip}^- + (r_{ip}^+ - r_{ip}^-)z_{ip} > 0\}$ denote the nodes that have positive production capacity for product $p \in P$, and let $E(y) \equiv \{(i, j) \in E: u_{ij}^- + (u_{ij}^+ - u_{ij}^-)y_{ij} > 0\}$ denote the set of arcs with positive capacity. A *path* associated with commodity $p \in P$ and demand node $k \in D_p$ is defined as a sequence of nodes $\{i_t\}_{t=0}^T$ such that $i_0 \in S_p(z)$; $(i_{t-1}, i_t) \in E(y),\ \forall\ t = 1, \ldots, T$; and $i_T = k$. A set of paths associated with commodity $p \in P$ demand node $k \in D_p$ is said to be *node-disjoint* provided that each node in $N \backslash \{k\}$ is included in at most one path in the set. (Note: This includes the restriction that node-disjoint paths corresponding to a demand node $k \in D_p$ associated with a product $p \in P$ must all begin at different supply nodes in $S_p(z)$.)

Objective function values are represented with variables C and V, which respectively correspond to cost and connectivity. The connectivity objective is motivated by the desire to encourage reliable service to demand nodes via ensuring that demand nodes can be serviced via multiple node-disjoint paths originating from unique suppliers; thus, if we build k node-disjoint paths into a particular demand node, we have ensured that (at least some) service can be provided to that demand node even if as many as $k - 1$ nodes in the network fail. In the mathematical model defined below, we evaluate connectivity at the node/product level; thus, v_{ip} will denote the number of paths into demand node $i \in D_p$ that originate from some supply node of product $p \in P$. In total, there are $\sum_{p \in P} |D_p|$ v-variables, which is upper-bounded by $|N||P|$ because $|D_p| \le |N|$ for all $p \in P$; however, appropriately relating each v_{kp}-value to the values of y and z will require $|E|$ new flow variables used to assess the number of node-disjoint paths associated with each product $p \in P$ and demand node $k \in D_p$. In what follows, these $|E|\left(\sum_{p \in P} |D_p|\right)$ flow variables are denoted by x'.

We now extend the node/product-level definition of connectivity into a single measure for the entire network. We could, in the spirit of the pioneering works on network connectivity (e.g., Even and Tarjan (1975) and Even (1975)), derive a network-level connectivity measure as $V \equiv \min_{p \in P,\, i \in D_p}\{v_{ip}\}$. In our discussion, we will refer to this network connectivity measure as *minimum node connectivity* (MNC). We found MNC to be inadequate for our application because it disregards the actual quantities d_{ip} of product $p \in P$ demanded at each node $i \in P$. To illustrate, Fig. 1 depicts a single-product network (i.e., with $P = \{1\}$) in which nodes $\{1'', 2''\}(\equiv S_1)$ supply product 1, nodes $\{1', 2'\}$ serve as transshipment nodes, and nodes $\{1,2,3,4,5\}(\equiv D_1)$ demand product 1 according to the d_{ip}-values given on the right side of the figure. In this case, $v_{i1} = 2,\ \forall\ i = 1, \ldots, 4$ because $1''$-$1'$-i and $2''$-$2'$-i form node-disjoint paths for each such i; however $v_{i5} = 1$ in this example because all paths from $S_1 = \{1'', 2''\}$ to 5 pass through node $1'$. The MNC for this example is $\min\{v_{11}, v_{21}, v_{31}, v_{41}, v_{51}\} = 1$ even though four of the five demand nodes, comprising $60(=\sum_{i=1}^4 d_{i1})$ of the $61(=\sum_{i=1}^5 d_{i1})$ units of demand, are connected to supply nodes by two disjoint paths.

This example can easily be extended (e.g., to 20,000 demand nodes of which 19,999 are twice-connected and the remaining node only once-connected) to demonstrate that MNC encourages network designs that provide equitable service to all demand nodes even if it means

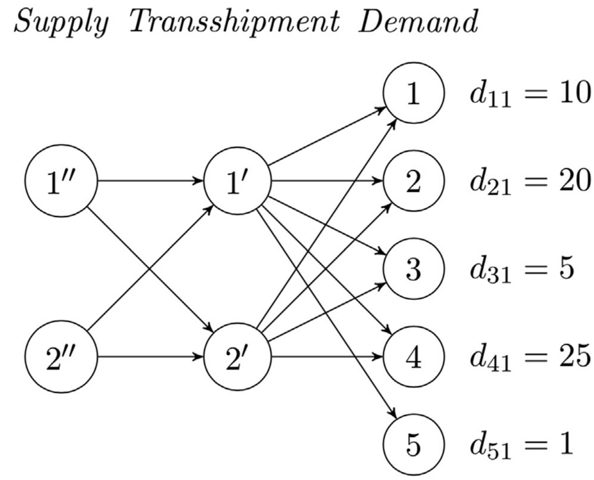


Fig. 1. Illustration of connectivity measures.

forgoing the opportunity to improve service to the highest-demanding nodes. Given that supply chain networks may have thousands of demand nodes in practice, and the quantities demanded may be highly variable across these nodes, we opted instead to measure network connectivity as $V \equiv \sum_{p \in P} \sum_{i \in D_p} d_{ip} v_{ip}$. This connectivity measure, which we refer to as *demand-weighted connectivity* (DWC), encourages network designs that provide the most reliable service to the highest-demanding nodes. To illustrate, the DWC for the network in Fig. 1 is $\sum_{i=1}^5 d_{i1} v_{i1} = 2(10 + 20 + 5 + 25) + 1(1) = 121$. Note that the relative additional reward that could be obtained by improving v_{i5} from 1 to 2 is small for DWC (which improves from 121 to 122) as compared to MNC (which improves from 1 to 2).

Given the above definitions, our model optimizes the supply chain network by minimizing cost (due to both network design expenses and commodity flow) and maximizing DWC. The cost to flow one unit of commodity p along arc (i, j) is represented by parameter b_{ijp}, and c_{ip} represents the cost to produce one unit of product p at supply node i. The amount of product p demanded at node i is represented by parameter d_{ip}. Sourcing decisions are captured by the variable w_{ip}, identifying the amount of product p produced at node i. Variables x_{ijp} represent the flow of product p on arc (i, j). Variables x'_{ijkp} indicate whether ($x'_{ijkp} = 1$) or not ($x'_{ijkp} = 0$) arc $(i, j) \in E$ is contained in one of the node-disjoint paths used to evaluate the connectivity associated with node/product pair $p \in P$, $i \in S_p$. A summary of the notation is provided below.

