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Multi-objective stochastic multi-site supply chain planning under demand uncertainty considering downside risk

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ABSTRACT

In this paper, a multi-period, multi-product, multi-site, multi-stage supply chain planning problem under demand uncertainty is considered. The problem is formulated as a two-stage stochastic linear programming model. In order to generate a robust supply chain planning solution, the downside risk is incorporated into the objective functions of the stochastic programming model as a risk measure. So, the proposed multi-objective stochastic model aims to simultaneously minimize the expected total cost, to minimize the lost customer demand level and to minimize the downside risk. The proposed solution approach yields to a front of Pareto optimal robust solutions. A fuzzy decision making approach is applied to select the most preferred solution among the Pareto optimal robust solutions. A numerical example from a real textile and apparel industry is addressed in order to illustrate the robustness of the supply chain network planning solutions and the effectiveness of the solution approach.

1. Introduction

In the context of multi-site supply chain management, integrated approaches for production and transportation activities planning need to be developed. Such approaches should coordinate all the production resources of the different plants starting from the procurement and storage of raw materials and ending with the shipping of finished products to the customer. The supply chain planning problem can be classified following the time horizon into three major categories: strategic, tactical, and operational (Fox, Barbuceanu, & Teigen, 2000). The focus of this work is to examine the tactical level of the supply chain planning. The optimization of cost and profit are the most commonly considered objectives in the literature of supply chain planning problem. Besides, the customer demand satisfaction level is another important criterion which reflects the performance of the supply chain (Wang, 2001). In fact, a low customer demand satisfaction level could lead to lost sales, high costs and unsatisfied customers. However, the minimization of the supply chain related costs and the maximization of customer demand satisfaction are contradictory objectives.

A lot of attempts have been made in the literature to model and to optimize multi-site supply chain planning problems. Most of these works rely on deterministic approaches that assume that all parameters of the optimization model are known with certainty. One can refer to Moon, Seo, Yun, and Gen (2006), Ryu and Pistikopoulos (2007), Lin and Chen (2007), Verderame and Floudas (2009), Shah and Ierapetritou (2012), Chen (2012) and Felfel, Ayadi, and Masmoudi (2014). In practice, real production planning problems are characterized by several sources of uncertainty such as market demand, sales price and unit cost. Different approaches have been developed in the literature to cope with uncertainty. According to Sahinidis (2004), they can be classified into four categories: robust optimization approach, fuzzy programming approach, stochastic programming approach and stochastic dynamic programming approach. Among the developed stochastic programming approaches, the two-stage stochastic programming technique (Birge & Louveaux, 1997; Dantzig, 1955) has proved its efficiency in solving real-world planning problems under uncertainty (Awudu & Zhang, 2013; Gupta & Maranas, 2003; Leung, Wu, & Lai, 2005). In this approach, the decision variables are partitioned into two sets. The first-stage decisions correspond to variables that need to be taken "here-and-now" prior to revelation of uncertainty. Subsequently, the second-stage decisions are made in "wait-and-see" mode after the revelation of the random events. Therefore, the objective function is calculated based on the first-stage variables and the expected second-stage recourse variables. Gupta and Maranas (2003) studied a multi-product multi-site supply chain planning problem under demand uncertainty using a two-stage stochastic programming approach. The supply chain decisions are divided into two categories: manufacturing decisions

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and logistics decisions. The manufacturing decisions are taken "here and now" before the realization of uncertainty while the logistics decisions are postponed in a "wait and see" mode. Leung et al. (2005) addressed a multi-site aggregate production planning problem under an uncertain environment based on a two-stage stochastic programming technique. The first-stage decisions include the amount of manufactured product in regular-time and overtime, volume of subcontracted products and number of required workers, hired workers and laid-off workers. Decisions such as inventory level of products and amount of under-fulfillment products are considered as second-stage decisions. Awudu and Zhang (2013) developed a two-stage stochastic programming model for a production planning problem in a biofuel supply chain under uncertainty. Amount of products to be produced and amount of raw materials to be purchased and consumed are considered as the first-stage decisions. Decisions such as backlog, lost sales and sold products quantity are considered as second stage decisions. In stochastic programming approach, the expected economic objective is optimized and the average value of the economic objective for all scenarios is improved. However, the stochastic programming technique does not allow to control the unfavorable outcomes and the decision makers are assumed to be risk-neutral in this approach. Felfel, Ayadi, and Masmoudi (2015a) proposed a novel two-stage stochastic model to deal with a multi-site production and transportation supply chain planning problem under demand uncertainty. The robustness of the supply chain planning solutions was then evaluated by means of risk and statistical measures. The results show that solutions robustness should be improved by considering risk management models.

In practice, the decision maker should define a suitable planning while managing the risk of having unfavorable outcomes. This can be considered by including a risk metric associated with the economic objective distribution in the stochastic model. This approach leads to a multi-objective optimization problem where the economic objective and the risk measure are two objective functions to be optimized. The variance is one of the metrics commonly used in the literature to manage the risk and to quantify the variability of the stochastic solution (Leung, Tsang, Ng, & Wu, 2007; Mirzapour Al-e-hashem, Baboli, Sadjadi, & Aryanezhad, 2011). However, the risk management approach based on the variance measure introduces nonlinearities into the mathematical model. Finding the optimal solution for these non-linear large scaled optimization problems becomes very difficult. Moreover, You, Wassick, and Grossmann (2009) demonstrated that managing the variance is not an effective tool to reduce the risk of having high costs. Indeed, the variance management model can give lower variance values but usually reduces the probability of obtaining lower costs and thus increases the risk of high costs. They demonstrated also that managing the financial risk and downside risk are more effective in reducing the probability of high cost than managing variance and variability. Besides, the downside risk outperforms the probabilistic financial risk because it avoids the use of binary variables which will make the size of the model very large with the increasing of scenarios number.

In multi-objective optimization problems, there is more than one objective function which conflict with each other. Hence, there is no solution that optimizes all the objective functions simultaneously. Instead, we are interested in a front of Pareto optimal solutions which represents the trade-off between the different objectives rather than a single solution. So, the task of the decision maker consists in obtaining the front of Pareto optimal solutions and selecting the most comprised solution according to his preferences. Previous work in supply chain optimization problem focused only on generating the front of Pareto optimal solutions and did not address the choice of the most preferred solution (Azaron, Brown, Tarim, & Modarres, 2008; Ben Yahia, Cheikhrouhou, Ayadi, & Masmoudi, 2013; Fahimnia, Farahani, Marian, & Luong, 2013; Franca, Jones, Richards, & Carlson, 2010; Guillen, Mele, Bagajewicz, Espuna, & Puigjaner, 2005; Guo, Wong, Li, & Ren, 2013; Mirzapour Al-e-hashem et al., 2011). Felfel, Ayadi, and Masmoudi (2015b) addressed a multi-objective multi-site supply network planning problem accounting for the minimization of the total cost and the maximization of the product quality level. A lexicographic minimax method is used in order to find a fair solution from the front of Pareto that satisfies equitably the considered objective functions. The main critic of this work is that the authors did not take into account uncertainty in the supply chain planning process. In addition, the lexicographic minimax method generates a fair solution but does not allow to select a solution from the set of Pareto optimal solutions with respect to specific preferences. Although many works in the literature focused on multi-objective supply chain planning problem, to the best of the authors' knowledge, no one of them has addressed the choice of the best solution from the front of Pareto optimal solutions according to the preferences of the decision maker. The fuzzy based decision making methods are widely applied to choose the most efficient solution according to the specific preference of the decision maker in multi-objective electric power system such as congestion management problem in power system (Esmaili, Ali, & Amjady, 2009; Esmaili, Amjady, & Ali, 2011) and electricity market clearing problem (Aghaei, Amjady, & Shayanfar, 2011; Aghaei, Shayanfar, & Amjady, 2010; Amjady, Aghaei, & Shayanfar, 2009). Ben Yahia, Ayadi, and Masmoudi (2015) proposed a bi-level fuzzy-based negotiation approach to model the collaborative planning between many partners of a decentralized manufacturing supply chain. A bi-objective planning model was developed and solved using a genetic algorithm to generate the front of Pareto solution. The obtained front of Pareto was used for negotiation to make the adequate decision by means of the proposed fuzzy logic approach.

