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Novel robust fuzzy programming for closed-loop supply chain network design under hybrid uncertainty

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Abstract. In this paper, a mixed-integer nonlinear programming model is developed for a general edible oil closed loop supply chain network design problem under hybrid uncertainty which is then transformed to its linear counterpart. In order to cope with the hybrid uncertainty in input parameters, scenario-based and fuzzy- based parameters, a new approach is proposed including a novel robust fuzzy programming and an efficient method based on the Me measure. Furthermore, the performance of the proposed model is compared with that of other models. Finally, numerical studies and simulation are performed to verify our mathematical formulation and demonstrate the benefits of the proposed model.

Keywords: Mixed-integer programming, edible oil supply chain, closed loop supply chain, Network design, robust possibilistic programming, stochastic programming

1. Introduction

An efficient and effective supply chain is a sustainable competitive advantage for organizations and it can help them to overcome the turbulent environments and the extreme competitive pressures. A supply chain is a network of departments, such as suppliers, production and distribution centers involved all movements and storage of raw materials, work-in-process inventory, and finished goods from the supplier to the end customer [20]. Generally, the supply chain network design addresses to facility's capacity and locations, and it determines the quantity of flow between them [1]. A Closed-Loop Supply Chain Network Design (CLSCND) includes the reverse and forward supply chain activities to maximize value creation over the entire life cycle of a product by using the design, control, and operation of a system [5]. The forward supply chain mainly includes products/raw materials moved from the upstream suppliers to the downstream customers. In addition, when the used/unsold products move from the customer to the upstream supply chain to recycle or reuses, it is called the reverse supply chain [6, 9].

On the other hand, given that in the real world, a large number of parameters such as demands, costs of facility location, manufacturing, and transportation are quite uncertain, while the supply chain design must be robust [16]. Since the closed-loop

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supply chain has an important role in reducing costs and improving service levels, many researchers have recently reviewed on the CLSCND problems under uncertainty. Generally, two categories of uncertainty are randomness and epistemic ones in the data [13]. The Randomness uncertainty is used when the parameters have the random nature so that they have a known distribution. The stochastic programming is the most common method to face this uncertainty. The Epistemic uncertainty applied, when the parameters are imprecise so that the decision makers are faced lack of knowledge. The Possibilistic Programming is usually used to confront this kind of uncertainty [12, 14, 19]. Stochastic, Fuzzy and Robust Programming are the three applied methods to deal with the uncertain parameters [12, 17].

Although there are the different types of uncertainties in the supply chain, a few studies address to hybrid uncertainty. Recently, Keyvanshokooh et al. [10], proposed a hybrid robust-stochastic programming model that considers the stochastic scenarios for transportation costs and polyhedral uncertainty sets in the demand and return quantities. Also, Farokh et al. [4] proposed a hybrid robust fuzzy approach to cope with two different types of uncertainties that are the operational and disruption risks. They used the Credibility-Constrained Programming (CCP) approach to deal with the epistemic uncertainty [see 11]. In all current possibilistic programming approaches, the credibility measure is defined as the average of its possibility and necessity. Although this method is useful to prevent from quiet pessimistic/optimistic decisions, it forces decision makers to adopt a moderate attitude between the optimistic and pessimistic ones. Recently, Xu and Zhou [20] introduced a new fuzzy measure, Me measure, which can fill the gap of credibility measure. In this model, the decision maker can use an optimistic-pessimistic parameter(*i.e.* λ), to consider a convex combination of a pessimistic or optimistic spectrum. Actually, in the real-world decision-making process, the Me measure enables decision makers to consider a combined attitude. But the main drawback of the model is that must be solved twice and the model's solutions are an interval value. Given the current literature and the mentioned gaps, a novel Robust Stochastic-Possibilistic Programming (RSPP) based on Me measure is developed for a general edible oil closed-loop supply chain network design problem. Using the proposed models, not only can we cope with the hybrid uncertainty of parameters (scenario- and fuzzy-based parameters), but also we can reply to the varying attitudes of the decision makers with a more flexible measure (optimistic-pessimistic parameter). This model can obtain the flexible solutions so that provided more information, according to the different optimistic-pessimistic attitudes of the decision makers. Finally, unlike Xu's model [20] which must be solved twice, the superiority of the RSPP model is that it can be solved only once.

The rest of the paper is organized as follows. In Section 2, we address to the problem description and formulation. Section 3 provides a novel Robust Stochastic-Possibilistic Programming (RSPP) model. In Section 4, the numerical problems developed to study the performance of the proposed model, and then experimental results are presented. Finally, Section 5 concludes this research and gives some key points for future research.

2. Problem description and formulation

In this section, a multi-product and multi-period closed-loop supply chain network design model is proposed that operates under hybrid uncertainty. The model aims to minimize supply chain cost and find the best possible structure of a general edible oil supply chain. The supply chain is an integrated multi-echelon network and considers both forward and reverse flows. The forward flows start with transporting crude oil from suppliers to the crude oil silos. According to production plans, crude oil transferred to the production centers. After processing, crude oils turn into edible oils including kinds of products such as tins and bottles edible oils. Manufactured products ship to distribution centers and then to customer zones. On the reverse flow, the unsold or outdated products are sent to the collection centers. Given that the collected oil can be re-usable after the chemical processing in the manufacturing centers, the oils are separated from their tin and plastic (pet) cans. Then the oils are shipped to the manufacturing centers and the tin and pet cans are transported to scrap market.

The main objective of the edible CLSCND problem is to choose the suppliers and determine the location and number of the distribution centers in a way to minimize the total cost under hybrid uncertainty. Decision makers should choose the best location among the potential facilities while considering several factors simultaneously, such as various capacities, geographic regions, opening cost of facilities, transportation cost and most importantly, demand of customers. In order to integrate tactical and strategic decisions and pay attention to a variety of customer needs, this model is considered multi-period and multi-product. Since In the real world decision making process, data may not be sufficient or available, therefore, the model is faced with parameters that have an uncertain nature. In addition, in an edible oil supply chain, considering the price of crude oil is global, many factors like political issues, currency prices and etc., can affect the price of some parameters such as crude oil prices and transportation costs. As a result, given that our model has a long-term horizon, we use the possibilistic approach under different scenarios to deal with uncertain parameters [see 4, 14].