SETS:

N	Set of all nodes in G
E	Set of all arcs in G
P	Set of all commodities
D_p, S_p	Set of nodes that demand, supply product $p \in P$
FS(i)	Set of all nodes leading out from node i
RS(i)	Set of all nodes with arcs ending at node i

NETWORK DESIGN VARIABLES:

z_{ip}	Indicates whether production capacity of commodity $p \in P$ is high ($z_{ip} = 1$) or low ($= 0$) at node $i \in N$
y_{ij}	Indicates whether flow capacity of arc (i, j) is high ($y_{ij} = 1$) or low ($= 0$)

NETWORK OPERATION VARIABLES:

w_{ip}	Amount of product $p \in P$ produced at node $i \in N$
x_{ijp}	Flow of product $p \in P$ on arc $(i, j) \in E$

NETWORK CONNECTIVITY VARIABLES:

x'_{ijkp}	Indicates whether arc $(i, j) \in E$ is on a node-disjoint path from some supply node of commodity $p \in P$ (i.e., $s \in S_p$) to demand node $k \in D_p$
v_{kp}	Number of node-disjoint paths to demand node $k \in D_p$ associated with commodity $p \in P$

PARAMETERS:

d_{ip}	Demand for commodity $p \in P$ at node $i \in D_p$
b_{ijp}	Cost per unit flow of commodity $p \in P$ on arc $(i, j) \in E$
c_{ip}	Cost per unit of commodity $p \in P$ produced at node $i \in N$
u_{ij}^+, u_{ij}^-	Flow capacity of arc $(i, j) \in E$ at the high level, low level
r_{ip}^+, r_{ip}^-	Production capacity for commodity $p \in P$ at node $i \in N$ at the high level, low level
f_{ij}	Cost incurred if flow capacity of arc (i, j) is at the high level
g_{ip}	Cost incurred if production capacity of commodity $p \in P$ at node $i \in N$ is at the high level

Thus, we optimize the objectives

$$\max V = \sum_{p\in P}\sum_{k\in D_p} d_{kp}v_{kp}, \tag{1}$$

$$\min C = \sum_{p\in P}\sum_{i\in N}(c_{ip}w_{ip} + g_{ip}z_{ip}) + \sum_{(i,j)\in E}\left(f_{ij}y_{ij} + \sum_{p\in P} b_{ijp}x_{ijp}\right), \tag{2}$$

subject to the constraints

$$\sum_{j\in \mathrm{RS}(i)} x_{jip} + w_{ip} = \sum_{j\in \mathrm{FS}(i)} x_{ijp} + d_{ip}, \quad \forall\, p \in P,\ i \in N, \tag{3}$$

$$w_{ip} \le r_{ip}^- + (r_{ip}^+ - r_{ip}^-)z_{ip}, \quad \forall\, p \in P,\ i \in N, \tag{4}$$

$$\sum_{p\in P} x_{ijp} \le u_{ij}^- + (u_{ij}^+ - u_{ij}^-)y_{ij}, \quad \forall\, (i, j) \in E, \tag{5}$$

$$x'_{ijkp} \le 1 - \mathbb{1}_{\{u_{ij}^-=0\}}(1-y_{ij}), \quad \forall\, p \in P,\ k \in D_p,\ (i, j) \in E, \tag{6}$$

$$\sum_{j\in \mathrm{FS}(i)} x'_{ijkp} \le 1 - \mathbb{1}_{\{r_{ip}^-=0\}}(1-z_{ip}), \quad \forall\, p \in P,\ k \in D_p,\ i \in S_p, \tag{7}$$

$$\sum_{j\in \mathrm{FS}(i)} x'_{ijkp} \le 1, \quad \forall\, p \in P,\ k \in D_p,\ i \in N\backslash(S_p \cup \{k\}), \tag{8}$$

$$\sum_{j\in \mathrm{FS}(i)} x'_{ijkp} - \sum_{j\in \mathrm{RS}(i)} x'_{jikp} = 0, \quad \forall\, p \in P,\ k \in D_p,\ i \in N\backslash(S_p \cup \{k\}), \tag{9}$$

$$\sum_{i\in \mathrm{RS}(k)} x'_{ikkp} = v_{kp}, \quad \forall\, p \in P,\ k \in D_p, \tag{10}$$

$$x_{ijp} \ge 0, \quad \forall\, p \in P,\ (i, j) \in E, \tag{11}$$

$$w_{ip} \ge 0, \quad \forall\, p \in P,\ i \in N, \tag{12}$$

$$y_{ij} \in \{0,1\}, \quad \forall\, (i, j) \in E, \tag{13}$$

$$z_{ip} \in \{0,1\}, \quad \forall\, i \in N,\ p \in P, \tag{14}$$

$$x'_{ijkp} \ge 0, \quad \forall\, p \in P,\ k \in D_p,\ (i, j) \in E, \tag{15}$$

$$v_{kp} \ge 0, \quad \forall\, p \in P,\ k \in D_p. \tag{16}$$

Objective (1) maximizes the DWC of the supply chain, and Objective (2) minimizes the total cost. Constraints (3) ensure flow balance and effectively require that *all* demand of each product is satisfied, while constraints (4) and (5) respectively enforce production capacity and flow capacity restrictions. Constraint sets (6)–(8) ensure proper use of the connectivity network over all nodes by enforcing the definition of node-disjoint paths. In particular, constraint set (6) limits the number of times an arc can be part of a node-disjoint path for shipping product $p \in P$ to demand point $k \in D_p$ to be at most one as long as the arc has positive flow capacity, and zero otherwise. For a given product $p \in P$ and a demand node $k \in D_p$, the constraint set (7) restricts the total number of node-disjoint paths beginning at a specific supplier to be at most one if the supplier's production is positive, and zero otherwise. Constraint set (8) enforces that there is at most one node-disjoint path, associated with demand point $k \in D_p$ for product $p \in P$, that passes through any transshipment node $i \in N\backslash(S_p \cup \{k\})$. Conservation of flow for the connectivity network is ensured by constraints (9), while constraints (10) set the total number of node-disjoint paths between suppliers and a demand point $k \in D_p$ for a product $p \in P$ by adding the number arcs entering node k that are part of a node-disjoint path for that demand point and product pair. Non-negativity and binary specifications for all variables are covered by constraints (11)–(16). When the binary variables in Model (1)–(16) are fixed, the problem separates by objective. The problem in the x'-variables is a minimum cost flow problem with integer right-hand-sides. Such a problem is known to possess an integer optimal solution (see, e.g., Bazaraa et al. (2004)) even when integrality constraints are not imposed explicitly.

