Journal of Industrial and Systems Engineering
Vol. 13, No. 3, pp. 153-171
Summer (July) 2021

A two-stage stochastic programming model for a perishable products supply chain network design considering resiliency and responsiveness

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Abstract

The present scenario of supply chain management is full of uncertainty due to the intrinsic complexity of operating environments. A perishable products supply chain is not an exception and is often vulnerable to disruptive incidents throughout all stages from upstream to downstream. To deal with such a challenge, a resilient structure of the supply chain with the capability to recover from or react to disruptions is approached in this study. To secure the supply chain operations, we investigate a set of proactive strategies, including signing contracts with backup suppliers, reserving extra capacity in production facilities, lateral transshipment, and keeping inventory. Using a two-stage stochastic programming model, this study examines the extent to which supply chain responsiveness and resilience are supportive. The proposed model is validated through a numerical example, and managerial insights are derived. The computational results are based on three analyses: (1) extracting the relationship between the cost function and the acceptable service levels, (2) examining the effectiveness of different strategies in managing disruptions, (3) and evaluating the accuracy of the two-stage stochastic programming approach in comparison with other approaches.

Keywords: supply chain management, perishable products, resilience, responsiveness, two-stage stochastic programming

1- Introduction

In recent years, due to consumer preferences for features such as freshness, quality and safety, the production of perishable products has been recognized as one of the main subgroups in production (Dutta & Shrivastava, 2020). Many industries, especially for the manufacture of food and high-technology products, are dealing with products that are inherently perishable (Hasani, Zegordi, & Nikbakhsh, 2012). These products are characterized with an associated expiration date and the values of products beyond their expiration data will decrease significantly, and customers will have a high sensitivity to competitors' offers. In general, perishable products referred to as products having at least one of the following conditions: (1) its quality drastically drops in proportion to the passage of time, (2) dangerous consequences are likely following its reduced functionality, and (3) its amount decreases gradually (Aliabadi, Yazdanparast, & Nasiri, 2019).

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ISSN: 1735-8272,

Like other types of supply chains, the network design problem performs a major function in the long-term survival and success of supply chains dealing with perishable products. Such a problem should be addressed tacking into account the particular characteristics of perishable products. General cases of supply chains for perishable products involve a variety of decision at strategic and tactical levels concerning the location and size of facilities to configure the supply chain network, production planning, demand management, and logistics management, to name few (Khalafi, Hafezalkotob, Mohamaditabar, & Sayadi, 2020).

In this regard, the structure of a perishable product supply chain is more complex, and its uncertainty and vulnerability is high as a result of being prone to decay and damage during operations, all of which increase the risk of supply chain disruption (Biuki, Kazemi, & Alinezhad, 2020).

As supply chain networks become more complex, their vulnerability to disruption risks increases dramatically (Pettit, Fiksel, & Croxton, 2010). In the current competitive setting, supply chain risk management has been in the concentration of attention. Referring to Tang's research, operational and disruption risks are two major categories of risks that supply chains are exposed to (Tang, 2006). Operational risks are related to those uncertainties expected in day-to-day operations and for the most part, are internal to the organization (e.g., variations in supply, demand, and cost and production and transportation equipment malfunction) (Chen, Sohal, & Prajogo, 2013). On the other hand, disruption risks are the outcomes of internal and external events originated from natural hazards, accidental or intentional acts, and could lead to disruptions to the supply chain's functionality, goals, and performance (Yazdanparast, Tavakkoli-Moghaddam, Heidari, & Aliabadi, 2018). In supply chain design studies, investigating the effects of this type of risks in any part of the network is usually performed in terms of different probabilistic scenarios (Fazli-Khalaf, Naderi, & Mohammadi, 2018). Going through the real-life cases, it can be understood that the negative operational and financial effects in the case of occurring disruption risks are much severe than those in the case of operational risks. Realizing the adverse consequences of disruptions, companies more than ever are seeking to create or expand their activities by adopting resilience thinking on supply chain management. Having capability to absorb the negative impacts of disruptions and retain the original function and structure, can be used as a practical definition for a resilient supply chain (Brusset & Teller, 2017). The resilience of a supply chain severely affected by its structure and design. In other words, accurately design of supply chains makes organizations more resilient to disruption risks (Sahebjamnia, Torabi, & Mansouri, 2015). Some of the most commonly applied resilience strategies in the supply chain design efforts comprise: multiple sourcing which is practical when the uncertainty in supply is high (e.g., Namdar, Li, Sawhney, and Pradhan (2018) and Meena and Sarmah (2013)), contracting with backup suppliers which accepts greater costs in exchange for higher reliability of supply (e.g., Hosseini and Barker (2016) and Ni, Howell, and Sharkey (2018)), facility fortification which is effective in maintaining higher production capacity after a disruptive event (e.g., Losada, Scaparra, and O'Hanley (2012) and Fattahi, Govindan, and Keyvanshokooh (2017)), capacity expansion which incurs a capital investment that is worth paying if compensates the increase in lost sales opportunities (e.g., Caunhye and Cardin (2018) and Rabbani, Yazdanparast, and Mobini (2019)), pre-positioning emergency inventory which is useful in dealing with the potential shortages of products (e.g., Lücker and Seifert (2017) and Rezapour, Farahani, and Pourakbar (2017)), and controlling flow and physical complexities which manages the total interactions between facilities and the whole domain of the network (e.g., Sharifi, Hosseini-Motlagh, Samani, and Kalhor (2020) and (Zahiri, Zhuang, & Mohammadi, 2017)).