The other main assumptions and limitations considered in the proposed model are as follows:

- A set of potential suppliers can supply raw materials (crude oils and components)
- A set of potential distribution centers, silos (warehouses), collection centers are considered with several different capacity levels.
- Locations of the factory and customers are fixed.
- A fixed percentage of demand in the previous period is considered as returned products
- The costs of raw material, distribution, and collection centers are as fuzzy scenario based variables.
- The fixed cost of opening the facilities are uncertain and described as fuzzy variables.
- A predefined value is determined as an average scrap fraction

The sets, parameters and variables are used to formulate the edible oil CLSCN are as follows:

Indices:

i Index of suppliers, $(i = 1, 2, \ldots, I)$ j Index of manufacturing centers, $(j = 1, 2, .., J)$

k Index of candidate locations for crude oil silos, $(k = 1, 2, .., K)$

l Index of candidate locations for distribution centers, $(l = 1, 2, \ldots, L)$

m Index of fixed locations of customer zones, $(m = 1, 2, \ldots, M)$

n Index of candidate locations for collection centers, $(n = 1, 2, .., N)$

o Index of fixed locations for the scraped tin and pet markets, $(o = 1, 2, \ldots, O)$ r Index of raw material(crude oils), $(r = 1, 2, \ldots, R)$ t Index of time periods, $(t = 1, 2, \ldots, T)$

w Index of transportation modes, $(w = 1, 2, \ldots, W)$

q Index of possible capacity levels for main DC, $(q = 1, 2, \ldots, Q)$

Parameters:

$\tilde{d}^{m}_{pmts}$ Demand of customer zone m for product p at period t under scenario s

$\tilde{d}_{rots'}{}^{m}$ Demand of customer zone o for raw material (scrap component) r at period t under scenarios

$\tilde{C}^{s}_{rits}$ Purchasing cost of raw material r from supplier i at the time period t in scenario s

C^{h}_{rkts} Processing cost of raw material r in silo k at the time period t in scenario s

$\tilde{c}^{f}_{pjts}$ Unit production cost of product p in manufacture center j at period t under scenario s

$\tilde{c}^{d}_{plts}$ Processing cost of product unit p in distribution center l at period t under scenario s

$\tilde{c}^{c}_{mts}$ Processing cost of raw material unit r at collection center n at period t under scenario s

$\tilde{f}^{d}_{kq}$ Fixed cost of opening distribution center l with capacity level q

$\tilde{f}^{h}_{kq}$ Fixed cost of warehouse (silo) k with capacity level q

$\tilde{f}^{c}_{nq}$ Fixed cost of opening collection center n with capacity level q

$\tilde{f}^{s}_{r,i}$ Fixed cost due to acquisition of raw material r from supplier i (this represents the cost of development of long-term partnership with the supplier to guarantee a good service level)

$\tilde{c}^{ts}_{rikwts}$ Transportation cost of raw material unit r from supplier i to warehouse (silo) k via transportation mode w at period t under scenario s.

$\tilde{c}^{th}_{rkjwts}$ Transportation cost of raw material unit r from warehouse (silo) k to production center j via transportation mode w at period t under scenario s.

$\tilde{c}^{tf}_{pjtwts}$ Transportation cost of product unit p from production center j to distribution center l via transportation mode w at period t under scenario s.

$\tilde{c}^{td}_{plmwts}$ Transportation cost of product unit p from distribution center l to customer zone m via transportation mode w at period t under scenario s.

$\tilde{c}^{tm}_{pmnwts}$ Transportation cost of product unit p from customer zone m to collection center n via transportation mode w at period t under scenario s

$\tilde{c}^{tc}_{mjwts}$ Transportation cost of raw material r from collection center n to production center j via transportation mode w at period t under scenario s

$\tilde{c}_{mowts}{'}^{tc}$ Transportation cost of raw material (scrap component) r from collection center n to customer zone o via transportation mode w at period t under scenario s

w_{rp} The amount of the raw material unit r used in product unit p

r_{pm} Rate of return percentage from customer zone m for product unit p

r^c_{rp} Average of recyclable product fraction p used in raw material r

$\widetilde{ca}^s_{ri}$ Maximum capacity of supplier i for raw material r at each period

$\widetilde{ca}^r_j$ Maximum capacity of production center j at each period

$\widetilde{ca}^f_k$ Maximum capacity of filling center k at each period

$\widetilde{ca}^h_{kq}$ Maximum capacity of raw material silo k with capacity level q at each period

$\widetilde{ca}^d_{lq}$ Maximum capacity of distribution center l with capacity level q at each period

$\widetilde{ca}^c_{nq}$ Maximum capacity of collection center n with capacity level q at each period

p_s Probability of the occurrence of scenario s

Variables:

Q^s_{rikwts} Quantity of raw material r shipped from supplier i to warehouse (silo) k via transportation mode w at period t under scenario s

Q^h_{rkjwts} Quantity of raw material r shipped from warehouse (silo) k to production center j via transportation mode w at period t under scenario s

Q^f_{pjtwts} Quantity of product p shipped from product center j to distribution center l via transportation mode w at period t under scenario s

Q^d_{plmwts} Quantity of product p shipped from distribution center l to customer zone m via transportation mode w at period t under scenario s

Q^m_{pmnwts} Quantity of product p shipped from customer zone m to collection center n via transportation mode w at period t under scenario s

Q^c_{rnjts} Quantity of raw material r shipped from collection center n to production center j via transportation mode w at period t under scenario s

$Q_{rnowts}{'}^c$ Quantity of raw material r shipped from collection center n to customer zone o via transportation mode w at period t under scenario s

y^s_{ri} 1 if a supplier i is selected for supplying raw material r, 0 otherwise

$y^d_{l,q}$ 1 if a distribution center with capacity level q is opened at location l, 0 otherwise

$y^h_{k,q}$ 1 if a warehouse with capacity level q is opened at location k, 0 otherwise

$y^c_{n,q}$ 1 if a collection center with capacity level q is opened at location n, 0 otherwise

Using the above notation, the CSCND problem can be formulated as follows:

$$
\begin{aligned}
\min z = & \sum f^s_{r,i}.y^s_{r,i} + \sum\sum\sum f^d_{l,q}.y^d_{l,q} \\
& + \sum\sum\sum f^h_{k,q}.y^h_{k,q} + \sum\sum\sum f^c_{n,q}.y^c_{n,q} \\
& + \sum\sum\sum\sum (c^s_{rits} + c^{ts}_{riawts}).Q^s_{rikwts} \\
& + \sum\sum\sum\sum (c^h_{rkts} + c^{th}_{rkjwts}).Q^h_{rkjwts} \\
& + \sum\sum\sum\sum (c^f_{pjts} + c^{tf}_{pjlwts}).Q^f_{pjlwts} \\
& + \sum\sum\sum (c^d_{plts} + c^{td}_{plmwts}).Q^d_{plmwts} \\
& + \sum\sum\sum (c^c_{rnts} + c^{tc}_{rnjwts}).Q^c_{rnjts} \\
& + \sum\sum\sum\sum c{'}^{tc}_{rnots}.Q{'}^{c}_{rnowts} \\
& + \sum\sum\sum\sum c^{tm}_{pmnwts}.Q^m_{pmnwts}
\end{aligned} \tag{1}
$$

