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A multi-objective stochastic programming approach for supply chain design considering risk

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ABSTRACT

In this paper, we develop a multi-objective stochastic programming approach for supply chain design under uncertainty. Demands, supplies, processing, transportation, shortage and capacity expansion costs are all considered as the uncertain parameters. To develop a robust model, two additional objective functions are added into the traditional comprehensive supply chain design problem. So, our multi-objective model includes (i) the minimization of the sum of current investment costs and the expected future processing, transportation, shortage and capacity expansion costs, (ii) the minimization of the variance of the total cost and (iii) the minimization of the financial risk or the probability of not meeting a certain budget. The ideas of unreliable suppliers and capacity expansion, after the realization of uncertain parameters, are also incorporated into the model. Finally, we use the goal attainment technique to obtain the Pareto-optimal solutions that can be used for decision-making.

1. Introduction

A supply chain (SC) is a network of suppliers, manufacturing plants, warehouses and distribution channels organized to acquire raw materials, convert these raw materials to finished products and distribute these products to customers. The concept of SC management, which appeared in the early 1990s, has recently raised a lot of interest since the opportunity of an integrated management of the SC can reduce the propagation of unexpected/undesirable events through the network and can affect decisively the profitability of all the members.

A crucial component of the planning activities of a manufacturing firm is the efficient design and operation of its SC. Strategic-level SC planning involves deciding the configuration of the network, i.e., the number, location, capacity and technology of the facilities. The tactical-level planning of SC operations involves deciding the aggregate quantities and material flows for purchasing, processing and distributing of products. The strategic configuration of the SC is a key factor influencing efficient tactical operations, and therefore has a long-lasting impact on the firm. Furthermore, the fact that the SC configuration involves the commitment of substantial capital resources over long periods of time makes the SC design problem an extremely important one.

Many attempts have been made to model and optimize SC design, most of which are based on deterministic approaches, see for example Bok et al. (2000), Timpe and Kallrath (2000), Gjerdrum et al. (2000) and many others. However, most real SC design problems are characterized by numerous sources of technical and commercial uncertainty, and so the assumption that all model

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parameters, such as cost coefficients, supplies, demand, etc., are known with certainty is not realistic.

In order to take into account the effects of the uncertainty in the production scenario, a two-stage stochastic model is proposed in this paper. Decision variables, which characterize the network configuration, namely those binary variables that represent the existence and the location of plants and warehouses of the SC, are considered as first-stage variables—it is assumed that they have to be taken at the design stage before the realization of the uncertainty. On the other hand, decision variables related to the amount of products to be produced and stored in the nodes of the SC and the flows of materials transported among the entities of the network are considered as second-stage variables, corresponding to decisions taken after the uncertain parameters have been revealed.

In traditional stochastic programming approaches, the objective function consists of the sum of the first-stage performance measure and the expected second-stage performance, and most commonly, the dominant uncertain parameters are the product demands. Approaches differ primarily in the selection of the decision variables and the way in which the expected value term, which in principle involves a multidimensional integral involving the joint probability distribution of the uncertain parameters, is computed.

There are a few research works addressing comprehensive (strategic and tactical issues simultaneously) design of SC networks using two-stage stochastic models. MirHassani et al. (2000) considered a two-stage model for multi-period capacity planning of SC networks. The authors used Benders decomposition to solve the resulting stochastic integer program. Tsiakis et al. (2001) also considered a two-stage stochastic programming model for SC network design under demand uncertainty. The authors developed a large-scale mixed-integer linear programming model for this problem. Alonso-Ayuso et al. (2003) proposed a branch-and-fix heuristic for solving two-stage stochastic SC design problems. Santoso et al. (2005) integrated a sampling strategy with an accelerated Benders decomposition to solve SC design problems with continuous distributions for the uncertain parameters. There are also some other papers in SC planning under uncertainty. Petkov and Maranas (1997), Gupta and Maranas (2003) and Gupta et al. (2000) incorporated the uncertain demands as multivariate-normal distributions. Then, they converted stochastic features of the problem into a chance-constraint programming problem. Goh et al. (2007) developed a stochastic model of the multi-stage global SC network problem, considering supply, demand, exchange and disruption as the uncertain parameters. However, the robustness of decision to uncertain parameters is not considered in above studies.

Although stochastic programming has been studied for four decades, conventional stochastic programming models are severely limited owing to its inability to handle risk aversion or decision-makers' preferences in a direct manner, subsequently excluding many important domains of application. Mulvey et al. (1995) presented an improved stochastic programming called robust programming capable of tackling the decision-makers' favored risk aversion. In this method, the variance term is simply added into the main objective function with an associated weighting parameter that represents the risk tolerance of the modeler, see for example Yu and Li (2000) and Lai and Ng (2005). This idea has also been used in some other areas, which are not directly related to the SC design problem. For example, Ahmed and Sahinidis (1998) used this construct to develop a linear programming recourse formulation for production planning in the presence of scenarios. Bok et al. (1998) also employed the penalized variance term and introduced an additional penalized term reflecting the underutilization of capacity.

The main disadvantages of traditional stochastic SC design approaches are as follows:

1. Minimizing cost or maximizing profit as a single objective is often the optimization focus (Cohen and Lee, 1989; Tsiakis et al., 2001).
2. Most multi-objective SC approaches are either deterministic (Chen et al., 2003) or only demand is considered as the source of uncertainty (Guillen et al., 2005).
3. Minimizing the risk reflected by the variance of the total cost and the financial risk has not been considered in existing comprehensive SC design models.
4. Reliability issues have not been considered during the strategic planning phase.

To overcome these disadvantages, we develop a robust stochastic programming approach for designing SCs under uncertainty. In our approach, not only demands, but also supplies, processing, transportation, shortage and capacity expansion costs are all considered as the uncertain parameters. Moreover, we assume that suppliers are unreliable and may lose their abilities to supply, like oil suppliers in the Middle East. The reliabilities of suppliers are known in advance, but the actual situations of suppliers become clear after building the facilities.

