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ORIGINAL RESEARCH

Stochastic multi-site supply chain planning in textile and apparel industry under demand and price uncertainties with risk aversion

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Abstract
A multi-product, multi-period, multi-site supply chain production and transportation planning problem, in the textile and apparel industry, under demand and price uncertainties is considered in this paper. The problem is formulated using a two-stage stochastic programming model taking into account the production amount, the inventory and backorder levels as well as the amounts of products to be transported between the different plants and customers in each period. Risk management is addressed by incorporating a risk measure into the stochastic programming model as a second objective function, which leads to a multi-objective optimization model. The objectives aim to simultaneously maximize the expected net profit and minimize the financial risk measured. Two risk measures are compared: the conditional-value-at-risk and the downside risk. As the considered objective functions conflict with each other's, the problem solution is a front of Pareto optimal robust alternatives, which represents the trade-off among the different objective functions. A case study using real data from textile and apparel industry in Tunisia is presented to illustrate the effectiveness of the proposed model and the robustness of the obtained solutions.

Keywords Multi-site supply chain · Textile and apparel industry · Multi-objective optimization · Stochastic programming · Risk management

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1 Introduction

The textile industry plays a significant role in the manufacturing and production base of many nations (Jatuphatwarodom et al. 2018). For instance, the textile and apparel manufacturing process includes different sub-processes such as knitting, embroidery and cloth making. Each process may involve more than one plant, establishing a multi-site supply network environment. Therefore, companies need to reconfigure their production policy and to take into consideration the coordination between the different entities of the supply network.

Due to highly today's competitive markets, textile and apparel companies are facing high pressure to manage their supply chains (SC). To achieve this goal, it is crucial to make a rigorous supply chain planning (SCP) related to the decisions from the procurement of raw materials to the shipping of finished products to the customer. SCP can be classified into three categories following the planning horizon: strategic, tactical, and operational (Chopra and Meindl 2010). In this work, the tactical level of the SCP is considered. According to Esmaeilikia et al. (2016), the use of tactical SC planning models with multiple flexibility options can help manage the usual operations efficiently and effectively, whilst improve the SC resiliency in response to inherent environmental uncertainties.

Products in textile and apparel industry are usually characterized by unpredictable demand. Indeed, during the planning horizon, customer demand can increase unexpectedly or drop sharply. Hence, demand fluctuations could be determined only at the end of the planning horizon. The under-estimation of overall demand leads to lost sales and unsatisfied customer. However, the over-estimation of the products demand results in high production and inventory costs. On the other hand, textile and apparel business is characterized by random selling prices since it depends on customer demand. Indeed, when the product demand rises, the companies tend to decrease the selling prices in order to match supply with demand. Accurately incorporating uncertainties into the SC production planning problem will result in better decision-making and will improve the expected net profit. According to Chiu and Choi (2016), if there are some sources of uncertainty such as demand uncertainty and supply uncertainty, the performance of the SC will also be affected and become uncertain. Moreover, in practice, most of the decision makers are risk averse and they would like to improve the net profit as well as to manage the risk of having low net profit. Therefore, it is crucial to generate a robust SCP solution, which can manage the resulting risk from demand and price uncertainties. The main idea in risk management is to incorporate the trade-off between the performance measure and the risk measures into the decision maker process, which leads to a multi-objective optimization problem.

In this paper, a comprehensive framework for a multi-product, multi-period, multi-site SCP problem under customer demands and selling prices uncertainties is proposed. A two-stage stochastic programming model is developed in order to incorporate uncertainties into the supply network decision-making process and to maximize the expected net profit. To solve the stochastic problem, decision variables such as the amounts of products to be produced and the volumes of products to be transported between the different manufacturing facilities are considered as first-stage decisions. Second-stage decisions are related with the inventory and backorder level as well as the finished products amounts to be transported to the customers. Furthermore, two risk measures are incorporated in the mathematical model in order to reduce the probability of incurring in low net profit. This formulation provides to the decision maker the opportunity to choose the most appropriate risk indicator. Then, two multi-objective optimization problems are obtained. In the first model, the net profit of the SCP and the conditional-value-at-Risk *"CVaR"* are optimized. Second, the downside risk

"DRisk" is optimized simultaneously with the expected net profit. In order to demonstrate the effectiveness of the proposed models and the robustness of the generated solutions, a real case study from textile and apparel industry in Tunisia is presented. The main contribution of this paper is to provide to the planner a front of Pareto optimal robust solutions for a multi-site SCP and transportation problem in textile and apparel industry that considers simultaneously demand and price uncertainties. This front of Pareto represents the trade-off between the different objectives. In addition, the decision maker can select the best alternatives according to his preferences and the appropriate risk management model.

The remainder of the paper is organized as follows. Background of the considered problem is presented in Sect. 2. The problem description is presented in Sect. 3, and the stochastic formulation of the considered problem is detailed in Sect. 4. Section 5 introduces the risk management model. The solution approach is described in Sect. 6. Computational results from a real world case study of textile and apparel supply network are presented in Sect. 7. Finally, conclusions and future research directions are drawn in Sect. 8.

2 Literature review

A lot of attempts have been made in the literature to model and optimize textile and apparel planning problems (Toni and Meneghetti 2000; Leung et al. 2003; Safra 2013; Mok et al. 2013; Felfel et al. 2016a, b; Ren et al. 2017). Toni and Meneghetti (2000) studied a textile and apparel SC production planning problem. They investigated the impact of material availability, production planning period length, as well as the relation between customer orders and production orders concerning color mix on system performance from a time-based point of view. A real example from a textile and apparel company in Italia was treated using a simulation model. Leung et al. (2003) addressed a multi-objective multi-site medium-term aggregate production planning problem using a goal programming approach. The considered objective functions are the maximization of profit as well as the utilization of import quota and the minimization of costs of workers hiring and laying-off. A real case study from a multinational lingerie company in Hong Kong is considered to show the effectiveness of the proposed model. Safra (2013) developed an integrated approach for production and distribution planning at tactical and operational levels in textile and apparel industry. The proposed approach aims to emphasize the flexibility of the production system by the implementation of a safety production capacity at the tactical planning level. Two mathematical models were developed to solve the tactical and the operational level of the planning problem. These models aim to minimize the total cost of a three-echelon SC as well as to satisfy the customer demand on time. Mok et al. (2013) proposed planning algorithms for automatic job allocations based on group technology and genetic algorithms in apparel manufacturing. Single-run and two-run genetic algorithms were suggested to optimize the job allocation problem. Real production data are used to show the effectiveness of the proposed method. Felfel et al. (2016a) addressed a multi-product multi-site production and transportation planning problem in the context of a Tunisian textile and apparel supply network. The authors proposed a multi-objective optimization formulation, which aims to minimize the total cost and to maximize the product quality level simultaneously. From the literature reviewed above, all these researches are dealing with deterministic modeling approach that assumes that all parameters of the optimization problem are known with certainty. In practice, the textile SCP problem is characterized by many sources of uncertainty such as customer demand, unit cost and selling price.