The main objective of this paper is to treat a tactical multi-objective, multi-product, multi-period, multi-stage, multi-site supply chain production and transportation planning problem under demand uncertainty. Solutions should be robust and should satisfy conflicting objectives considering decision makers preferences. The rest of the paper is organized as follows. The problem description is presented in Section 2. Section 3 introduces the mathematical formulation of the considered problem. The proposed solution approach is described in Section 4. Section 5 details the application of the developed approach to a real world case from textile and apparel industry as well as the corresponding computational results. Finally, conclusions and future research directions are drawn in Section 6.

2. Problem statement

2.1. Description of the planning problem

The supply chain considered in this paper consists of many production stages. Each stage may include more than one manufacturing plant forming a multi-site supply network structure as illustrated in Fig. 1. A delivery lead time is considered in the transportation of semi-finished and finished products between plants belonging to successive stages and between the last stage plants and customers respectively. The demand of finished products is a random variable. The considered problem aims simultaneously to minimize the expected total cost, to minimize the lost customer demand level, and to minimize the downside risk of incurring in high cost. Despite the fact that the downside risk has been used in other works, to the best of the authors' knowledge, this is the first time that the total cost, the customer demand satisfaction

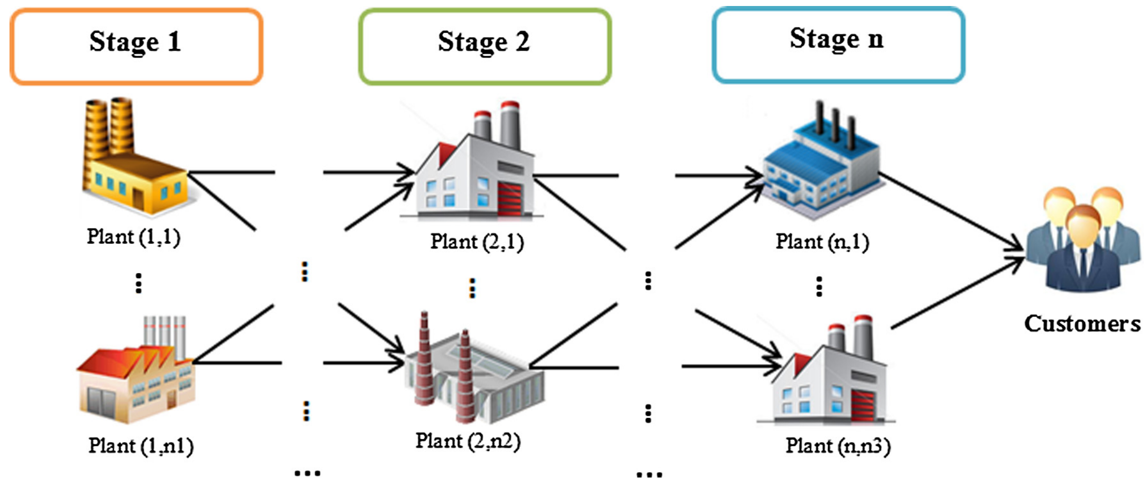

Fig. 1. Multi-site supply chain structure.

level and the downside risk are considered simultaneously in a multi-objective multi-site supply chain planning production and transportation problem to produce a robust planning under uncertainty.

The total cost includes production, inventory, penalty cost on lost demand and transportation costs. Decisions to be made include the production amount at each plant, the inventory amount of finished or semi-finished products, the lost demand quantity and the flow of products between the different plants and customers.

The purpose of this paper is to develop a multi-objective mathematical formulation for this problem and to generate a front of Pareto optimal solutions that represent the trade-off between the different objective functions. Besides, the best Pareto solution should be selected from this front of Pareto according to the preferences of the decision maker.

2.2. Assumptions

It is worth noting that the considered multi-site supply chain planning model is built on the following assumptions:

- The uncertain demand is defined under different scenarios and is assumed to follow a discrete distribution associated with known probability.
- Since the demand is uncertain, shortage of products may occur in each period, which is assumed to be lost demand.
- There is no initial amount of inventory and lost demand.
- A delivery time is considered in the transportation of the products between the different plants of the network and between plants and customers.
- There is no waste of products during the transportation of products. The production yield is not considered in order to simplify the mathematical formulation of the production planning problem."

3. Mathematical formulation

Due to the existence of uncertainty, the deterministic model is not appropriate to find the optimal solution of the supply chain planning problem. Therefore, a two-stage stochastic linear programming model is proposed in order to incorporate demand uncertainty in the decision making process. To solve the stochastic problem, decisions such as the amount of products to be produced at each plant and the amount of products to be transported between upstream and downstream plants are taken "here and now" before the revelation of the uncertainty. Other decision variables such as the inventory size, the amounts of lost customer demand and the flow of finished products to be shipped to the customer are made in a "wait and see" fashion. To formulate the mathematical model, let's consider the following notations:

Sets and indices

L_i	set of direct successor plant of i
ST_j	production stage (j = 1,2,...,N)
i, i'	production plant index (i, i' = 1,2,...,I_j) where i belongs to stage ST_j and plant i' belongs to stage ST_{j+1}
k	product index (k = 1,2,...,K)
t	period index (t = 1,2,...,T)
s	scenario index (s = 1,2,...,S)

Decision variables

P_{ikt}	production amounts of product k at plant i in period t
S^s_{ikt}	inventory level of product k at the end of period t in plant i corresponding to scenario s
JS^s_{ikt}	inventory level of semi-finished product k at the end of period t in plant i corresponding to scenario s
$Dlost^s_{kt}$	lost demand amounts of finished product k for scenario s in period t
$TR_{i \to i',kt}$	amounts of product k transported from plant i to plant i' in period t
$TR^s_{i \to CUS,kt}$	amounts of product k transported from plant i belonging to the last stage ST_N to customer for scenario s in period t
$Q_{i,k}$	amounts of product k received by plant i for scenario s in period t
LD^s	lost demand level for scenario s

Parameters

cp_{ik}	unit production cost for product k at plant i
$ct_{i \to i',k}$	unit transportation cost between plant i and i' for product k
$ct_{i \to CUS,k}$	unit transportation cost between the plant i belonging to the last stage and the customer
cs_{ik}	unit inventory cost of finished or semi-finished product k at plant i
pe_k	penalty cost of product k
$capp_{it}$	production capacity at plant i in period t [min]