A responsive supply chain should be capable of adaptation to disruptive situations in the supply chain structure. Despite the substantial research on designing and managing supply chains dealing with perishable products, the quantitative dependence of the supply chain responsiveness on resiliency has remained unclear. In fact, addressing resiliency in a supply chain environment characterized by inevitable and unpredictable disruptive events necessitates a modeling and optimization framework that accommodated dynamism and complexity. Concerning our introductory discussion, our research effort examines a new perishable product supply chain network considering the two mainstream topics of responsiveness and resiliency. The distinctive features of this problem compared to those reported in the literature are as follows:

- Jointly consideration of resiliency and responsiveness paradigms in designing a supply chain network dealing with perishability of products,
- Investigating the reinforcement effect of the resiliency on the supply chain responsiveness, and
- Both introducing and constructing proactive resilience enablers in designing a supply chain network dealing with perishability of products.

The present research attempt is developed in the following sections. Section 2 is devoted to briefly reviewing the relevant literature. Our problem setting is described in section 3. The mathematical formulation and definition of its components are given in section 4. The description of an illustrative example of the problem and the associated numerical results are provided in section 5. A discussion on the conclusions and proposals for further research in the field are suggested in the last section.

2- Literature review

As mentioned previously, considering the limited shelf-life of perishable products, their supply chain is more complex compared to the ones associated with non-perishable products. In addition, the use of special refrigerated distribution vehicles is necessary to avoid quality losses of products. To support the integrated management of a perishable product supply chain, La Scalia, Nasca, Corona, Settanni, and Micale (2017) developed a controlling mechanism to manage and guarantee the safety and quality of products in agreement with goals of economic efficiency and sustainability. The study by Hiassat, Diabat, and Rahwan (2017) gave emphasis to the perishable product supply chain in defending the claim that integration of the decisions at strategic, tactical, and operational levels provides superior outcomes in managing supply chains. Dellino, Laudadio, Mari, Mastronardi, and Meloni (2018) developed a decision support system combining forecasting and optimization tools to support the supply of fresh and quickly perishable products.

In addition to food products, other perishable items have also been taken into consideration in the literature. Considering the perishability of blood products, Fahimnia, Jabbarzadeh, Ghavamifar, and Bell (2017) formulated a stochastic mathematical model in the context of supply chain network design for blood supply operations in disaster management. The blood supply network under investigation is designed for maximum efficiency (an objective function for cost minimization) and effectiveness (an objective function for delivery time minimization). The authors developed a hybrid solution approach that is composed of the epsilon-constrained and Lagrangian relaxation approaches to handle the model. Research conducted by Ensafian, Yaghoubi, and Yazdi (2017) incorporated the age of platelet and pattern of ABO and Rhesus (Rh) blood group among blood donors into the platelet supply chain to enhance the platelet transfusion services in terms of quality and safety factors. Zahiri, Tavakkoli-Moghaddam, Mohammadi, and Jula (2014) designed a transportation network applicable for organ transplant centers considering the constraint on how long it may take for organs to remain out of body for the transplant operation. Hosseini-Motlagh, Samani, and Homaei (2020) established a two-stage stochastic formulation with two conflicting objectives to determine location and allocation decisions as well as inventory management policies in operating a blood products supply chain network. Planning for the management of perishable products in the context of disaster management forms the subject of the research by Rezaei-Malek, Tavakkoli-Moghaddam, Zahiri, and Bozorgi-Amiri (2016), Tavana, Abtahi, Di Caprio, Hashemi, and Yousefi-Zenouz (2018), and Akbarpour, Torabi, and Ghavamifar (2020). The key issue in the pre-disaster stage is deciding about the renewal strategy of medical supplies, while the issue of the post-disaster stage is the distribution plan of the products. Also, product perishability is critical in pharmaceutical supply chains, and this importance has been highlighted in the research of Zahiri, Jula, and Tavakkoli-Moghaddam (2018). Finally, the perishability considered in the study of Hasani et al. (2012) is consistent with industries deal with high-tech products.

Multi-period supply chain models which have real-life applications should take into account uncertainty because input parameters change over time. Yavari and Geraeli (2019) examined a closed-loop supply chain for a dairy production system under the absence of perfect knowledge about demands as well as parameters involved in the reverse logistic chain such as return rate of deliveries and their quality in a multi-period planning horizon. The authors developed an innovative robust model to minimize the economic and environmental objectives. Imran, Salman Habib, Hussain, Ahmed, and M Al-Ahmari (2020) introduced the objective of priority index maximization in the study of supply chains of perishable products under uncertainty to evaluate the performance measures of players involved in the supply chain domain. Onggo, Panadero, Corlu, and Juan (2019) applied a simheuristic algorithm, which integrated Monte Carlo simulation with a metaheuristic algorithm to capture the stochastic demands in an inventory-routing problem. Zandkarimkhani, Mina, Biuki, and Govindan (2020) addressed a bi-objective optimization problem in the presence of cost and lost demand minimization objectives for multi-periods and multi-products. The authors considered demand as uncertain and uncertainty was modeled based on fuzzy theory and chance constrained programming.

Evaluation of the performance for modern supply chain networks depends on simultaneously considering conflicting performance metrics. Heidari-Fathian and Pasandideh (2018) approached the issue of sustainability in designing an organ transplant transportation network with the consideration of minimizing the economic and environmental impacts of the activities within the supply chain network. Chan, Wang, Goswami, Singhania, and Tiwari (2020) tried to achieve efficient food logistics operations by defining four objective functions at a time, namely minimization of the total costs, maximization of the product quality through offering the best possible service level to customers, maximization of the emissions from transportation activities, and minimization of the delivery lead time. Sahraeian and Esmaeili (2018) focused on the fact that customer satisfaction is inversely proportional to the waiting times in distribution of perishable products. In line with this view, they addressed a tri-objective vehicle routing problem which included objective functions to minimize the traveling costs, customer’s delays, and greenhouse gas emissions. Yavari and Zaker (2019) investigated the design of a supply chain network for a dairy industry, where electric power network failures are prevalent. Total network costs along with total amount of greenhouse gas emissions were considered as the performance measures in their study.