Several works in textile and apparel industry dealt with one stochastic parameter such as uncertain customer demand (Karabuk 2008; Kong 2008; Ait-alla et al. 2014; Felfel el al. 2016b). Many other works took into account more than one random parameter such as unit production cost, unit inventory cost, labor cost, shortage cost and customer demand (Leung et al. 2005, 2007). Leung et al. (2005) noted as a perspective of their work that considering selling prices can offer scope for making the production planning a more beneficial basis for decision-making. On the other hand, products selling price are usually considered in the literature as deterministic parameter and it is not treated as source of uncertainty despite of its uncertain and negotiable character. To the best of authors' knowledge, there is no prior work that considers selling price uncertainty in textile and apparel SCP problem.

Although the product price uncertainty is not considered in textile industry, the product price is treated as a source of uncertainty in other fields. Wang and Fang (2001) proposed an aggregate production planning problem with multiple objectives where the product price, market demands, production capacity, work force level, and unit cost to subcontract are considered as fuzzy sets. Chen and Lee (2004) addressed a multi-product, multi-stage, multi-period scheduling problem for a multi-echelon supply chain under market demand and product price uncertainties. The uncertain demands were modeled as a number of discrete scenarios with given probabilities while the product prices are described as fuzzy variables. Awudu and Zhang (2013) proposed a multi-product biofuel SC production planning problem under demand and price uncertainties. Demands of end products follow normal probability distribution with known mean and standard deviation, while the end product price uncertainty is molded using the geometric Brownian motion. In that paper, customer demand and product price are modeled using jointly distributed discrete random variables.

A lot of attention has been given in the literature to incorporate uncertainty into textile SC decision-making process in order to improve the economic objective. Many approaches have been applied in the literature to cope with uncertainty such as robust optimization approach, fuzzy programming approach, stochastic programming approach, and stochastic dynamic programming approach. The two-stage stochastic programming approach (Birge and Louveaux 1997) is widely used in the literature to integrate uncertainty in mathematical programming model. Typically, the two-stage stochastic programming approach comprises two types of decisions: the first stage decisions that have to be made "here and now" before the revelation of uncertainty and the second stage decisions that can be made after the revelation of uncertain events ("wait and see" decisions). Hence, the objective function is equal to the combination of the first stage variables and the second stage expected recourse variables.

The stochastic programming approach has been successfully applied in textile and apparel industry (Leung et al. 2005; Kong 2008; Karabuk 2008). Leung et al. (2005) developed a two-stage stochastic programming model in order to minimize the total cost of a multi-site aggregate medium-term production planning problem under an uncertain environment. The first-stage decisions include the amount of production in regular-time and overtime, the amount of subcontracted products as well as the number of required workers, hired workers and laid-off workers. The second-stage decisions involve the amount of inventory and the level of under-fulfilment products. A real case study from a multinational lingerie company situated in Hong Kong was given in order to show the effectiveness of the proposed model. Kong (2008) addressed a multi-period aggregate production planning problem under seasonal demand uncertainty in apparel industry. A stochastic linear programming model was developed to minimize the total cost involving production cost, outsourcing cost and inventory cost. Karabuk (2008) proposed a stochastic programming model for a multi-period yarn production planning problem under demand uncertainty in textile industry. The author considered a single objective function, which aims to minimize the total cost consisting of rover changeover cost, inventory carrying cost and frame changeover cost. A two-step preprocessing algorithm was developed to address the computational complexities of the obtained large-scale optimization problem. Although these works tackle the uncertainty involved in textile and apparel planning problems, the robustness of the generated solutions is not guarantee since they do not consider risks.

The main drawback of the stochastic programming approach is that it is a risk neutral approach, which does not allow the control of the unfavorable outcomes. However, the decision maker may have different attitudes toward the risk. Hence, the financial risk should be controlled and managed according to the decision maker preferences. Leung et al. (2007) dealt with a multi-site production planning problem under uncertainty for a multinational lingerie company located in Hong Kong. A robust optimization model based on the variance as the risk measure was proposed in order to minimize the total costs including production cost, inventory cost, labor cost and workforce changing cost. The authors mentioned as a critic of their work that the application of the robust optimization might generate higher costs than stochastic programming approach because the penalty cost is considered in the robust optimization formulation. Ait-alla et al. (2014) addressed a production planning problem under demand uncertainty in fashion apparel industry. The robust model originally developed by Leung et al. (2007) was adopted as the benchmark mathematical formulation based on the conditional value at Risk as a risk measure. The authors considered a single objective function, which aims to maximize the total profit revenue while satisfying a *CVaR* constraint. Felfel et al. (2016b) proposed a fuzzy decision-making approach for a multi-objective, multi-period, multi-product, multi-site, multi-stage SCP problem under demand uncertainty. The stochastic programming model aims to minimize simultaneously the expected total cost, the lost customer demand level and the downside risk.

3 Problem statement

This study is motivated by the planning problem faced by medium and small enterprises located in south of Tunisia in textile and apparel industry. The structure of supply network taken as a reference in this study is shown in Fig. 1. 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 the cloth making stage, which contains four plants forming a multi-site supply network manufacturing environment. In such structure, the production activities should be well coordinated in order to fulfill the customer demand, to improve the capacity utilization of the manufacturing plants and to avoid excessive inventories.

The four first processes are intermediate operations providing semi-finished products. However, cloth making converts the semi-finished products into finished products that are packaged and delivered to the customers. The supply network is formed of a central plant (Textile-International "TE-INTER") and five subcontractors. TE-INTER is composed of three internal production departments: cutting, cloth making and packaging. TE-INTER subcontracts part of his activities for two main reasons. The first reason is the lack of skills and resources in the fields of embroidery, printing and dyeing. The second reason is the need of expansion of production capacity of cloth making in order to satisfy customer demands. In other words, TE-INTER can plan and execute some of the operations of cloth making and leave the remainder production activities to one or more of his subcontractor. A distribution lead time is taken into account for the transportation of products between the different entities of the network.

