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Supply network design: Risk-averse or risk-neutral?

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ABSTRACT

In this paper, we investigate a supply network design in supply chain with unreliable supply with application in the pharmaceutical industry. We consider two types of decision making policies: (1) a risk-neutral decision-making policy that is based on a cost-minimization approach and (2) a risk-averse policy wherein, rather than selecting facilities and identifying the pertinent supplier–consumer assignments that minimize the expected cost, the decision-maker uses a Conditional Value-at-Risk (CVaR) approach to measure and quantify risk and to define what comprises a worst-case scenario. The CVaR methodology allows the decision-maker to specify to what extent worst-case scenarios should be avoided and the corresponding costs associated with such a policy. After introducing the underlying optimization models, we present computational analysis and statistical analysis to compare the results of the risk-averse and risk-neutral policies. In addition, we provide several managerial insights.

1. Background and literature review

In addition to the invention of new products, human population changes and economic globalization are causing greater volumes of raw materials and finished products to move through the supply chain. In some supply chains, such as healthcare/pharmaceutical, global pharmaceutical outsourcing is also creating a complex and risky supply chain environment. That is because medical products flow from raw source materials to finished products for consumers between regions. At every stage in this process, risks of contamination, diversion, counterfeit, and adulteration arise. Furthermore, even a slight supply disruption or material contamination can stop the production and flow of goods to the market and can result in catastrophic events such as patient illness or death.

Several disruptions in healthcare/pharmaceutical supply chains have already occurred. For example, in 2004, the disruption of the supply of a flu vaccine manufacturer in Bristol, UK had disastrous consequences. The UK government stopped production when US regulators inspected a manufacturing plant and found evidence of bacterial contamination problems. This reduced the US's supply of the vaccine by nearly 50% during the 2004–2005 flu season (Everett & Baker, 2004). Pharmaceutical and healthcare supply chains are also susceptible to disruptions caused by contamination. Heparin, a widely-used blood-thinning medicine that is made from pig intestines, was contaminated by an undetected outbreak of blue ear pig disease in China in 2008. This contamination led to 81 patient deaths and to hundreds of allergic reactions in the US (Usdin, 2009). The investigation of the event involved several government agencies, university researchers, and a biotech company that had a generic heparin under FDA review. Although no one understood at the time what was causing the reactions, members of Congress concluded that the issue was the result of "regulatory failure" because of news reports that the FDA had not inspected a Chinese heparin production facility (Usdin, 2009). Another recent story is the multistate meningitis outbreak that occurred in 2012 in the USA and contaminated the injected medication, causing several deaths and infections. The investigation revealed the lack of proper inspections at the raw material supplier's facility (Bell & Khabbaz, 2013).

These incidents accentuate the need to consider the risks and supply disruptions to pharmaceutical supply chains and also reveal the prevalence of receiving tainted materials from suppliers in the design and planning stages. Deceived by the small likelihood of such disruptions, managers tend to underestimate the impact of such mishaps. Nevertheless, the objective of the majority of the papers reviewed in this study was to describe cost minimization approaches with the assumption that decision-makers are risk-neutral. The risk-neutral policy may arise due to forces of globalization, which encourage firms to aggressively design their supply network base around the world in order to find opportunities for reducing supply chain costs. However, emphasizing supply chain costs may make that chain fragile and more susceptible to the risk of disruption.

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A small body of literature has addressed the risk-averse approach to decision-making in the supply chain network design. With the objective of either minimizing the expected opportunity loss or minimizing the maximum opportunity loss, Current, Ratick, and ReVelle (1998) studied problems in which the total number of facilities to be located is uncertain over a planning horizon. Gaonkar and Viswanadham (2007) developed a model for selecting suppliers to minimize the expected shortfall under disruption. The general idea is to match demand and supply using cost as the single criterion. Some other researchers also developed risk-based analytical approaches to supplier selection and evaluation (Lee, 2009; Micheli, 2008; Ravindrana, Bilsela, Wadhwab, & Yangc, 2010).

Some researchers applied the concept of mean–variance optimization (see Markowitz Harry (1952)) in the supply chain network design problem (Hanink, 1984; Hodder, 1984; Hodder & Dincer, 1986; Jucker & Carlson, 1976; Liu & Nagurney, 2010; Tomlin, 2006; Wu, Li, Wang, & Cheng, 2009). In this application, the firms consider both costs and risks in their model by using a mean–variance approach to minimize the expected total cost and valuation of the risk. The objective function is of the form $Z = E(\tilde{s}) - \lambda Var(\tilde{s})$ where $\tilde{s}$ denotes the random payoff and λ is a measure of risk aversion (Liu & Nagurney, 2010). However, several limitations are associated with this mean–variance formulation. For instance, the estimate of risk by mean–variance is only suitable when returns are normally distributed (see Pardalos, Migdalas, and Baourakis (2004).)

Other researchers have used Value at Risk (VaR) to make strategic/tactical decisions in the supply chain network design (Alonso-Ayuso, Escudero, Garın, Ortuño, & Pérez, 2005; Gan, Sethi, & Yan, 2004; Luciano, Peccati, & Cifarelli, 2003; Ravindran, Ufuk Bilsel, Wadhwa, & Yang, 2010; Wagner, Bhadury, & Peng, 2009). VaR is a risk measure that mostly focuses on rare events and provides the value that can be expected to be lost during severe, adverse market fluctuations (Cornuejols & Tütüncü, 2007). There are some problems associated with VaR, which will be discussed in Section 2.2. Therefore, these issues led some researchers to use an alternative measure called Conditional Value-at-risk (CVaR) in a few areas such as portfolio optimization (Krokhmal, Palmquist, & Uryasev, 2002), transportation and fleet allocation (Yin, 2008), market/demand selection (Chahar & Taaffe, 2009), electricity procurement (Carrión, Philpott, Conejo, & Arroyo, 2007), and facility location (Daskin, Hesse, & Revelle, 1997). By utilizing the CVaR concept, Chen, Daskin, Shen, and Uryasev (2006) addressed an uncapacitated stochastic p-median problem in which the objective was to minimize the expected regret associated with a subset of worst-case scenarios whose collective probability of occurrence is not more than 1-α. In their model, the demand and the distance between the demand nodes and the facilities were stochastic.

In this research, we focus on the risks inherent in the pharmaceutical supply chain. We consider two types of decision-making policies. A risk-neutral decision-making policy is based on the cost minimization approach. In this approach, the decision-maker defines the set of decisions that minimize the expected cost. We also consider a risk-averse policy wherein, rather than selecting facilities that minimize the expected cost, the decision-maker uses a CVaR approach to measure and quantify risk and to define what qualifies as a worst-case scenario. This methodology allows the user to specify the extent to which these worst-case scenarios should be avoided.

The goal of our model is to design a single-period, single-product pharmaceutical supply chain network with capacitated facilities to hedge against the risk of sending tainted materials to consumers. We focus on supply disruptions that impact the loss of all or a substantial fraction of the production at a set of facilities in the same geographic area due to the production of tainted materials.

A key parameter in our model is the consideration of the inspection of the production facility. This aspect of the work was inspired by tragedies such as the heparin incident (Usdin, 2009). If the risk of shipping tainted materials can be minimized prior to such tragedies, then producers can decrease liability and improve consumer safety. Insights into how our model should be configured to avoid the risk of tainted products reaching consumers are of interest to several types of supply chains such as healthcare, pharmaceutical, cosmetic and beauty, and food and dairy industries.

In this research, we also perform a logistic regression statistical analysis to identify the factors that impact our strategic decisions in both the CVaR and cost minimization models. To the best of our knowledge, the problem we address and the regression model we use have not been previously used in this type of research.