$caps_{it}$	storage capacity at plant i in period t
$capt_{i\to i',t}$	transportation capacity at plant i in period t
D^s_{kt}	demand of finished product k for scenario s in period t
b_k	time needed for the production of a product k [min]
DL	delivery time of the transported quantity
yd_i	production yield at plant i
π^s	the occurrence probability of scenario s where $\sum_{s=1}^{S}\pi^s = 1$
MLD	maximum value for lost demand level

Objective functions

$E[Cost]$	expected total cost
$E[LD]$	expected lost demand level
$DRisk_\Omega$	downside risk

Two-stage stochastic programming formulation

$$\begin{aligned}\mathrm{Min}\,E[Cost] = \sum_{s=1}^{S}\pi^s\sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{I}(cs_{ik}(S^s_{ikt}+JS^s_{ikt}) + pe_k Dlost^s_{k,t}\\ + ct_{i\to CUS,k}TR^s_{i\to CUS,kt}) + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{I}(cp_{ik}P_{ikt}\\ + ct_{i\to i',k}TR_{i\to i',kt})\end{aligned} \tag{1}$$

$$\mathrm{Min}\,E[LD] = \sum_{s=1}^{S}\pi^s LD^s = \sum_{s=1}^{S}\pi^s \times 100 \times \frac{\sum_{t=1}^{T}\sum_{k=1}^{K}Dlost^s_{kt}}{\sum_{t=1}^{T}\sum_{k=1}^{K}D^s_{kt}} \tag{2}$$

$$LD^s \leqslant MLD \quad \forall s \tag{3}$$

$$S^s_{ik,t} = S^s_{ik,t-1} + P_{ikt} - \sum_{i'\in L_i}TR_{i\to i',kt}, \quad \forall i\in ST_{j<N},\ \forall k,t,s \tag{4}$$

$$S^s_{ik,t} = S^s_{ik,t-1} + P_{ikt} - TR^s_{i\to CUS,kt}, \quad \forall i\in ST_{j=N}, k,t,s \tag{5}$$

$$JS^s_{ik,t} = JS^s_{ik,t-1} + Q_{ikt} - P_{ikt}, \quad \forall i,k,t,s \tag{6}$$

$$Dlost^s_{kt} = D^s_{kt} - TR^s_{i\to CUS,kt}, \quad \forall k,t,s \tag{7}$$

$$Q_{i'k,t+DL} = \sum_{i'\in L_i}TR_{i\to i',kt}, \quad \forall i,k,t,s \tag{8}$$

$$\sum_{k=1}^{K}\frac{b_k}{yd_i}P_{ikt} \leqslant capp_{it}, \quad \forall i,t \tag{9}$$

$$\sum_{k=1}^{K}S^s_{ikt} + JS^s_{ikt} \leqslant caps_{it}, \quad \forall i,t,s \tag{10}$$

$$\sum_{k=1}^{K}TR_{i\to i',kt} \leqslant captr_{it}, \quad \forall i,t,s \tag{11}$$

$$P_{ikt},\ S^s_{ikt},\ JS^s_{ikt},\ TR_{i\to i',kt},\ TR^s_{i\to CUS,kt},\ Q_{i,k},\ Dlost^s_{kt} \geqslant 0, \quad \forall i,k,t,s \tag{12}$$

The mathematical formulation of the considered problem is detailed in the following lines. It should be noted that each product delivered by a manufacturing plant i to its successor plant i' will be considered by plant i' as a semi-finished product. In this paper, we assume that "product" refers to delivered product and "semi-finished product" refers to received product. "Finished product" denotes the product produced at the last production stage and that should be transported to the customer. The first objective function (1) aims to minimize the expected total cost including production cost, inventory cost, penalty cost on lost demand and transportation cost. The occurrence probability of each scenario is considered in order to calculate the expected total cost. The second objective function (2) aims to minimize the lost demand level. Nevertheless, the mathematical formulation of the second objective function could lead to unrealistic solutions and do not provide an operational policy to avoid a lost demand level. Furthermore, it does not allow to control the variability of the objective function for the different scenarios. In order to overcome these difficulties, we consider a maximum value for the lost demand level (MLD) that must not be exceeded in all the scenarios as detailed in Eq. (3). The value of MLD can be defined by plotting and analyzing the histogram of the lost demand distribution for different MLD levels. This value is then fixed based on the decision maker preferences with respect to his judgment on the acceptable probability of high lost demand. Constraint (4) represents the balance for the inventory level of products in each production stage except the last stage. Constraint (5) provides the balance for inventory in the last production stage. Constraint (6) provides the inventory balance for the semi-finished products. Constraint (7) represents the balance equation for lost products demand. Constraint (8) represents the balance for transportation between the different production plants. The set of constraints (9)–(11) ensure that the production capacity, storage capacity and transportation capacity are respectively respected. Constraint (12) is the non-negativity restriction on the decision variables.

It should be noted that the fixed set up cost is included in the unit production cost (cp). In fact, the unit production cost of a product k (cp_k) in textile and apparel industry is calculated as follows:

$$cp_k = cm \times b_k$$

where cm denotes the cost per minute and b_k is the time needed for the production of a product k. The cm value is calculated as following (Hohenegger & Miller, 2015):

$$cm = \frac{Total\ costs}{Total\ minutes\ available} = \frac{Total\ costs}{Total\ working\ hours \times 60 \times number\ of\ workers}$$

where the total costs include all the factory's costs such as wages, taxes, utilities, rent, insurance, electricity, quality control, maintenance, management and fixed set up costs.

The risk management represents an important issue when developing the stochastic programming model in order to control the risk associated with unfavorable scenarios. The most popular way to manage the risk is to include a risk metric in the stochastic programming model, thus leading to a multi-objective optimization model where the total cost and the risk measure are two objective functions to be optimized in addition to the lost demand level. The downside risk can be formulated as follows:

$$DRisk_\Omega = E[\psi_{s\Omega}] \tag{13}$$

$$\text{where } \psi_{s\Omega} = \begin{pmatrix} Cost^s - \Omega & if\ Cost^s > \Omega \\ 0 & otherwise \end{pmatrix} \quad \forall s \tag{14}$$

$\psi_{s\Omega}$ is a positive variable that measures deviation between the scenario cost value ($Cost^s$) and a target Ω. Downside risk ($DRisk_\Omega$) is defined as the expected value of the positive variable $\psi_{s\Omega}$. In order to integrate this metric within the mathematical model, the set of constraints defined by Eqs. (15)–(17) should be added to the developed model formulated by Eqs. (1)–(12).

$$\min DRisk_\Omega = \sum_{s}\pi^s\psi^s \tag{15}$$

$$\psi^s \geqslant Cost_s - \Omega, \quad \forall s \tag{16}$$

$$\psi^s \geqslant 0, \quad \forall s \tag{17}$$

4. Description of the solution approach

4.1. Generation of the front of Pareto optimal robust solutions

The considered two-stage stochastic programming model includes three objective functions: the minimization of expected total cost, the minimization of the worst case lost demand level and the minimization of downside risk. Since these objective functions are in conflict with each other, we consider a multi-objective planning problem whose solution is a front of Pareto-optimal alternatives representing the trade-off among the different objectives. This means that, in a set of Pareto optimal solutions, we cannot have a better value of one of the objective functions without deteriorating at least the value of another objective function.