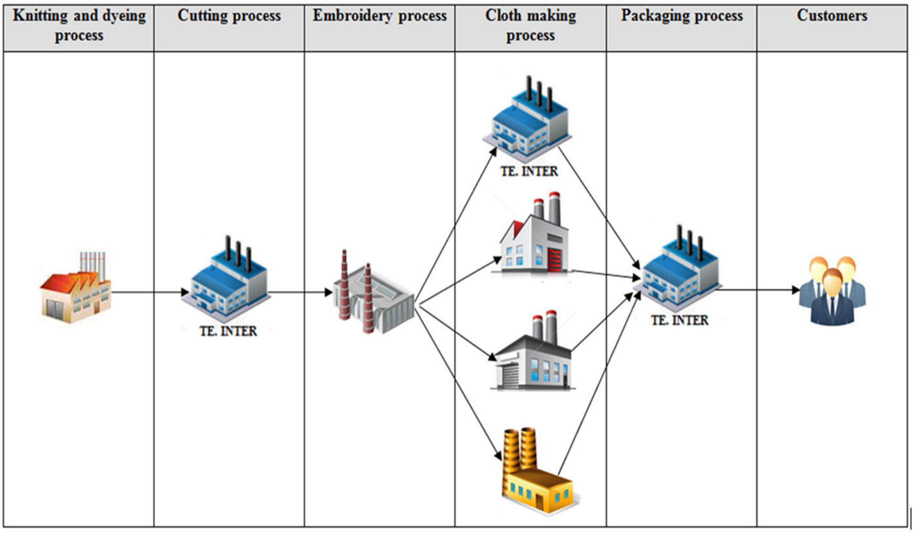

Fig. 1 The multi-site supply network environment of textile and apparel industry

In textile and apparel industry, products are usually characterized by volatile demand and short life cycle. The selling prices of finished products are also random with known probability distributions. It should be noted that products prices depend on customer demand. Indeed, when the stochastic demand of the products increases the proposed price decreases.

The main objective of this problem is to maximize the expected net profit as well as to minimize the financial risk associated with the optimal plan of the textile and apparel network. The expected net profit is obtained by subtracting the expected total costs from the total incomes. The total cost includes production, inventory, backorder and transportation costs. Decisions to be made involve the amount of products to be produced at each plant, the amount of inventory of finished or semi-finished products, the backorder level and the flows of materials between the different entities of the supply network taking into account customer demand and selling price uncertainties.

4 Two-stage stochastic programming model

Due to the uncertainty of products demand and selling price, the deterministic model is inappropriate to improve the economic performance. Thus, a two-stage stochastic programming model is applied in order obtain the optimal planning of the textile and apparel supply network under uncertainties. It is assumed that the uncertain parameters are considered in the stochastic programming model as a set of discrete scenarios associated with known probability. It is worthwhile mentioning that the stages of the stochastic programing model correspond to different steps of decision making and it is not related to time periods. In the two-stage stochastic programming model, the decision variables are divided into two sets. The production amounts in each manufacturing plant and the quantity of products to be transported between upstream and downstream plants are made "here and now" before the true value of uncertainties are revealed. Other decision variables such as inventory and backorder size, flow of finished products to be shipped to the customer are postponed in a "wait-and-see" mode after the revelation of uncertainties. The objective of the optimization model is to determine

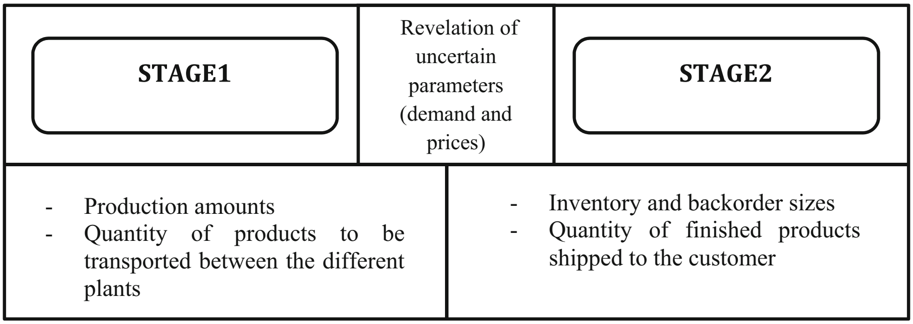

Fig. 2 Decision taken in each stage of the stochastic model

the first-stage decisions variables in a manner that the expected net profit, calculated based on the first-stage and the second-stage decision variables, is maximized. Figure 2 illustrates the decisions taken in each stage of the stochastic programming model.

4.1 Mathematical formulation

To formulate the mathematical model, the following indices parameters and decision variables are introduced:

Indices

L_i	Set of direct successor plant of i
ST_j	Set of stages of the manufacturing process ($j = 1, 2, \ldots, N$)
i, i'	Production plant index ($i, i' = 1, 2, \ldots, I_j$) where plant i belongs to stage n and plant i' belongs to stage $n+1$
k	Product index ($k = 1, 2, \ldots, K$)
t	Period index ($t = 1, 2, \ldots, T$)
s	Scenario index ($s = 1, 2, \ldots, S$)

Decision variables

P_{ikt}	Production amounts of product k at plant i in period t in regular-time
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
BD^s_{kt}	Backorder 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 i' in period t
$TR^s_{i\to CUS,kt}$	Amounts of product k transported from the last plant i 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

Parameters

cp_{ik}	Unit production cost for product k in regular-time at plant i
$ct_{i\rightarrow i',k}$	Unit transportation cost between plant i and i' of production for product k
$ct_{i\rightarrow CUS,k}$	Unit transportation cost between the last plant i and the customer
cs_{ik}	Unit inventory cost of finished or semi-finished product k at plant i
cb_k	Unit backorder cost of product k
pr_{kt}^s	Unit selling price of finished product k for scenario s in period t
$capp_{it}$	Production capacity at plant i regular-time in period t (min)
$caps_{it}$	Storage capacity at plant i in period t
$capt_{i\rightarrow i',t}$	Transportation capacity at plant i in period t
D_{kt}^s	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
π^s	The occurrence probability of scenario s where $\sum_{s=1}^{S}\pi^s=1$
yd_i	Production yield at plant i

Formulation

$$\begin{aligned} Max\ E[NPV] = \sum_{s=1}^{S}\pi^s \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{I}&(pr_k^s TR_{i\rightarrow CUS,kt}^s - cs_{ik}(S_{ikt}^s + JS_{ikt}^s) \\ &- ct_{i\rightarrow CUS,k}TR_{i\rightarrow CUS,kt}^s - cb_k BD_{k,t}^s) \\ &- \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{I}(cp_{ik}P_{ikt} + ct_{i\rightarrow i',k}TR_{i\rightarrow i',kt}) \end{aligned} \tag{1}$$

$$S_{ik,t}^s = S_{ik,t-1}^s + P_{ikt} - \sum_{i'\in L_i} TR_{i\rightarrow i',kt},\quad \forall i\in ST_{j<N},\ \forall k,t,s \tag{2}$$

$$\sum_{i=1}^{I} S_{ik,t}^s = \sum_{i=1}^{I} S_{ik,t-1}^s + P_{ikt} - TR_{i\rightarrow CUS,kt}^s,\quad \forall i\in ST_{j=N}, k,t,s \tag{3}$$

$$JS_{ik,t}^s = JS_{ik,t-1}^s + Q_{ikt} - P_{ikt},\quad \forall i,k,t,s \tag{4}$$

$$BD_{kt}^s = BD_{k,t-1}^s + D_{kt}^s - TR_{i\rightarrow CUS,kt}^s,\quad \forall k,t,s \tag{5}$$

$$Q_{i'k,t+DL} = \sum\nolimits_{i'\in L_i} TR_{i\rightarrow i',kt},\quad \forall i,k,t,s \tag{6}$$

$$\sum_{k=1}^{K} b_k * P_{ikt} \le capp_{it}\forall i,t,\quad \forall i,t \tag{7}$$

$$\sum_{k=1}^{K} S_{ikt} + JS_{ikt} \le caps_{it},\quad \forall i,t,s \tag{8}$$

$$\sum_{k=1}^{K} TR_{i\rightarrow i',kt} \leq captr_{it}, \quad \forall i, t, s \tag{9}$$

$$P_{ikt}, S^s_{ikt}, JS^s_{ikt}, TR_{i\rightarrow i',kt}, TR^s_{i\rightarrow CUS,kt}, Q_{i,k}, BD^s_{kt} \geq 0, \quad \forall i, k, t, s \tag{10}$$