$s.t.$

$$\sum_k \sum_w Q^s_{rikwts} \le ca^s_{ri}.y^s_{ri} \forall r, i, t, s \tag{2}$$

$$\sum_k \sum_w \sum_p Q^f_{pjlwts} \le ca^f_j \forall p, j, t, s \tag{3}$$

$$\sum_r \sum_j \sum_w Q^h_{rkjwts} \le \sum_q ca^h_{kq}.y^h_{kq} \forall k, t, s \tag{4}$$

$$\sum_p \sum_m \sum_w Q^d_{plmwts} \le \sum_q ca^d_{lq}.y^d_{lq} \forall l, t, s \quad (5)$$

$$\sum_m \sum_p \sum_w Q^m_{pmnwts} \le \sum_q ca^c_{nq}.y^c_{nq} \forall n, t, s \quad (6)$$

$$\sum_k Q^h_{rkjwts} + \sum_n Q^c_{rnjts} = \sum_p \sum_l w_{rp}.Q^f_{pjlts} \forall r, j, w, t, s \quad (7)$$

$$\sum_k Q^h_{rkjwts} = \sum_k Q^s_{rkjwts} \forall r, k, w, t, s \quad (8)$$

$$\sum_k Q^f_{pjlwts} = \sum_m Q^d_{plmwts} \forall p, l, w, t, s \quad (9)$$

$$\sum_p \sum_m r^c_{rp} Q^m_{pmnwts} = \sum_k Q^c_{mjwts} \forall r, n, w, t, s \quad (10)$$

$$\sum_p \sum_m (1 - r^c_{pr}).Q^m_{pmnwts} = \sum_j Q_{mowts}{}^{rc} \forall r, n, w, t, s \quad (11)$$

$$\sum_l \sum_w Q^d_{plmwts} \ge d^m_{pmts} \forall p, m, t, s \quad (12)$$

$$\sum_n \sum_w Q_{mowts}{}^{rc} \ge d_{rots}{}^{rm} \forall r, o, t, s \quad (13)$$

$$\sum_n \sum_w Q^m_{pmnwts} \ge d^m_{pmts}.r_{pm} \forall p, m, t, s \quad (14)$$

$$\sum_q y^h_{kq} \le 1 \forall k \quad (15)$$

$$\sum_q y^d_{l,q} \le 1 \forall l \quad (16)$$

$$\sum_q y^c_{nq} \le 1 \forall n \quad (17)$$

$$Q^s_{rikwts}, Q^h_{rkjwts}, Q^f_{pkts}, Q^d_{plmwts}, Q_{mowts}{}^{rc}, Q^m_{pmnwts}, Q^c_{rnjwts} \ge 0, \quad (18)$$

$$y^s_{ri}, y^d_{l,q}, y^d_{l,q}, y^h_{k,q}, y^c_{n,q} \in \{0, 1\} \quad (19)$$

Equation (1) minimizes total cost of objective function including fixed cost to establish contracts with suppliers, fixed opening costs, transportation and processing costs. Constraints (2-6) are the capacity constraints on suppliers, production,distribution, and collection centers respectively. Constraints (7-11) ensure the material/product flow balances at each supplier, raw material silo, production center, distributions and collection centers. Constraints (12-13) correspond to satisfy the demands of customer zones. Constraint (14) represents that the returned products of all customers are collected in the collection centers. Constraint (15-17) ensures that just one capacity level of must be used for each opened centers. Finally, the Equations (18, 19) enforce the binary and non-negativity constraints on the corresponding decision variables.

As the related literature shows, the edible oil CLSCND is faced with hybrid uncertainty. A set is scenario-based parameters and the other one is fuzzy-based parameters. As a result, a novel robust stochastic-possibilstic (RSPP) is proposed in this paper to cope with the hybrid uncertain parameters. Indeed, the RSPP model is a combination of three approaches based on Me measure. First, possibilstic programming to deal with the fuzzy-based parameters. Second, stochastic programming to cope with scenario-based parameters, and finally robust optimization to adjust the conservatism level of output results with regard to uncertainty of parameters.

3. Robust programming

As mentioned in the literature section, possibilistic programming (PP) is used to deal with epistemic parameters. One of the famous PP methods is Possibilistic chance-constrained programming (PCCP). The PCCP can be used two different kinds of the fuzzy number such as, trapezoidal and triangular fuzzy numbers. Furthermore, in the PCCP model, decision makers can satisfy the possibilistic chance constraints by using mathematical concepts of mean value and fuzzy numbers and considering the minimum confidence level (α) [see 12, 16]. The PCCP model has two kinds of standards: Possibility (Pos) and Necessity (Nec). Given the decision maker's attitude, the Pos is the maximum possiblity level of occurrence of possibilistic parameters (i.e. Most optimistic) and the Nec is the minimum possiblity level [8, 11]. The main drawback of the credibility measure is that the decision makers should only consider the midpoint of the pessimistic and optimistic spectrum. Recently, Xu and Zhou [20] introduced a new fuzzy measure, Me measure, which can fill the gap of credibility measure. In this model, the decision maker can use an optimistic-pessimistic parameter (*i.e*λ) to consider a convex combination of a pessimistic or optimistic spectrum. Actually In the real-world decision-making process, the Me measure enables decision makers to consider a combined attitude [see 12, 21]. This measure can be defined as follows:

$$\begin{aligned} Me\{A\} &= Nec\{A\} + \lambda(Pos\{A\} - Nec\{A\}) \\ &= \lambda\, Pos\{A\} + (1-\lambda)\, Nec\{A\} \end{aligned} \tag{20}$$

As is clear from Equation (20), it can be concluded that:

If $\lambda = 1$, then Me = Pos (i.e. DM considers the maximum chance for an uncertain parameter).

If $\lambda = 0$, then Me = Nec (i.e. DM considers the minimum chance for an uncertain parameter).

If $\lambda = 0.5$, then Me = Cr (i.e. DM considers the average chance for an uncertain parameter).