The outcome of our models and the statistical analysis enable managers to select the most qualified suppliers for their pharmaceutical supply chain and to make capacity allocation and inspection implementation decisions under both risk-neutral and risk-averse policies. The proposed models also determine when and where inspections and monitoring should be performed to prevent tainted material from reaching consumers (patients). This study will aid practitioners designing supply chains and policy makers devising various disruption mitigation strategies on the costs and risks in the pharmaceutical supply chain.

In this paper, the mathematical formulations of both the risk-neutral and risk-averse policies are introduced in Section 2. In Section 3 the data generation method is presented. Computational experiments and sensitivity analysis are discussed in Section 4. Section 5 contains our statistical analysis. Finally, Section 6 includes our conclusions and our recommendations for future work.

2. Framework and mathematical formulations

2.1. The cost minimization model

We utilize a mixed integer stochastic programming model that is formulated as a two-stage optimization problem. The selection of the facilities is considered at the first stage and is modeled as a binary decision. The second-stage decision variables include tactical decisions that are made after the realization of the random events (supply disruption) is known. The second-stage of the formulation indicate the capacity allocation decisions as well as the decision to inspect each facility. This stage is referred to as a capacity allocation problem in which cost is minimized by allocating the capacity and determining whether or not inspection should be applied in each selected facility. The inspection decision is modeled as a binary variable for each facility. The model enables us to determine when and where inspections should be implemented with the intent of reducing the amount of tainted product shipping to consumers. Consider a supply chain network $\mathcal{N} = (L, C)$ where L is the set of facilities and C is the set of consumers. In the first stage, x_l is 1 if facility l is selected and is 0 otherwise (where $l \in L$ is an index for facilities). Let $Q(x, \tilde{s})$ represent the optimal solution of the second-stage problem corresponding to the first-stage decision variable x and the random scenario $\tilde{s}$. Thus, the stochastic formulation of the problem can be written as

$$\min \sum_{l \in L} x_l f_l + \mathrm{E}[Q(x, \tilde{s})] \tag{1}$$

$$\text{subject to } x_l \in \{0, 1\} \ \forall l \in L, \tag{2}$$

where $\mathrm{E}[Q(x, \tilde{s})]$ is the expected cost taken with respect to random scenario $\tilde{s}$ which indicates the realization of a facility's state. The objective (1) in the first-stage problem is the sum of the cost of selecting facilities. The first-stage constraint (2) restricts the

decision variables x_l to be binary. Given a feasible first-stage solution vector x, the objective of the second-stage problem for random scenario$\tilde{s}$ minimizes the sum of the allocation (shipping) cost of the untainted products, the cost of shipping tainted product, the cost of discarding tainted product after inspection, and the cost of inspection. In this model, we discard tainted products. An alternative is to repair (or rework) the tainted product, an option which we may consider in future research.

To deal with the uncertainty in the second stage, a scenario-based modeling approach is proposed that has been used in stochastic programing problems (Alonso-Ayuso, Escudero, Garin, Ortuno, & Pérez, 2003; Shapiro, 2008). In the second stage, let us consider random scenario $\tilde{s}$ to have a discrete distribution $\Pr(\tilde{s} = s) = \rho_s$ where ρ_s is the probability of occurrence for scenario s . Given a finite set of scenarios, with associated probabilities ρ_s, $E[Q(x,\tilde{s})]$ can be evaluated as $E[Q(x,\tilde{s})] = \sum_{s\in S}\rho_S Q(x,s)$. Hence, we can present the deterministic equivalent of the formulation (1). To simplify, we denote this as the Supply Chain Design (SCD) model. We first summarize the complete notation for the SCD as sets and parameters:

Sets

C	the set of consumers, indexed by c
L	the set of candidate facilities, indexed by l
S	the set of realized scenarios, indexed by s

Parameters

f_l	the fixed cost of opening facility l
κ_l	the capacity of facility l
b_c	the total demand of consumer c
n_l	the fixed cost of implementing an inspection at candidate facility l
λ_{lc}	the cost of shipping an untainted product from facility l to consumer c
o_{lc}	the penalty cost for shipping a tainted product from facility l to consumer c
γ_{lc}	the cost of discarding a tainted product at facility l after inspection originally destined for consumer c
ρ_s	the probability of occurrence for scenario s
q_{ls}	the fraction of tainted products produced at facility l in scenario s
r_{ls}	the fraction of tainted products produced at facility l after inspection in scenario s (we assume $q_{ls} > r_{ls}$)

To make the definitions of q_{ls} and r_{ls} clearer, suppose that, under scenario s, the extent of failures at the unreliable facility l is given by $q_{ls} = 0.20$ and $r_{ls} = 0.05$. This means that for every 100 units of production at facility l, $100q_{ls} = 20$ of them will be tainted. If no inspection is implemented, these 20 tainted units will be shipped to consumers. If inspection is implemented, 15 of these 20 tainted units will be detected and discarded while $100r_{ls} = 5$ units will be undetected and shipped to consumers.

Decision variables

$$x_l = \begin{cases} 1, & \text{if facility } l \text{ is selected,} \\ 0, & \text{else} \end{cases}$$

$$z_{ls} = \begin{cases} 1, & \text{if inspection is implemented at facility } l \text{ in scenario } s, \\ 0, & \text{else} \end{cases}$$

p_{lcs}	the number of products shipped from facility l to consumer c in scenario s
k_{lcs}	number of tainted products produced at facility l intended to be shipped to consumer c in scenario s
d_{lcs}	number of tainted products discarded at facility l intended to be shipped to consumer c after inspection in scenario s

The deterministic equivalent of the stochastic formulation is proposed in (Madadi, Kurz, Mason, & Taaffe, 2012). For the convenience of the reader, we also present the formulation in the following. Note that the second-stage decision variables are indexed by a scenario index. The SCD model follows.

$$[\text{SCD}]\ \min \sum_{l\in L} x_l f_l + \sum_{s\in S}\rho_s \left(\sum_{l\in L}\sum_{c\in C}\lambda_{lc}[(1-q_{ls})p_{lcs}] + \sum_{l\in L}\sum_{c\in C} o_{lc}k_{lcs} + \sum_{l\in L}\sum_{c\in C}\gamma_{lc}d_{lcs} + \sum_{l\in L} n_l z_{ls} \right) \tag{3}$$

$$\text{subject to} \sum_{c\in C}[(1-q_{ls})p_{lcs} + k_{lcs} + d_{lcs}] \le \kappa_l x_l \quad \forall l \in L, s \in S \tag{4}$$

$$k_{lcs} + d_{lcs} = q_{ls}p_{lcs} \quad \forall c \in C, l \in L, s \in S \tag{5}$$

$$k_{lcs} - (r_{ls})p_{lcs} \leqslant M(1 - z_{ls}) \quad \forall c \in C, l \in L, s \in S \tag{6}$$

$$d_{lcs} - (q_{ls} - r_{ls})p_{lcs} \leqslant M(1 - z_{ls}) \quad \forall c \in C, l \in L, s \in S \tag{7}$$

$$d_{lcs} \le M(z_{ls}) \quad \forall c \in C, l \in L, s \in S \tag{8}$$

$$\sum_{l\in L}[(1-q_{ls})p_{lcs} + k_{lcs}] = b_c \quad \forall c \in C, s \in S \tag{9}$$

$$z_{ls} \leqslant x_l \quad \forall l \in L, s \in S \tag{10}$$

$$k_{lcs}, d_{lcs}, p_{lcs} \geqslant 0 \quad \forall c \in C, l \in L, s \in S \tag{11}$$

$$z_{ls} \in \{0,1\} \quad \forall l \in L, s \in S \tag{12}$$

$$x_l \in \{0,1\} \quad \forall l \in L \tag{13}$$

The objective function (3) in the first stage problem is the sum of fixed cost of selecting facilities. The second stage consists of four distinct terms. The first term, $(\sum_{l\in L}\sum_{c\in C}\lambda_{lc}[(1-q_{ls})p_{lcs}])$, represents the expected transportation cost of shipping untainted products. The second term $(\sum_{l\in L}\sum_{c\in C}o_{lc}k_{lcs})$ and the third term $(\sum_{l\in L}\sum_{c\in C}\gamma_{lc}d_{lcs})$ represent the penalty cost of supplying tainted products for the consumers and the cost of discarding tainted products, respectively. Finally, the last term $(\sum_{l\in L}n_l z_{ls})$ is the cost of inspection, which is implemented at a facility site.