The e-constraint method, proposed by Chankong and Haimes (1983), is considered among the most popular method to generate a set of Pareto solutions for multi-objective optimization problems. The e-constraint method has been widely applied in multi-objective supply chain planning problems (Franca et al., 2010; You & Grossmann, 2008). The principle of the e-constraint method consists in considering one of the objective functions as a function to be optimized and the others as constraints with allowable bounds. The multi-objective stochastic programming supply chain planning problem corresponding to the e-constraint method can be expressed as follows:

$$\begin{aligned} &\min\{E[\text{cost}]\} \\ &\text{subject to Eqs. (1), (3)–(12), (15) and (17);} \\ &MLD \leqslant \varepsilon_1^{k_1}; \\ &DRisk_\Omega \leqslant \varepsilon_2^{k_2}; \end{aligned} \tag{18}$$

The set of Pareto-optimal solutions can be obtained by altering the different values of $\varepsilon_1^{k_1}$ and $\varepsilon_2^{k_2}$. It should be noted that each point of the Pareto curve represents a planning configuration. In order to apply the e-constraint method, the ranges of the objective functions MLD and $DRisk_\Omega$ should be calculated. The payoff table (Cohan, 1978) is used in order to compute these ranges. The obtained payoff table for the considered supply chain problem is expressed as follows:

$$\Phi = \begin{bmatrix} E[\text{cost}]^* & MLD & DRisk_\Omega \\ E[\text{cost}] & MLD^* & DRisk_\Omega \\ E[\text{cost}] & MLD & DRisk_\Omega^* \end{bmatrix} \tag{19}$$

where $E[\text{cost}]^*$, MLD^* and $DRisk_\Omega^*$ represent the optimum values of the considered objective functions obtained by minimizing each objective individually. Besides, the values of the other objective functions that correspond to the optimum value of each objective are calculated to fill the remaining payoff table.

The Utopia point (Aghaei et al., 2011) is defined as a specific point in the objective space where all the objective functions are simultaneously at their best values. The Utopia point A^U is expressed as follows:

$$A^U = \left[E[\text{cost}]^U,\ MLD^U,\ DRisk_\Omega^U\right] = \left[E[\text{cost}]^*,\ MLD^*,\ DRisk_\Omega^*\right] \tag{20}$$

On the other hand, the Nadir point is defined as a point where all objective functions are simultaneously at their worst values. The Nadir point A^N is expressed as:

$$A^N = \left[E[\text{cost}]^N,\ MLD^N,\ DRisk_\Omega^N\right] \tag{21}$$

where $E[\text{cost}]^N = \max E[\text{cost}]$, $MLD^N = \max MLD$ and $DRisk_\Omega^N = \max DRisk_\Omega$.

Then, the ranges r_1 and r_2 that correspond to MLD and $DRisk_\Omega$ objectives are calculated based on the Utopia and Nadir points as follows:

$$r_1 = MLD^N - MLD^U \tag{22}$$

$$r_2 = DRisk_\Omega^N - DRisk_\Omega^U \tag{23}$$

After that, the obtained ranges r_1 and r_2 are divided into q_1 and q_2 intervals and the values of $\varepsilon_1^{k_1}$ and $\varepsilon_2^{k_2}$ are calculated as follows:

$$\varepsilon_1^{k_1} = MLD^U + k_1 * \frac{r_1}{q_1}; \quad k_1 = 0, 1, \ldots, q_1. \tag{24}$$

$$\varepsilon_2^{k_2} = DRisk_\Omega^U + k_2 * \frac{r_2}{q_2}; \quad k_2 = 0, 1, \ldots, q_2. \tag{25}$$

The methodology to solve the considered multi-objective problem can be described as follows:

Step 1: Fix a target Ω for calculation of the downside risk.
Step 2: Set the initial values for each objective function $\varepsilon_1^{k_1}$ and $\varepsilon_2^{k_2}$.
Step 3: Solve the proposed model.
Step 4: Repeat Steps 2 and 3 to find the other Pareto-optimal solutions.

It is worth noting that the downside risk can be managed by both varying the values of the target Ω or $\varepsilon_2^{k_2}$. So, if the decision maker is not satisfied with the configuration obtained in Step 4, he can select another value of Ω and then repeat Steps 2–4.

4.2. Fuzzy-based selection of the preferred solution

After generating the set of Pareto optimal solutions, the decision maker needs to choose the best compromised solution following his preferences. In this work, a fuzzy satisfying decision making approach is adopted (Esmaili et al., 2009, 2011). A linear membership function (μ_i) is defined for the objective functions by Eqs. (26) and (27). This membership function measures the optimality degree of the ith objective function of the kth Pareto optimal solution. Eqs. (26) and (27) provide the fuzzification process for the objective functions to be minimized or maximized respectively:

$$\mu_{i\min}^k = \begin{cases} 1 & F_i^k \leqslant F_i^{Min} \\ \frac{F_i^{Max} - F_i^k}{F_i^{Max} - F_i^{Min}} & F_i^{Min} \leqslant F_i^k \leqslant F_i^{Max} \\ 0 & F_i^k \geqslant F_i^{Max} \end{cases} \tag{26}$$

$$\mu_{i\max}^k = \begin{cases} 0 & F_i^k \leqslant F_i^{Min} \\ \frac{F_i^k - F_i^{Min}}{F_i^{Max} - F_i^{Min}} & F_i^{Min} \leqslant F_i^k \leqslant F_i^{Max} \\ 1 & F_i^k \geqslant F_i^{Max} \end{cases} \tag{27}$$

where F_i^{Min} and F_i^{Max} are the minimum and the maximum values of ith objective function. Moreover, F_i^k represents the value of the ith objective function of the kth Pareto optimal solution. For our case study, only Eq. (26) is considered because all the objective functions have to be minimized. The whole membership function (μ^k) of the kth Pareto solution is defined as follows:

$$\mu^k = \frac{\sum_{i=1}^{p} w_i * \mu_{i\min}^k}{\sum_{i=1}^{p} w_i} \tag{28}$$

where w_i represents the weighting factor of the ith objective function and p represents the number of the objective functions (p = 3 in our case). It should be noted that $w_i \geqslant 0$ and $\sum_{i=1}^{p} w_i = 1$. The weighting factors values w_i can be selected based on the importance of the different objective functions. The most preferred solution is the one characterized with the maximum overall membership function μ^k.

5. Computational results

The main purpose of this section is to verify the robustness of the supply chain planning solution and the effectiveness of the proposed strategy using real industrial data from textile and apparel industry. The related input data are described in Section 5.1. Then, the multi-objective model is solved and the obtained results are detailed in Section 5.2. The solution approaches were implemented in LINGO14.0 package program and MS-Excel 2010 with an INTEL(R) Core (TM) and 2 GB RAM.