The first objective function of our proposed model is the minimization of the sum of first-stage investment costs and the expected second-stage processing, transportation, shortage and capacity expansion costs. To develop a robust model, two additional objective functions are added into the final model. The first additional objective function is the minimization of the variance of the total cost. The variance of the total cost should be considered in the model, because when we focus only on the expected total cost, the design scheme may be suboptimal if the total cost substantially varies because of randomness. Practically, the variance of the total cost is difficult to interpret. Therefore, it is necessary to introduce a new objective function to clearly capture the notion of risk. This objective function is the minimization of the financial risk. The financial risk associated with a design project under uncertainty is defined as the probability of not meeting a certain cost level or budget.

Although the ideas of variance and financial risk have been considered in other areas, but to the best of our knowledge, it is the first time they are considered all together in a multi-objective scheme to design robust SCs under uncertainty and unreliable suppliers. Moreover, the idea of capacity expansion at the second stage, after the realization of uncertain parameters, is also incorporated into the model. Using this idea, we have the option of expanding the capacities of plants and warehouses, if we face favourable economic conditions with large demands.

Since the expected total cost, the variance of the total cost and the financial risk are in conflict with each other, it is proposed to set up a multi-objective design problem whose solution will be a set of Pareto-optimal possible design alternatives representing the trade-off among different objectives rather than a unique solution. To the best of our knowledge, only ε–constraint method (Guillen et al., 2005) and fuzzy optimization (Chen and Lee, 2004) have been used to solve multi-objective SC design models. We use the goal attainment technique, see Hwang and Masud (1979) for details, to solve the resulting multi-objective problem.

The present work formulates the SC design problem as a multi-objective stochastic mixed-integer nonlinear programming problem, which is solved by using the goal attainment technique. This formulation takes into account not only SC expected total cost, but also the risk reflected by the variance of the total cost and the financial risk. The result of the model provides a set of Pareto-optimal solutions to be used by the decision-maker in order to find the best SC configuration according to his/her preferences.

This paper is organized as follows. In Section 2, we describe the SC design problem. Section 3 presents the multi-objective SC design problem considering risk. In Section 4, we explain about the goal attainment technique to solve the multi-objective problem. Section 5 presents the computational experiments. Finally, we draw the conclusion of the paper in Section 6.

2. Problem description

We first describe a deterministic mathematical formulation for the SC design problem. Consider an SC network $G = (N, A)$, where N is the set of nodes and A is the set of arcs. The set N consists of the set of suppliers S, the set of possible processing facilities P and the set of customer centers C, i.e., $N = S \cup P \cup C$. The processing facilities include manufacturing centers M and warehouses W, i.e., $P = M \cup W$. Let K be the set of products flowing through the SC.

The SC configuration decisions consist of deciding which of the processing centers to build. We associate a binary variable y_i to these decisions: $y_i = 1$ if processing facility i is built, and 0 otherwise. The tactical decisions consist of routing the flow of each product $k \in K$ from the suppliers to the customers. We let x_{ij}^k denote the flow of product k from a node i to a node j of the network where $(ij) \in A$, and z_j^k denote shortfall of product k at customer center j, when it is impossible to meet demand. A deterministic mathematical model for this SC design problem is formulated as follows (see Santoso et al. (2005) for more details):

$$\text{Min} \quad \sum_{i\in P} c_i y_i + \sum_{k\in K}\sum_{(ij)\in A} q_{ij}^k x_{ij}^k + \sum_{k\in K}\sum_{j\in C} h_j^k z_j^k$$

$$\text{s.t.} \tag{1.1}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \tag{1.2}$$

$$\sum_{i\in N} x_{ij}^k - \sum_{l\in N} x_{jl}^k = 0 \quad \forall j \in P, \quad \forall k \in K \tag{1.3}$$

$$\sum_{i\in N} x_{ij}^k + z_j^k \geqslant d_j^k \quad \forall j \in C, \quad \forall k \in K \tag{1.4}$$

$$\sum_{j\in N} x_{ij}^k \leqslant s_i^k \quad \forall i \in S, \quad \forall k \in K \tag{1.5}$$

$$\sum_{k\in K} r_j^k \left(\sum_{i\in N} x_{ij}^k \right) \leqslant m_j y_j \quad \forall j \in P \tag{1.6}$$

$$x_{ij}^k \geqslant 0 \quad \forall (ij) \in A, \quad \forall k \in K \tag{1.7}$$

$$z_j^k \geqslant 0 \quad \forall j \in C, \quad \forall k \in K \tag{1.8}$$

In the above model, c_i denotes the investment cost for building facility i, q_{ij}^k denotes the per-unit cost of processing product k at facility i and/or transporting product k on arc (ij), and h_j^k denotes the per-unit penalty incurred for failing to meet demand of product k at customer center j. The objective function (1.1) consists of minimizing total investment, tactical and shortage costs. Constraint (1.2) enforces the binary nature of the configuration decisions for the processing facilities. Constraint (1.3) enforces the flow conservation of product k across each processing node j. Constraint (1.4) requires that the total flow of product k to a customer node j plus shortfall should exceed the demand d_j^k at that node. Constraint (1.5) requires that the total flow of product k from a supplier node i should be less than the supply s_i^k at that node. Constraint (1.6) enforces capacity constraints of the processing nodes. Here, r_j^k denotes per-unit processing requirement for product k at node j. The capacity constraint then requires that the total processing requirement of all products flowing into a processing node j should be smaller than the capacity m_j of facility j if it is built ($y_j = 1$). If facility j is not built ($y_j = 0$), the constraint will force all flow variables $x_{ij}^k = 0$ for all $i \in N$. Finally, the last set of constraints enforces the non-negativity of the flow variables and shortfalls.