Constraint set (4) requires a facility to be open if any portion of the consumer demand is served from the facility. In addition, constraint set (4) ensures that the total consumer demand assigned to any facility does not exceed the facility's capacity. Constraint sets (5)–(8) together represent the amount of tainted product that is shipped to the consumer. Hence, without inspection, when $z_{ls} = 0$, constraint set (8) implies that $d_{lcs} = 0$. Given constraint set (5), all of the tainted products will reach the consumer. However if inspection is implemented, constraint sets (6) and (7) imply that only products passing inspection (which may include some tainted products) will be shipped to the consumer. Constraint set (9) requires that the demand of every consumer be met. Constraint set (10) implies that inspection is applied only to the selected set of facilities. Constraint set (11) requires that k_{lcs}, d_{lcs}, and p_{lcs} are positive values. Finally, constraint sets (12) and (13) place binary restrictions on variables z_{ls} and x_l.

2.2. The Conditional Value-at-Risk (CVaR) concept

The CVaR builds upon the measure called Value-at-Risk (VaR). VaR is a popular method to measure risk in a portfolio. VaR focuses on all outcomes below a specific level. Therefore, given a probability α, VaR answers the question: "What is the maximum loss

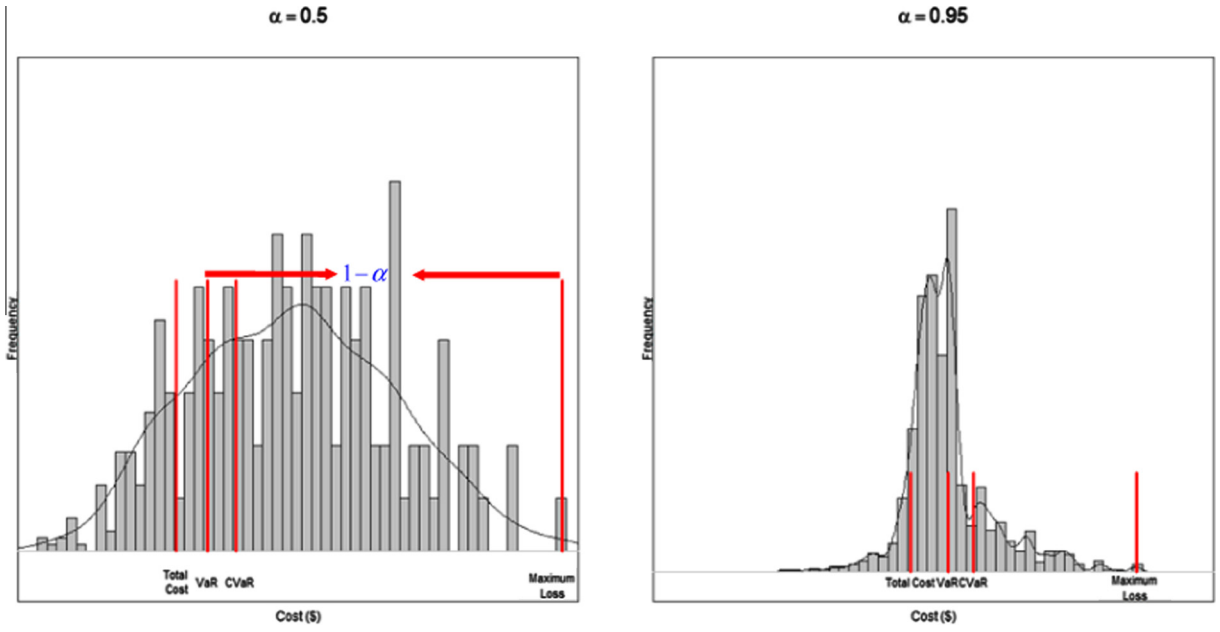

Fig. 1. Illustration of relation between CVaR and VaR.

associated with 100α% probability over a target horizon?" Despite the popularity of VaR in finance and risk management, this technique has a few important undesirable properties. Artzner, Delbaen, Eber, and Heath (1999) pointed out that VaR is not a coherent measure of risk since it fails to hold the sub-additivity property. Therefore, the VaR of a portfolio can be higher than the sum of VaRs of the individual assets in the portfolio (i.e., $f(x+y) \leqslant f(x)+f(y)$ where $f(.)$ is the risk measure). Moreover, VaR is difficult to optimize when it is calculated using the scenario-based approach (Rockafellar & Uryasev, 2000). These reasons have led us to use an alternative measure CVaR.

The CVaR measure leads to a minimization of VaR because CVaR is greater than or equal to VaR (see Fig. 1 and Eq. (17)). The CVaR measure considers those outcomes in which losses over a specific period of time exceed VaR. In other words, we allow $(1-\alpha)100\%$ of the outcomes to exceed VaR, and the average value of these outcomes is represented by CVaR. Generally, α indicates the level of conservatism that a decision-maker is willing to adopt. As α approaches one, the range of acceptable worst-cases becomes narrower in the corresponding optimization problem. Fig. 1 clarifies the concept of CVaR and demonstrates that CVaR is the conditional expected value exceeding the VaR. The gray bars represent the scenarios. All the scenarios to the right of VaR are the worst-case scenarios. Fig. 1 also illustrates the relationship between CVaR and VaR and indicates the fact that CVaR is always greater than or equal to VaR. The distribution is skewed to the right and therefore, the number of worst-case outcomes is reduced when α is increased to 95%.

We provide the formal definition of VaR and CVaR in the following equation. Consider, for example, a random variable $\tilde{x}$ that represents loss from an outcome. Given a risk level α ($\alpha \in (0,1)$), the VaR of the random variable $\tilde{x}$ is given by

$$\mathrm{VaR}_{\alpha}[\tilde{x}] := \min\{\eta : \Pr(\tilde{x} \geqslant \eta) \leqslant 1-\alpha\}. \tag{14}$$

Given Eq. (14), the CVaR at risk level α, is defined by Rockafellar and Uryasev (2000) as

$$\mathrm{CVaR}_{\alpha}[\tilde{x}] = \mathrm{E}\{\tilde{x} | \tilde{x} \geqslant \mathrm{VaR}_{\alpha}(\tilde{x})\}. \tag{15}$$

Rockafellar and Uryasev (2000) proved that for a minimization problem, the CVaR can be computed as the optimal objective value of

$$\mathrm{CVaR}_{\alpha}(\tilde{x}) = \min\{\eta + \frac{1}{1-\alpha}\max(\tilde{x}-\eta, 0)\ \}. \tag{16}$$

In Rockafellar and Uryasev also proved that for a set of pre-defined scenarios with corresponding probabilities, Eq. (16) can be transformed into a linear programming model by introducing the auxiliary variables $\tau_i (i = 1, ..., N)$ and for $\alpha \in (0,1)$ as

$$\min \quad \eta + \frac{1}{1-\alpha}\sum_{i=1}^{N}\rho_i\tau_i \tag{17}$$

$$\text{subject to}: \quad \tau_i \geq L_i - \eta \quad \forall i, \tag{18}$$

$$\tau_i \geqslant 0 \quad \forall i, \tag{19}$$

where L_i is the realization of the expected loss related to scenario i (Rockafellar & Uryasev, 2000).