2.2. Solution method

Due to our use of multiple objective functions, there is no one "best" solution that can be offered. As such, the goal is to present efficient solutions, wherein any improvement in one objective function value is met with a decrement in another objective function value. This "tradeoff" between competing objective function values is characterized by the *Pareto curve*, or *efficient frontier*. Many methodologies exist in the literature for determining the Pareto curve of a given multiobjective program. Ehrgott (2005) discusses various scalarization and non-scalarization techniques for solving these types of problems. One of the most well known strategies is the weighted-sum method, which can produce the entirety of the efficient frontier only when all of the efficient frontier's points are boundary points of the efficient frontier's convex envelope. We have opted to use the ε-constraint method, which generates the entire frontier even when this condition does not hold, as is frequently the case for integer-constrained problems. Although there are other methods that can be used to generate or approximate the efficient frontier (e.g., hybrid of the weighted-sum method and the ε-constraint method (Ehrgott, 2005), the elastic-constraint method (Ehrgott and Ryan, 2002), or Benson's method (Benson, 1978)), we have not attempted to identify a "most efficient" solution method as part of this research.

In order to solve our nonconvex multiobjective mixed-integer linear program, the ε-constraint method iteratively solves a single objective problem (in our case, using cost as the objective) and constraining the other objective(s). The ε-constraint method produces all of the *efficient solutions* (Olagundoye, 1971), including the *weakly efficient solutions*, as long as ε is chosen appropriately. Due to the discrete nature of our second objective, DWC, we chose to express that objective function with ε-constraints. Moreover, we introduce a small weight $\alpha > 0$ for DWC in the objective function in order to force the x'_{ijkp}-variables towards their upper bounds as expressed in (6)–(8). That is, we solve

$$\min\ C - \alpha V, \tag{17}$$

$$\text{s.t. } V \ge \varepsilon, \tag{18}$$

Constraints (3)–(15),

for each integer value of ε from 1 up to the maximum DWC-value that admits a feasible solution under constraints (3)–(15). Any positive value of α is sufficient to ensure v_{kp} take on their maximum values—enabling a correct calculation of DWC—in an optimal solution to model (17)–(18). We have chosen to utilize $\alpha = 10^{-6}$ in all of our experiments.

3. Illustrative examples

We now illustrate our model using an example motivated by supply chain acquisitions. When one organization acquires another, they purchase the entire supply chain of the company. Within the two supply chains, there may exist overlaps in service and/or capacity that could benefit from consolidation. It is also possible that the combined demand associated with the supply chain necessitates additional capacity. When making decisions regarding which elements of the combined network to integrate into the existing network, companies must also consider the possibility of adding new facilities or transportation lanes to the network in order to better satisfy the objectives of minimum cost and maximum connectivity.

Consider the distribution networks of two companies, Company A and Company B, where Company A is acquiring Company B. Within this example, we demonstrate how the cost for a supply chain increases as the DWC increases, and we show that the model bears no preference towards utilizing the acquiring company's assets rather than integrating those of the company being purchased. The original, pre-acquisition, supply chain networks for Company A and Company B are shown in Fig. 2a and 2b, respectively.

Suppliers are denoted by **S**, warehouses are denoted by **W**, cross-docking stations are denoted by **CD**, and demand points are denoted by **D**. We assume a single-commodity network, wherein suppliers S1, S2, and S3 all produce the same product that is demanded by customers D1, D2, D3, D4, and D5. The instance parameters are described in Tables 1 and 2 for Company A and Company B, respectively.

Prior to acquisition, both companies act independently. Their respective Pareto optimal solutions are shown in Table 3. Due to the network available for Company B, it cannot attain a DWC greater than 150, since there is exactly one node-disjoint path between supplier S3 and each customer. That is, Company B is unable to take precautions in its supply chain in case of disruptions. Fig. 3a illustrates Company A's network with a DWC of 225 and Fig. 3b shows company B's network with a DWC of 150.

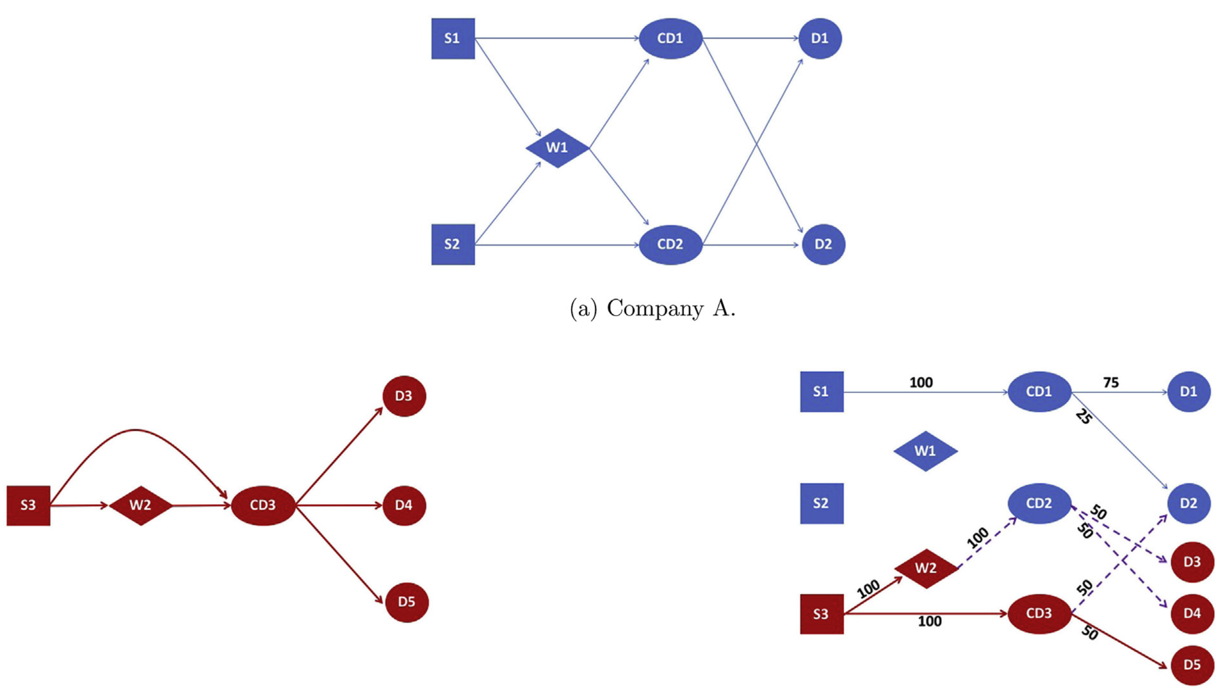
Once Company A acquires Company B, it must make decisions regarding the elements of Company B's supply chain that it will integrate into its existing network. Due to the increase in demand from acquiring Company B's customers, it is appropriate to consider other options, such as an additional warehouse space or alternate shipping routes that were not previously considered because demand levels did not warrant it. Fig. 2c illustrates the merged network, where Company A's current network is shown in bold, Company B's network is shown in dashed lines, and additional possibilities are represented by thin lines. The additional parameters are shown in Table 4.