It will be convenient to work with the following compact notation for models (1.1)–(1.8):

$$\text{Min} \quad c^T y + q^T x + h^T z$$

$$\text{s.t.} \tag{2.1}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \tag{2.2}$$

$$Bx = 0 \tag{2.3}$$

$$Dx + z \geqslant d \tag{2.4}$$

$$Sx \leqslant s \tag{2.5}$$

$$Rx \leqslant My \tag{2.6}$$

$$x \in R_{+}^{|A| \times |K|}, \quad z \in R_{+}^{|C| \times |K|} \tag{2.7}$$

Above vectors c, q, h, d and s correspond to investment costs, processing/transportation costs, shortfall costs, demands and supplies, respectively. The matrices B, D and S are appropriate matrices corresponding to the summations on the left-hand side of the expressions (1.3)–(1.5), respectively. The notation R corresponds to a matrix of r_j^k, and the notation M corresponds to a matrix with m_j along the diagonal.

We now propose a stochastic programming approach based on a recourse model with two stages to incorporate the uncertainty associated with demands, supplies, processing costs, transportation costs, shortage costs and capacity expansion costs.

In a two-stage stochastic optimization approach, the uncertain parameters are considered as random variables with an associated probability distribution and the decision variables are classified into two stages. The first-stage variables correspond to those decisions that need to be made here-and-now, prior to the realization of the uncertainty. The second-stage or recourse variables correspond to those decisions made after the uncertainty is unveiled and are usually referred to as wait-and-see decisions. After the first-stage decisions are taken and the random events realized, the second-stage decisions are subjected to the restrictions imposed by the second-stage problem. Due to the stochastic nature of the performance associated with the second-stage decisions, the objective function, traditionally, consists of the sum of the first-stage performance measure and the expected second-stage performance; refer to Birge and Louveaux (1997) for more details.

It is assumed that we have the option of expanding the capacities of plants and warehouses after the realization of uncertain parameters. Clearly, when we face favourable economic conditions with high demands, at the second-stage, it may be reasonable to expand the capacities of sites, even if unit expansion costs are relatively high.

Considering vectors e, f, O and $\xi = (q,\ h,\ f,\ d,\ s)$ as capacity expansions, per-unit expansion costs, expansion limits and random data, respectively, the two-stage stochastic model is formulated as follows:

$$\begin{aligned}&\text{Min} \quad c^T y + E[G(y,\xi)]\\ &\text{s.t.}\end{aligned} \tag{3.1}$$

$$y \in Y \subseteq \{0,1\}^{|P|} \tag{3.2}$$

where $G(y,\xi)$ is the optimal value of the following problem:

$$\begin{aligned}&\text{Min} \quad q^T x + h^T z + f^T \mathrm{e}\\ &\text{s.t.}\end{aligned} \tag{3.3}$$

$$Bx = 0 \tag{3.4}$$

$$Dx + z \geqslant d \tag{3.5}$$

$$Sx \leqslant s \tag{3.6}$$

$$Rx \leqslant My + \mathrm{e} \tag{3.7}$$

$$e \leqslant Oy \tag{3.8}$$

$$x \in R_{+}^{|A| \times |K|}, \quad z \in R_{+}^{|C| \times |K|}, \quad \mathrm{e} \in R_{+}^{|P|} \tag{3.9}$$

Note that the optimal value $G(y,\xi)$ of the second-stage problem (3.3)–(3.9) is a function of the first-stage decision variable y and a realization $\xi = (q,\ h,\ f,\ d,\ s)$ of the uncertain parameters. The expectation in (3.1) is taken with respect to the joint probability distribution of uncertain parameters.

In the above problem, decision variables, which represent the existence of the different nodes of the SC, are considered as first-stage variables as it is assumed that they have to be taken at the design stage before the uncertain parameters are unveiled. On the other hand, decision variables related to the amount of products to be produced and stored in the nodes of the SC, the flows of materials transported among the entities of the network, shortfalls at the customer centers and the amount of expansion of the capacities of sites are considered as second-stage variables.

It should be mentioned that stochastic programming is generally difficult to handle and implement. The readers may refer to van Delft and Vial (2004), which describes a powerful tool for practical implementation of stochastic programming in an SC problem.

In this paper, the uncertainty associated with demands, supplies, processing, transportation, shortage and capacity expansion costs is represented by a set of discrete scenarios with given probability of occurrence. Such scenarios together with their associated probabilities, and also the reliabilities of suppliers are provided as input data into the model. The difficulty of continuous distributions is avoided by introducing discrete scenarios, or combinations of discrete samples of all the uncertain parameters using Monte Carlo simulation. This approach is explained in detail at the end of Section 4.

3. Multi-objective supply chain design problem

As explained, to develop a robust model, two additional objective functions are added into the traditional SC design problem. The first is the minimization of the variance of the total cost, and the second is the minimization of the probability of not meeting a certain budget. However, by considering the variance of the total cost as an objective function, we actually introduce nonlinearity into the proposed model, but that is the only nonlinear term in the final mathematical program.

We also assume that some suppliers may lose their abilities to supply, like oil suppliers in the Middle East. The reliabilities of suppliers are known in advance. But the situations of suppliers will actually clear after building the facilities. So, we will have $2^{|S|}$ scenarios for the situations of suppliers, in some of them one or more suppliers are unable to supply. If in each scenario, some suppliers are unable to supply, those suppliers with their external links can be easily dropped off from further consideration. So, it will affect the topology of network and decrease the number of decision variables and constraints of the final mathematical model. An alternative method to deal with unreliable suppliers is to set the supply values of the unreliable suppliers in the corresponding scenarios to zero.

Let T be the set of scenarios with given probability of occurrence associated with demands, supplies, processing costs, transportation costs, shortage costs and capacity expansion costs. Such scenarios together with their associated probabilities must be provided as input data into the model.

A different value for the sum of the first-stage and the second-stage costs is obtained for each particular realization of uncertain parameters. The proposed model accounts for the minimization of the sum of first-stage and the expected second-stage costs, minimization of the variance of second-stage costs and the minimization of financial risk or the probability of not meeting a certain budget.