2.3. The CVaR model

In expanding the formulation of the SCD model for a risk-averse objective, we define η as a decision variable denoting the optimal value for VaR. The CVaR is a weighted measure of η and the costs are greater than η. We define τ_s as the tail loss for scenario s, where tail loss is defined as the amount by which the loss in scenario s exceed η. Given Eq. (17) and the SCD model, a risk-averse supply chain network model with unreliable supply sources for $\alpha \in (0,1)$ is defined as

$$[\mathrm{SCD}-\mathrm{CVaR}] \quad \min \eta + \frac{1}{1-\alpha}\sum_{s\in S}p_s\tau_s \tag{20}$$

subject to: (4)–(13),

$$\tau_s \geqslant \sum_{l\in L}x_l f_l + \sum_{l\in L}\sum_{c\in C}\{\lambda_{lc}[(1-q_{ls})p_{lcs}] + o_{lc}k_{lcs} + \gamma_{lc}d_{lcs}\} + \sum_{l\in L}n_l z_{ls} - \eta \quad \forall s \in S, \tag{21}$$

$$\tau_s \geqslant 0 \quad , \forall s \in S. \tag{22}$$

In the above formulation, constraint set (21) computes the tail cost for scenario s. Constraint set (22) indicates that we only consider the scenarios in which the loss exceeds η.

3. Generation of test instances

We follow the methodology in Madadi et al. (2012) for data generation and summarize it here for the convenience of the reader. Let 0 indicate that a facility is operating at full capacity with no tainted material produced and let 1 indicate that a facility is not working at full capacity. Let $\Theta_l \in [0.50, 0.95]$ be the probability of facility l being in State 0 and let it also denote the reliability of the facility l, drawn from a continuous uniform distribution. The assumption that all facilities have an identical probability of working or failing is relaxed (Snyder & Daskin, 2005). If a facility is in State 1, the proportion of tainted product is randomly selected from a continuous uniform distribution in the range [0.10, 0.30]. The proportion of tainted product that is detected after inspection is randomly drawn from a continuous uniform distribution which is in the range [0.01, 0.09].

To determine the probability of scenario $s(\rho_s)$, we need to define a scenario. A scenario is defined as an event where a subset of facilities (say L') are in State 0 and where facilities in the set $L \setminus L'$ are in State 1. Given the number of facilities $|L|$, the total number of scenarios in which at least one facility is in State 1 is given by $\sum_{i=1}^{|L|}\binom{|L|}{i} = 2^{|L|} - 1$. Including the scenario in which all facilities are in State 0, the total number of scenarios is $2^{|L|}$. Hence, the probability of realizing a scenario $s \in S$ is defined as $\rho_s = \prod_{l\in L'}\Theta_l \prod_{l\in L\setminus L'}(1-\Theta_l)$. We list other assumptions as follows:

- The fixed cost of opening a facility is drawn from a discrete uniform distribution between \$1,000,000 and \$2,000,000.
- The demand for each consumer is drawn from a discrete uniform distribution between 100 and 300 units.
- The cost of inspection at each facility is drawn from a discrete uniform distribution between \$50,000 and \$100,000.
- The cost of shipping untainted products is drawn from a discrete uniform distribution between \$100 and \$1000.
- The penalty cost of shipping tainted products is drawn from a discrete uniform distribution between \$10,000 and \$20,000.
- The cost to discard is equal to 25% of the penalty cost of shipping untainted products.
- The fraction of tainted products produced at facility l is correlated with the probability of facility l being in State 0. Hence, more reliable facilities produce less tainted products.
- The cost of selecting a facility is correlated with the capacity so that the highest capacity has the highest selection cost.
- The cost of inspection is correlated to the percentage of improvement, which is the difference between q_l and r_l.
- The total capacity is tight and is 35% higher than the total demand before implementing inspection and discarding tainted items.

4. Computational experiments

This section presents numerical studies on both the SCD and the SCD-CVaR models, as outlined above, in order to highlight the differences between risk-neutral and risk-averse policies.

The optimization problem is modeled by using the AMPL mathematical programming language and solved with Gurobi 4.5.6. Each problem instance is solved on four cores (threads = 4) of a Dell Optiplex 980 with an Intel Core i7 860 Quad @ 2.80 GHz and 16 GB RAM. The operating system is Windows 7 Enterprise 64-bit. In our computational analysis, we terminate Gurobi when the CPU time limit of 14,400 s is reached.

All of our computational experiments are based on the data that was generated from the procedure presented in Section 3. We considered ten data instances for a supply chain network consisting of five facilities and five consumers. We selected five levels of α: 0.50, 0.65, 0.75, 0.85 and 0.95. Results comparing the derived solutions from the SCD model with those from the SCD-CVaR model, under various risk-level values, are summarized in Table 1. Note that all 10 data instances were solved to optimality for both the SCD and the SCD-CVaR models.

Our observations indicate that higher values of α imply a higher level of risk-aversion and a narrower range of worst-case scenarios. From Table 1, it can be observed that the average expected cost, VaR, and CVaR increase with associated increases to α values. This is because, as a decision-maker or a supply chain designer becomes more risk-averse, he or she is willing to accept a higher total cost in order to avoid more worst-case scenarios. Hence, our derived SCD-CVaR model restricts the number of scenarios that exceed VaR, and the right-hand tail cost will be minimized at the price of increasing the total expected cost (see Fig. 1).

In Table 1, we have divided the expected total cost into the fixed cost, expected untainted delivered cost, the expected tainted penalty cost, the expected discard cost, and the expected inspection cost. As per the results obtained, the fixed cost increases with respect to increasing risk-level α. The reason for this increase is that, for higher values of risk-level, the average number of selected facilities gradually increases. However, in SCD-CVaR$_{\alpha\in\{0.85,0.95\}}$, even though the average number of selected facilities is identical, the corresponding average fixed costs are different. The difference is because increasing the risk-level α also leads to the selection of different types of facilities. In Fig. 2, we show the output for one data instance in order to illustrate this observation. We notice that the number of selected facilities and/or the type of the facility changes with respect to the value of α. For instance, in the SCD-CVaR$_{\alpha=0.95}$ model, Facility 1 is not selected. In contrast, in the SCD-CVaR$_{\alpha=0.85}$ model, Facility 5 is not selected, which is a facility with a higher fixed cost.

Another key observation from Table 1 (also illustrated in Fig. 3) is that becoming more risk-averse results in remarkable increases in the cost of shipping untainted products to consumers. This implies that capacity allocation decisions change by varying α.

Table 1
A comparison between optimal solutions to the SCD and SCD-CVaR models with various risk-levels.