Notice that after acquiring Company B, Company A, now referred to as Company A+B, creates additional routes that did not exist in either network. Since we are aware of efficient solutions for Company A and Company B yielding DWC-values of 225 and 150, respectively, we note that Company A+B's supply chain (Fig. 3c) does not utilize the optimal supply chain for each individual company to achieve a DWC of 375. It creates the routes from CD2 to D3 and from CD2 to D4, as well as the

Table 1
Instance parameters for Company A.

Arcs	u_{ij}^-	u_{ij}^+	b_{ijp}	f_{ij}
S1→CD1	0	200	637	50
S1→W1	0	200	709	50
S2→CD2	0	200	732	50
S2→W1	0	200	912	50
W1→CD1	0	200	584	50
W1→CD2	0	200	395	50
CD1→D1	0	200	210	50
CD1→D2	0	200	190	50
CD2→D1	0	200	498	50
CD2→D2	0	200	384	50

Nodes	d_{ip}	r_{ip}^-	r_{ip}^+	c_{ip}	g_{ip}
S1	–	0	100	1.9	20
S2	–	0	100	1.7	20
W1	–	–	–	–	–
CD1	–	–	–	–	–
CD2	–	–	–	–	–
D1	75	–	–	–	–
D2	75	–	–	–	–



(a) Company A.

(b) Company B.

(c) Exhaustive network after acquisition.

Fig. 2. Unsolved comprehensive supply chain networks of Companies A, B, and A+B.

Table 2
Instance parameters for Company B.

Arcs	u_{ij}^-	u_{ij}^+	b_{ijp}	f_{ij}
S3→CD3	0	200	39	50
S3→W2	0	200	156	50
W2→CD3	0	200	177	50
CD3→D3	0	200	690	50
CD3→D4	0	200	935	50
CD3→D5	0	200	969	50

Nodes	d_{ip}	r_{ip}^-	r_{ip}^+	c_{ip}	g_{ip}
S3	–	0	200	1.5	30
W2	–	–	–	–	–
CD3	–	–	–	–	–
D3	50	–	–	–	–
D4	50	–	–	–	–
D5	50	–	–	–	–

Table 3
Pareto optimal solutions for Company A (left) and Company B (right).

Company A		Company B	
Cost ($)	DWC	Cost ($)	DWC
156,765	225	135,755	150
156,815	300		

route from CD3 to D2. Furthermore, after acquisition, Company A closed its own supply facility S2 after acquiring S3; demand is met by combining the resources of the two companies. Thus, we see that supply chain network design following an acquisition is influenced by cost and connectivity without preference towards pre-existing assets. More specifically, the total cost for such a supply chain is $255,540, a 12.6% savings from maintaining the established supply chains. Table 5 shows

Table 4
Cross network instance parameters for Company A+B.

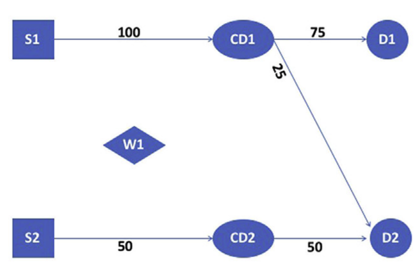
Arcs	u_{ij}^-	u_{ij}^+	b_{ijp}	f_{ij}
S1→W2	0	200	873	50
S2→W2	0	200	664	50
S2→CD3	0	200	702	50
S3→W1	0	200	85	50
W2→CD2	0	200	248	50
CD2→D3	0	200	315	50
CD2→D4	0	200	561	50
CD2→D5	0	200	787	50
CD3→D2	0	200	531	50

Table 5
Pareto optimal solutions for the merged network.

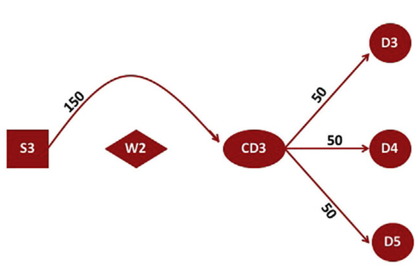
Cost ($)	DWC
255,540	375
255,590	450
255,640	525
255,690	575
255,740	625
255,790	675

the full list of Pareto optimal solutions for the merged network.

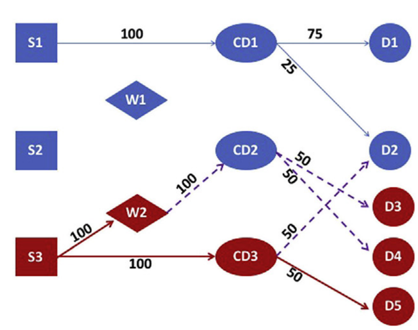
These types of decision-making scenarios are not unique to the application areas presented here. Network reorganization is a challenge commonly encountered within military and humanitarian aid supply chains in addition to traditional manufacturing supply chains. Rather than continuing to make the complicated supply chain decisions associated with an acquisition by guess or gut feel, the proposed model offers an unbiased, mathematically-based tool for examining multiple, non-dominated solutions representing varying levels of network



(a) Supply chain network of Company A with a DWC of 225. The amount of flow across each arc is displayed.



(b) Supply chain network of Company B with a DWC of 150. The amount of flow across each arc is displayed.



(c) Supply chain network of Company A+B with a DWC of 375. The amount of flow across each arc is displayed.

Fig. 3. Optimal supply chain networks for given DWC-values of 225, 150, and 375, for Company A (top), Company B (bottom left), and Company A+B (bottom right), respectively.

connectivity and cost. In the following section, we further examine our model by applying it to an industry-furnished dataset.