The objective function (1) aims to maximize the expected profit $E[NPV]$ calculated by subtracting the total expected cost from the expected income. The occurrence pbability π^s of each scenario s is taken into account in order to calculate the expected income and the expected total cost. The total cost involves the production cost of each plant, the products inventory cost, the backorder cost, the transportation cost of semi-pducts between upstream and downstream plants and transportation cost of finished products to customers. Constraint (2) is the balance for the inventory level of products in each production stage except the last stage. Constraint (3) denotes the balance equation for end of period inventory in the last production stage. Constraint (4) represents the inventory balance for the semi-finished products. Constraint (5) represents the balance equation for shortage in finished product demand. Constraint (6) provides the balance for transportation between the different manufacturing plants. Constraint (7) guarantees that the production capacity is respected. Constraint (8) limits the products inventory level. Constraint (9) makes sure that the amounts of transported products cannot exceed the transportation capacity. Constraint (10) represents the non-negativity restriction on the decision variables.

5 Risk management models

The risk management is an important issue when developing the stochastic programming model in order to control the risk of having low net profits. However, the stochastic programming approach aims to optimize the expected net profit without reflecting the variability over different scenarios. Indeed, the stochastic approach is risk-neutral and does not guarantee that the stochastic solution will perform at a certain level over all realizations of uncertain parameters. Therefore, it is crucial to extend the abovementioned stochastic model to a risk management model. According to DuHadway et al. (2017), it is critical to choose the appropriate strategies for SC risk management to avoid disruptive. The underlying idea of risk management is to incorporate the trade-off between expected net profit and financial risk within the decision making which leads to a multi-objective optimization problem.

The variance (Markowitz 1952) is a popular risk measure widely used in the literature to control the variability of performance. However, this risk measure has two significant drawbacks (Bonfill et al. 2004). First, the variance is a symmetric measure and many optimal solutions could be discarded in the attempt of reducing the dispersion of the expected values around the mean. The second drawback is that the variance introduces nonlinearities into the mathematical model, which increases the problem complexity.

5.1 Managing *CVaR*

In this paper, the *CVaR*, proposed by Uryasev and Rockafellar (2001), Rockafellar and Uryasev (2002), is defined as the financial risk metric. Gebreslassie et al. (2012) demonstrated that the *CVaR* management is very effective in reducing the probability of high costs.

The value-at-risk (*VaR*) is a risk measure, which represents a percentile of a loss distribution. Given the same confidence level α, the *VaR* is a lower bound for *CVaR* (Sarykalin et al.

2008). In this paper, *VaR* is defined as the minimal profit of a production plan over a specific time horizon at a specified confidence level (α) It should be noted that α belongs to [0, 1]. Furthermore, a non-negative deviation ψ_s between the scenario profit NPV^s and the VaR value is defined. If the NPV^s is greater than VaR, ψ_s should be enforced to zero. The above relationships can be formulated as follows:

$$VaR \geq 0 \tag{11}$$

$$\psi_s \geq VaR - NPV^s, \quad \forall s \tag{12}$$

$$\psi_s \geq 0, \quad \forall s \tag{13}$$

The *CVaR* at the confidence level α can be formulated as follows:

$$CVaR(x, \alpha) = VaR + \frac{\sum\limits_{s \in S} \pi^s \cdot \psi_s}{1 - \alpha} \tag{14}$$

So, the *CVaR* management model can be formulated by the following equations:

$$\begin{array}{l} \max\ E[\text{NPV}] \\ \min\ CVaR(x, \alpha) = VaR + \frac{\sum_{s \in S} \pi^s \cdot \psi_s}{1-\alpha} \\ \text{subject to Eqs.(2)–(10);} \\ VaR \geq 0 \\ \psi_s \geq VaR - NPV^s, \quad \forall s \\ \psi_s \geq 0, \quad \forall s \end{array} \tag{15}$$

5.2 Managing downside risk

The second proposed approach aims to minimize the downside risk (*DRisk*) of having low net profits. The *DRisk* can be formulated as follows:

$$DRisk_{\Omega} = E[\varphi^s] \tag{16}$$

$$\text{where} \quad \varphi^s = \begin{cases} \Omega - NPV^s \ if \ \Omega > NPV^s \\ 0 \ \ otherwise \end{cases} \quad \forall s$$

$$\Omega \geq 0 \tag{17}$$

where φ^s is a positive variable that measures deviation between a target Ω and the scenario profit value (NPV^s). Downside risk () is defined as the expected value of the positive variable φ^s. So, the *DRisk* management model can be formulated by the following equations:

$$\begin{array}{l} \max\ E[\text{NPV}] \\ \min\ Risk_{\Omega} = \sum\limits_{s} \pi^s \varphi^s \\ \text{subject to Eqs. (2)–(10);} \\ \Omega \geq 0 \\ \varphi^s \geq \Omega - NPV^s, \quad \forall s, \\ \varphi^s \geq 0, \quad \forall s \end{array} \tag{18}$$

6 Solution approach

The solution of the above problem is a front of Pareto optimal solutions. The e-constraint method, first presented by Haimes et al. (1971), can be applied to solve the multi-objective optimization problem. In this method, one of the objective functions is selected to be optimized and the other objective functions are transformed into constraints with allowable bounds ε. The *CVaR* management model corresponding to the e-constraint method can be modeled as below:

$$\begin{aligned}
&\max\ E[\text{NPV}] \\
&CVaR(x,\alpha) \leq \varepsilon \\
&\text{subject to Eqs. (2)–(10);} \\
&VaR \geq 0 \\
&\psi_s \geq VaR - NPV^s, \quad \forall s \\
&\psi_s \geq 0, \quad \forall s
\end{aligned} \tag{19}$$

The *DRisk* management model corresponding to the e-constraint method is given by:

$$\begin{aligned}
&\max\ E[\text{NPV}] \\
&DRisk_{\Omega} \leq \varepsilon \\
&\text{subject to Eqs. (2)–(10);} \\
&\Omega \geq 0 \\
&\varphi^s \geq \Omega - NPV^s, \quad \forall s, \\
&\varphi^s \geq 0, \quad \forall s
\end{aligned} \tag{20}$$

Subsequently, the bound level ε is successively altered in order to generate the entire front of Pareto optimal solutions.