A number of researchers have incorporated service level constraints into classical supply chain models. They typically achieve optimal inventory levels for each storage location in the presence of service level constraints by adopting base-stock policies and developing optimal or innovative methods (Woerner, Laumanns, & Wagner, 2018). Ernst and Powell (1998) studied a distribution system in which the manufacturer incurs financial incentives to improve the service level of the retailer. Sethi, Yan, Zhang, and Zhou (2007) found that the two factors of optimal order quantity in the first stage and maximum expected profit are monotone with the target service level. They extended their analysis to the situation when order cancellation is permitted and the channel coordination issue. Katok, Thomas, and Davis (2008) considered a supplier who delivers products to a retailer through inventory holding. The supplier undertook to meet the meet the agreed fill rate or service level within a specified time horizon. Li, Xu, and Ye (2011) proposed a discount mechanism for coordination of a supply chain consisting of a vendor and a buyer who faces service level constraints. Jha and Shanker (2013) considered an integrated supply chain model that includes service level constraints corresponding to each buyer to find the optimal order quantity, procurement time, and buyer safety factor simultaneously. Sawik (2016) adopted two different service level measure, including the expected worst-case order fulfillment rate and the demand fulfillment rate to study the worst-case optimization of service level.

Disruptions in supply chains are generally due to natural disasters (e.g., Elluru, Gupta, Kaur, and Singh (2019), Marufuzzaman and Ekşioğlu (2017), and Mari, Lee, and Memon (2014)), man-made accidents such as fires, strikes and terrorism (e.g., Jabbarzadeh, Fahimnia, Sheu, and Moghadam (2016) and (DuHadway, Carnovale, & Hazen, 2019)), and severe legal disruptions. To lessen the effect of disruptions on business performance, it is necessary to control the adverse effects by making full use of its favorable characteristics, including resilience, redundancy, robustness, and flexibility. Actually, resilience is a concept mainly referring to the adaptability of a supply chain network to cope with or respond to disruptive situations and its building is through creating redundancy, which is narrowly associated with robustness and flexibility (Xu, Zhang, Feng, & Yang, 2020). In order to create and promote resilience in supply chain networks and deal with uncertainties arising from operational risks as well as natural and man-made disruptions, Torabi, Baghersad, and Mansouri (2015) sought to establish business continuity plans of suppliers, strengthen suppliers, and cooperation with reliable suppliers. Ratick, Meacham, and Aoyama (2008) addressed a set covering location model for (1) deciding about the number and optimal location of reliable facilities at different coverage intervals and (2) creation of backup capacities in some existing facilities. The purpose of the study conducted by (Hasani & Khosrojerdi, 2016) is to build a global supply chain network under uncertainties and interdependent disruptions for the aim of maximizing the profit after tax. To overcome the disruptions, adopting six resilience strategies, consisting of (1) dispersion of facilities, (2) fortification of the infrastructure, (3) semi-products manufacturing, (4) multiple supply, (5) inventory holding, and (6) use of a bill of materials were examined. The developed model by Namdar et al. (2018) integrates strategies such as signing contracts with backup suppliers by paying a part of the contract price in advance in exchange for allocating a certain amount of raw materials at an agreed price to the buyer, the ability to immediately buy raw materials at market prices when needed, and cooperation and visibility of the buyer and suppliers which is a strong way to avoid disruption risks. Rezapour et al. (2017) considered the existence of two types of risk, intense market competition and the risk of losing market share and low reliability of suppliers' performance as their motivation for building a resilient supply chain network. They examined the three strategies of inventory prepositioning, planning for the use of backup capacity in suppliers, and multiple supply in the design phase and how they affect the improvement of supply chain performance. Schmitt and Singh (2012) examined the effects of inventory holding and making backup capacity for processes in a supply chain network that faces two types of risks, including supply disruptions and demand uncertainties. Khalili, Jolai, and Torabi (2017) studied the issue of integrated production and distribution planning assuming the vulnerability of operational facilities as well as shipment routes to the risk of disruptions. As strategies for dealing with disruptive events, considering additional capacity in manufacturing centers, planning for backup layer in shipment routes, and storage of safety stock inventory were used in this study. Jabbarzadeh, Fahimnia, and Sabouhi (2018) proposed a two-stage formulation for planning a sustainable and resilient supply chain. The supplier sustainability indices were identified, quantified, and aggregated and the score of each supplier was calculated using a clustering approach in the first stage. Subsequently, a bi-objective optimization model, with the aim of deciding on supply and marketing issues in terms of supplier selection and order allocation and the extent to which resilience strategies are exploited (i.e., making contract with backup suppliers and extending the available facilities) was developed in the second stage to ensure the continuity of operations in the event of a disruption.

The research attempts reviewed so far contains two major gaps in the context of designing supply chain networks dealing with perishable products. First, a clear gap is illustrated in addressing disruptive events by incorporating resilience enablers in the supply chain structure. In this regard, we consider policies such as contracting with backup suppliers, preparing extra capacity in manufacturing centers, the possibility of lateral transshipment between manufacturing centers, and inventory management to enhance the supply chain performance against disruption risks. Moreover, the joint taking into account supply chain responsiveness and resilience in tackling the uncertainties has not been highlighted in the previous studies of supply chains with perishable products. To overcome these shortcomings and fulfill the requirements that will be discussed in the next section, we develop a stochastic optimization model with the aim of achieving responsive and resilient supply chain operations at minimum costs under random location-based disruptions.