4. Industrial case study

Our research is motivated by the dynamic and uncertain environment in which today's supply chains operate. Supply chains are always evolving in an attempt to deliver better products and/or services to consumers more reliably and/or efficiently. Changes to an established supply chain may be desirable (or necessary) in order to effectively respond to changing supply/demand processes or the introduction of new products and/or services. Additionally, a supply chain redesign may be warranted based upon coordination and/or competition with providers of related products and/or services. These factors drive frequent corporate mergers and acquisitions, both of which necessitate reevaluating supply chain designs. When an acquisition takes place, decisions must be made regarding what elements of the acquired company's supply chain to incorporate into the acquiring company's supply chain and what elements to eliminate. On one hand, incorporating elements of the acquired company's supply chain creates additional capacity and/or redundancy to shield against the effects of a potential disruption; however, on the other hand, consolidation may present an opportunity to leverage economies of scale. These decisions are complex, motivating the development of decision support models that weigh the cost/risk tradeoffs associated with network (re)design decisions.

We now demonstrate our multi-objective network design methodology using an industry-furnished test case. This case represents a US-based $15+ billion food company's ("ParentCo") consideration of acquiring a smaller, competing business ("ChildCo") that produces similar and/or desirable products. ParentCo's network contains two echelons of supply nodes. First, live animals are initially processed at an intake facility (A-nodes in Fig. 4) in ParentCo's current supply chain. The raw food products produced by the intake facilities are shipped to one of ParentCo's further processing sites (B-nodes in Fig. 4), where additional preparation and/or seasoning occurs. Once the food items have completed all required processing, they are shipped to a ParentCo testing and packaging center (a subset of the J-nodes in Fig. 4) to complete the production process. Finally, upon passing final inspection, ParentCo's finished, packaged food items are sent to customer demand nodes such as grocery stores and warehouse clubs (a subset of the K-nodes in Fig. 4) in ParentCo's current supply chain.

Prior to any acquisition activities, ChildCo owned and operated a single supply echelon of raw material intake and processing facilities

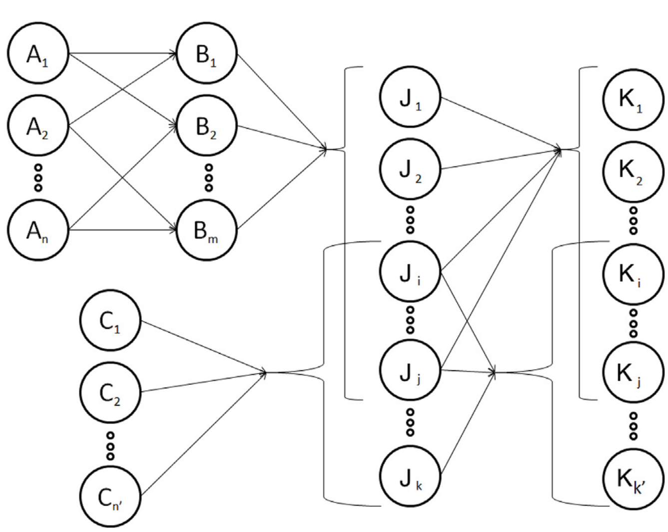


Fig. 4. Generalized Network with Two Types of Supply Nodes.

(C-nodes in Fig. 4). As was the case with ParentCo, ChildCo's processed raw materials are sent to testing and packaging locations (which may or may not be disjoint from ParentCo's J-nodes in Fig. 4). Quality-tested ChildCo products are finally sent to customer demand locations which may or may not overlap with ParentCo's K-nodes in Fig. 4.

In any acquisition, the acquiring company has many options to consider for how to structure or organize the new, aggregate supply chain's operations. Our multi-objective network design methodology can help supply chain architects to evaluate the tradeoff between the aggregate supply chain's total cost and the connectivity of the overall, aggregate supply chain network.

We consider an aggregate ParentCo + ChildCo network containing 544 nodes and over 2600 arcs. Of these nodes, 27 are ParentCo's supply nodes (i.e., A-nodes) and 55 are ChildCo's supply/further processing nodes (i.e., C-nodes). Further, our case study data contains 15 ParentCo J-nodes and 17 ChildCo J-nodes—these two sets of nodes do share some locations in common. Combining both ParentCo's and ChildCo's demand points results in 389 total demand nodes, all of which must have their demand satisfied. A total of 735 arcs exist in ParentCo's original network, and 1895 potential arcs, comprised of both ChildCo's current arcs and new arc options that initially do not exist in either company's network, must now be considered in terms of connectivity and cost savings potential purposes (e.g., an arc from a ParentCo J-node to an acquired ChildCo K-node). The data from this case study instance is available by request from the authors.

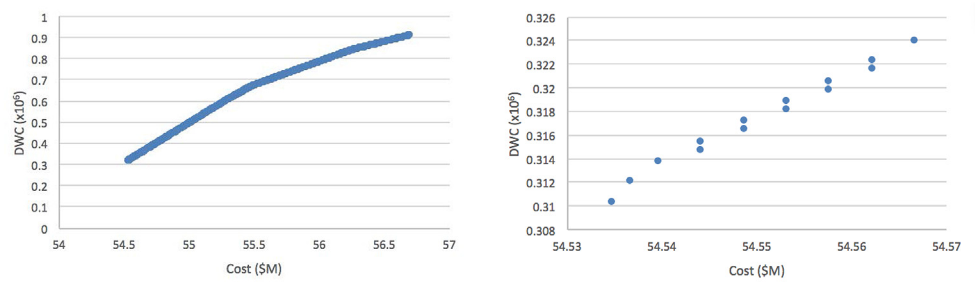
The model outlined in Section 2.2 is coded in AMPL and analyzed using Gurobi 7.5.1 as the solver. Computation was performed using eight threads on a PC running an Intel i7 5960 × 3.7 GHz processor with 128 GB of RAM. Our Gurobi analyses conclude when either 1) a feasible solution is found with an optimality gap of less than or equal to 0.0005% or 2) the 1 h time limit per thread elapses, whichever occurs first.

The scale of the modeled supply chain networks reflects the application of our model: the acquisition of a business that produces goods similar to those of the acquiring company. We consider both the activation of the acquired network, as well as the possible activation of additional arcs within the combined network. Parameter values were obtained by utilizing summary statistics/calculations from the actual data provided by the company. Demand was distributed uniformly across the available demand nodes to disguise actual practice, but the scale of the demand values were preserved. Furthermore, capacity limits were based on an assumed 90% utilization, as disclosed by the company. We examine both single commodity and multiple commodity cases. Within the multiple commodity case, every supply node does not produce each commodity, nor is each commodity demanded at each demand node. However, each commodity has approximately 80% of its supply nodes in common with the other commodities in order to cause multiple commodities to share capacity on arcs.