The financial risk associated with a design project under uncertainty is defined as the probability of not meeting a certain target cost level. For the two-stage stochastic problem, the financial risk associated with a certain budget Ω can be rewritten with the help of binary variables as follows:

$$\text{Risk} = \sum_{l=1}^{L} p_l u_l \tag{4}$$

where p_l denotes the occurrence probability of the lth scenario, $L = |T| \times 2^{|S|}$ denotes the total number of scenarios including those related to the reliabilities of suppliers and u_l is a new binary variable defined for each scenario as follows:

$$u_l = \begin{cases} 1 & \text{if } Cost_l > \Omega, \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $Cost_l$ is the total cost when the lth scenario is realized.

Considering V as a very large constant value (approaching infinity), the proper multi-objective stochastic model for our SC design problem would be

$$\text{Min} \quad c^T y + \sum_{l=1}^{L} p_l (q_l^T x_l + h_l^T z_l + f_l^T e_l) \tag{6.1}$$

$$\text{Min} \quad \sum_{l=1}^{L} p_l \left(q_l^T x_l + h_l^T z_l + f_l^T e_l - \sum_{l=1}^{L} p_l (q_l^T x_l + h_l^T z_l + f_l^T e_l) \right)^2 \tag{6.2}$$

$$\text{Min} \quad \sum_{l=1}^{L} p_l u_l$$

s.t. (6.3)

$$Bx_l = 0 \quad l = 1, \ldots, L \tag{6.4}$$

$$Dx_l + z_l \geqslant d_l \quad l = 1, \ldots, L \tag{6.5}$$

$$Sx_l \leqslant s_l \quad l = 1, \ldots, L \tag{6.6}$$

$$Rx_l \leqslant My + e_l \quad l = 1, \ldots, L \tag{6.7}$$

$$e_l \leqslant Oy \quad l = 1, \ldots, L \tag{6.8}$$

$$c^T y + q_l^T x_l + h_l^T z_l + f_l^T e_l - \Omega \leqslant V u_l \quad l = 1, \ldots, L \tag{6.9}$$

$$y \in Y \subseteq \{0, 1\}^{|P|}, \quad u \in U \subseteq \{0, 1\}^L \tag{6.10}$$

$$x \in R_+^{|A| \times |K| \times L}, \quad z \in R_+^{|C| \times |K| \times L}, \quad e \in R_+^{|P| \times L} \tag{6.11}$$

Objective function (6.1) is related to the expected total cost or the sum of the first-stage and the expected second-stage costs. Objective function (6.2) is related to the variance of second-stage costs or the variance of total cost. Objective function (6.3) is related to the financial risk. Constraint (6.8) enforces the capacity expansion limit for each processing facility, if it is built. According to constraint (6.9), if the total cost for a scenario is greater than a certain budget Ω, then the binary variable associated with that particular scenario will be equal to 1, which increases the financial risk (6.3) by the corresponding probability. Otherwise, if the total cost for a scenario is smaller than Ω, then the binary variable associated with this scenario will be equal to 0, because we intend to minimize (6.3). Therefore, this situation will not change the value of financial risk.

Using a multi-objective model in an SC context is not an artificial one, as we know from "portfolio optimization" that it is not possible to give any monetary value to risk, which leads to the concept of "efficient frontier" defined by Markowitz (1952, 1959). We may treat volatility and expected return as proxies for risk and reward. Out of the entire universe of possible portfolios, certain ones will optimally balance risk and reward. These comprise what Markowitz called an efficient frontier of portfolios. This frontier is a curve in the "risk vs expected return" space. If it was possible to replace risk by reward/loss, then we would have had only a single dot in this space representing the optimal portfolio. But we know from finance theory that it is not the case; having said that it is possible only if one can clearly define his/her utility function (a relation between risk and return).

Now, the question is how to define the firm's utility function in an SC. We will show in one SC problem (Section 5) that the relationship between cost, variance and risk is not clear, and that decision-makers need support in determining what that utility function should be—they need to see the effect of weighting the criteria differently before they can make their decision, and obviously, setting a single function does not guarantee us a Pareto-optimal solution. That is why we are adopting a multi-objective approach to this SC problem.

4. Goal attainment technique

We use the goal attainment technique, which is a variation of goal programming technique, to solve the multi-objective problem. Goal attainment method is one of the multi-objective techniques with priori articulation of preference information given. In this method, the preferred solution is sensitive to the goal vector and the weighting vector given by the decision-maker; the same as the goal programming technique.

Goal attainment method has fewer variables to work with and is a one-stage method, unlike interactive multi-objective techniques, so it will be computationally faster. Therefore, in terms of computational time, it is one of the best techniques to solve our SC problem, whose deterministic equivalent form is a large-scale mixed-integer nonlinear program. We successfully applied the goal attainment technique in solving a number of real-world multi-objective problems arising in reliability optimization (Azaron et al., 2007a), project management (Azaron et al., 2007b) and production systems (Azaron et al., 2006), and it is for the first time that we use this technique to solve a multi-objective SC design problem and to generate its Pareto-optimal solutions.

This method requires setting up a goal and weight, b_j and g_j ($g_j \geqslant 0$) for $j=1, 2, 3$, for the three mentioned objective functions. The g_j relates the relative under-attainment of the b_j. For under-attainment of the goals, a smaller g_j is associated with the more important objectives. When g_j approaches 0, then the associated objective function should be fully satisfied or the corresponding objective function value should be less than or equal to its goal b_j. g_j, $j=1, 2, 3$, are generally normalized so that $\sum_{j=1}^{3} g_j = 1$. The proper goal attainment formulation for our problem is

$$\text{Min} \quad w$$

$$\text{s.t.} \tag{7.1}$$

$$c^T y + \sum_{l=1}^{L} p_l (q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l) - g_1 w \leqslant b_1 \tag{7.2}$$

$$\sum_{l=1}^{L} p_l \left(q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l - \sum_{l=1}^{L} p_l (q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l) \right)^2 - g_2 w \leqslant b_2 \tag{7.3}$$