3- Problem statement

Our optimization problem concerning production and distribution planning in a supply chain dealing with perishable items focuses on a four-echelon supply chain network, composed of multi raw material suppliers, multi manufacturers, multi distribution centers, and multi retailers. In the supply chain network, firstly, the raw materials are purchased from the suppliers and then converted to the final products constrained by the bill-of-material relations in the manufacturing centers. The delivery system is planned in such a way to deliver products to retailers directly by manufacturers or indirectly by distribution centers. The distribution centers are used to store the perishable products, until their expiration dates, to be shipped to retailers and satisfy their demands.

In the supply chain network, location-based disruptions may occur at any part of the first two echelons, consequently influencing the serviceability of the supply chain network. A set of stochastic scenarios with pre-specified occurrence probabilities are used to define such disruptions. Incorporating a number of resilience strategies in the proposed supply chain network increases the adaptability of the supply chain network against uncertainties, these strategies are as follows:

- signing contracts with backup suppliers;
- reserving extra capacity in production facilities;
- lateral transshipment between facilities at the same echelon; and
- keeping inventory.

We consider the above-mentioned resilience enablers in formulating a two-stage stochastic model. A coordination mechanism is assumed to be performed to maximize the cost-efficiency of the supply chain while the minimum customer satisfaction level is satisfied. The various strategic and tactical decisions which are involved in this model are those associated with the configuration of the supply chain network, i.e., locating and sizing the new facilities, determining the level of capacity expansion in the available facilities, and selecting the suppliers, material requirement planning in terms of the quantity of purchases from different suppliers, production planning in terms of the quantity of productions in manufacturing centers, transportation planning in terms of the quantity of shipments throughout the supply chain network, as well as the lateral transshipment amounts within echelons, and the inventory planning.

The underlying assumptions of the problem to provide a better approximation to reality are as follows:

- The time horizon is finite.
- In establishing new facilities, the candidate locations and possible capacities are known.
- Both multi-product and multi-period parameters are considered in the production-distribution supply chain.
- The perishable products are characterized by specific lifetime periods.
- Deterioration has not been considered during transportation.
- There is no demand for expired products.
- The distribution centers face known demands.
- The backup suppliers are not influenced by the disruptions and their capacity is infinite.
- The inventory holding is intended in the facilities for both the raw materials and final products.
- The material flow is permitted only between every two consecutive echelons except for lateral transshipments.
- Backordering is allowed.

4- Mathematical formulation

4-1- Scenario-based robust optimization

Robust optimization, first approached by Mulvey and Ruszczyński (1995), is a potentially valuable tool for management of decision processes in uncertain environments. When the realizations of critical parameters are expressed using a set of scenarios, robust optimization is applicable to seek the favored risk aversion or service-level requirements. The framework is equipped with two mechanisms, namely solution robustness and model robustness to create solutions with less sensitivity to realizations of the scenarios. The former aims to keep the final solution "close" to optimal for any possible scenario, while the latter states that the solution must be "almost" feasible for any realization of the scenarios. With respect to the fact that having both feasibility and optimality conditions is unlikely in most cases, the robust optimization model overcomes the tradeoff between the conflicting mechanisms of solution and model robustness by incorporating DM’s preference.

Mulvey and Ruszczyński (1995) concentrated on optimization problems with two kinds of constraints, one of which is free of scenario-dependent parameters and called here as structural constraints, while the other is subject to uncertainty and known as control constraints. To formulate such constraints, variables with same name appear: structural variables which are not adjustable with realizations of random parameters and control variables which are characterized by adjustability with realization of uncertain parameters. With this perspective in mind, the general structure of the robust optimization is elaborated on the basis of LP model (1) to (4) in the following.

$$Min\ C^T x + d^T y \tag{1}$$

s.t.

$$A x = b \tag{2}$$

$$B x + C y \le e \tag{3}$$

$$x , y \ge 0 \tag{4}$$

The key feature of this model is that some components of the model is assumed to be uncertain in terms of future scenarios. A set of scenarios $s \in \{1, 2, ..., S\}$ with probability ρ_s and $\sum_{s \in S} \rho_s = 1$ is considered to represent the probable conditions in reality. In this regard, for each scenario $s \in S$, the set of realizations $\{d_s , B_s , C_s , e_s\}$ is associated with the coefficients. Also, the model encompasses both structural variables x and control variables y_s . In better words, the objective function in equation (1) turns into random variable $\xi_s = C_s^T x + d_s^T y_s$ with occurrence probability ρ_s . In addition, equation (2), which is free of randomness, is a structural constraint, while equation (3) represents a control constraint whose components may be contained randomness.

To derive the robust optimization formulation, some modifications in the framework of model (1) to (4) are necessary. First of all, error vector δ_s is included in equation (2) for the computation of the infeasibility occurred in the control constraints. Then, the function of model robustness is added to the objective function to penalize violations occurred in the control constraints. As mentioned previously, since the robust optimization takes a multi-criteria objective form to provide the tradeoff between the two mechanisms, the reformulated objective function also includes the solution robustness function. Formulation of the solution robustness function can be performed in different ways; for example, Mulvey and Ruszczyński (1995) employed the initial objective function mean plus a constant coefficient (λ) of its standard deviation. In order to enable the formulation to generate a spectrum of solutions based on the tradeoff between the two types of robustness, the goal programming weight ω is multiplied by the model robustness function. The robust formulation up to this point is summarized in model (5) to (10).

$$Min\ \sigma(x , y_1 , y_2 , ..., y_S) + \omega\, \phi(\delta_1 , \delta_2 , ..., \delta_S) \tag{5}$$

s.t.