	SCD	SCD-CVaR$_{\alpha=0.50}$	SCD-CVaR$_{\alpha=0.65}$	SCD-CVaR$_{\alpha=0.75}$	SCD-CVaR$_{\alpha=0.85}$	SCD-CVaR$_{\alpha=0.95}$
CVaR	6,648,481	7,080,578	7,226,298	7,382,727	7,540,617	7,797,082
VaR	5,945,612	6,673,971	6,850,485	6,992,332	7,335,176	7,587,006
Avg. expected total cost	6,587,944	6,790,520	6,910,247	6,972,212	7,214,093	7,250,803
Avg. fixed cost	5,210,752	5,694,548	5,861,480	5,943,178	6,247,912	6,257,492
Avg. expected untainted delivered cost	592,174	632,791	643,899	652,651	681,041	687,738
Avg. expected tainted penalty cost	755,792	403,878	339,150	304,849	204,321	228,408
Avg. expected inspection cost	26,185	52,314	58,365	63,418	68,202	68,566
Avg. expected discard cost	3041	6988	7353	8117	8685	8599
Avg. no. of selected facilities	3.4	3.8	3.9	3.9	4.1	4.1

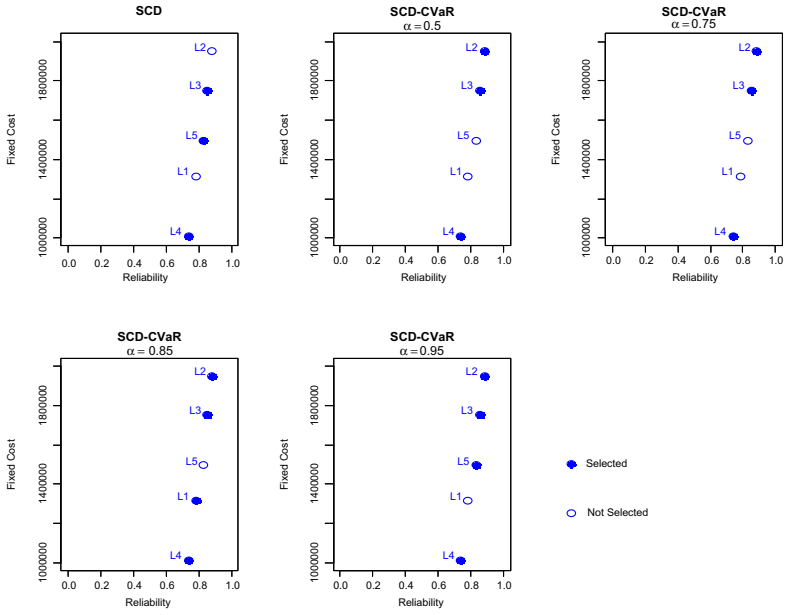

Fig. 2. Fixed cost vs. reliability on facility selection at various risk levels.

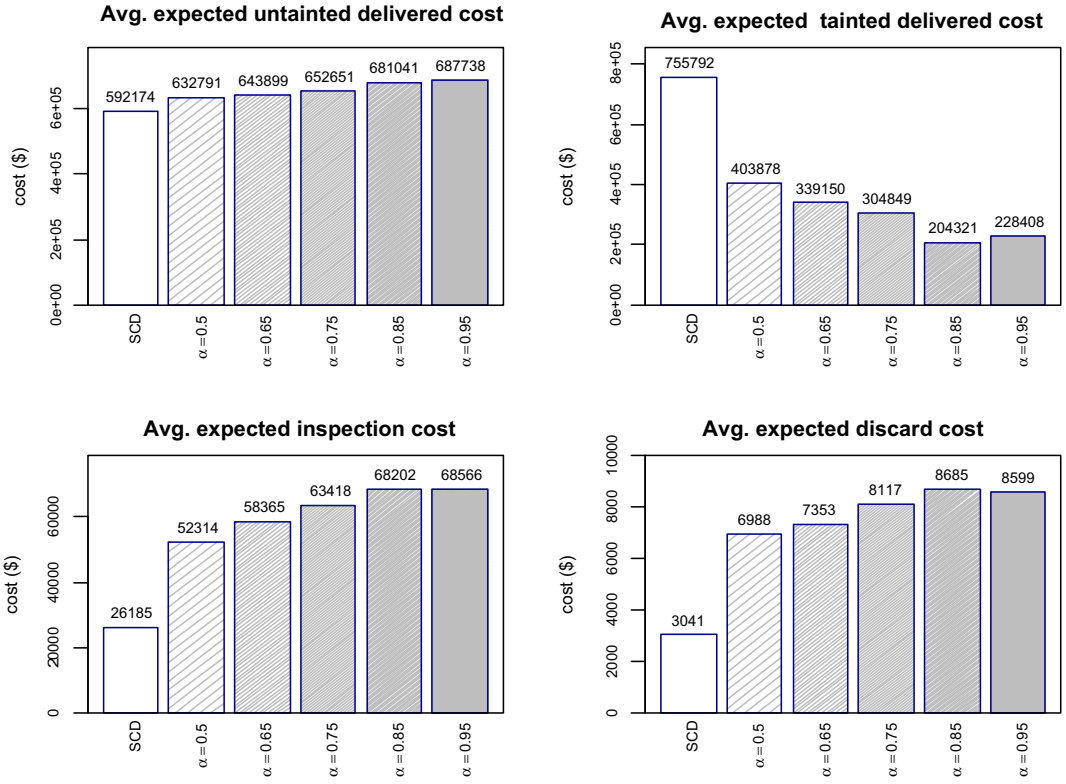

Fig. 3. Expected costs for various risk-level values.

We observe growth in the cost of inspection with respect to level of risk aversion level particularly for $\alpha \in \{0.85, 0.95\}$. This increase noticeably indicates that increasing α leads to conducting more inspections in the facilities. Additionally, a remarkable reduction in the expected penalty cost of shipping tainted products is noticeable. Given Eqs. (5)–(8), we notice that k_{lcs} and d_{lcs} are auxiliary decision variables that depend solely on variables p_{lcs} and z_{ls}. The implementation of more inspections at the facilities and larger values of shipping untainted products results in the discarding of more tainted products and, subsequently, a reduction in the number of tainted products shipped. Furthermore, inspection decisions at the facilities under different scenarios change as the value of α changes.

As an example, let us consider Scenario 24, where all facilities are in State 1, except for Facility 4, and Scenario 32 where all facilities are in State 1. As illustrated in Fig. 4, in the SCD model for Scenario 24, inspection is only implemented in Facility 5, whereas in the SCD-CVaR$_{\alpha=0.95}$, inspection is implemented in Facilities 3 and

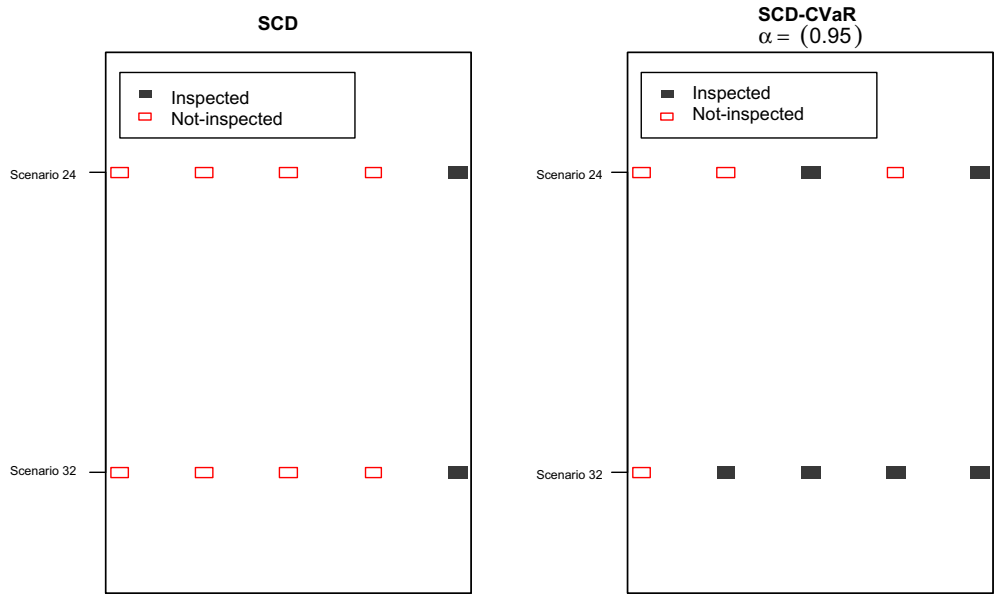

Fig. 4. Inspection decisions at the facilities under different scenarios and various risk levels.