The general measures of $\xi \le x, \xi \ge x$ are as follows:

$$Me\{\tilde{\xi} \le x\} = \begin{cases} 0 & if\ x \le r_1 \\ \lambda \frac{x-r_1}{r_2-r_1} & if\ r_1 \le x \le r_2 \\ \lambda & if\ r_2 \le x \le r_3 \\ \lambda + (1-\lambda)\frac{x-r_1}{r_2-r_1} & if\ r_3 \le x \le r_4 \\ 1 & if\ x \le r_4 \end{cases} \tag{21}$$

$$Me\{\tilde{\xi} \ge x\} = \begin{cases} 1 & if\ x \le r_1 \\ \lambda + (1-\lambda)\frac{r_2-x}{r_2-r_1} & if\ r_1 \le x \le r_2 \\ \lambda & if\ r_2 \le x \le r_3 \\ \lambda \frac{r_3-x}{r_4-r_3} & if\ r_3 \le x \le r_4 \\ 0 & if\ x \le r_4 \end{cases} \tag{22}$$

Also, the expected value of ξ can be defined based on Me measure as follows [see 21]:

$$\begin{aligned} E^{Me}\left[\tilde{\xi}\right] &= \int_0^{+\infty} Me\{\tilde{\xi} \ge x\}dx - \int_{-\infty}^{0} Me\{\tilde{\xi} \le x\}dx \\ &= \frac{1-2\lambda}{2}(r_1+r_2) + \frac{\lambda}{2}(r_3+r_4) \end{aligned} \tag{23}$$

3.1. The Basic PCCP (BPCCP) model

Here, for the convenience of work, the compact form of the CLSCN model is used. The x_s, y are decision variables where x_s corresponds to continuous variables and y represent the binary variables. A, B, N and, S are coefficient matrices and c, d, f represent the parameters of the model. The vectors c and d correspond to scenario-based parameters which are transportation costs, manufacturing costs, holding costs and demands, respectively. Also, the vectors f and N indicate to fuzzy-based parameters which represent opening cost and capacities of facilities respectively.

$$\begin{aligned} & Min z = \tilde{f} y + \tilde{c}_s x_s \\ & s.t. \\ & Ax_s \ge \tilde{d}_s, \\ & Bx = 0, \\ & Sx_s \le \tilde{N} y, \\ & y \in \{0,1\}, x \ge 0, \end{aligned} \tag{24}$$

Taking into account the Me measure, and according to Pishvaee et al. [16] the Basic Stochastic-possibilistic Programming (BSPP) model is as follows:

$$\begin{aligned} & Min E[z] = E[\tilde{f}]y + E[\tilde{c}_s]x_s \\ & s.t. \\ & Me\{Ax_s \le \tilde{d}_s\} \ge \alpha_s, \\ & Bx = 0, \\ & Me\{Sx_s \le \tilde{N}y\} \ge \beta_s \\ & y \in \{0,1\}, x \ge 0 \end{aligned} \tag{25}$$

Xu and Zhou proposed two approximation models which are called upper approximation model (UAM) and the lower approximation model (LAM) [see 21]. These models can be defined as follows:

$$LAM \begin{cases} Min\ E[z] = E\left[\tilde{f}\right] y + E\left[\tilde{c}_s\right] x_s \\ s.t. \\ Pos\left\{ Ax_s \ge \widetilde{d}_s \right\} \ge \alpha_s, \\ Bx = 0, \\ Pos\left\{ Sx_s \le \widetilde{N} y \right\} \ge \beta_s, \\ y \in \{0,1\}, x \ge 0, \end{cases} \quad and$$

$$UAM\begin{cases} Min\ E[z] = E\left[\tilde{f}\right] y + E[\tilde{c}_s]\, x_s \\ s.t. \\ Nec\left\{Ax_s \geq \widetilde{d}_s\right\} \geq \alpha_s, \\ Bx = 0, \\ Nec\left\{Sx_s \leq \widetilde{N} y\right\} \geq \beta_s, \\ y \in \{0,1\}, x \geq 0, \end{cases} \tag{26}$$

As can be seen from Equation (26), the proposed model by Xu and Zhu should be solved two times (i.e. once, UAM problem must be solved and the next time, the LAM is solved). In fact, unlike the credibility measures, the Me measure has piecewise functions [see 21]. almost the same as the credibility measure [22], the model is as follows:

$$LAM\begin{cases} Min\ E[z] = E\left[\tilde{f}\right] y + E[\tilde{c}_s]\, x_s \\ s.t. \\ Ax_s \geq (1-\alpha_s)d_{1s} + \alpha_s d_{2s}, \\ Bx = 0, \\ Sx_s \leq [(1-\beta_s)N_4 + \beta_S N_3]\, y, \\ y \in \{0,1\}, x \geq 0, \end{cases}$$

$$UAM\begin{cases} Min\ E[z] = E\left[\tilde{f}\right] y + E[\tilde{c}_s]\, x_s \\ s.t. \\ Ax_s \geq (1-\alpha_s)d_{3s} + \alpha_s d_{4s}, \\ Bx = 0, \\ Sx_s \leq [(1-\beta_s)N_2 + \beta_S N_1]\, y, \\ y \in \{0,1\}, x \geq 0, \end{cases} \tag{27}$$

3.2. Robust stochastic-possibilistic programming (RSPP)

One of the drawbacks of the BPCCP model is that the model is not sensitive to deviations from the optimal value in the objective function (optimality robustness) and deviations from the RHS of chance constraints (feasibility robustness) [see 2]. Thus, given the parameters of the model are hybrid uncertainty (i.e. scenario-based and fuzzy based parameters), a novel hybrid robust stochastic-possibilistic programming is presented which is a combination of robust optimization, stochastic programing and possibilistic programming based on the Me measure. The RSPP model can be defined as follows:

$$\begin{aligned} &Min\ E[z] + \gamma(z_{\max} - z_{\min}) + \omega \sum_s p_s.\,|E[z] - E[z_s]| \\ &+\delta_1 \sum_S P_S \left[d_{4s} - \frac{(\alpha_s - \lambda)\widetilde{d}_{4s} + (1-\alpha_s)d_{3s}}{1-\lambda}\right] \\ &+\delta_2 \sum_S P_S \left[\frac{(\upsilon_s - \lambda)N_{1s} + (y - \upsilon_s)N_{2s}}{1-\lambda} - N_{1s}.y\right] \end{aligned} \tag{28}$$

$s.t.$

$$LAM\begin{cases} Ax_s \geq (1-\alpha_s)d_{1s} + \alpha_s d_{2s}, \\ Bx = 0, \&\&\&\& \\ Sx_s \leq [(1-\beta_s)N_4 + \beta_S N_3]\, y, \\ y \in \{0,1\}, x \geq 0, \end{cases}$$

$$UAM\begin{cases} Ax_s \geq (1-\alpha_s)d_{3s} + \alpha_s d_{4s}, \\ Bx = 0, \\ Sx_s \leq [(1-\beta_s)N_2 + \beta_S N_1]\, y, \\ y \in \{0,1\}, x \geq 0, \end{cases}$$