7 Computational results

In order to demonstrate the effectiveness of the proposed model and the robustness of the obtained solutions, a real-world numerical example from textile and apparel industry is presented. The industrial case is described in Sect. 7.1. Then, the obtained results are detailed in Sect. 7.2. First, the results of the two-stage stochastic programming model are compared with the deterministic model in order to show the effectiveness of the stochastic programming model. Subsequently, we apply the *CVaR* management model described in Sect. 5 and we discuss the results of maximizing the expected net profit versus minimizing the *CVaR*. In addition, the *DRisk* management model is applied and the results are compared to those of the *CVaR* management model.

The solution approaches were implemented in LINGO15.0 package program and MS-Excel 2010 with an INTEL(R) Core (TM) and 2 GB RAM.

7.1 Industrial case description

A numerical example from a real-world textile and apparel supply network in Tunisia is developed. The planning horizon covers 2 months and the length of the considered period is 1 week. Based on past sales records and future long-term and short-term contracts, the future economy can be assumed to be one of four scenarios: poor, fair, good or boom. The customer demand and unit selling prices of the finished products P1 and P2 under each

Table 1 Finished product demand and unit selling price

Period	Probability	Product 1		Product 2	
		Demand	Price	Demand	Price
T1 → T5	–	0	0	0	0
T6	0.15	2600	16.1	2450	18.33
	0.35	2050	16.93	2010	18.99
	0.25	1630	17.56	1670	19.5
	0.25	1310	18.04	1430	19.86
T7	0.25	2900	15.65	2750	17.88
	0.3	2200	16.7	2120	18.82
	0.25	1800	17.3	1640	19.54
	0.2	1590	17.62	1520	19.72
T8	0.2	3100	15.35	2900	17.65
	0.35	2750	15.88	2500	18.25
	0.3	2010	16.99	1850	19.23
	0.15	1650	17.53	1600	19.6

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)

scenario are detailed in Table 1. It should be noted that customer demand and selling prices are two joint discrete random variables. Hence, the total number of scenarios for the stochastic SCP problem is equal to 4^3=64. The different plants indices are given in Table 2. Table 3 describes the available capacity of production in each plant. It is noted that the production capacity differs from one period to another because of the absenteeism. In Table 4, the production and inventory unit costs are given. Table 5 reports the transportation unit cost and the transportation capacity. Table 6 provides information about the processing time of the different manufacturing processes.

7.2 Results

In this section, the proposed formulation is tested according to different computational properties. First, the influence of realistic problem size is investigated. Then, sensitivity analysis related to production yield is performed. After that, the effectiveness of the stochastic pro-

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

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

posed programming model is studied. In addition, the developed risk management models are applied. Finally, the solution quality is investigated according to the applied risk management model and the problem parameters.

7.2.1 Problem size effect

In order to test the efficiency of the formulation and the resolution method, different instances are generated. These instances are obtained by varying the number of periods and products. The corresponding number of variables and constraints as well as the CPU time are detailed in Table 7. Figure 3 shows the evolution of the CPU time for the different instances. One can notice from Fig. 3 and Table 7 that the CPU time for computing the Pareto of optimal solutions grows exponentially with problem size, especially when the number of products is greater than 30. Moreover, even for very important problem size, where the number of variables reaches 1,702,977, the CPU time necessary for resolution is only one hour.

Table 7 Size of the tested instances

Instance	Number of products	Number of periods	Number of variables	Number of constraints	CPU time (s)
1	1	8	16,986	11,972	3
2	1	16	38,732	21,124	5
3	2	8	33,661	23,634	10
4	2	16	76,748	41,156	16
5	5	8	83,286	57,540	33
6	5	16	170,862	101,252	75
7	10	8	166,161	114,500	108
8	10	16	341,097	201,412	324
9	30	8	497,661	342,340	708
10	50	8	829,161	570,180	1902
11	30	16	1,022,037	602,052	2084
12	50	16	1,702,977	1,002,692	3870

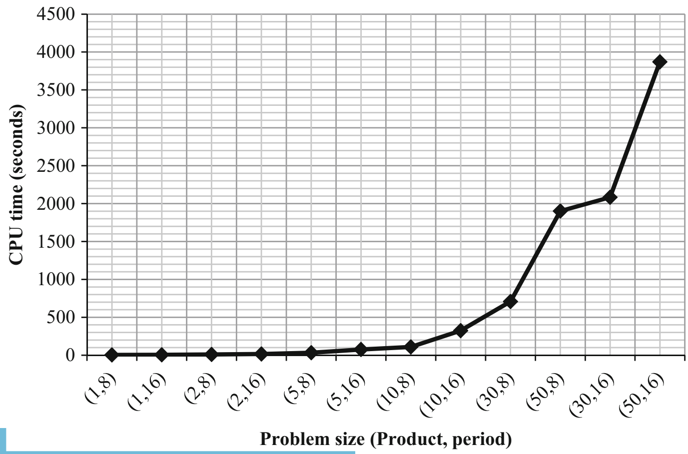

Fig. 3 Evolution of the CPU time according to the problem size

Table 8 Variation of the expected total cost by changing the production yield value

Production yield (yd_i)	Expected profit E[*NPV*]	Variation of the expected profit (%)
1	102,786	–
0.95	102,740	0.04
0.9	102,695	0.09
0.85	102,649	0.13
0.8	102,604	0.18
0.75	102,558	0.22
0.7	102,475	0.30
0.65	102,330	0.44
0.6	102,130	0.64

7.2.2 Sensitivity of the production yield

A sensitivity analysis related to production yield is performed in order to understand the consequences of a change in the production yield on the objective values. Many tests have been conducted by changing the values of the production yield for uncertain and fixed selling price. The obtained solutions as well as the variation of the expected profit are reported in Table 8. The variation of the expected profit is computed as follows:

$$\text{Variation } (\%) = 100\left|\frac{E[NPV]_{(yd_i=1)} - E[NPV]_{(yd_i)}}{E[NPV]_{(yd_i=1)}}\right| \tag{21}$$

As shown in Table 8, the obtained results are not too sensitive regarding to the change in the production yield value since the variation of the expected profit does not exceed 0.64% for all the tests. Thus, we will consider that the value of production yield is equal to one in the rest of the paper.

7.2.3 The two-stage stochastic model investigation

In this section, the solution of the two-stage stochastic model (TSM) and the solution of deterministic model (DTM) are firstly compared to show the effectiveness of the stochastic programming model. As it can be seen in Fig. 4, the expected net profit (NPV) of TSM is significantly higher than the DTM one. In addition, the expected selling price of TSM is greater than the DTM one. Moreover, the expected inventory and backorder costs of TSM are lower than the DTM costs. However, the production and transportation costs are higher for TSM than DTM in order to satisfy more customer demand. These results suggest that obvious profit can be achieved using the stochastic programming model.