$$\sum_{l=1}^{L} p_l u_l - g_3 w \leqslant b_3 \tag{7.4}$$

$$Bx_l = 0 \quad l = 1, \ldots, L \tag{7.5}$$

$$Dx_l + z_l \geqslant d_l \quad l = 1, \ldots, L \tag{7.6}$$

$$Sx_l \leqslant s_l \quad l = 1, \ldots, L \tag{7.7}$$

$$Rx_l \leqslant My + e_l \quad l = 1, \ldots, L \tag{7.8}$$

$$e_l \leqslant Oy \quad l = 1, \ldots, L \tag{7.9}$$

$$c^T y + q_l^T x_l + h_l^T z_l + f_l^T e_l - \Omega \leqslant V u_l \quad l = 1, \ldots, L \tag{7.10}$$

$$y \in Y \subseteq \{0,1\}^{|P|}, \quad u \in U \subseteq \{0,1\}^L \tag{7.11}$$

$$x \in R_+^{|A| \times |K| \times L}, \quad z \in R_+^{|C| \times |K| \times L}, \quad \mathrm{e} \in R_+^{|P| \times L} \tag{7.12}$$

Lemma 1. If $(y^*, u^*, x^*, z^*, \mathrm{e}^*)$ is Pareto-optimal, then there exists a b, g pair such that $(y^*, u^*, x^*, z^*, \mathrm{e}^*)$ is an optimal solution to the optimization problem (7).

The optimal solution using this formulation is sensitive to b and g. Depending on the values for b, it is possible that g does not appreciably influence the optimal solution. Instead, the optimal solution can be determined by the nearest Pareto-optimal solution from b. This might require that g be varied parametrically to generate a set of Pareto-optimal solutions. In the next section, we consider several pairs of b and g to generate different Pareto-optimal solutions.

The mixed-integer nonlinear programming problem (7) has $(|A| \times |K|+|C| \times |K|+|P|) \times L+1$ continuous decision variables, excluding slack variables, $|P|+L$ binary variables and $(|A| \times |K|+2 \times |C| \times |K|+|P| \times |K|+|S| \times |K|+3 \times |P|+1) \times L+3$ constraints.

In case the random data vector $\xi = (q, h, f, d, s)$ follows a known continuous joint distribution, one should resort to a sampling procedure, for example Santoso et al. (2005), to solve the proposed model. In the sampling strategy, a random sample $\xi^1, \xi^2, \ldots, \xi^Q$ of Q realizations of the random vector ξ is generated. Then, considering $L = Q \times 2^{|S|}$ in this case, the proper goal attainment formulation can be approximated as

$$\text{Min} \quad w$$

$$\text{s.t.} \tag{8.1}$$

$$c^T y + \frac{1}{L} \sum_{l=1}^{L} (q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l) - g_1 w \leqslant b_1 \tag{8.2}$$

$$\frac{1}{L-1} \sum_{l=1}^{L} \left(q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l - \frac{1}{L} \sum_{l=1}^{L} (q_l^T x_l + h_l^T z_l + f_l^T \mathrm{e}_l) \right)^2 - g_2 w \leqslant b_2 \tag{8.3}$$

$$\frac{1}{L} \sum_{l=1}^{L} u_l - g_3 w \leqslant b_3 \tag{8.4}$$

$$Bx_l = 0 \quad l = 1, \ldots, L \tag{8.5}$$

$$Dx_l + z_l \leqslant d_l \quad l = 1, \ldots, L \tag{8.6}$$

$$Sx_l \leqslant s_l \quad l = 1, \ldots, L \tag{8.7}$$

$$Rx_l \leqslant My + \mathrm{e}_l \quad l = 1, \ldots, L \tag{8.8}$$

$$e_l \leqslant Oy \quad l = 1, \ldots, L \tag{8.9}$$

$$c^T y + q_l^T x_l + h_l^T z_l + f_l^T e_l - \Omega \leqslant V u_l \quad l = 1, \ldots, L \tag{8.10}$$

$$y \in Y \subseteq \{0,1\}^{|P|}, \; u \in U \subseteq \{0,1\}^L \tag{8.11}$$

$$x \in R_+^{|A| \times |K| \times L}, \quad z \in R_+^{|C| \times |K| \times L}, \quad \mathrm{e} \in R_+^{|P| \times L} \tag{8.12}$$

where the expected total cost, the variance of the total cost and financial risk are approximated by (8.2), (8.3) and (8.4), respectively.

Let v_Q and $\hat{y}_Q$ be the optimal value and the optimal solution vector, respectively, of the approximated problem (8). Clearly, for a particular realization $\xi^1, \xi^2, \ldots, \xi^Q$ of the random vector, problem (8) is deterministic. It is possible to show that under mild regularity conditions, as the sample size Q increases, v_Q and $\hat{y}_Q$ converge with probability one to their true counterparts, see Kleywegt et al. (2001). The performance of the sampling strategy is beyond the scope of this paper and can be considered as a direction for future research in this area.

5. Numerical experiments

Consider the SC network design problem depicted in Fig. 1 (modified from Yu and Li, 2000). A wine company is willing to design its SC. This company owns three customer centers located in three different cities L, M and N. Uniform-quality wine in bulk (raw material) is supplied from four wineries located in A, B, C and D. There are four possible locations E, F, G and H for building the bottling plants.

For simplicity, without considering other market behaviors (e.g. novel promotion, marketing strategies of competitors and market-share effect in different markets), each market demand merely depends on the local economic conditions. Assume that the future economy is either boom, good, fair or poor, i.e. four situations with associated probabilities of .13, .25, .45 or .17, respectively. The unit production costs and market demands under each scenario are shown in Table 1.