$$A x = b \tag{6}$$

$$B_s x + C_s y_s - \delta_s \le e_s \quad ; \forall s \in S \tag{7}$$

$$\sigma(x , y_1 , y_2 , ..., y_S) = \sum_{s \in S} \rho_s \xi_s + \lambda \sum_{s \in S} \rho_s \left(\xi_s - \sum_{s' \in S} \rho_{s'} \xi_{s'} \right)^2 \tag{8}$$

$$\phi(\delta_1 , \delta_2 , ..., \delta_S) = \sum_{s \in S} \rho_s \delta_s \tag{9}$$

$$x , y_s \ge 0 \quad ; \forall s \in S \tag{10}$$

It is worth mentioning that this formulation is based on the earlier attempt by Mulvey and Ruszczyński (1995) to construct a robust decision-making framework. However, the presence of the quadratic term $\sum_{s \in S} \rho_s \left(\xi_s - \sum_{s' \in S} \rho_{s'} \xi_{s'} \right)^2$ in the formulation results in drastic computational complexity of the approach. Hence, the last modification is converting model (5) to (10) into a LP model. For this purpose, Yu and Li (2000) supplement the squared function with the absolute value function and then linearize it using their proposed technique that introduces a set of deviational variables in the non-negative domain per scenario (θ_s). In addition to the changes in the objective function, a new constraint is also needed. The LP version of the robust programming is presented in equation (11) to (14).

$$Min\ \sigma'(x, y_1, y_2, ..., y_S) + \omega\, \phi(\delta_1, \delta_2, ..., \delta_S) \tag{11}$$

s.t.

Equations (5), (6), (8), and (9)

$$\sigma'(x, y_1, y_2, ..., y_S) = \sum_{s\in S}\rho_s\, \xi_s + \lambda \sum_{s\in S}\rho_s \left(\left(\xi_s - \sum_{s'\in S}\rho_{s'}\, \xi_{s'} \right) + 2\theta_s \right) \tag{12}$$

$$\xi_s - \sum_{s\in S}\rho_s\, \xi_s + \theta_s \geq 0 \quad ;\forall s \in S \tag{13}$$

$$\theta_s \geq 0 \quad ;\forall s \in S \tag{14}$$

4-2- The proposed two-stage stochastic model

This section provides the notations used in the formulation of our proposed problem along with its mathematical formulation.

Sets

A	pool of suppliers, each one is represented by $a \in A$
$A' \subset A$	pool of backup suppliers, each one is represented by $a \in A'$
M	pool of manufacturing centers, each one is represented by $m \in M$
D	pool of potential locations for establishing distribution centers, each one is represented by $d \in D$
R	pool of retailers, each one is represented by $r \in R$
L	pool of capacity levels in establishing distribution centers, each one is represented by $l \in L$
K	pool of raw materials, each one is represented by $k \in K$
P	pool of products, each one is represented by $p \in P$
T	pool of time periods, each one is represented by $t \in T$
S	pool of stochastic disruptions, each one is represented by $s \in S$

Parameters

ec_{dl}	fixed cost of establishing distribution center $d \in D$ with capacity level $l \in L$
sc_a	cost of signing a contract with backup supplier $a \in A'$
ac_m	unit cost of extending manufacturing center $m \in M$
tc_{ij}	unit cost of transportation from node i to node j
pc_{ka}	unit cost of purchasing raw material $k \in K$ from supplier $a \in A$
mc_{pm}	unit cost of producing product $p \in P$ at manufacturing center $m \in M$
hc^1_{km}	unit cost of inventory holding for raw material $k \in K$ at manufacturing center $m \in M$
hc^2_{pd}	unit cost of inventory holding for product $p \in P$ at distribution center $d \in D$
bc_{pr}	unit penalty cost for uncovered demands of retailer $r \in R$ for product $p \in P$ in each time period
q_{prt}	demand for product $p \in P$ by retailer $r \in R$ in time period $t \in T$
sv_{ak}	maximum supply capacity of supplier $a \in A$ in providing raw material $k \in K$
mv_{mp}	maximum production capacity of manufacturing center $m \in M$ in producing product $p \in P$

dv_l	capacity of a distribution center at capacity level $l \in L$
lv_{is}	percentage of capacity of facility $i \in (A \cup M)$ which is disrupted under scenario $s \in S$
uv_m	maximum extendable capacity of manufacturing center $m \in M$
α	acceptable service level for each customer
τ_k^1	lifetime of raw material $k \in K$
τ_p^2	lifetime of product $p \in P$
β_{kp}	quantity of raw material $k \in K$ used in producing a unit of product $p \in P$
π	weight coefficient of strategic costs

Decision variables

X_{dl}	equals to1 if distribution center $d \in D$ with capacity level $l \in L$ is established; 0, otherwise
Y_a	equals to1 if a contract is signed with backup supplier $a \in A'$; 0, otherwise
Z_m	additional production capacity in manufacturing center $m \in M$
U_{kmts}^1	quantity of inventory of raw material $k \in K$ which is available in manufacturing center $m \in M$ at the end of time period $t \in T$ under scenario $s \in S$
U_{pdts}^2	quantity of inventory of product $p \in P$ which is available in distribution center $d \in D$ at the end of time period $t \in T$ under scenario $s \in S$
E_{amk}	quantity of raw material $k \in K$ which is purchased by manufacturer $m \in M$ from supplier $a \in A$
W_{mdpts}^1	quantity of product $p \in P$ which is transferred from manufacturer $m \in M$ to distributor $d \in D$ in time period $t \in T$ under scenario $s \in S$
W_{mrpts}^2	quantity of product $p \in P$ which is transferred from manufacturer $m \in M$ to retailer $r \in R$ in time period $t \in T$ under scenario $s \in S$
W_{drpts}^3	quantity of product $p \in P$ which is transferred from distributor $d \in D$ to retailer $r \in R$ in time period $t \in T$ under scenario $s \in S$
$W_{mm'kts}^4$	quantity of raw material $k \in K$ which is transferred from manufacturer $m \in M$ to manufacturer $m' \in M$ in time period $t \in T$ under scenario $s \in S$
B_{prdts}	a part of retailer $r \in R$'s demand for product $p \in P$ which could not be satisfied by distribution center $d \in D$ in period $t \in T$ under scenario $s \in S$

$$Min\ f(x)=\sum_{s\in S}p_s\xi_s+\lambda\sum_{s\in S}p_s\left[\left(\xi_s-\sum_{s'\in S}p_{s'}\xi_{s'}\right)+2\theta_s\right]+\omega\sum_{s\in S}p_s\left(\delta^+_{rmts}+\delta^-_{rmts}\right) \tag{15}$$

s.t.