In order to evaluate the impact of uncertainties on the planning process, we use two stochastic well-known measures: the expected value of perfect information (*EVPI*) and the value of stochastic solution (*VSS*) (Birge and Louveaus 1997). The *EVPI* is defined as the maximum value of loss when the information about the future is incomplete. It can be formulated as:

$$EVPI = WS - TSP \tag{22}$$

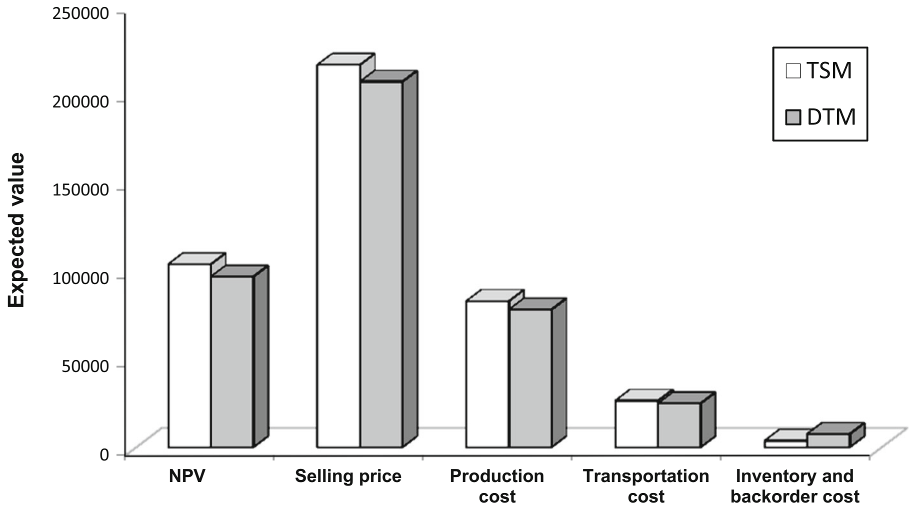

Fig. 4 Expected values of the stochastic and the deterministic models

Table 9 Stochastic programming parameters

WS	TSP	EEV	*VSS* = TSP – EEV	*EVPI* = WS – TSP	EVPI/WS (%)	VSS/EEV (%)
118,443.5	102,786	96,595.54	6190.46	15,657.5	13.22	6.41

WS denotes the optimal solution of the "wait and see" model and TSP denotes the optimal solution of two-stage stochastic programming model. *VSS* is the difference between the optimal solution of the two-stage programming model and the optimal solution of the deterministic model (EEV). If the *VSS* is positive, then the solution of stochastic programming model is better than the solution of the deterministic model. It is formulated as follows:

$$VSS = TSP - EEV \tag{23}$$

The EVPI is then computed by: EVPI = WS – TSP = 15,657.5.

As shown in Table 9, the EVPI/WS ratio shows the significant impact of demand and price uncertainties on the obtained solution (13.22%). Hence, it is crucial to have better forecast about the random demand and price scenarios. Then, the *VSS* is calculated: VSS = 6190.46. According to this result, using the TSM can lead to better profit by 6.41% more than the deterministic model, as reported in Table 9. It is clear that the stochastic programming model outperforms the deterministic model for the considered SCP problem.

7.2.4 Risk management models study

First, we apply the *CVaR* management model developed in Sect. 5. The trade-off between the *CVaR* measure and the expected net profit is investigated by applying the e-constraint method. Three Pareto curves are obtained for different confidence levels (α = 0.9, α = 0.95 and α = 0.99), as shown in Fig. 4. The solutions presented by the Pareto curves are feasible but they do not outperform the front of Pareto optimal solutions. It is worth to noting that

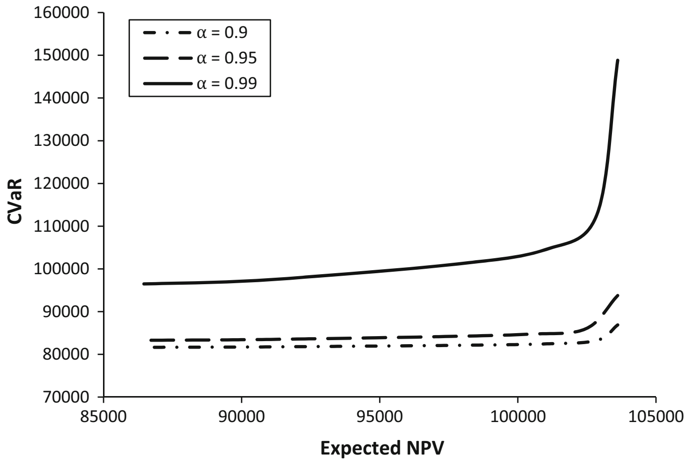

Fig. 5 Pareto curve for the expected net profit and *CVaR*

each solution of the front of Pareto implies a specific SC configuration and a set of planning decisions.

As it is seen in Fig. 5, there is a significant conflict between the expected net profit and the *CVaR* since improvements in net profit can only be achieved by the increasing of the *CVaR*. We can also observe from this Figure that when the confidential level α increases the *CVaR* value increases too by the definition of the *CVaR*. Thus, increasing the value of α denotes a higher level of risk and leads to a more risk averse policy.

In order to compare the obtained results after and before managing the *CVaR*, we draw the net profit distributions as illustrated in Fig. 6. Here, we choose the confidence level as 0.95. As it is seen in Fig. 6, the distribution of net profit before *CVaR* management presents a non-negligible probability of incurring in low net profit due to the dispersion of net profit values in the right-hand side. It is also noted that the distribution of profit for *CVaR* = 85,990.4 presents more low net profit than the distribution for *CVaR* = 84,724.78. Moreover, the cumulative distributions of net profit over the different scenarios are presented in Fig. 7. This Figure indicates that the cumulative curves obtained after managing the *CVaR* lie below the curve before managing the *CVaR* for low net profit values. However, these two curves intersect the curve before *CVaR* management at some point.

Afterwards, we apply the *DRisk* management model developed in Sect. 5. Figure 8 shows the trade-off between the *DRisk* measure and the expected net profit. It helps the decision maker to select the suitable configuration. The Pareto illustrates the significant conflict between *DRisk* and the expected net profit. Figure 9 presents the comparison between the net profit distributions before and after *DRisk* management model application. Two *DRisk* values are considered, which are 594 and 694. The distribution of net profit before *DRisk* management presents a non-negligible probability of incurring in low net profit due to the dispersion of net profit values in the right-hand side. One can note that, after applying the risk management model, the probability of having high values of net profit increases and reaches 12%.