The supplies, transportation costs and shortage costs are considered as deterministic parameters. In all, 475,000, 425,000, 500,000 and 450,000 are investment costs for building each bottling plant E, F, G and H, respectively. In all, 65.6, 155.5, 64.3, 175.3, 62, 150.5, 59.1, 175.2, 84, 174.5, 87.5, 208.9, 110.5, 100.5, 109, 97.8 are the unit costs of transporting bulk wine from each winery A, B, C and D to each bottling plant E, F, G and H, respectively. The unit costs of transporting bottled wine from each bottling plant E, F, G and H to each distribution center L, M, and N, respectively, are 200.5, 300.5, 699.5, 693, 533, 362, 163.8, 307, 594.8, 625, 613.6, 335.5. The unit shortage costs at each distribution center L, M and N are 10,000, 13,000 and 12,000, respectively. In all, 375, 187, 250 and 150 are the maximum amount of bulk wine that can be shipped from each winery A, B, C and D, respectively, if it is reliable. In all, 315, 260, 340 and 280 are the capacities of each bottling plant E, F, G and H, respectively, if it is built.

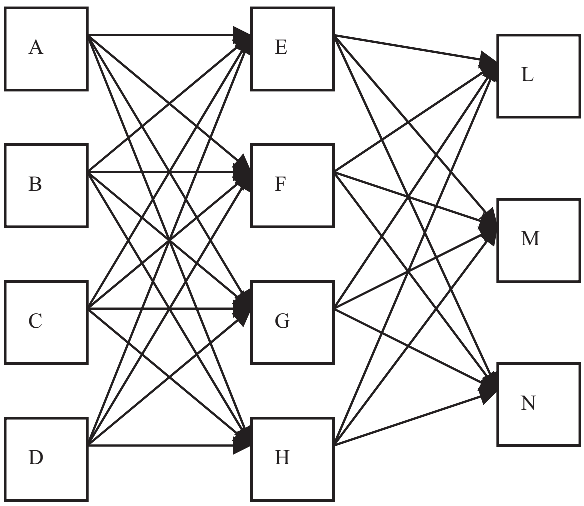

Fig. 1. The supply chain design problem of the wine company.

We also have the option of expanding the capacity of bottling plant F, if it is built. In all, 100, 80, 60 and 50 are the unit capacity expansion costs, when the future economy is boom, good, fair or poor, respectively. In addition, we cannot expand the capacity of this plant more than 40 units in any situation. Moreover, winery D is an unreliable supplier and may lose its ability to supply the bottling plants. The reliability of this winery is estimated as .9. So, the total number of scenarios for this SC design problem is equal to $4 \times 2 = 8$.

Clearly, this system produces one type of product and the processing facilities include only manufacturing centers M. So, the per-unit processing requirements r_j^k are all equal to 1 and $W = \phi$.

This problem attempts to minimize the expected total cost, the variance of the total cost and the financial risk in a multi-objective scheme while making the following determinations:

(a) Which of the bottling plants to build (first-stage variables)?
(b) Amount of bulk wine to be bottled in each bottling plant, amount of bulk wine and bottled wine to be transported among the entities of the network, amount of shortfall at each customer center and finally amount of expansion of the capacity of bottling plant F, if it is built (second-stage variables)?

We use goal attainment formulation (7) to solve this multi-objective SC design problem. The mathematical model has 12 binary variables, 257 continuous decision variables and 407 constraints.

Table 1
Characteristics of the problem

Future economy	Demands			Unit production costs				Probabilities
	L	M	N	E	F	G	H	
Boom	400	188	200	755	650	700	800	.13
Good	350	161	185	700	600	650	750	.25
Fair	280	150	160	675	580	620	720	.45
Poor	240	143	130	650	570	600	700	.17