5.1. Case study

The considered case study is a supply network from the textile and apparel industry in Tunisia wherein the finished product is processed through different production stages. The textile and apparel manufacturing process consists of five main stages: knitting and dyeing, cutting, embroidery, cloth making and packaging. Each production stage includes one plant except cloth making stage which contains four plants establishing a multi-site supply network manufacturing environment as illustrated in Fig. 2. The considered supply network is composed of an internal plant (Textile-International "TE-INTER") and five subcontractors: a dyer and a knitter, an embroiderer and three cloth makers. The TE-INTER company is formed of three manufacturing departments which are cutting, packaging and cloth making. Other activities such as knitting, dyeing and embroidery are subcontracted because of the lack of technical competence and resources. Some cloth making operations can be also subcontracted in order to extend the production capacity and to fulfill all the customer demand. A distribution lead time is taken into account in shipping finished and semi-finished products between the different plants of the network and between plants and customers.

The proposed approach has been evaluated with real data from the considered textile multi-site network. The planning horizon of the planning problem covers two months and the considered period represents one week. In textile and apparel industry, products are usually characterized by volatile demand and short life cycle. On the basis of past sales records and future long-term and short-term contracts, the customer demand can be assumed to be one of four scenarios. The demand of the finished product P1 and P2 under each scenario are reported in Table 1. So, the total number of scenarios for the supply chain planning problem is equal to $4^3 = 64$. The different plant indices are reported in Table 2. Table 3 describes the production capacities of the different plants. Table 4 provides information about production and inventory unit costs. The transportation unit cost and capacity are shown in Table 5. The processing time of the different manufacturing processes is reported in Table 6.

5.2. Results

5.2.1. Sensitivity analysis of the production yield variation

A sensitivity analysis related to production yield is performed in order to evaluate the impact of its variation on solutions optimality. Several tests have been conducted by changing the values of the production yield for different *MLD* levels. The obtained results as well as the variation of the expected total cost are reported in Table 7. It should be noted that the variation of the expected total cost is calculated following Eq. (29)

$$\text{Variation }(\%) = 100\left|\frac{E[Cost]_{(yd_i=1)} - E[Cost]_{(yd_i)}}{E[Cost]_{(yd_i=1)}}\right| \tag{29}$$

Results reported in Table 7 show that the variation of production yield has not a significant influence on solutions optimality, since corresponding variation of the expected total cost does not exceed 0.58% for all the tests. Therefore, the production yield will be fixed at the value 1 in the rest of the paper.

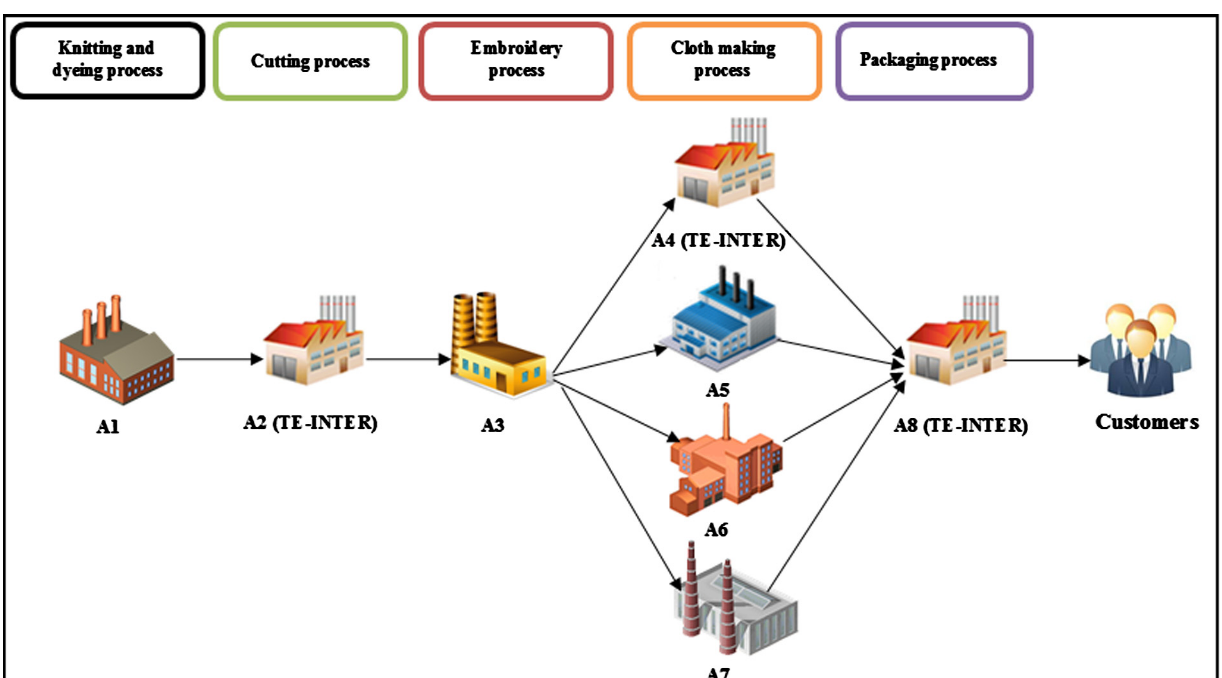

Fig. 2. The textile multi-site supply network structure.

Table 1
Finished product demand.

Scenario	T1 → T5		T6			T7			T8		
	P1	P2	P1	P2	PROB	P1	P2	PROB	P1	P2	PROB
S1	0	0	2650	2430	0.25	3030	2910	0.22	2800	2610	0.27
S2	0	0	2050	1910	0.32	2440	2280	0.25	2340	2170	0.33
S3	0	0	1760	1450	0.25	1660	1550	0.2	2030	1840	0.21
S4	0	0	1040	920	0.18	1310	1240	0.33	1180	1060	0.19

PROB: probability.

Table 2
Plant indices and designation.

Plants	Designation
A1	Knitting and dyeing subcontractor
A2	Cutting (TE-INTER)
A3	Embroidery subcontractor
A4	Cloth making (TE-INTER)
A5	Cloth making subcontractor #1
A6	Cloth making subcontractor #2
A7	Cloth making subcontractor #3
A8	Packaging (TE-INTER)

Table 3
Production capacity [min].

Plants	T1	T2	T3	T4	T5	T6	T7	T8
A1	57,600	54,720	57,600	60,480	54,720	54,720	51,840	54,720
A2	28,800	31,680	34,560	25,920	31,680	23,040	28,800	23,040
A3	43,200	40,320	46,080	37,440	40,320	40,320	43,200	40,320
A4	86,400	77,760	74,880	83,520	77,760	83,520	89,280	83,520
A5	31,680	34,560	25,920	28,800	34,560	37,440	31,680	37,440
A6	54,720	48,960	46,080	60,480	48,960	63,360	51,840	63,360
A7	17,280	20,160	20,160	14,400	20,160	17,280	23,040	17,280
A8	17,280	20,160	14,400	17,280	20,160	23,040	20,160	23,040

5.2.2. The stochastic front of Pareto optimal solutions

In this section, the developed solution approach in Section 4.1 is applied to solve the multi-objective supply chain planning problem in order to generate the set of Pareto-optimal solutions. To fix the levels of *MLD*, the histogram representing the lost demand distribution for different *MLD* levels is drawn in Fig. 3. As shown in Fig. 3, the probability to have a lost demand less than 2% is more than 45% for the different *MLD* levels. However, the probability to reach high lost customer demand increases with the increase of the *MLD* level. Indeed, the dispersion of lost demand values in the right-hand side increase by increasing the *MLD* level. In our case, the *MLD* is fixed between 1% and 30%. In fact, the *MLD* level of 30% presents a significant probability of having high lost demand. This probability may attain 22.06% to have a lost demand level greater than 15%.