5. In the SCD model and for scenario 24, Facility 3 utilizes 99% percent of its capacity (consumers 3, 4, and 5 use 27%, 32%, and 40%). In the SCD-CVaR$_{\alpha=0.95}$model, Facility 3 utilizes 84% percent of its capacity (consumers 2 and 5 use 33% and 81%, respectively). Furthermore, in Scenario 32, inspection is performed in all selected facilities for SCD-CVaR$_{\alpha=0.95}$, whereas Facility 5 is the only facility that is inspected in the SCD model. In the SCD model and for Scenario 32, Facility 3 utilizes 100% percent of its capacity (consumers 2, 3, and 4 use 44%, 15%, and 41%, respectively). In the SCD-CVaR$_{\alpha=0.95}$model, Facility 3 utilizes 80 percent of its capacity (consumers 3, 4 and 5 use 23%, 41%, and 16%, respectively).

Finally, recall that increasing α leads to a higher average number of selected facilities. This can be justified because a risk-averse decision-maker provides more capacity (by selection of more facilities) in order to be able both to perform more inspections and to discard more tainted products and still satisfy the total demand. The most salient conclusion that can be drawn from these results is that the risk-averse policy results in different strategic and tactical decisions compared to the risk-neutral policy, which is probably a more suitable design for a pharmaceutical supply network. However, we should note that the magnitude of change is also highly dependent upon the value of the risk level. In the next section, we utilize a sensitivity analysis for the further investigation of this subject.

4.1. Sensitivity analysis

Our computational experiments display the sensitivity of the solution relative to the various values of the risk level (i.e., α). In this section, we analyze the SCD and the SCD-CVaR outcomes for various settings of some of the parameters in order to provide insights that can assist decision-makers. We compare the results of our sensitivity analysis to the results obtained in our computational analysis, which we refer to as the "base case." We also perform the single-factor experiment in order to observe the effect of each cost factor. To make the results more interpretable and for the sake of simplicity, we consider the SCD model along with SCD-CVaR$_{\alpha\in\{0.50,0.85\}}$ in our sensitivity analysis. Table 2 presents the settings for each parameter used in the sensitivity analysis.

Table 2
Parameter setting for sensitivity analysis.

Parameter	Range (s) of the parameters
Fixed cost of selecting a facility (f_l)	U[300 k, 500 k], U[2 M, 3 M]
Fixed cost of implementing an inspection (n_l)	U[25 k, 50 k], U[75 k, 150 k]
Cost shipping tainted products (o_{lc})	U[5 k, 10 k], U[15 k, 30 k]

4.1.1. Varying fixed cost of selecting a facility (f_l)

In this section, we examine the sensitivity of the fixed cost. For this purpose, let us first assume that our facilities are small-size facilities where the fixed cost of selecting a facility is drawn from a discrete uniform distribution between 300,000 and 500,000. We also consider larger size facilities where the fixed cost of selecting a facility is drawn from a discrete uniform distribution between 2,000,000 and 3,000,000. Note that we keep all other parameters constant. We use the same ten data instances that were previously described, changing only the fixed cost of selecting a facility. Table 5 summarizes the results. Note that the numbers in parentheses denote the reduction or growth in the costs compared to values obtained in the "base case."

For the case where $f_l \in$ U[300 k, 500 k] , the average number of selected facilities increases as the fixed cost decreases in both the SCD model and SCD-CVaR model. We do not observe a notable change in the average expected cost of shipping untainted products. We observe a remarkable reduction in both the average expected penalty cost of shipping tainted products and the average expected cost of discarding tainted products, particularly in the SCD and SCD-CVaR$_{\alpha=0.50}$models. This is a consequence of an increase in the average number of selected facilities as well as the implementation of more inspections at these facilities. For SCD-CVaR$_{\alpha=0.85}$, we observe an increase in the average expected cost of inspection and a slight change in the average expected cost of discarding tainted products. We observe that the ability to reduce the fixed cost of selecting a facility results in increasing the average number of selected facilities and subsequently implementation of more inspection at the facilities particulary in the risk-neutral policy.

We notice that the average number of selected facilities drastically decreases when $f_l \in$ U[2 m, 3 m] . We also observe a considerable increase in the average expected penalty cost of shipping tainted products and a decrease in the average expected cost of

discarding tainted products, which are the consequence of considerable reduction in the implementation of inspection at the facilities. The reason for these changes is because of the reduction in the average number of selected facilities, which causes the decrease of the available capacity. Hence, the inspection at the facilities is refused and the tainted products are not discarded in order to provide enough capacity to be able to satisfy the total demand of consumers (i.e., to satisfy constraint set (9)). As a result, we observe that higher fixed costs of selecting a facility results in a reduction in implementation of inspection at the facilities and subsequently, increased quantities of tainted products reaching consumers.

4.1.2. Varying fixed cost of implementing an inspection (n_l)

As shown in Table 6, for $n_l \in U[25\text{ k}, 50\text{ k}]$, despite some slight variations, we observe that average fixed cost, average expected penalty cost of shipping tainted products, and average number of selected facilities are all insensitive to the change. In the SCD and SCD-CVaR$_{\alpha=0.50}$ models, we note that while the inspection cost decreases considerably, the average discard cost increases and the average expected penalty cost of shipping tainted products decreases, which is more considerable in the SCD-CVaR$_{\alpha=0.50}$ model. We also note an increase in the average expected cost of discarding tainted products which implies that the reduction in cost of implementing inspection results in more inspections being performed, as would be expected.

For $n_l \in U[75\text{ k}, 150\text{ k}]$, we observe a reduction in the number of selected facilities as α increases. This reduction is also valid when compared to the base case and the case where $n_l \in U[25\text{ k}, 50\text{ k}]$. We observe that, for high inspection cost cases and also for higher values of α, the SCD-CVaR model tends to select more reliable facilities, whereas for lower inspection costs, the tendency is toward selecting facilities with larger capacities. Hence, we observe lower fixed costs for $n_l \in [75\text{ k}, 150\text{ k}]$ compared to the base case and also $n_l \in [25\text{ k}, 50\text{ k}]$. The corresponding analysis is presented in more detail in Section 5. The results also show a reduction of inspection implementation in both the SCD and SCD-CVaR$_{\alpha=0.50}$ models and 26 percent and 11 percent decreases in the average expected costs of discarding tainted products for $\alpha = 0.50$ and $\alpha = 0.85$, respectively. This reduction results in a nearly six percent increase in the average expected penalty cost of shipping tainted products, which is still 56 percent less than what we observe for $\alpha = 0.50$. The obtained result indicates that managers and decision-makers should either maintain inspection costs at the lowest possible value or become more risk-averse when the cost of inspection implementation is high.

4.1.3. Varying penalty cost of shipping tainted products (o_{lc})

Table 7 reports the relative differences in the optimal cost expectations and the average number of selected facilities with respect to changes in the penalty cost of shipping tainted products. For $o_{lc} \in U[5\text{ k}, 10\text{ k}]$, there is a considerable reduction in the average number of selected facilities for both SCD-CVaR$_{\alpha=0.50}$ and SCD-CVaR$_{\alpha=0.95}$. For the SCD model, the average number of selected facilities is insensitive to the change. We also notice a remarkable reduction in the inspection cost and the average expected discard cost, particularly in the SCD and SCD-CVaR$_{\alpha=0.50}$ models. This reduction implies the implementation of fewer inspections at the facilities. These observations indicate that the use of a low penalty cost for shipping tainted products results in decisions that do not support the detection of tainted materials nor the selection of enough facilities to protect against requiring shipping tainted products.