Similar to BSPP model, the first term in the objective function corresponds to expected value of z. The second term indicates to the optimality robustness that can be controlled through minimizing the maximum possible value (i.e.$z_{\max}$) and minimum possible value (i.e.$z_{\min}$). In fact, the second term is optimality robustness under fuzzy-based parameters. We call this term as fuzzy-based deviation from the optimal value in the objective function (i.e. possibilistic deviation) and it can be defined as Equations (29, 30). Also γ corresponds the weight (importance) of the possibilistic deviation against the other terms in objective function. Indeed, this term (i.e.γ) minimize the maximum deviation from the minimum deviation [see 4, 15].

$$z_{\max} = f_4.y + \sum_s p_s.c_{4s}.y_s \tag{29}$$

$$z_{\min} = f_1.y + \sum_s p_s.c_{1s}.y_s \tag{30}$$

The third term addresses the scenario-based uncertainties which called scenario-based deviation from the optimal value in the objective function (i.e. stochastic deviation). This term determines amount of violation of the expected value of objective function ($E[z]$) from the expected value of objective function under each scenario ($E[z_s]$) and it can be defined as Equation (31). In fact, the third term shows that there is a deviation between optimality robustness under fuzzy-based parameters and optimality robustness under scenario-based parameters which should be controlled. Also ω corresponds the weight (importance) of the stochastic deviation against the other terms in the objective function.

$$E[z_s] = \left[\frac{1-\lambda}{2}(f_1 + f_2) + \tfrac{\lambda}{2}(f_1 + f_2)\right].y + \left[\frac{1-\lambda}{2}(c_{1s} + c_{2s}) + \tfrac{\lambda}{2}(c_{3s} + c_{4s})\right] x_s \tag{31}$$

In addition, the fourth and fifth terms in the objective function determine the feasibility robustness in which δ_1, δ_2 are the penalty rates for violating of the RHS of chance constraints. As can be seen in Equation (31), the third term denotes an absolute term that can be linearized using the approach proposed by Yu [21]. According to this approach, one additional variable θ_s along with a constraint is added to the problem. Furthermore, since N (i.e. Technological coefficient matrix) is an uncertain parameter, then the RSPP model would be a non-linear mathematical programming. Therefore, one additional variable $v_s = \beta_s.y$ can be defined to formulate the linear equivalent of the model that is defined as Equation (32). Also, the parameter M is a sufficient large number. Finally, three constraints are added to the model to control the auxiliary variable vector v. Infact, we will have: $when\ y = 0, then\ v = 0;\ and\ when\ y = 1,\ then\ v = \beta$

$$Min\,E[z] + \gamma(z_{\max} - z_{\min}) + \omega \sum_s p_s\{(E[z] - E[z_s]) + 2\theta_s\}$$
$$+\delta_1 \sum_s P_s \left[d_{4s} - \frac{(\alpha_s - \lambda)\tilde{d}_{4s} + (1-\alpha_s)d_{3s}}{1-\lambda}\right] +$$
$$+\delta_2 \sum_s P_s \left[\frac{(v_s - \lambda)N_{1s} + (y - v_s)N_{2s}}{1-\lambda} N_{1s}.y\right]$$

$$LAM \begin{cases} Ax_s \geq (1-\alpha_s)d_{1s} + \alpha_s d_{2s}, \\ Bx = 0, \&\&\&\&\&(31) \\ Sx_s \leq [(1-\beta_s)N_4 + \beta_S N_3]\, y, \\ v_s \leq M.y \\ v_s \geq M.(y-1) + \beta_s \\ v_s \leq \beta_s \\ y \in \{0,1\}, x \geq 0 \end{cases} \tag{31}$$

$$UAM \begin{cases} Ax_s \geq (1-\alpha_s)d_{3s} + \alpha_s d_{4s}, \\ Bx = 0, \\ Sx_s \leq [(1-\beta_s)N_2 + \beta_S N_1]\, y, \\ v_s \leq M.y \\ v_s \geq M.(y-1) + \beta_s \\ v_s \leq \beta_s \\ y \in \{0,1\}, x \geq 0, \end{cases}$$

4. Implementation and evaluation

In this section, In order to evaluate the usefulness and performance of the proposed models, several numerical experiments are implemented and the related results are reported in this section. In this study, the general edible oil CLSCN design problem has four potential locations for distribution centers and silos, as well as three potential locations for recovery center. Moreover, there are three capacity level including 5000, 10,000 and 15,000 tons for each potential locations. Furthermore, two types of suppliers were considered: (1) Suppliers of the crude oil (such as, Palm and Colsa) located in different part of the world. (2) Suppliers of the components (such as, tin sheets and Plastic bottle preform). Supplied crude oils are transported by ships and are unloaded at the crude oils warehouses (silos), and then by trucks or trains are transported to crude oil silos. Then crude oils are transported by trucks or trains to manufacture centers. Also, purchased components (tin sheets and plastic cans or preform) are transported by trucks to manufacture center. Generally, three kinds of vehicles are considered include: ships, trucks and trains. Since the proposed model is multi-product and multi-period, and different scenarios (4 scenarios), as well as due to space limitation, without losing generality of the proposed multi-product model, in this paper the production-distribution network of the single product is chosen. Also, the number of customer zone is considered ten. Yearly demands have a uniform distribution and each period of time indicates three months of the planning horizon.

As shown in Table 1, four scenarios are considered corresponding to low, normal, high, and very high situations with unequal probabilities. Then, for each scenario, fuzzy parameters are generated. To generate the trapezoidal fuzzy parameters, four prominent points, i.e., the most likely ($c^m = c_2$, c_3), the most

Table 1
The Random values of fuzzy scenarios based parameters in the test instance

Scenarios Parameters	Low	Normal	High	Very high
p_s	0.2	0.25	0.25	0.3
$\widetilde{d}^{m}_{pmts}$	U (30,100)	U (80,150)	U (130,200)	U (180,250)
$\widetilde{dr'}^{m}_{rots}$	U (20,40)	U (40,60)	U (60,80)	U (80,100)
c^{h}_{rkts}	U (400,500)	U(450,550)	U(550,650)	U (650,750)
$\tilde{c}^{s}_{rits}$	U (500,600)	U (600,700)	U (700,800)	U (800,900)
$\widetilde{c}^{f}_{pjts}$	U (2000,2500)	U(2500,3000)	U(3000,3500)	U(3500,4000)
$\widetilde{c}^{d}_{plts}$	U (800,1200)	U(1000,1400)	U(1200,1600)	U(1400,1800)
$\widetilde{c}^{c}_{rnts}$	U (800,1000)	U(1000,1200)	U(1200,1400)	U(1400,1600)
$\widetilde{c}^{ts}_{rikwts}$	U (800,1050)	U(1000,1250)	U(1100,1350)	U(1200,1450)
$\widetilde{c}^{th}_{rkjwts}$	U (350,450)	U (400,500)	U (450,550)	U (500,600)
$\tilde{c}^{tf}_{klts}$	U (350,450)	U (400,500)	U (450,550)	U (500,600)
$\widetilde{c}^{td}_{plmwts}$	U (500,700)	U (600,800)	U (700,900)	U (800,1000)
$\widetilde{c}^{tm}_{pmnwts}$	U (450,650)	U (600,800)	U (650,850)	U (750,950)
$\widetilde{c}^{tc}_{rnjwts}$	U (350,450)	U (400,500)	U (450,550)	U (500,600)
$\tilde{c}_{nots'}^{tn}$	U (150,250)	U (200,300)	U (250,350)	U (300,400)