The front of Pareto optimal solutions of the optimization problem are given in Fig. 4. It should be noted that each point of the represented Pareto in Fig. 4 entails a specific set of supply chain planning decisions. In order to better understand the trade-off between the different objective functions, the Pareto solutions are projected in 2D representations for specific values of *DRisk* and *MLD* as shown in Figs. 5 and 6 respectively. The Pareto optimal solutions for the expected total cost and the lost demand level for a fixed downside risk value ($DRisk = 0$) are illustrated in Fig. 5. According to Fig. 5, there is a significant conflict between the expected total cost and the lost demand level. The expected total cost is increased with a decrease in demand lost level. Besides, from Fig. 6, the Pareto optimal solutions with a fixed $MLD = 5\%$

Table 4
Unit production cost and inventory unit cost.

Unit cost	Product	A1	A2	A3	A4	A5	A6	A7	A8
(cp)	P1	1.72	0.72	0.9	1.75	1.9	1.65	1.5	0.38
	P2	2.5	0.57	1.42	2.6	2.3	2.83	2.1	0.29
(cs)	P1, P2	0.3	0.1	0.15	0.12	0.1	0.11	0.1	0.2

Table 5
Unit cost and capacity of transportation.

	Capacity	Unit cost (P1,P2)
A1 → A2	9100	0.6
A2 → A3	8700	0.45
A3 → A4	7500	0.37
A3 → A5	7500	0.52
A3 → A6	7500	0.65
A3 → A7	7500	0.34
A5 → A8	2500	0.49
A6 → A8	5000	0.35
A7 → A8	1500	0.27
A8 → Customer	10,000	0.5

Table 6
Processing time [min].

Product	A1	A2	A3	A4	A5	A6	A7	A8
P1	8	4	4.5	11	10.5	12	13	3
P2	10	2.5	6.5	16.5	15.5	14	16	2.5

Table 7
Variation of the expected total cost by changing the production yield value.

MLD	Production yield (yd_i)	Expected total cost	Variation of the expected total cost (%)
1%	1	133664.2	–
	0.9	133755.2	0.07
	0.8	133916.7	0.19
	0.7	134437.3	0.58
5%	1	128020.4	–
	0.9	128111.5	0.07
	0.8	128227.7	0.16
	0.7	128596.7	0.45
10%	1	121894.4	–
	0.9	121985.5	0.07
	0.8	122076.6	0.15
	0.7	122322.7	0.35
20%	1	111,572	–
	0.9	111636.4	0.06
	0.8	111721.2	0.13
	0.7	111867.3	0.26
30%	1	105005.1	–
	0.9	105060.3	0.05
	0.8	105115.7	0.11
	0.7	105192.9	0.18

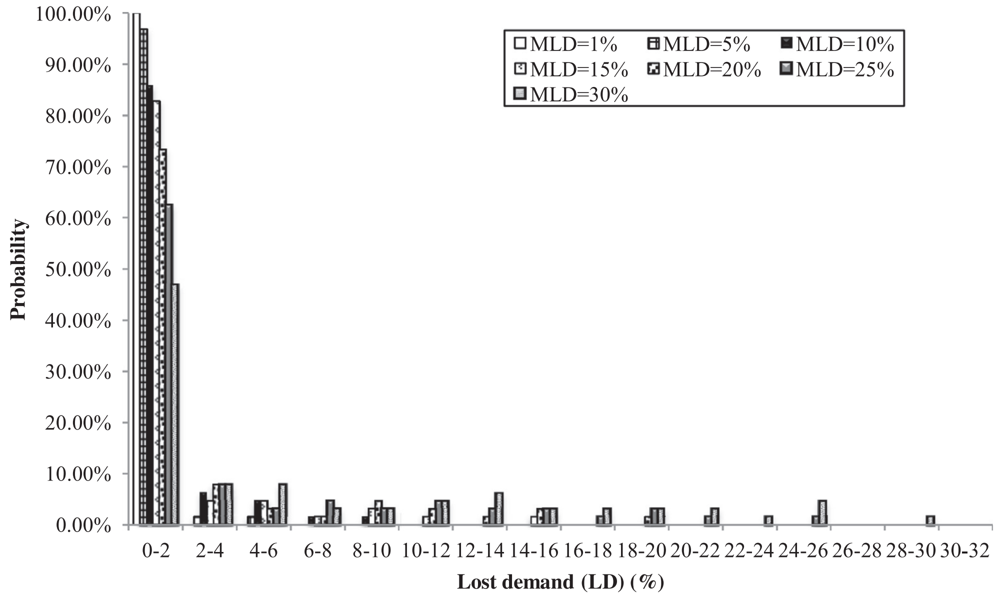

Fig. 3. Lost demand distribution.

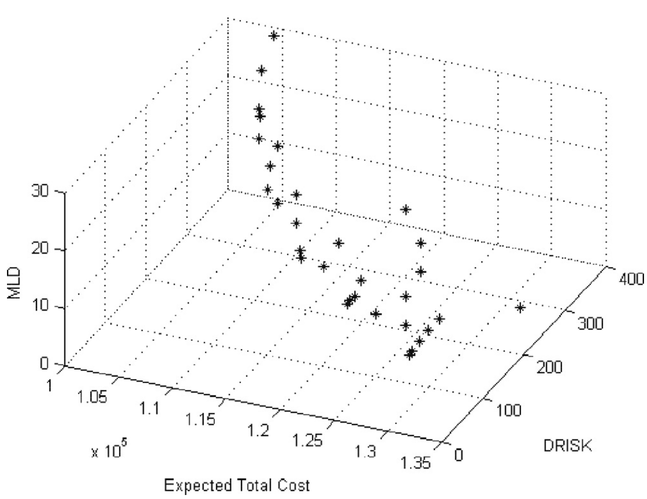

Fig. 4. Pareto optimal solutions distribution.

shows that the expected total cost and the downside risk are conflicting with each other. The generated Pareto optimal solutions help the decision maker to select a proper configuration.

5.2.3. Downside risk management

In this section, we focus on the downside risk management. Therefore, we fix the lost demand level to a predefined value and the target Ω value to 130.000 while minimizing the expected total cost. The proposed model is then solved for a fixed value of $MLD = 5\%$ and different values of $\varepsilon_c^{k_2}$.

The comparison of the expected total cost probability distribution after and before downside risk management is reported in Fig. 7. As shown in Fig. 7, the distribution of total cost before downside risk management presents a non-negligible probability of incurring in high cost due to the dispersion of cost values in the right-hand side. Besides, the cumulative distributions of total cost over all of the scenarios are plotted in Fig. 8. This figure shows that the cumulative curve obtained after risk management lies below the curve before risk management for low total cost values. However, these two curves intersect each other at some point.