4.1. Results

Implementing the ε-constraint method described in Section 2.2, we obtain an approximation (subject to the 0.0005% optimality tolerance used in Gurobi) of the Pareto frontier (hereinafter referred to as the Pareto frontier) composed of approximately efficient solutions (hereinafter called efficient solutions) for each commodity case study. For the single-commodity case as shown in Fig. 5a, the Pareto frontier appears to be piecewise linear from a macro-viewpoint. By examining a subset of the curve, we can see both the strongly efficient and weakly efficient solutions (Fig. 5b). It took approximately 4 h of CPU time in order to determine 516 efficient solutions of the Pareto frontier.

Similarly, when we examine the three-commodity case, we again find the totality of the Pareto frontier to appear to be piecewise linear (Fig. 6a), but if we examine a smaller subsection, we notice otherwise (Fig. 6b). It required approximately 12 h of CPU time to determine a 1,533-solution Pareto frontier, from which we were able to remove an



(a) Plot of the Pareto frontier.

(b) Enhanced section of Pareto frontier, showing both strongly efficient and weakly efficient solutions.

Fig. 5. Single-commodity Pareto curve.

additional 12% of the solutions that were actually dominated (as a result of the Gurobi optimality gap tolerance).

Moreover, we can examine how the computation time increases as the problem scales. Utilizing the same data set as in Section 4, we generated two additional instances for both the single-commodity and three-commodity cases—one with 182 nodes and 754 arcs and the other with 363 nodes and 1,714 arcs. We generate the approximate efficient frontier for each instance given the machine/solver parameters outlined in Section 4 and summarize the computational time needed to obtain the entire Pareto frontier in Table 6.

For both the single-commodity and three-commodity cases, there is some threshold such that the solve time begins to decrease as the instance size increases. Prior to this inflection point, the two are directly related. As the problem size grows, the set of possible paths increases resulting in longer run times. However, after some threshold problem size, the problems become easier to solve. A potential explanation for this is that, although the problem size is growing, it is possible that the number of nodes in one stage of the supply chain (i.e., A-, B-, C-, J-, or K-nodes) grows disproportionately slow relative to the other stages. A consequence of this is that the DWC becomes limited by the slower-growing stage, and as a result, there may be many alternative solutions (via taking subsets of the nodes from the other stages) that lead to the same DWC-value. In this scenario, the DWC objective may pose more of a challenge on smaller instances than on larger instances.

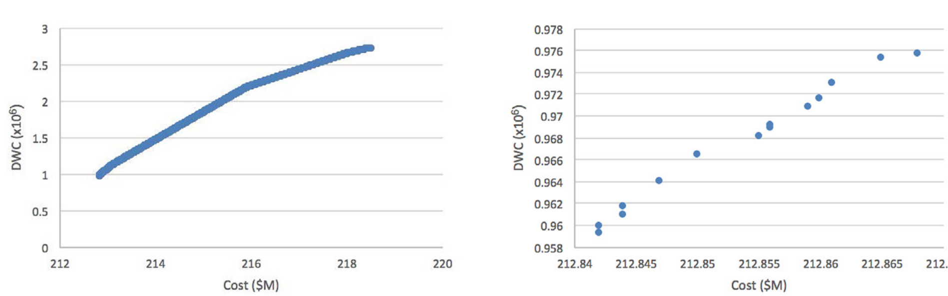
Table 6 shows how the number of simplex iterations performed by Gurobi is far greater for the 363-node case than is required to solve the 544 nodes for both the one and three product cases, respectively. In fact, the correlation coefficient for the number of simplex iterations with solve time for an instance is 0.96 (0.87) for the single (three) product, 363-node case. Further, the correlation coefficient for the number of branch-and-cut nodes that Gurobi evaluated with solve time was 0.93 and 0.86 for the single and three product cases with 363 nodes, respectively. As the correlation coefficients for the 544-node cases are of similar magnitude for both number of simplex iterations and branch-and-cut nodes evaluated, the difference in instance solution times is strongly related to the commercial solver's solution approach on each problem instance.

As an additional observation from Table 6, instances with more commodities require longer computation time. For the largest instance (544 nodes and 1,714) we believe the solver reaches optimality quicker for the three-commodity case than the single-commodity case due to the specific network used in Section 4.

The model is conceived as a high-level, strategic decision-making tool. As such, it would be run only when supply chain redesigns are under consideration. Additionally, the decisions suggested by the model may have an impact on the profitability of a company; if a redesign is improperly handled, the resulting loss of revenue or excessive costs incurred can be significant. Thus, allowing the optimization software to run for up to 24 h is appropriate given the frequency and timeline associated with the model's use.

4.2. Network resiliency

Section 4.1 analyzes the tradeoff between cost and DWC for given supply chain. We posit, moreover, that the connectivity metric of DWC directly corresponds to a network's resilience, where a more reliable system results from a higher cost network. In order to show a network's DWC-level is directly related to its ability to withstand disruptions, we subjected a network to a variety of node-failure scenarios. In particular, we considered model (17)–(18) and generated the efficient frontier for the one product, 544-node case as depicted in Fig. 5a. We sorted the non-dominated solutions by DWC-value and extracted the 10th, 25th, 50th, 75th, and 90th percentile solutions. These DWC-levels can be envisioned as corresponding to different levels of "conservatism" where



(a) Plot of the Pareto frontier.

(b) Enhanced section of Pareto frontier, showing both strongly efficient and weakly efficient solutions.

Fig. 6. Three-commodity Pareto curve.

Table 6
Computational time and problem size for each instance.

	Nodes	13	182	363	544	182	363	544
	Arcs	25	754	1714	2632	754	1714	2632
	Products	1	1	1	1	3	3	3
Variables	Binary	153	4188	25,449	1,026,524	11,078	73,144	3,074,306
	Linear	44	405	1007	3566	1207	3049	10,696
Constraints	Equality	64	1112	7294	195,434	3335	21,883	585,911
	Inequality	349	1410	9668	1,962,570	4630	32,998	5,889,835
Solve Time (s)	Mean	0.09	0.10	2735.92	28.56	1.22	3044.51	27.98
	0th Percentile	0.1	0.1	0.7	0.9	0.6	30.0	14.3
	25th Percentile	0.1	0.1	5.1	2.7	0.7	152.3	20.3
	50th Percentile	0.1	0.1	270.8	3.9	0.7	310.4	24.0
	75th Percentile	0.1	0.1	1062.3	7.6	0.8	782.9	32.1
	100th Percentile	0.1	0.1	23,981.0	164.3	5.3	25,568.8	186.4
Simplex Iterations	25th Percentile	164	39	5739	4381	2202	198,059	36,825
	50th Percentile	218	40	1,158,967	4811	2623	454,136	40,181
	75th Percentile	227	43	4,731,037	6224	3168	964,962	43,185
	100th Percentile	248	54	84,804,100	198,250	9466	82,705,299	153,902
Branch & Cut Nodes	25th Percentile	1	0	16	1	1	4824	1
	50th Percentile	1	0	422,760	1	1	29,384	1
	75th Percentile	1	0	1,491,031	70	1	38,160	1
	100th Percentile	1	0	22,437,284	58,395	1	5,741,618	5310

Table 7
Number of nodes with unmet demand and the percentage of unmet demand for a given DWC-level of the one product, 544-node case under various node-failure probabilities.