For $o_{lc} \in U[15\text{ k}, 30\text{ k}]]$, we observe a notable increase in the number of selected facilities in the SCD and SCD-CVaR$_{\alpha=0.50}$ models. We also notice increases in the inspection cost and the average expected discard cost in the SCD and SCD-CVaR$_{\alpha=0.50}$ models. However, in the SCD-CVaR$_{\alpha=0.95}$ model, the average number of selected facilities and the average expected penalty cost of shipping tainted products are both insensitive to the change. The results decidedly indicate that decision-makers should consider the high penalty cost of shipping tainted products when dealing with both the risk-neutral policy and the risk-averse policy. Our result also supports the position that managers and decision-makers should avoid considering a low penalty cost for shipping tainted products when they are willing to be highly risk-averse.

5. Predictive modeling

In this research, we will perform predictive modeling based on the SCD and SCD-CVaR models. Given our computational analysis, we noticed that in some circumstances and for some parameters, it may be difficult to predict or determine which facilities are selected or unselected; it may also be difficult to interpret the output of the model. We perform a regression analysis in order to identify the factors for predicting the selection of a facility in the SCD and SCD-CVaR frameworks at various risk levels and to analyze relationships among variables. The second purpose for conducting a regression analysis is to assess the likelihood of selection for each individual facility at various risk levels. Hence, we utilize logistic regression method in this study.

5.1. Description of the data source

We use a set of continuous predictor variables that are hypothesized to be associated with the dependent variable, which is the status of a facility (selected/unselected). The predictors for facility l include the following: the reliability of the facility (Θ_l), the fixed cost of opening the facility (f_l), the capacity of the facility (κ_l), the fixed cost of implementing an inspection at the facility (n_l), the total demand of the consumers ($b = \sum_{c \in C} b_c$), the fraction of tainted products at the facility l (q_{ls}); the fraction of tainted products at facility l after inspection (r_{ls}); and risk level (α). We will investigate the impact of these factors on the status of a facility. The status of a facility is represented by an indicator variable defined as follows:

$$y_l = \begin{cases} 1, & \text{if facility } \ l \ \text{ is selected}, l \in L \\ 0, & \text{else}. \end{cases}$$

We use 86 data files for a specific case containing five facilities and five consumers to illustrate the predictive modeling. We consider seven levels for the risk level α: 0, 0.50, 0.65, 0.75, 0.85, 0.95, and 0.99. In total we will have 3010 ($86 \times 5 \times 7$) observations. Given the procedure we conducted in order to generate the test data in Section 3, multicollinearity exists between some of the independent variables. For instance, the capacity of a facility and the fixed cost of opening a facility are highly correlated (Pearson's correlation = 0.71) as is the fraction of tainted products at facility l and the fixed cost of implementing an inspection at a facility (Pearson's correlation = 0.73). To overcome this issue of multicollinearity, we remove the fixed cost (f_l) variable from our model and we combine capacity and total demand of consumers ($b = \sum_{c \in C} b_c$), which we define as $\Gamma_{l,1} = \frac{\kappa_l}{\sum_{c \in C} b_c}$. This ratio indicates the portion of the total demand that can be supplied by facility l. In addition, we remove inspection cost from our model and consider $\Gamma_{l,2} = 1 - (q_l - r_l)$. This fraction indicates the maximum percent of untainted products that we can expect from facility l after performing inspection. Therefore, we consider α, Θ_l, $\Gamma_{l,1}$, and $\Gamma_{l,2}$ as our independent variables. In the next section, we discuss our regression model.

5.2. Regression model description

The predictive model in this research was implemented in the software package R. The regression coefficient for risk level α is highly significant (p-value < 0.0001). The maximum percent of untainted products, Γ_2, is significant (p-value = 0.0006). We also notice that reliability of the facility, Θ, and it is interaction with the risk level, $\alpha\Theta$, are significant (with p-value = 0.004 and p-value = 0.03, respectively).

We also consider a model with only significant predictors by employing a stepwise selection procedure. The Stepwise Logistic Regression (SLR) method allows the model to be assessed as it is being built. In SLR, predictor variables are selected for inclusion or exclusion from the regression model in a sequential manner (see Cohen (2003) for details). We considered the interaction between the independent variables to describe how the effect of a predictor variable o facility selection depends on the level/value of other predictor variables. The smallest Akaike Information Criterion (AIC) approach was used to select the best model.

The coefficients from the estimated regression model after performing the stepwise procedure are summarized in Table 3. We observe that performing a stepwise procedure resulted in of the removal of several interaction terms as well as reducing the AIC by nearly three units. Given the logistic coefficients in Table 8, the resulting regression model with interaction is:

$$\hat{Y}_l = 40.369 - 15.08\alpha - 35.94\Theta - 18.96\Gamma_1 - 46.41\Gamma_2 + 9.45\alpha\Theta + 9.71\alpha\Gamma_2 + 29.69\Theta\Gamma_2 + 60.15\Gamma_1\Gamma_2. \quad (23)$$

We present an example here in order to clarify the interpretation of our regression model. Consider α (shown in Table 3) that is statistically significant (p-value < 0.0001). From Eq. (23), it can be shown that the change in the logit (i.e., log odds) with a 0.25 unit increase in α when other variables are held constant is

$$\hat{Y}_{l,\Delta\alpha} = \hat{Y}_l^{\alpha+0.25} - \hat{Y}_l^{\alpha} = -3.77 + 2.36\Theta + 2.43\Gamma_2. \quad (24)$$

Eq. (24) implies that increasing α leads to a reduction in the probability of selection if Θ and/or Γ_2 go down. We perform some predictions in the next section to evaluate this further.

5.3. Prediction

To evaluate the predictive strength of the model based on the estimated logistic coefficients in Table 3, we use observations for a set of facilities consisting of five facilities in our prediction. We consider two levels of α i.e., $\alpha \in \{0.50, 0.95\}$. The data and the result of the prediction are presented in Table 4. The results in Table 4 indicate that reliability has substantially impacts the selection of the facilities. Another notable observation is that Facility 5 has the lowest reliability but the largest capacity. The likelihood of selecting Facility 5 when $\alpha = 0.50$ is 0.995. However, after increasing the value of α to 0.95, the likelihood of selection decreases to 0.965. This decline indicates the selection of more reliable facilities in the risk-averse policy. We can therefore state that there is a higher likelihood of selection for more reliable facilities as well as facilities with higher Γ_2 in the risk-averse model. These results may enable facilities to analyze their situation and compare it with other facilities (competitors) as they attempt to change their behaviors in order to increase their likelihood of selection. The results can also assist decision-makers to identify and analyze factors for predicting the selection of a facility. We believe that other

Table 3
Logistic regression model result after performing SLR.

Research model predictors	Logistic coefficients	Standard error	z value (significance level)	Pr(>|z|)
(Intercept)	40.36	8.30	4.86***	0.00000
α	−15.08	3.53	−4.27***	0.00002
Θ	−35.94	8.56	−4.19***	0.00003
Γ_1	−18.96	23.20	−0.81	0.41390
Γ_2	−46.41	10.11	−4.59***	0.00000
$\alpha\Theta$	9.45	2.42	3.91***	0.00009
$\alpha\Gamma_2$	9.71	4.85	2.00*	0.04520
$\Theta\Gamma_2$	29.69	9.74	3.04**	0.00230
$\Gamma_1\Gamma_2$	60.15	27.91	2.15*	0.03120

Significant codes: '.' $p < 0.1$; AIC = 1285.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 4
Likelihood of selection of facilities.