$$\begin{aligned}\xi_s=\pi\Bigg(&\sum_{d\in D}\sum_{l\in L}ec_{dl}X_{dl}+\sum_{a\in A'}sc_aY_a+\sum_{m\in M}ac_mZ_m\\&+\sum_{k\in K}\sum_{a\in A}\sum_{m\in M}\sum_{t\in T}pc_{ka}E_{amk}\\&+\sum_{p\in P}\sum_{m\in M}\sum_{t\in T}mc_{pm}\left(\sum_{d\in D}W^1_{mdpts}+\sum_{r\in R}W^2_{mrpts}\right)\\&+\sum_{k\in K}\sum_{m\in M}\sum_{t\in T}hc^1_{km}U^1_{kmts}+\sum_{p\in P}\sum_{d\in D}\sum_{t\in T}hc^2_{pd}U^2_{pdts}\\&+\sum_{p\in P}\sum_{r\in R}\sum_{d\in D}\sum_{t\in T}bc_{pr}B_{prdts}\\&+\sum_{i\in M}\sum_{j\in M}\sum_{k\in K}\sum_{t\in T}tc_{ij}W^4_{ijpts}+\sum_{i\in(M\cup D)}\sum_{j\in(D\cup R)}\sum_{p\in P}\sum_{t\in T}tc_{ij}\left(W^1_{ijpts}+W^2_{ijpts}+W^3_{ijpts}\right)\end{aligned}\quad ;\forall s\in S \tag{16}$$

$$\xi_s-\sum_{s'\in S}p_{s'}\xi_{s'}+\theta_s\geq 0\quad ;\forall s\in S \tag{17}$$

$$\sum_{l\in L}X_{dl}\leq 1\quad ;\forall d\in D \tag{18}$$

$$Z_m\leq uv_m\quad ;\forall m\in M \tag{19}$$

$$\sum_{m\in M}E_{amk}\leq sv_{ak}\quad ;\forall a\in A,\ k\in K \tag{20}$$

$$E_{amk}\leq M_{Big}Y_a\quad ;\forall a\in A',\ m\in M,\ k\in K \tag{21}$$

$$\sum_{p\in P}\left(\sum_{d\in D}W^1_{mdpts}+\sum_{r\in R}W^2_{mrpts}\right)\leq\left(mv_{mp}+Z_m\right)\quad ;\forall m\in M,\ t\in T,\ s\in S \tag{22}$$

$$\sum_{p\in P}\sum_{r\in R}W^3_{drpts}\leq\sum_{l\in L}dv_lX_{dl}\quad ;\forall d\in D,\ t\in T,\ s\in S \tag{23}$$

$$\sum_{m'\in M}W^4_{mm'kts}\leq\sum_{a\in A}E_{amk}\quad ;\forall m\in M,\ k\in K,\ t\in T,\ s\in S \tag{24}$$

$$U^1_{kmts}=U^1_{km(t-1)s}+\sum_{a\in A}lv_{as}E_{amk}-\sum_{m'\in M}W^4_{mm'kts}-\sum_{p\in P}\beta_{kp}\left(\sum_{d\in D}W^1_{mdpts}+\sum_{r\in R}W^2_{mrpts}\right)-\delta^+_{kmts}+\delta^-_{kmts}\quad ;\forall m\in M,\ k\in K,\ t\in T,\ s\in S \tag{25}$$

$$U^2_{pdts}=U^2_{pd(t-1)s}+\sum_{m\in M}W^1_{mdpts}-\sum_{r\in R}W^3_{drpts}-\sum_{r\in R}B_{prd(t-1)s}+\sum_{r\in R}B_{prdts}\quad ;\forall d\in D,p\in P,\ t\in T,\ s\in S \tag{26}$$

$$U^1_{kmts}\leq\sum_{t\leq\tau\leq t+\tau^1_r}\sum_{p\in P}\beta_{kp}\left(\sum_{d\in D}W^1_{mdp\tau s}+\sum_{r\in R}W^2_{mrp\tau s}\right)\quad ;\forall m\in M,k\in K,\ t\in T,\ s\in S \tag{27}$$

$$U^2_{pdts}\leq\sum_{t\leq\tau\leq t+\tau^2_p}\sum_{r\in R}W^3_{drp\tau s}\quad ;\forall d\in D,p\in P,\ t\in T,\ s\in S \tag{28}$$

$$\sum_{t\in T}\left(\sum_{d\in D}W^3_{drpts}+\sum_{r\in R}W^2_{mrpts}\right)=\sum_{t\in T}q_{prt}\quad ;\forall r\in R,p\in P,\ s\in S \tag{29}$$

$$\frac{\sum_{d\in D}W^3_{drpts}+\sum_{m\in M}W^2_{mrpts}}{q_{prt}}\geq\alpha\quad ;\forall r\in R,p\in P,\ t\in T,\ s\in S \tag{30}$$

$$B_{prdTs}=0\quad ;\forall p\in P,r\in R,\ d\in D,\ s\in S \tag{31}$$

$$X_{dl},Y_a\in\{0,1\} \tag{32}$$

$$Z_m, U^1_{kmts}, U^2_{pdts}, E_{amk}, W^1_{mdpts}, W^2_{mrpts}, W^3_{drpts}, W^4_{mm'kts}, B_{prdts}, \theta_s, \delta^+_{kmts}, \delta^-_{kmts} \geq 0 \tag{33}$$