Table 2
Pareto-optimal solutions

No.	g_1	g_2	g_3	b_1	b_2	b_3	Ω	E	F	G	H	Mean	Variance	Risk	Time
1	E−6	.99999	E−8	185E4	E9	.1	218E4	1	1	1	0	2,007,034	109,871E5	.13	2:21
2	E−4	.99989	E−8	185E4	E8	.1	218E4	1	1	1	0	2,086,941	246,917E4	.13	2:49
3	.01	.98999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,184,688	133,134E3	.397	2:52
4	.01	.98999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,184,467	134,974E3	.13	3:11
5	.1	.89999	E−9	185E4	E9	.1	221E4	1	1	0	1	2,221,661	912,376E3	.13	4:15
6	.1	.89999	E−8	185E4	E9	.1	221E4	1	1	1	0	2,150,000	715,080E3	.13	0:46
7	.1	.89999	E−8	185E4	E8	.1	221E4	1	1	1	0	2,188,285	103,045E3	.13	0:48
8	.1	.89999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,186,120	127,592E3	.4	2:21
9	.1	.89999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,184,467	134,974E3	.13	3:51
10	.1	.89999	E−7	185E4	E8	.1	218E4	1	1	1	0	2,192,098	105,670E3	.73	1:01
11	.1	.89999	E−7	185E4	E9	.1	218E4	1	1	1	0	2,132,511	100,254E4	.13	5:12
12	.25	.74999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,186,493	125,924E3	.442	2:30
13	.25	.74999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,184,503	137,060E3	.13	4:01
14	.25	.74999	E−8	185E4	E9	.1	218E4	1	1	1	0	2,184,596	146,415E3	.13	3:51
15	.5	.49999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,187,987	121,750E3	.535	2:26
16	.5	.49999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,184,582	134,462E3	.155	0:41
17	.75	.24999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,188,794	115,646E3	.622	1:48
18	.75	.24999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,184,893	133,072E3	.217	1:59
19	.9	.09999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,192,212	106,300E3	.73	1:54
20	.9	.09999	E−9	185E4	E8	.1	218E4	1	1	1	0	2,185,957	128,321E3	.38	5:21
21	.9	.09999	E−9	185E4	E9	.1	218E4	1	1	1	0	2,184,470	135,165E3	.13	2:48
22	.9	.09999	E−9	185E4	E10	.1	218E4	0	1	1	1	2,192,825	110,321E4	.13	3:55
23	.99	.00999	E−8	185E4	E8	.1	218E4	1	1	1	0	2,194,198	100,677E3	.777	1:23
24	.99	.00999	E−8	185E4	E9	.1	218E4	1	1	1	0	2,184,469	135,041E3	.13	1:10
25	.9999	E−4	E−8	185E4	E8	.1	218E4	1	1	1	0	2,192,571	100,007E3	.777	2:51
26	.99999	E−6	E−9	220E4	E2	.1	222E4	1	0	0	0	1022E5	0	1	1:16
27	9E−4	.9991	E−8	185E4	E8	.1	220E4	1	1	1	0	2,159,937	444,064E3	.13	2:03
28	E−5	.99999	E−9	185E4	E8	.1	220E4	1	1	1	0	2,007,034	109,871E5	.13	1:56
29	E−8	.99999	E−8	185E4	E9	.1	220E4	0	1	1	0	1,853,385	310,218E6	.13	2:37
30	9E−6	.99999	E−6	200E4	E8	.1	222E4	1	1	1	0	2,046,929	531,427E4	.013	0:55
31	9E−6	.99999	E−6	185E4	E9	.1	222E4	1	1	1	0	2,007,034	109,871E5	.013	2:32
32	E−6	.99999	E−6	185E4	E10	.1	221E4	1	1	1	0	2,007,034	109,871E5	.13	2:16
33	E−7	.99999	E−7	185E4	E10	.1	221E4	0	1	1	0	1,878,088	290,880E6	.13	2:18
34	E−7	.99999	E−9	185E4	E10	.1	210E4	1	1	1	0	2,104,936	232,243E4	.13	1:48
35	.099	.9	.001	185E4	E7	.1	220E4	1	1	1	0	2,205,472	132,316E2	1	1:18
36	.099	.9	.001	185E4	E9	.1	220E4	1	1	1	0	2,132,510	100,257E4	.13	3:10
37	.08999	.91	3E−7	185E4	E7	.1	220E4	1	1	1	0	2,205,337	135,929E2	1	1:57
38	.09	.90999	2E−7	185E4	E7	.1	220E4	1	1	1	0	2,206,307	136,992E2	.913	2:14
39	.005	.99499	E−6	185E4	E8	.1	220E4	1	1	1	0	2,181,185	165,906E3	.13	3:02
40	.009	.99	.001	185E4	E8	.1	220E4	1	1	1	0	2,184,267	136,769E3	.13	2:48
41	.009	.99	.001	185E4	E9	.1	220E4	1	1	1	0	2,131,358	103,095E4	.13	2:12
42	.49999	.5	5E−7	185E4	E7	.1	220E4	1	1	1	0	2,209,452	108,300E2	.93	1:49
43	.89999	.1	5E−7	185E4	E7	.1	220E4	1	1	1	0	2,222,635	970,609E1	.983	6:06
44	.89999	.1	E−9	185E4	E10	.1	221E4	0	1	1	1	2,215,469	851,956E3	.13	2:30
45	.79999	.2	2E−6	185E4	E7	.1	220E4	1	1	1	0	2,209,999	930,143E1	1	3:51
46	.94999	.05	5E−6	185E4	E6	.1	220E4	1	1	1	0	2,215,476	101,924E1	1	4:23
47	.98999	.01	E−5	185E4	E6	.1	220E4	1	1	1	0	2,215,543	100,369E1	1	1:26
48	.99899	.001	E−5	215E4	E6	.1	220E4	1	1	1	0	2,239,909	251,188	1	1:46
49	.9989	.001	E−4	215E4	E5	.1	220E4	1	1	1	0	2,221,516	100,072	1	3:26
50	.99989	E−4	E−6	215E4	E5	.1	220E4	1	0	1	1	2,279,960	61,998	1	3:47
51	.99998	E−6	E−5	220E4	E4	.1	220E4	1	0	1	1	2,278,040	2229	1	4:31
52	.99999	E−6	E−6	220E4	E2	.1	220E4	1	1	1	1	2,689,734	0	1	3:24
53	.99998	E−6	E−5	220E4	E4	.1	222E4	1	1	1	0	2,225,870	4104	1	3:48
54	.99999	E−6	E−6	220E4	E2	.1	222E4	1	1	1	0	2,224,348	57	1	4:39
55	.99989	E−4	E−6	200E4	E6	.1	225E4	1	1	1	0	2,215,559	10,0002E1	0	1:29

Then, we use LINGO 10 to solve the problem on a PC Pentium IV 2.1-GHz processor and to generate different Pareto-optimal solutions. Table 2 shows 55 generated Pareto-optimal configurations (1 means the bottling plant is built and 0 otherwise), the values of the expected total cost, the variance of the total cost, the financial risk and the computational times (mm:ss).

To generate the Pareto-optimal solutions, b, g and Ω are varied manually. When one of the parameters is varied and the others are fixed, changing the output shows its sensitivity with respect to that parameter. According to the obtained absolute minimum values for the expected total cost, the variance of the total cost and the financial risk, by solving the associated single objective problems, b_3 is fixed at .1, b_2 is varied from 100 to 10,000,000,000, b_1 is varied from 1,850,000 (close to the absolute minimum expected total cost) to 2,200,000 (close to the absolute minimum expected total cost plus three times of the maximum goal for the standard deviation of the total cost), g_1 is varied from .00000001 to .99999, g_2 is varied from .000001 to .99999, g_3 is varied from .000000001 to .001 and Ω is varied from 2,100,000 to 2,250,000.

As mentioned, the weights relate the relative under-attainment of the goals and a smaller g_j is associated with the more important objectives. For each goal vector b, the corresponding weight vector g can be obtained using Saaty's method of pairwise comparisons (Hwang and Yoon, 1981). For each pair of b and g, the solution is Pareto-optimal. If we are not satisfied with any Pareto-optimal solution or there are much differences between some of the obtained objective function values and the corresponding goals, the g vector should be modified. For example, if the obtained financial risk value is much greater than .1, g_3 should be decreased (e.g. 10 times) and both g_1 and g_2 should be increased from their earlier values, appropriately, in which the summation of g_j remains unchanged. This process continues with several different pairs of b and g, and several Pareto-optimal solutions are generated that can be used for decision-making.