		Unsatisfied	
Failure Probability	DWC-level	Nodes	% Demand
0.50%	10.00%	0.80	0.53%
	25.00%	0.73	0.46%
	50.00%	0.70	0.45%
	75.00%	0.57	0.40%
	90.00%	0.33	0.25%
1.00%	10.00%	2.27	1.40%
	25.00%	1.60	1.06%
	50.00%	1.33	0.89%
	75.00%	0.97	0.64%
	90.00%	0.93	0.62%
5.00%	10.00%	8.53	5.46%
	25.00%	8.40	5.20%
	50.00%	8.26	5.02%
	75.00%	5.33	3.39%
	90.00%	3.83	2.60%

we conjecture that the higher-percentile solutions should better withstand disruption. For each percentile solution, we fixed the network (i.e., we fixed all y_{ij}- and z_{ip}-variables to the given solution values), we eliminated constraints (6)–(10), and allowed demand/supply restrictions (i.e., constraints (3)) to be soft. With the network pre-defined, we converted the objective into a min-cost flow objective in order to measure the number of nodes whose demand was unsatisfied as well as the percentage of unmet demand within the network. We subjected each node in the respective networks to a given probability of failure, such that if a node fails, all arcs emanating from and terminating with that node also fail. Using failure probabilities of 0.5%, 1%, and 5%, we generated 30 scenarios per probability. Table 7 summarizes the results. Note that the number of unsatisfied demand nodes and the percentage of unmet demand strictly decreases as the DWC-level increases. Additionally, as the failure probability increases, the number of unsatisfied demand nodes and the percentage of unmet demand strictly increases for a given DWC-level. Thus, we see that increasing the DWC-level concurrently improves the network's resiliency.

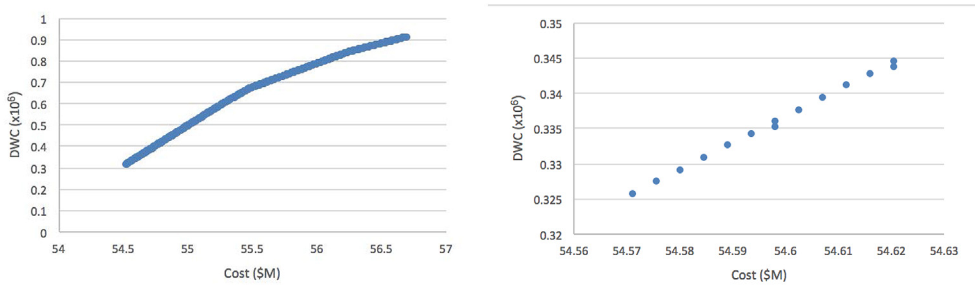
Table 7 shows that "conservation" levels actually drive a design that is more tolerant to failure. It is important to mention that there may be cases in which DWC and resiliency are not necessarily directly related. That is, DWC is only a proxy for the network's ability to withstand disruption, and hence it is possible to see the network's ability to withstand disruption decrease for higher DWC-values. More specifically, a network may have a demand node that is highly connected, and although adding an additional node-disjoint path to that demand node will increase the network's DWC, it does not necessarily improve the network's resilience; the additional path to the highly connected node does not mitigate a failure along any path to the other demand nodes. Thus, although the number of unsatisfied demand nodes and the percentage of unmet demand strictly decreases as the DWC-level increases, the magnitude of that change is not constant.

4.3. Model extension

Note that by requiring a set of node-disjoint paths to have no common nodes except for the demand node, our model accounts for supplier failure in constructing a resilient network. If we do not consider supplier failure, then we may redefine *node-disjoint* such that a set of paths associated with a demand node $k \in D_p$ need only have unique transshipment nodes. That is, we allow multiple paths emanating from a given supplier to a given customer. This relaxation is achieved by changing constraint set (7) in the model outlined in Section 2 to

$$\sum_{j \in \mathrm{FS}(i)} x'_{ijkp} \le |\mathrm{FS}(i)|(1 - \mathbb{1}_{\{r_{ip}^{-}=0\}}(1 - z_{ip})), \quad \forall\, p \in P,\ k \in D_p,\ i \in S_p, \tag{19}$$

Utilizing the same solution methodology and optimality tolerance, we obtain the Pareto curve for the single-commodity case (Fig. 7a) and three-commodity case (Fig. 8a). Both curves appear to be piecewise linear at low resolutions due to the density of the points. Increasing the resolutions of both highlights the discrete nature of the graphs by showing the strongly efficient and weakly efficient solutions (see Figs. 5b and 6b). It took 14 h of CPU time to find 536 non-dominated solutions for the single-commodity case. The three-commodity case took approximately 12 h of CPU time to determine a 1531-solution Pareto frontier, from which we were able to remove an additional 12% of the solutions that were actually dominated (as a result of the Gurobi optimality gap tolerance).



(a) Plot of the Pareto frontier.

(b) Enhanced section of frontier, showing both strongly efficient and weakly efficient solutions.

Fig. 7. Single-commodity Pareto curve when supplier failure is not considered.

For both the single- and three-commodity instances, each of the formulations (Section 4.1 and Section 4.3) result in an approximately piecewise-linear efficient frontier (see Figs. 7a and 8a) in which there are two points of interest in which the rate at which the DWC increases for a unit increase in cost changes. More specifically, we see that as we move northeast along the Pareto curve a unit increase in the DWC requires a larger increase in the cost.