Facility	Reliability	Γ_1	Γ_2	$\alpha = 0.05$		$\alpha = 0.50$		$\alpha = 0.75$		$\alpha = 0.95$	
				Probability	Logit	Probability	Logit	Probability	Logit	Probability	Logit
3	0.6	0.11	0.84	0.127	−1.93	0.078	−2.47	0.059	−2.76	0.047	−3.00
4	0.56	0.2	0.75	0.954	3.04	0.874	1.94	0.790	1.32	0.697	0.83
1	0.87	0.13	0.81	0.025	−3.68	0.038	−3.24	0.048	−2.99	0.057	−2.80
2	0.84	0.29	0.8	0.826	1.56	0.861	1.83	0.878	1.98	0.891	2.10
5	0.56	0.35	0.72	0.999	7.26	0.997	5.97	0.995	5.26	0.991	4.68

Table 5
Comparison between optimal solutions to the SCD and SCD-CVaR models at varying fixed cost.

	SCD		SCD-CVaR$_{\alpha=0.50}$		SCD-CVaR$_{\alpha=0.85}$	
	$f_l \in$ [300 k, 500 k]	$f_l \in [2M, 3M]$	$f_l \in$ [300 k, 500 k]	$f_l \in [2M, 3M]$	$f_l \in$ [300 k, 500 k]	$f_l \in [2M, 3M]$
CVaR	–	–	2,699,462	11,185,483	2,986,515	12,304,789
VaR	–	–	2,441,975	10,398,995	2,769,522	12,016,346
Avg. expected total cost	2,538,062	10,514,286	2,575,433	10,541,546	2,580,181	11,156,932
Avg. fixed cost	1,642,266	8,994,122	1,675,595	9,021,022	1,678,277	9,877,415
Avg. expected untainted delivered cost	587,447	597,569	627,086	619,172	665,388	682,336
Avg. expected tainted penalty cost	232,563(−70%)	907,643(20%)	191,559(−53%)	884,026(118%)	152,864(−26%)	562,063(146%)
Avg. expected inspection cost	68,523(162%)	13,203(−50%)	73,607(41%)	15,126(−70%)	74,960(10%)	30,200(−55%)
Avg. expected discard cost	7262(138%)	1748(−42%)	7587(9%)	2201(−68%)	8690(0.1%)	4918(−43%)
Avg. No. of selected facilities	4.1	3.5	4.1	3.5	4.2	3.6

Table 6
Comparison between optimal solutions to the SCD and SCD-CVaR models at varying inspection cost.

	SCD		SCD-CVaR$_{\alpha=0.50}$		SCD-CVaR$_{\alpha=0.85}$	
	$n_l \in$ [25 k, 50 k]	$n_l \in$ [75 k, 150 k]	$n_l \in$ [25 k, 50 k]	$n_l \in$ [75 k, 150 k]	$n_l \in$ [25 k, 50 k]	$n_l \in$ [75 k, 150 k]
CVaR	–	–	6,374,835	7,156,224	5,959,766	7,641,170
VaR	–	–	5,980,693	6,472,782	5,777,634	7,355,175
Avg. expected total cost	6,569,842	6,620,171	6,778,385	6,631,208	7,170,790	6,875,733
Avg. fixed cost	5,210,752	5,210,752	5,728,242	5,438,567	6,247,912	5,900,643
Avg. expected untainted delivered cost	592,205	592,152	627,905	628,970	673,660	672,033
Avg. expected tainted penalty cost	751,566(−0.6%)	775,485(3%)	389,182(−3%)	500,763(25%)	203,685(−0.3%)	217,280(6%)
Avg. expected inspection cost	12,265(−52%)	38,865(48%)	26,052(−50%)	57,763(10%)	36,790(−45%)	78,032(13%)
Avg. expected discard cost	3054(0.4%)	2942(−4%)	7003(0.4%)	5144(−26%)	8743(0.7%)	7745(−11%)
Avg. No. of selected facilities	3.4	3.4	3.8	3.6	4.1	3.9

Table 7
Comparison between optimal solutions to the SCD and SCD-CVaR models at varying shipping tainted cost.

	SCD		SCD-CVaR$_{\alpha=0.50}$		SCD-CVaR$_{\alpha=0.85}$	
	$o_{lc} \in$ [5 k, 10 k]	$o_{lc} \in$ [15 k, 30 k]	$o_{lc} \in$ [5 k, 10 k]	$o_{lc} \in$ [15 k, 30 k]	$o_{lc} \in$ [5 k, 10 k]	$o_{lc} \in$ [15 k, 30 k]
CVaR	–	–	5,595,021	6,990,944	6,313,611	7,438,295
VaR	–	–	5,340,650	6,604,175	6,138,267	7,060,782
Avg. expected total cost	6,000,543	6,605,522	6,044,112	6,737,116	5,923,728	6,806,913
Avg. fixed cost	5,068,814	5,373,692	5,090,760	5,887,011	4,986,871	5,938,188
Avg. expected untainted delivered cost	582,557	485,849	614,505	516,871	622,027	559,015
Avg. expected tainted penalty cost	340,375 (−55%)	698,080(−8%)	326,791(−19%)	258,296(−36%)	298,379(42%)	232,984(14%)
Avg. expected inspection cost	7,971(−70%)	43,276(65%)	10,916(−79%)	67,946(30%)	15,086(−77%)	68,406(0.2%)
Avg. expected discard cost	826(−72%)	4625(52%)	1140(−83%)	6991(0.05%)	1365(−84%)	8421(−2%)
Avg. No. of selected facilities	3.3	3.7	3.3	4.0	3.4	4.1

important implications can be achieved in practice through these results in order to facilitate decision making process.

6. Conclusions and future research

In this paper, we presented a supply network design problem with application in the pharmaceutical industry to hedge against unreliability of capacity and prevent shipping of tainted materials to the consumers. We studied a risk-neutral decision-making policy and a risk-averse decision-making policy. We characterized the trade-off between the risk and cost, which provides several insights on the impact of risk-aversion on the facilities' optimal decisions in a pharmaceutical supply chain. Our studies demonstrated how strategic and tactical decisions change with respect to the risk level. We found that an increase in the risk level α leads to the selection of not only more reliable facilities but also a different number of facilities. The risk-averse policy also resulted in fewer worst-case scenarios as compared to the risk-neutral policy. Our computations also revealed that becoming more risk-averse resulted in remarkable increases in the cost of shipping untainted products to consumers. A regression analysis was also employed to identify the factors for predicting the selection of a facility in both the risk-neutral and risk-averse policies.

The significance of this research is threefold. First, to the best of our knowledge there is no currently available research to evaluate the pharmaceutical (or healthcare) supply chain network design. Secondly, there is also little prior research to date that investigates supply chain risk within the context of the pharmaceutical supply chain. As pharmaceutical availability and drug safety clearly are key components to effective patient quality of care, our models can assist supply chain designers enhance patient safety and quality of patient care. Furthermore, Insights into how our model should be configured to avoid the risk of tainted products reaching consumers are of interest to several types of supply chains such as healthcare, pharmaceutical, cosmetic and beauty, and food and dairy industries. Finally, the results also enable facilities to analyze their situation and compare it with other facilities (competitors) and change their behaviors in order to increase their likelihood of selection.

There are some interesting future research extensions. An interesting extension of the presented work is to include demand uncertainty and/or seasonal demand as they exist in real world pharmaceutical supply chain. Moreover, we assumed an inspection and discard approach, which is not a valid assumption in some supply chains like the automotive and electronics industries. This assumption can be shifted to an inspection and fix (rework) approach where defective products can be repaired after detecting. Ultimately, we have considered instances that included five facilities. However, experience from solving the models using commercial software indicated that the number of facilities can dramatically increase the computational time. We also think that it is important to design and develop heuristic techniques to obtain acceptable solutions to these larger size problems in reasonable runtimes and with good solution quality.

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