For example, the first set of g in Table 2 (instance 1) implies that one dollar deviation of the expected total cost from 1,850,000 is about 1,000,000 times as important as one unit deviation of the variance of total cost from 1,000,000,000 and the same important as .01 deviation of the financial risk from .1. In this instance, the goal and weight for the expected total cost and weight for financial risk are relatively low, which causes the solution to have low expected total cost and risk values. In instance 26, we have a high budget Ω, and a low financial risk weight g_3, which seems to indicate that the solution should have a low risk value, but the goal for variance, b_2, is very low, with a low weight g_2, and in the solution this overrides risk, and the variance is minimized.

The lowest expected cost is from instance 29, with a value of 1,853,385. This has relatively low risk, but high variance. The optimal variance is obtained in two separate instances (26 and 52), but these give widely different values for cost (2.69E6 or 1.02E8). The optimal financial risk is obtained in instance 55, with a cost of 2.22E6, a variance of 1.00E6 and a budget of 2.25E6. So, the expected cost ranges from 1.85E6 to 1.02E8. If we aim for a financial risk of .13, within the budget of 2.20E6, then the variance can still range from 1.37E8 to 3.10E11, and the cost ranges from 1.85E6 to 2.18E6.

In order to make sense of this, and to arrive at an appropriate solution, the decision-maker needs to see this range of outcomes, to be able to trade-off one criteria against the other in terms of the results. So, by solving this SC design problem, it is concluded that the relationship between cost, variance and risk is not clear and it is not possible to easily define a utility function (a relation between risk and return). That is why we are adopting a multi-objective approach to this SC problem.

According to the numerical results, increasing goal for the variance and also decreasing weight for the expected total cost cause the financial risk to be decreased. Moreover, increasing goal for the variance causes both the expected total cost and the financial risk to be decreased. Also, increasing goal for the expected total cost causes the variance of the total cost to be decreased. So, it seems by increasing goal for any of the objectives, we give more space for other objectives to be improved. It is also concluded that there are some positive correlations between the expected cost and the financial risk.

It is also seen that in most instances we have to build the bottling plant in F, which is expandable, and then expand it when we either face boom economy or reliable suppliers. For example, in instance 5, where the bottling plants are built in E, F and H, the capacity of F should be expanded 40, 31.4 and 40 units, when the economy is boom and D is reliable (scenario 1), the economy is fair and D is reliable (scenario 3) and the economy is boom and D is not reliable (scenario 5), respectively.

In order to evaluate the performance of the proposed method in solving larger cases, we consider another problem with 10 suppliers, 10 plants and 10 customer centers with the same number of unreliable suppliers, expandable plants and scenarios as the earlier case. In this case, the unit production costs, market demands and capacity expansion costs are uncertain, while the other parameters are supposed to be certain following the similar pattern of the earlier case. Then, it is solved on the same computer and 10 new Pareto-optimal solutions are generated. The mean computational time for this medium size case is equal to 14:18, while the mean computational time in 55 generated Pareto-optimal solutions of the earlier small size case was equal to 2:41.

In order to show the sensitivity of the numerical solution with respect to the number of scenarios, we also conduct two more experiments with 4 and 16 scenarios. In the smaller case with 4 scenarios, it is assumed that all suppliers are reliable. In the bigger case with 16 scenarios, it is assumed that the future economy will have eight situations, instead of four in the original problem, and one of the suppliers is unreliable. In both cases, the uncertain parameters are the unit production costs, capacity expansion costs and market demands, but with different values for each scenario, while the other parameters are all certain following the same pattern of the original problem. Then, 10 new Pareto-optimal solutions for each of the new problems are generated. The mean computational time for the smallest size case with 4 scenarios and the largest size case with 16 scenarios are equal to 0:57 and 6:46, respectively, comparable to 2:41 in the original case with 8 scenarios. So, it seems the proposed model can at least solve the medium size cases with limited number of scenarios in acceptable CPU time.

6. Conclusion

Determining the optimal SC configuration is a difficult problem since a lot of factors and objectives must be taken into account when designing the network under uncertainty. The proposed model in this paper accounts for the minimization of the expected total cost, the variance of the total cost and the financial risk in a multi-objective scheme to design a robust SC network. Therefore, this approach seems to be a good way of capturing the high complexity of the problem.

According to the numerical experiments, considering risk directly affects the design of the SC networks under uncertainty. By using this methodology, the trade-off between the expected total cost and risk terms can be obtained. The interaction between the design objectives has been shown. This way of generating different possible configurations will help the decision-maker determine the best design among all generated Pareto-optimal solutions based on his/her preferences.

We used the goal attainment technique, which is a variation of the goal programming technique, to solve the multi-objective SC design problem and to generate the Pareto-optimal solutions. Goal attainment method is one of the multi-objective techniques with priori articulation of preference information given. This method has the same disadvantages as those of goal programming, namely, the preferred solution is sensitive to the goal vector and the weighting vector given by the decision-maker. However, the goal attainment method has fewer variables to work with, and therefore is one of the best methods to solve this large-scale mixed-integer nonlinear programming problem, in terms of computational time. In this regard, using a meta-heuristic approach such as genetic algorithm or simulated annealing in solving large-scale cases would be suitable.

An interactive multi-objective technique such as SWT or STEM can also be used to solve the multi-objective problem (6). The main disadvantage of the interactive approaches is that the number of variables and also the number of stages which we need to solve the associated single-objective optimization problems to get the final solution are much more than the goal attainment technique. So, in terms of computational time, the goal attainment technique is much better than any interactive multi-objective technique for solving the SC design problem proposed in this paper.

The proposed model can also be extended to the multi-period case considering the associated production, transportation and especially inventory-holding costs at different time intervals. In this case, the suppliers' lifetimes can also be considered as independent random variables with time-dependent continuous or discrete distributions such as exponential or geometric. Then, we will need to develop a proper stochastic optimal control model to solve the resulting problem.

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