The objective function of the optimization problem in equation (15) which aims to minimize the total costs is formulated through stochastic variables of $\xi_s, \theta_s, \delta^+_{kmts}, \delta^-_{kmts}$, and how to calculate these variables are discussed in the following. Equation (16) calculates the stochastic variable ξ_s in the objective function formulation, and includes cost of facility establishment, cost of additional production capacity preparation, and cost of contracting with backup suppliers in the first term, raw material supply costs in the second term, production and inventory holding costs in the second two terms, penalties for backordered demands in the fifth term, and transportation costs in the sixth terms. Equation (17) is similar to equation (13) and calculates the values of θ_s. Equation (18) states that establishing more than one facility at each candidate location is not allowed and if such a facility is chosen for construction, its capacity is limited by a set of capacity levels. Equation (19) takes care of the maximum extendable production capacity in incorporating one of the reliance enabler strategies in the network structure. Equations (20) - (23) enforce the capacity limitation of facilities associated with suppliers, manufacturers, and distributors, respectively. Equation (24) considers the possibility of lateral transshipment between manufacturing centers. Equations (25) and (26) are the flow conservation law for manufacturers and distributors, respectively. Equations (27) and (28) are just to ensure the fact that the inventory management operations in production and distribution facilities are based on the limited lifetime of materials. Equation (29) declares the necessity of meeting all the demands by the end of the last time period. Equation (30) ensures the minimum service level of retailers. Equation (31) states that there should not be any backordered demand at the end of the planning horizon. Equations (32) and (33) determines the decision variables types in the mathematical formulation.

5- Computational results

The applicability of the current modeling effort is tested in this section for a randomly generated numerical example. This example is associated with a multi-echelon supply chain network that is partly influenced by natural disasters. The framework of the supply chain under investigation is depicted in figure 1. As can be understood from figure 1, there is a set of six suppliers, each of which acts as a primary or backup supplier with a difference in its reliability against disruptions. These suppliers offer three types of raw materials to the manufacturers. There are also three manufacturing centers in the network that are responsible for producing three types of perishable products. This possibility is recognized in the proposed formulation to add extra production capacity to the available manufacturing centers to strengthen them against possible disruptions. Then, in order to satisfy the customers' demands, products are delivered to the 15 retailers directly by manufacturers or indirectly by distribution centers. Actually, to lessen the transportation costs, it is possible to establish a set of manufacturing centers in five candidate locations and according to three relevant capacity levels. It is worth mentioning that our example examines four disruption scenarios, including a scenario without disruption occurrence and three subsequent scenarios with different levels of consequences on suppliers and manufacturers. The values of other parameters are reported in table 1.

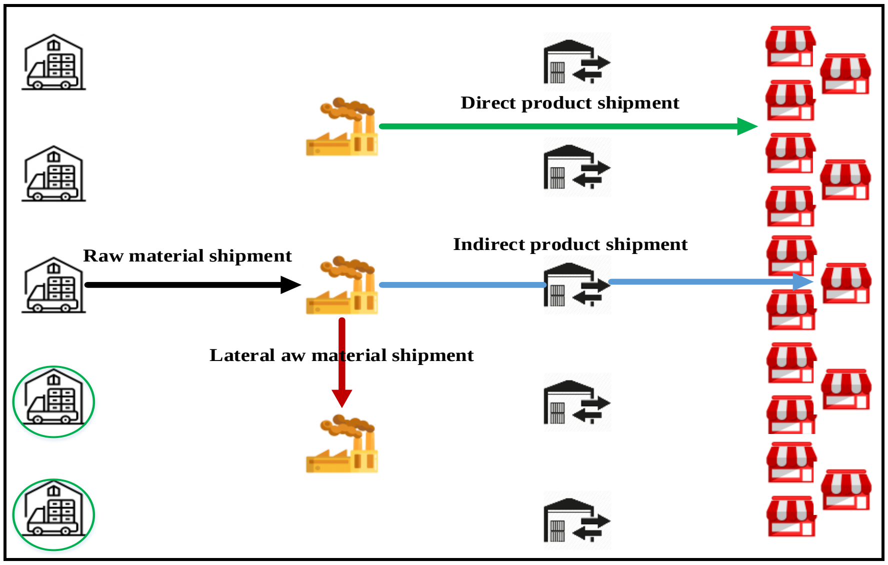

Fig. 1 the supply chain framework in the illustrative example

Table 1. The uniform distribution of parameters in the illustrative example

Parameter	Distribution interval	Parameter	Distribution interval
ec_{dl}	10^5 Uniform [1, 15]	sc_a	10^2 Uniform [3, 5]
ac_m	10^2 Uniform [1, 9]	tc_{ij}	10^{-2} Uniform [5, 10]
pc_{ka}	Uniform [3, 5]	mc_{pm}	Uniform [1, 3]
hc^1_{km}	Uniform [0.3, 0.6]	hc^2_{pd}	Uniform [0.4, 0.8]
bc_{pr}	Uniform [0.5, 0.9]	q_{prt}	Uniform [10, 40]
sv_{ak}	10^3 Uniform [0.5, 10]	mv_{mp}	10^2 Uniform [10, 15]
dv_l	10^2 Uniform [10, 15]	lv_{is}	Uniform [0.1, 0.5]
uv_m	Uniform [5, 20] (%)	α	Uniform [50, 100] (%)
τ^1_k , τ^2_p	Uniform [2, 5]	β_{kp}	Uniform [1, 2.5]