Table 2
Random data for fuzzy parameters in the test instance

Parameters	**The most likely values**	**parameters**	**The most likely values**
$\tilde{f}^{d}_{lq}$	U(120000,140000)	$\widetilde{ca}^{s}_{ri}$	U (1000,2000)
$\tilde{f}^{h}_{kq}$	U (150000,200000)	$\widetilde{ca}^{h}_{j}$	U (1000,1400)
$\tilde{f}^{c}_{nq}$	U (100000,150000)	$\widetilde{ca}^{f}_{k}$	U (500,700)
$\tilde{f}^{s}_{ri}$	U (30000,50000)	$\widetilde{ca}^{d}_{l}$	U (200,300)
w_{rp}	U (0,2)	$\widetilde{ca}^{c}_{n}$	U (200,350)
r_{pm}	U (0.2,0.4)	r^{c}_{rp}	U (0.1,0.25)

pessimistic ($c^p = c_1$) and the most optimistic values ($c^{\circ} = c_4$) are estimated for each imprecise parameter [see 14]. First, the most likely (c^m) value of each parameter is generated randomly using the uniform distributions. Then, without loss of generality two random numbers (r_1, r_2) are generated between 0.2 and 0.5using uniform distribution, and the most pessimistic (c^p) and optimistic (c°) values of a fuzzy numberare calculated as follows: $c^{\circ}=(1+r_1).c^{m},$ $c^p = (1 - r_2).c^m$. All parameters are generated randomly according to the uniform distributions specified in Table 1 and 2. The instances are solved by GAMS 24.8 using CPLEX solver.

4.1. Robustness analysis

In order to evaluate the performance of the proposed model several sensitivity analyses are performed on the coefficients of scenario deviations and possibilistic deviations. In fact, optimality robustness and feasibility robustness of the RSPP model are evaluated using the change in the coefficients γ, ω, δ_1, δ_2 respectively. Figs. 2–5 show the results of the sensitivity analysis of the second and third terms of the objective function. Figs. 2–5 show the results of the sensitivity analysis of the second and third terms of the objective function. Fig. 2 reveals the obtained result of UAM model whereas the Fig. 3 is related to the LAM model. They show that when the coefficient of possibilistic deviation (i.e.γ) increases, the optimal expected value increases and possibilistic deviation decreases. Similarly, Figs. 4 and 5 demonstrate the effect of changes in ω on the mean cost and the Scenario deviation of the LAM and UAM models, respectively. As can be seen, by increasing the coefficient of scenario deviation (i.e.ω), the optimal expected value increases and scenario deviations decreases. According to the Figs. 2–5, it can be said that when $\omega = 0/\gamma = 0$ the model has the highest values of possibilistic deviations and scenario deviation. As a result, decision makers can be faced with a high risk.

4.2. Comparative analysis

As mentioned earlier, a robust stochastic-possibilistic programming (RSPP) is a combination of robust optimization, possibilistic programming

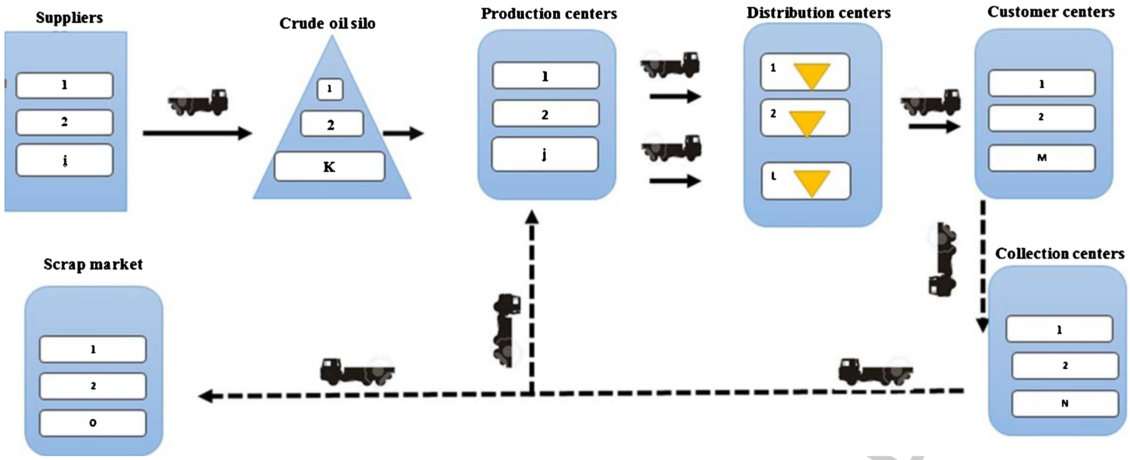

Fig. 1. the structure of the edible oil closed-loop supply chain network.

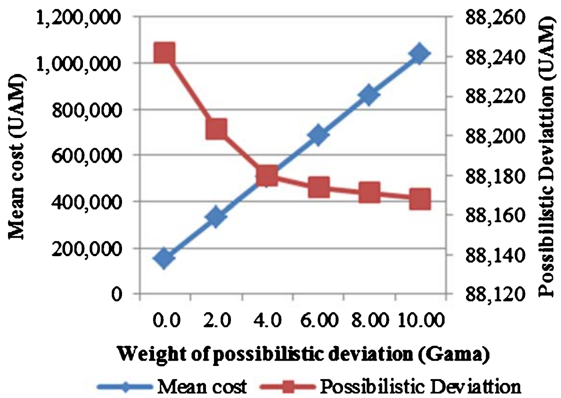

Fig. 2. The effect of changes in γ on the mean cost and the possibilistic deviation of the LAM model.