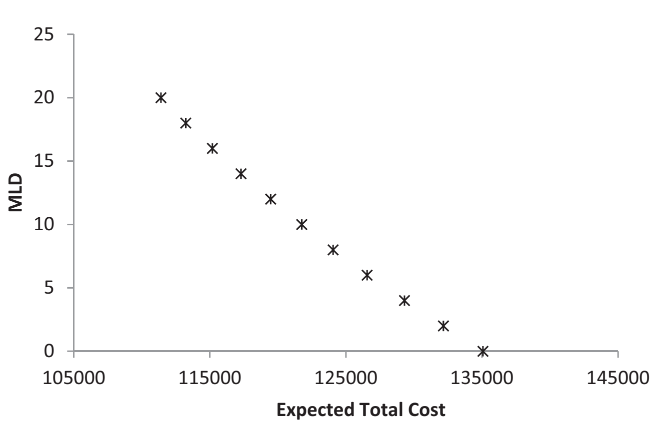

Fig. 5. Projection of the Pareto optimal solutions for ($DRisk_{\Omega} = 0$).

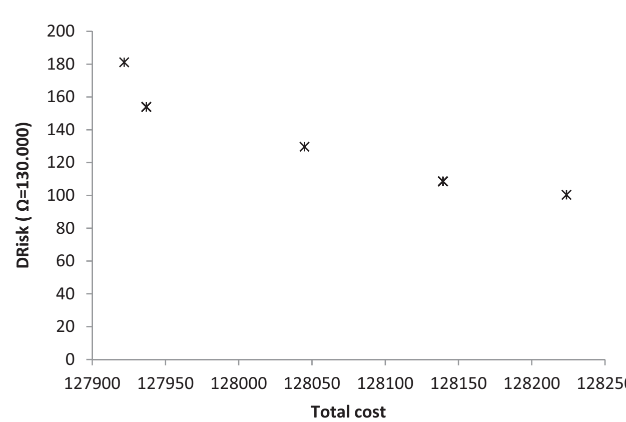

Fig. 6. Projection of the Pareto optimal solutions for ($MLD = 5\%$).

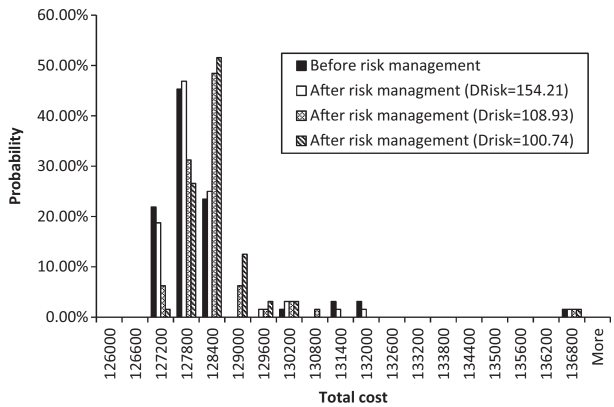

Fig. 7. Total cost distributions after and before risk management (Target Ω = 130.000).

The obtained results after and before risk management are detailed in Table 8. In order to emphasize the reduction of risk and cost for the downside risk management model a metric is defined as follows:

$$\text{Reduction gap}\,(\%) = 100 \times \frac{\textit{Value after Risk managment} - \textit{Value before Risk managment}}{\textit{Value before Risk managment}} \tag{30}$$

As can be seen in Table 8, the downside risk value decreases from 181.55 to 154.21, 108.93 and 100.74 for the different Pareto optimal solutions after risk management which represents a reduction of 15.06%, 40.00% and 44.51% respectively. However, the expected total cost increases after risk management from 127921.778 to 127936.868, 128139.293 and 128223.625 which represents an increase of 0.01%, 0.17% and 0.24% respectively. It is clear from this table that the downside risk has been significantly reduced despite the little increase in the expected total cost.

In order to evaluate the performance of this method, the worst case cost is used as an alternative risk metric. This metric was demonstrated to be an effective tool to reduce the probability of unfavorable scenarios in the scheduling of batch plants under uncertain market demand (Bonfill, Bagajewicz, Espuña, & Puigjaner, 2004). Using this metric in the proposed stochastic programming model results in a multi-objective optimization problem in which the expected total cost, the lost demand level and the worst case total cost (*WC Cost*) are three objective functions to

Table 8
Cost comparison after and before risk management (Target Ω = 130.000).

	Expected total cost	DRisk	DRisk reduction (%)	Total cost reduction (%)
Before risk management	127921.778	181.55	0	0
After risk management	127936.868	154.21	15.06	−0.01
	128139.293	108.93	40.00	−0.17
	128223.625	100.74	44.51	−0.24

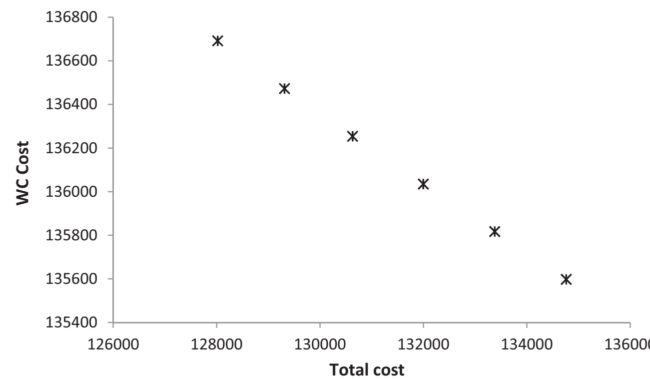

Fig. 9. Pareto optimal solutions for the expected total cost and the worst-case cost for *MLD* = 5%.

be minimized. It is worthwhile mentioning that the worst case is obtained from the maximum total cost over all the scenarios as follows:

$$Cost^s \leqslant WC\ Cost \tag{31}$$

where $Cost^s$ represents the different values of total cost calculated for each scenario once the demand uncertainty is revealed. The reader can also refer to Felfel, Ayadi, and Masmoudi (2015c) for a detailed mathematical formulation of the considered supply chain planning problem using the worst case approach.

The solution of this problem is a set of Pareto optimal solutions that reveals the tradeoffs between the different objective functions. This set of Pareto solutions is obtained by solving the optimization stochastic model by means of the e-constraint method. The front Pareto optimal solutions for the expected total cost and the worst case total cost for a fixed *MLD* = 5% is illustrated in

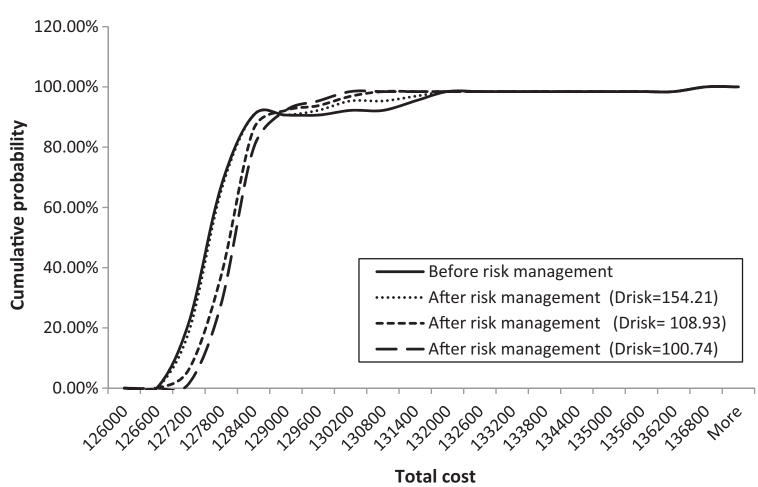

Fig. 8. Total cost cumulative distributions after and before risk management (Target Ω = 130.000).