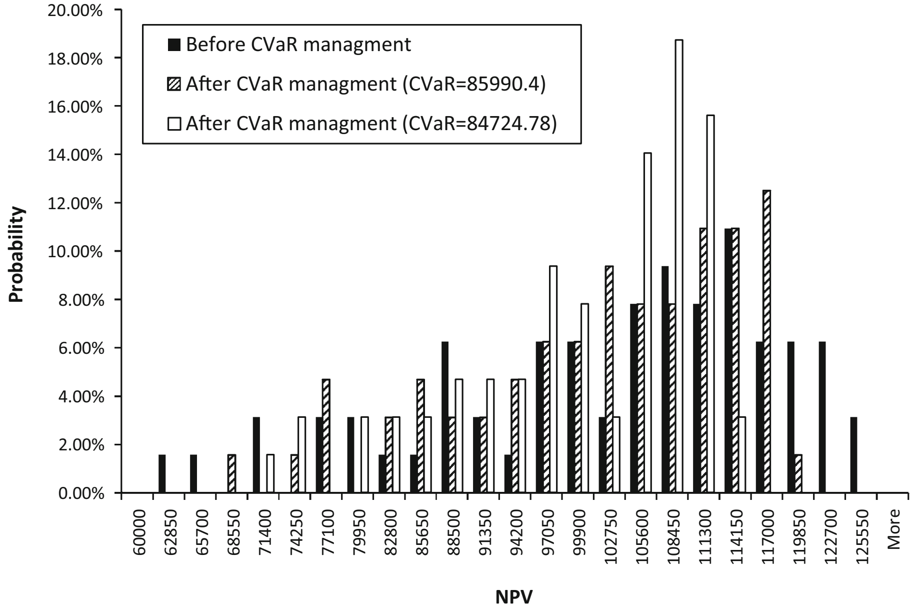

Fig. 6 Net profit cumulative distributions after and before *CVaR* management ($\alpha = 0.95$)

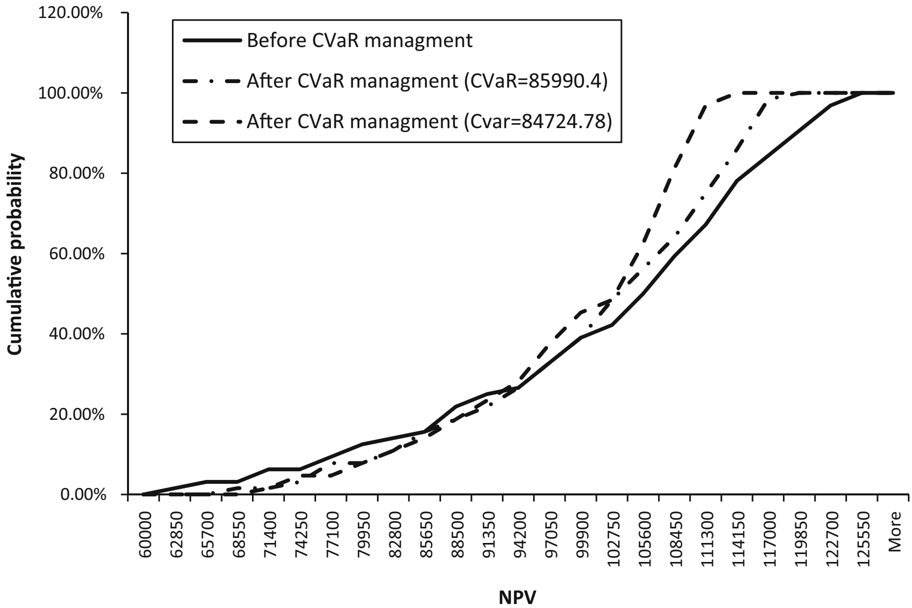

Fig. 7 Net profit distributions after and before *CVaR* management ($\alpha = 0.95$)

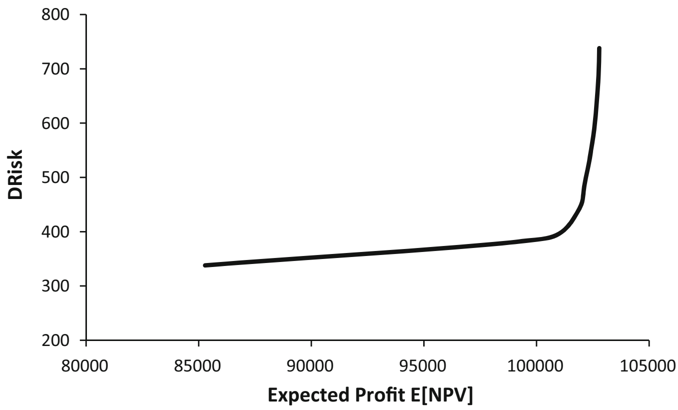

Fig. 8 Pareto curve for the expected net profit and DRisk

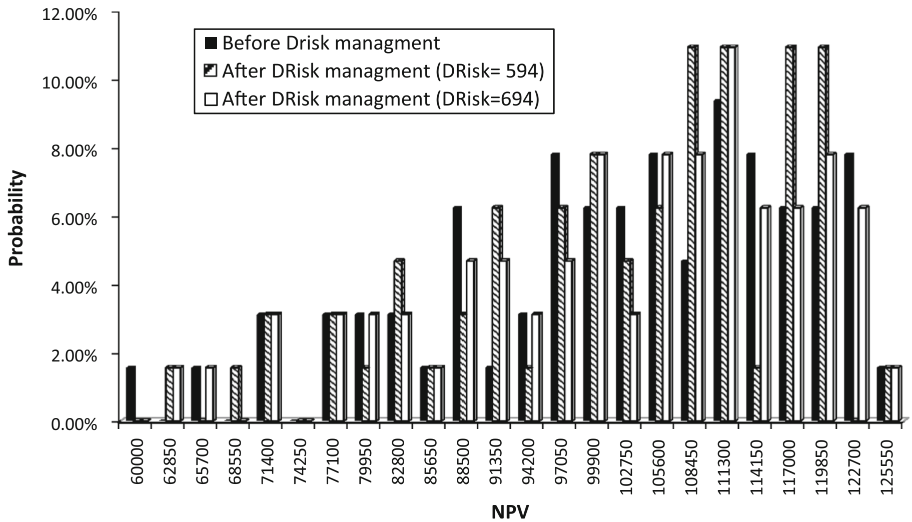

Fig. 9 Net profit cumulative distributions after and before *DRisk* management

In order to emphasize the reduction of the *CVaR* as well as the *DRisk* and the expected net profit for the *CVaR* management model and the *DRisk* management model, a metric is defined as follow:

$$\text{Reduction gap } (\%) = 100 \frac{\text{Value after risk managment} - \text{Value before risk managment}}{\text{Value before risk managment}} \tag{24}$$

Table 10 illustrates the influence of the variation of the demand shapes and selling price uncertainty on the expected net profit and the *CVaR* value. The first solution S1 represents the objective functions values before risk management. After applying the *CVaR* management model, the reduction of the expected profit is insignificant in the case of increasing demand with fixed selling price, and does not exceed 0.4%. It increases in the case of uncertain selling price, but still modest. The lowest reduction of the expected profit is observed in the case of

Table 10 Influence of the variation of problem parameters on the expected net profit and the *CVaR* value