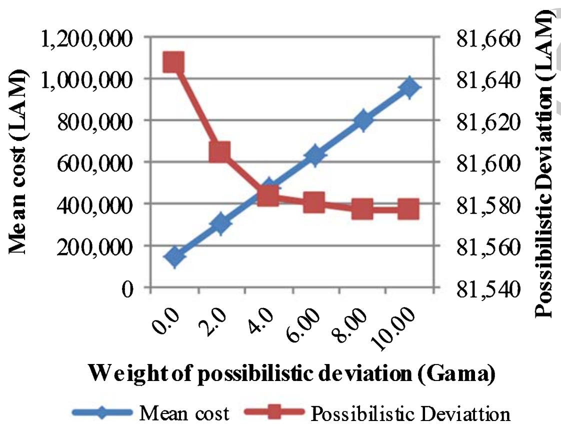

Fig. 3. The effect of changes in γ on the mean cost and the possibilistic deviation of the UAM model.

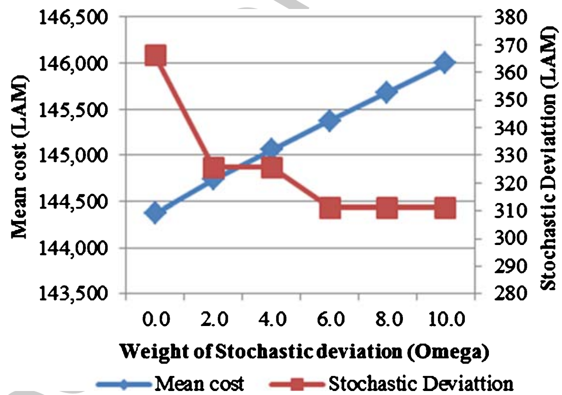

Fig. 4. The effect of changes in ω on the mean cost and the Scenario deviation of the LAM model.

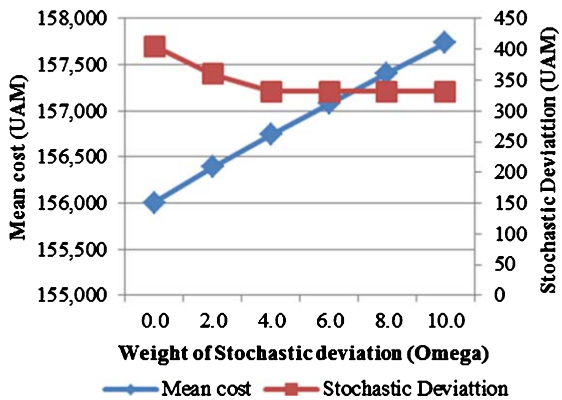

Fig. 5. The effect of changes in ω on the mean cost and the Scenario deviation of the UAM model.

and stochastic programming based on Me measure. This method is more flexible than credibility measure and helps decision makers to consider a convex combination of the extreme attitudes using an optimistic-pessimistic parameter. Using the proposed model, not only can we cope with the hybrid uncertainty of parameters (scenario-based and fuzzy-based parameters), but also we can reply to the varying attitudes of the decision makers with a more flexible measure (optimistic-pessimistic parameter). The RSPP model can obtain flexible solutions which can provide more information according to different optimistic-pessimistic attitudes of the decision makers. Here, a sensitivity analysis is performed on optimistic-pessimistic attitudes (λ) and the confidence levels (α, β). The obtained results (i.e. Table 3) represent differences between different optimistic-pessimistic attitudes and the different confidence levels.

We assume that α, β have the same value and we change the values of optimistic-pessimistic attitudes.

We assume that λ has the same value and we change the values of α, β.

The following Table 1 shows the optimal value of the RSPP model for both of the UAM and LAM models by changing the parameters (i.e.α, β *and* λ

According to Table 3, the RSPP model provides interval solution that the obtained result of the UAM and LAM arethe upper bond and lower bond of the model, respectively. When α, β has the same value, by increasing the values of λ, the optimal value of the objective function (Z^*) gets worse (i.e. Z^* increases), and vice versa. Indeed, we could say that: When the objective function is Minimization, λ is a pessimistic parameter, and when the objective function is Maximization, λ is an optimistic parameter. Also, Table 3 shows that under the same optimistic-pessimistic parameter when the α, βincreases, the Z^* increases. In fact, whenhas the same value, by increasing α, β the feasible region shrinks, and we will have worse solution and on the contrary, when the α, β decrease, due to the expansion of the feasible region, we will find better solutions. Figs. 6 and 7 show the effect of changes in optimistic-pessimistic parameter and confidence levels on the objective function, respectively.

Given the Table 3, in the similar hybrid robust models including credibility measure, the decision maker can only consider the average risk between optimistic and pessimistic attitudes that is related to $\lambda = 0.5$. In fact, in these models, the decision maker can have only one choice which it can hardly be appropriate in the real world decision-making process. But in the RSPP model, all options can be considered to deal with various risks in the model through the optimistic-pessimistic parameter, so the decision maker can choose the best option, considering the type of attitudes and model characteristics.

To sum up, the proposed models can cope with both fuzzy and stochastic imprecise parameters, simultaneously. On the other hand, this model can obtain flexible solutions which can provide more information to the decision maker. In fact, the optimistic or pessimistic attitude of decision-makers toward the goals of the problem determines the value of λ, and their conservative level toward the satisfaction of constraints specifies the value of α, β.

Given the Table 3, in the similar hybrid robust models including credibility measure such as Farokh et al. [4], the decision maker can only consider the average risk between optimistic and pessimistic attitudes that is related to$\lambda = 0.5$. In fact, in these models, the decision maker can have only one choice which it can hardly be appropriate in the real world decision-making process. But in the RSPP model, all options can be considered to deal with various risks in the model through the optimistic-pessimistic parameter, so the decision maker can choose the best option, considering the type of attitudes and model characteristics. Also, in comparison with the model proposed by Xu and Zhu [20], it can be said that the RSPP model is only solved once, while the Xu's model must be solved twice. The UAM and LAM are the upper bond and lower bond of the model, respectively. This means that once for UAM, the model is solved, and the upper bond of interval value is obtained. Similarly, the LAM model is performed and the lower bond of the solution is obtained. Therefore the model's solutions are an interval value. In addition, in the Xu's model, λ exists only in the objective function. Thus, the impact of optimistic or pessimistic attitude of decision makers is only on the optimality of the objective function and does not affect the feasibility of the model.

To sum up, by using the RSPP model, we can cope with both fuzzy and stochastic imprecise parameters, simultaneously. On the other hand, this model can obtain flexible solutions which can provide more information to the decision maker. In fact, the optimistic or pessimistic attitude of decision-makers toward the goals of the problem determines the value of λ, and their conservative level toward the satisfaction of constraints specifies the value of α, β.

Table 3
Sensitivity analysis with different parameters.