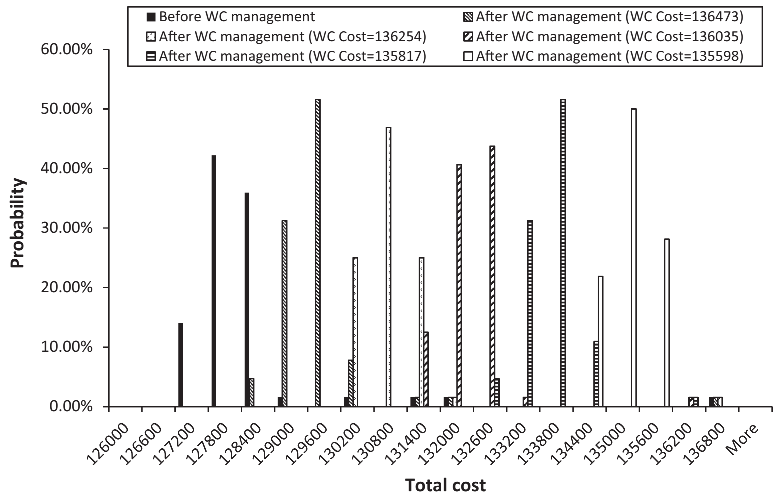

Fig. 10. Total cost distributions after and before worst case management.

Table 9
Cost comparison after and before worst case management for *MLD* = 5%.

	Expected total cost	*WC Cost*	*WC Cost* reduction (%)	Total cost reduction (%)
Before worst case management	127921.78	136,692	0	0
After worst case management	129,312	136,473	0.16	−1.09
	130,629	136,254	0.32	−2.12
	131,997	136,035	0.48	−3.19
	133,378	135,817	0.64	−4.27
	134,761	135,598	0.80	−5.35

Table 10
The most preferred solution for different sets of weighting factors.

	Case 1 w1 = 0.2, w2 = 0.4, w3 = 0.4		Case 2 w1 = 0.5, w2 = 0.25, w3 = 0.25		Case 3 w1 = 0.8, w2 = 0.1, w3 = 0.1	
	Objective function	μ_i^k	Objective function	μ_i^k	Objective function	μ_i^k
F1: Expected total cost	128223.62	0.14	116226.50	0.58	104836.07	1.00
F2: MLD	5	0.89	15	0.54	30	0.00
F3: DRisk	100.4041	0.99	147.0049	0.83	382.738	0.00
μ^k	0.782		0.632		0.80	

Fig. 9. According to Fig. 9, there exist a significant conflict between the expected total cost and the worst case cost. In fact, when the worst case cost decreased the expected total cost increased and vice versa.

The histogram of the total cost distribution before and after the worst case management is shown in Fig. 10. By comparing these results with the case of *DRisk* (Fig. 7), it is shown that the probability to reach high total costs becomes much more important after risk management using worst case cost than using *DRisk*, especially when minimizing worst case cost values. The expected total cost and the worst case cost for each Pareto solution are reported in Table 9. As shown in Table 9, the worst case total cost decreases from 136,692 to 136,473, 136,254, 136,035, 135,817 and 135,598 after worst case management. However, the corresponding expected total cost after worst case management increases from 127921.78 to 129,312, 130,629, 131,997, 133,378 and 134,761 which represents an increase of 1.09%, 2.12%, 3.19%, 4.27% and 5.35% respectively as detailed in Table 9. We can see from Table 9 that the *WC Cost* is reduced whereas there is an important increase in the total expected cost in comparison with the increase of the expected total cost after *DRisk* management shown in Table 8. In fact, the range of expected total cost increase is from 1.1% to 5.3% when managing the worst case while the expected total cost increase does not exceed 0.24% when managing *DRisk*. These results prove the effectiveness of the proposed formulation, that manages the downside risk, in reducing the risk of high total cost.

5.2.4. Selecting a solution from the front of Pareto optimal solutions

After generating the front of Pareto optimal solutions by solving the optimization problem, the fuzzy satisfying decision making approach proposed in Section 4.2 is applied. This approach aims to help the decision-maker to select the best compromise solution among 31 generated Pareto solutions according to his preference. The fuzzy approach was applied for different sets of weighting factors and the most preferred solutions are reported in Table 10. The whole membership function of the most preferred solution indicates how much the solution is ideal. As it is seen in Table 10, the weighting factors in case 1 were selected in this way: (w1 = 0.2, w2 = 0.4 and w3 = 0.4). The lost demand level is 5%, a value that is very close to its ideal value (2%) which is confirmed by its high membership value of 0.89. Besides, the downside risk is 100.4041 which is very close to its ideal value equal to 97.58.

This result is confirmed by its membership value equal to 0.99. However, the expected total cost value is 128223.62 which is far from its ideal value 104836.07. Indeed, its low membership value of 0.14 verifies that the obtained cost is not an ideal value.

In practice, the expected total cost may be considered more important for the decision maker than the other objective functions. Therefore, higher weighting factors values of 0.5 and 0.8 have been assigned to the total cost in case 2 and case 3 respectively. The total cost decreased to 116226.50 in case 2 and its membership value is improved from 0.14 to 0.58 while both of *DRisk* and *MLD* membership value are reduced. It is worthwhile mentioning that the three objective functions are conflicting with each other. In case 3, we assign a larger weighing factor of 0.8 to the cost. As shown in Table 10, the total cost is even more reduced and attain its ideal value of 104836.07 while the other objective functions reach their worst value with a membership of zero. So, there is always a trade-off among the considered objective functions. In order to control this trade-off, the weighting factors should be selected appropriately according the importance associated to each objective function by the decision maker.

6. Conclusion

In this paper, a decision-making approach for a multi-objective, multi-stage, multi-product and multi-period planning problem under customer demand uncertainty is proposed. The main scientific contribution of this work is to equip decision makers with a global approach, for the considered problem that supports them in the whole planning development process. The proposed approach allows to generate a robust front of Pareto optimal solutions and to provide the decision maker with a procedure to select the adequate solution respecting his preferences.

Based on the application of the proposed approach to a real case study from the textile and apparel industry and the comparison of corresponding results with another established method, the effectiveness of the proposed approach is highlighted. Indeed, the obtained planning solutions after managing downside risk are significantly less risky with a *DRisk* reduction that reaches 44% counter a negligible increase in the expected total cost that does not exceed 1%.

As future work, the proposed formulation can be improved by the integration of production yield as well as the consideration of other sources of uncertainty such as production unit cost. Moreover, the uncertain customer demand is modeled in this work through a discrete probability distribution. This probability distribution can be, in some practical cases, difficult to be identified. In this case, the uncertain demand can be modeled as fuzzy numbers. Further research needs so to be done in order to incorporate fuzzy demand into the proposed decision-making approach. Besides, treating production capacity as a decision variable represents an interesting future work to meet uncertain demands and to determine the optimum utilization of production resources.

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