Fixed selling price					Uncertain selling price				
Pareto optimal solution	Expected profit E[NPV]	CVaR	Reduction of the expected profit (%)	Reduction of the CVaR (%)	Pareto optimal solution	Expected profit E[NPV]	CVaR	Reduction of the expected profit (%)	Reduction of the CVaR (%)
Decreasing demand									
S1	104,810	95,064	–	–	S1	101,333	89,631	–	–
S2	104,769	94,567	0.039	0.523	S2	101,313	89,131	0.020	0.558
S3	104,726	94,067	0.080	1.049	S3	101,292	88,631	0.040	1.116
S4	104,658	93,567	0.145	1.575	S4	101,248	88,131	0.084	1.674
S5	104,580	93,067	0.219	2.101	S5	101,172	87,631	0.159	2.231
S6	104,495	92,567	0.301	2.115	S6	100,993	87,131	0.336	2.244
Increasing demand									
S1	104,574	110,118	–	–	S1	102,786	94,752	–	–
S2	104,568	109,618	0.01	0.45	S2	102,775	94,252	0.01	0.53
S3	104,562	109,118	0.01	0.91	S3	102,752	93,752	0.03	1.06
S4	104,556	108,618	0.02	1.36	S4	102,714	93,252	0.07	1.58
S5	104,548	108,118	0.02	1.82	S5	102,670	92,752	0.11	2.11
S6	104,533	107,618	0.04	2.27	S6	102,621	92,252	0.16	2.64
Variable demand									
S1	111,924	88,222	–	–	S1	105,226	85,940	–	–
S2	111,884	87,725	0.036	0.563	S2	105,219	85,440	0.007	0.582
S3	111,829	87,225	0.085	0.570	S3	105,212	84,940	0.013	1.164
S4	111,774	86,725	0.134	1.697	S4	105,187	84,440	0.037	1.745
S5	111,586	86,225	0.302	2.264	S5	104,990	83,940	0.224	2.327
S6	111,286	85,725	0.570	2.280	S6	104,748	83,440	0.454	2.341

Table 11 Influence of the variation of problem parameters on the expected net profit and the *DRisk* value

Fixed selling price					Uncertain selling price				
Pareto optimal solution	Expected profit E[NPV]	DRisk	Reduction of the expected profit (%)	Reduction of the DRisk (%)	Pareto optimal solution	Expected profit E[NPV]	DRisk	Reduction of the expected profit (%)	Reduction of the DRisk (%)
Decreasing demand									
S1	104,810	1506	–	–	S1	101,333	963	–	–
S2	104,725	1406	0.081	6.640	S2	101,314	914	0.019	5.088
S3	104,579	1306	0.220	13.280	S3	101,293	864	0.039	10.280
S4	104,407	1206	0.385	19.920	S4	101,249	814	0.083	15.472
S5	104,232	1106	0.551	26.560	S5	101,174	764	0.157	20.665
S6	104,038	1006	0.737	28.450	S6	101,000	714	0.329	21.882
Increasing demand									
S1	104,574	1506	–	–	S1	102,786	738	–	–
S2	104,562	1456	0.01	3.32	S2	102,752	688	0.03	6.78
S3	104,548	1406	0.02	6.64	S3	102,671	638	0.11	13.55
S4	104,510	1356	0.06	9.96	S4	102,558	588	0.22	20.33
S5	104,437	1306	0.13	13.28	S5	102,370	538	0.40	27.10
S6	104,355	1256	0.21	16.60	S6	102,136	488	0.63	33.88
Variable demand									
S1	111,924	822	–	–	S1	105,226	594	–	–
S2	111,885	774	0.035	5.839	S2	105,219	544	0.007	8.418
S3	111,831	724	0.083	11.922	S3	105,212	494	0.013	16.835
S4	111,776	674	0.132	18.005	S4	105,187	444	0.037	25.253
S5	111,595	624	0.294	24.088	S5	104,990	394	0.224	33.670
S6	111,295	574	0.562	25.840	S6	104,748	344	0.454	36.765

variable demand with uncertain selling price (0.007%). The highest reduction of the expected profit is observed as well in the case of variable demand but with fixed selling price (0.57%). From one solution to another, the reduction of the expected profit increases especially in the case of variable demand. Moreover, one can notice that this reduction, in the case of fixed selling price, is lower than that of the case of uncertain selling price. Besides, the reduction of the *CVaR* is more significant and almost the same in all cases. It varies from 0.5 to 2.64%. The highest and lowest reduction of the *CVaR* are observed in the case of increasing demand.

Table 11 illustrates the influence of the variation of the demand shapes and selling price uncertainty on the expected net profit and the *DRisk* value. The application of the *DRisk* management model increases the reduction of the expected profit, but it stills small and does not exceed 0.75%. One can notice that the reduction of the net profit in the case of variable demand, with fixed and uncertain selling prices, is almost the same for both risk management models. Like for the *CVaR* management model, the lowest reduction of the expected profit is observed in the case of variable demand with uncertain selling price. However, the highest reduction of the expected profit is observed in the case of decreasing demand with fixed selling price. The reduction of the *DRisk* is very important and reaches 37% in the case of variable demand with uncertain selling price. In addition, it is noticed that the *DRisk* is reduced especially in the case of uncertain selling price.

In conclusion, both risk management models slightly reduce the expected net profit. However, using the *DRisk* management model decreases notably the financial risk.

8 Conclusion

In this work, we developed a two-stage stochastic programming model to incorporate the demand and price uncertainties within the decision making process of a multi-site SCP problem from textile and apparel industry.

This paper contributes to the literature from three main respects. First, it proposes multi-objective stochastic programming model to simultaneously maximize the expected net profit and minimize the financial risk. Second, unlike previous works, the developed model takes into account the demand uncertainty as well as selling price uncertainty simultaneously. Finally, the consideration of two risk measures and their comparison allow the decision maker to choose the suitable configuration for the studied case.

The computational results of the studied case show that the stochastic model outperforms the deterministic model and leads to higher profit by 6.41%. In order to find better SCP solution, two risk management models were developed. First, the *CVaR* is incorporated into the stochastic programming model as a second objective, which leads to a multi-objective optimization model. Second, the *DRisk* is incorporated into the stochastic programming model as a second objective. For both risk management models, a set of Pareto-optimal solutions is generated, which demonstrates the tradeoff between objective functions while considering demand uncertainty as well as selling price uncertainty. These Pareto offers different useful configuration for the decision maker, who will select the suitable one.

Despite the *CVaR* management approach seems to be effective in reducing the expected net profit risk and identifying robust SCP solutions, the *DRisk* management model is more effective. In fact, the *DRisk* management approach decreases notably the financial risk for fixed as well uncertain selling prices. Therefore, it is more profitable to use *DRisk* measure than *CVaR* measure.

The extension of this study is to evaluate and select the best alternative among the front of Pareto optimal solutions according to the decision maker preferences.

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