$\lambda \backslash \alpha, \beta$	0	0.2	0.4	0.6	0.8	1
0.5	[123214,130213]	[130255,137654]	[137295,145095]	[144336,152536]	[151377,159977]	[158418,167418]
0.6	[123838,130836]	[130914,138313]	[137990,145790]	[145066,153267]	[152142,160744]	[159218,168221]
0.7	[124839,131476]	[131973,138988]	[139107,146500]	[146241,154012]	[153375,161524]	[160509,169040]
0.8	[125460,132100]	[132631,139648]	[139806,147198]	[146985,154748]	[154168,162298]	[161355,169843]
0.9	[126082,133080]	[133278,140685]	[140492,148290]	[147967,155895]	[154092,163501]	[162107,171106]
1	[126704,133702]	[133944,141342]	[141184,148982]	[148424,156622]	[155664,164262]	[162904,171903]

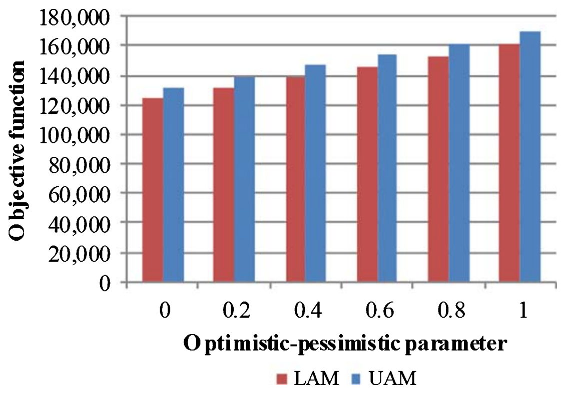

Fig. 6. The effect of changes in optimistic-pessimistic parameter (λ) on the objective function.

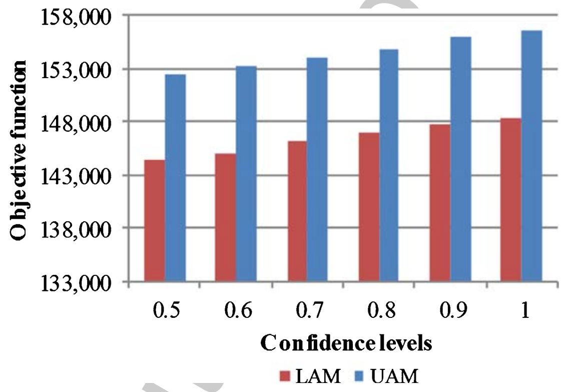

Fig. 7. The effect of changes in confidence levels (α, β) on the objective function.

4.3. Simulation of the results

In this section, the desirability and robustness of the RSPP model are evaluated under nominal data. To do so, 10 realizations are performed using random sets with uniform distribution, and then the realization model is formulated using the obtained result under nominal data ($x*$, $y*$) [see 14]. The compact form of the realization model is as follows:

$$\begin{aligned} & min\ Z = f^{real} \cdot Y^* + c_s^{real} \cdot x_s^* + \delta_1 S_1 + \delta_1 S_2 \\ & s.t. \\ & S.X_s^* \leq N^{real} \cdot Y^* + S_1 \\ & A \cdot X_s^* + S_2 \geq d^{real} \\ & B \cdot X_s^* = 0 \\ & S_1, S_2 \geq 0. \end{aligned} \tag{33}$$

In Equation (33), the amount of the violation of each constraint is shown using the new decision variables S_1, S_2. Also, the average, the standard deviation (SD) and coefficient of variation (CV) are used to measure the proposed model under different realizations. Table 4 shows the obtained results.

As Table 4 shows, for a high amount of the confidence levels ($\alpha, \beta = 0.9$), the BSPP model has the worst performance regarding the mean cost and standard deviation. On the other hand, the best performance of BSPP model is related to the low value of confidence levels ($\alpha, \beta = 0.7$). The reason is that by increasing the α, β the feasible region decreases and this means that decision-makers have a risk-averse (i.e. fully conservative) attitude. Also, when $\alpha, \beta = 0.7$ the feasible region increases and the BSPP model gets the better values. As can be seen in Table 4, the obtained result from both RSPP and BSPP models are closed together, and they have rather a similar value.

Finally, it should be noted that the RSPP model always has lower mean costs and standard deviation of costs with regard to different realizations of uncertain parameters. Indeed, the feasibility and optimality robustness are considered by the RSPP model. Then, violations of objective function and constraints are efficiently controlled via applying optimality robustness terms. Thus, it is quite justifiable to be applied the RSPP model under uncertainty situation for such Problem.

Table 4
The performance of the proposed models under realizations.

No. of realization	BSPP $\alpha, \beta = 0.7$	BSPP $\alpha, \beta = 0.8$	BSPP $\alpha, \beta = 0.9$	RSPP
1	[153614,157753]	[154957,161841]	[162407,169285]	[151098,159184]
2	[151370,159824]	[158661,164351]	[161284,166131]	[150234,158302]
3	[150477,156275]	[157382,162603]	[160231,165342]	[151237,157409]
4	[151017,158995]	[154655,160671]	[162856,167905]	[149260,156473]
5	[150195,159903]	[157699,163761]	[160749,167055]	[152713,155329]
6	[151251,157472]	[156038,164527]	[163550,169188]	[150259,157621]
7	[154097,158602]	[158075,162153]	[164301,167545]	[148764,158774]
8	[152654,158940]	[156302,165107]	[165108,170123]	[149605,158442]
9	[151045,159521]	[155385,164358]	[162704,169827]	[152298,159068]
10	[153473,157749]	[159448,163722]	[161242,168750]	[149976,157198]
Mean	[151919,158303]	[156860,163309]	[162443,168115]	[1505444,157789]
SD	[1143,1215]	[1191,1339]	[1350,1550]	[1502,1728]

5. Conclusion

In this paper, we addressed the gap in the area of closed loop supply chain network design (CLSCND) under hybrid uncertainty conditions. To this aim, first a mixed integer programming model was presented that minimize the objective function. Second, since the proposed model includes two kinds of uncertainty for parameters, scenario-based and fuzzy- based parameters, a novel robust stochastic-possibilistic programming (RSPP) and an efficient method based on the Me measure was proposed to cope with uncertain parameters. In order to evaluate the performance of the RSPP model, an industrial case study was considered. The results showed that the proposed model not only can control both scenario and the possibilistic deviation, but also it can consider a convex combination of the extreme attitudes and can provide more information according to different optimistic-pessimistic attitudes of the decision makers.

As guidance for future research, the model addressed in this paper can be enhanced on the robust flexible programming. In addition, extending the edible oil supply chain model to a sustainable supply chain by incorporating environmental and social indicators can be considered. Finally, for models with large dimensions, the use of heuristic models can be useful.

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