We have utilized DWC as a connectivity measure and have justified its use relative to other connectivity metrics in the literature. Still, utilizing DWC as an objective may lead to network designs that are conservative: It will take a significant number of node failures before a demand node is disconnected from supply. If less-conservative solutions are desired, the DWC metric can be modified (e.g., by defining connectivity using a less-restrictive arc-disjoint paths interpretation) to drive towards solutions that incorporate redundancy in distribution channels (i.e., arcs) even if there is little redundancy among facilities. An additional pitfall of DWC is that it does not ensure each node-disjoint path is actually capable (in terms of capacity) of satisfying a given node's demand. To ensure each node's demand could be satisfied in the event of k node failures would require imbedding within the network design model a network interdiction model of the variety studied by Wood (1993). Because network interdiction models are notoriously difficult to solve in their own right, we have opted not to pursue such an approach at this time.

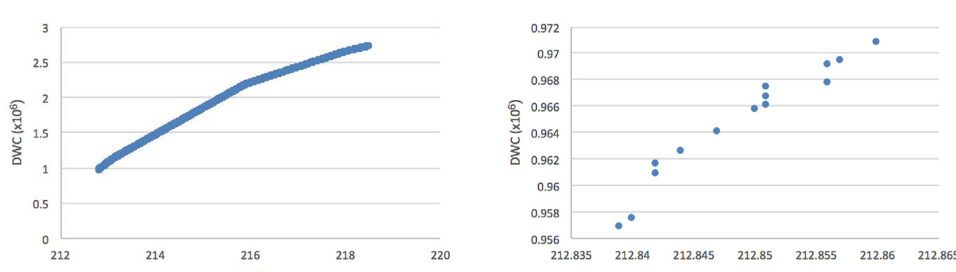
4.4. Managerial insights

Since model (17)–(18) is a high-level, strategic decision-making tool, it is relevant to discuss the managerial insights that can be derived. With regards to acquisition, we have shown in Section 3 that the model has no bias towards the acquiring company's pre-existing infrastructure and will merge the set of networks to create a minimum cost supply chain for a given DWC. Moreover, the example in Section 3 also demonstrated that the maximum DWC-value of the combined network was greater than the sum of the maximum DWC-values of the individual networks and could be attained at a lower cost. However, this result is supply chain dependent.

We analyze the benefits of acquisition by generating a set of instances such that the size ratio between Company A and Company B varied. By computing the maximum DWC-value for each network (i.e., A, B, and the aggregated network), and subsequently determining the minimum cost that could be achieved with that DWC-value, we were able to calculate the cost savings and DWC improvement obtained through acquisition. Table 8 summarizes these results. The instances were derived by decomposing the three-commodity industrial data set utilized in Section 4 (i.e., the 8:5 column in Table 8) into two networks, where some node locations are common to both networks. In some cases the maximum DWC-value of the combined network was less than the sum of the maximum DWC-values of the individual networks, while in others it was more. Their associated costs, though, were lower in all instances. In these examples, we see the tradeoff between network connectivity and cost. Moreover, notice that the cost savings increases as the two companies are more similar in size.

Given two mutually disjoint networks, though, it is possible that acquisition results in no cost and no DWC increase/decrease. We verified this claim by generating a single-commodity instance such that there is no overlap between the supply chains. The set of cross-network arcs was not exhaustive, however, in order to better relate to real-world policies. Table 9 summarizes the results of this instance. Note that the cost and the DWC from the aggregated network is exactly equal to the sum of the cost and the DWC from the separate networks.

Whether or not merging two networks will result in savings or increased connectivity is largely case-based. However, the managerial insights can be generalized for certain categories of supply chains. For example, when two supply chains are both comparably sized and contain overlap in facility locations, one can expect a significant cost



(a) Plot of the Pareto frontier.

(b) Enhanced section of Pareto frontier, showing both strongly efficient and weakly efficient solutions.

Fig. 8. Three-commodity Pareto curve when supplier failure is not considered.

Table 8
Cost savings of acquisition for various individual network sizes.

		Ratio of number of nodes Company A:Company B					
		8:5	1:1	2:1	3:1	1:2	1:3
Nodes	Company A	399	249	399	399	125	86
	Company B	249	249	203	129	249	249
	Combined Network	544	418	515	458	308	272
DWC	Company A	1,872,300	1,034,500	1,872,300	1,872,300	109,200	26,600
	Company B	1,010,700	1,010,700	103,700	21,000	1,010,700	1,010,700
	Combined Network	2,710,400	2,004,600	1,872,300	1,872,300	1,169,300	1,053,800
	Improvement	−6.4%	−2.0%	−5.5%	−1.1%	4.2%	1.6%
Cost	Company A	$215,593,000	$136,988,000	$215,593,000	$215,593,000	$43,885,700	$12,113,700
	Company B	$74,309,000	$74,309,000	$61,882,500	$30,533,200	$74,309,000	$74,309,000
	Combined Network	$218,516,000	$153,128,000	$224,629,000	$219,428,000	$93,316,400	$76,866,900
	Savings	24.6%	27.5%	19.0%	10.8%	21.0%	11.1%

Table 9
Instance where aggregating disjoint networks A and B results in no benefit.

	Company A	Company B	Combined Network
Suppliers	3	3	6
Warehouses/Cross-Docks	6	4	10
Customers	30	20	50
DWC	3900	2550	6450
Cost	$3,021,400	$1,510,940	$4,532,340

savings. Since the supply chains are similarly designed, there can be little improvement in connectivity when merging the networks as compared to maintaining them separately. On the hand, when companies are geographically isolated, it may be better suited to maintain the pre-existing supply chains independently, without any inter-network shipping.

5. Conclusions and future work

We have investigated the impact of considering both cost and connectivity when combining supply chain networks in a post-acquisition environment from a deterministic optimization viewpoint. This problem is motivated by interviews with industry contacts and familiarity with several real-world scenarios. For this problem, we have contributed a network design optimization model that utilizes cost and connectivity objectives in evaluating network flow and network design decisions. We outlined an illustrative example for model validation and applied the model to an industry-motivated case study to derive insights for the application of corporate acquisition. Although solutions to our model will vary by instance, we have identified for our case study instance how an appropriately executed acquisition might lead to reducing costs and increasing connectivity. In the future, we aim to extend the model to incorporate storage capabilities throughout the supply chain as well different risk levels associated with a given arc. In particular, it would be helpful for the model to account for the likelihood of a given arc or facility to fail and to construct the optimal supply chain at a minimal cost such that the likelihood of meeting demand is within a certain threshold. Strengthening the connectivity measure (i.e., in the vein of the "imbedded network interdiction model" described at the end of Section 4.3) to better account for network failure would be an interesting follow-on investigation as well.

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