The given problem is implemented in GAMS software, and the optimal solution is calculated using the CPLEX solver. Figure 2 indicates the total costs required to attain a set of acceptable service levels ranged from 0.5 to 1. It is worth mentioning that the CPU time required to achieve each solution is lower than or equal to 531s. As illustrated, the objective function value of the formulation (i.e., total costs) is increased with increment in the service level. Therefore, the curve in figure 2 confirms the direct relationship between the acceptable service level of the supply chain and its associated costs. However, the changes in the objective function do not follow a linear pattern. More precisely, the curve can be approximately divided into three regions:

(1) The acceptable service levels between 0.5 and 0.6 in equation (30) result in the same optimal solutions. In fact, a service level lower than 0.6 imposes great penalties for unmet demands, and it is necessary to balance the penalty costs with other cost components to achieve the least costs of the network, which means the increment of the left-hand side of equation (30) to the extent of 0.6.

(2) The acceptable service levels between 0.6 and 0.9 approximately follow the trend line of the curve. As a result of this behavior, the system planner can estimate the required budget for achieving a specific service level.
(3) The service levels greater than 0.9 show the ideal serviceability of the supply chain in exchange for a significant increment in the investment costs of the network.

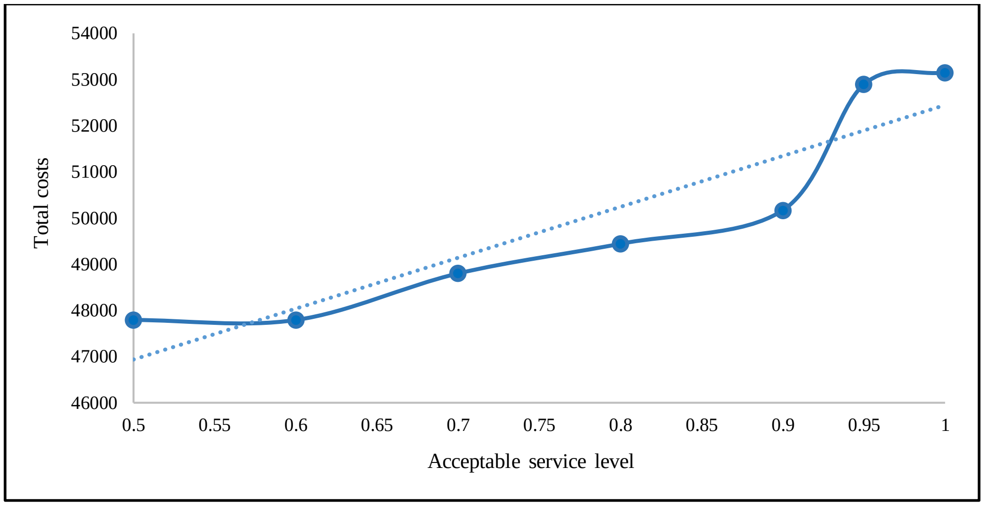

Fig. 2. The objective function values for different acceptable service level

Figure 3 compares the expected values of the components of the objective function based on service level α=0.9. We call this problem the base case. It is clearly observed that a considerable portion of the total costs, at about 75% of the total, is associated with production costs, fixed investment costs, and raw material purchasing costs. In the following, we investigate the effectiveness of the four resilience enablers in mitigating disruption risks based on the base case.

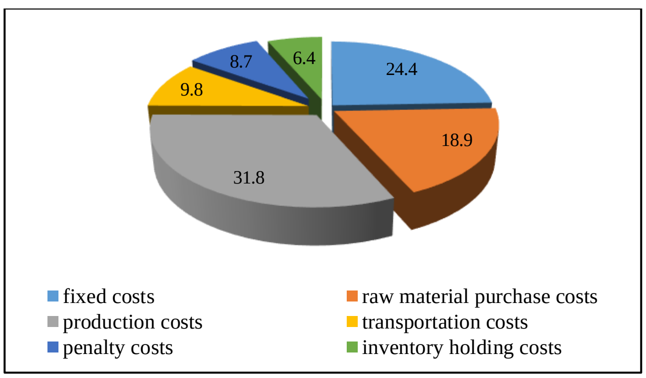

Fig. 3 The share of cost components in the cost function (the base case)

To evaluate the significance and effectiveness of the resilience strategies, we conduct four experiments, each of which lacks one of the strategies in its mathematical formulation. Table 2 reports the values of the cost components for each experiment along with their percentage of decrease or increase. The findings reveal the importance of all the strategies in capturing disruptions to maintain the supply chain's responsiveness. However, two strategies of keeping inventory and contacting with backup suppliers are the most important ones in which their absence could increase the supply chain costs up to 11% compared to the base case. Note that since the acceptable service level in all the experiments is fixed at 0.8, the production costs are relatively similar and we avoid reporting the details of this cost component.

Table 2. The effect of ignoring resilience enablers on the cost components

	Contracting with backup suppliers	Capacity expansion	Lateral transshipment	Inventory holding
Total costs	54,181 (↑ 8%)	52,175 (↑ 4%)	51,673 (↑ 3%)	55,686 (↑ 11%)
Fixed costs	14,791 (↑ 21%)	13,200 (↑ 8%)	13,797 (↑ 13%)	20,270 (↑ 65%)
Raw material purchase costs	9,373 (↓ 1%)	9,652 (↑ 2%)	10,386 (↑ 9%)	9,355 (↓ 1%)
Transportation costs	4,985 (↑ 1%)	4,643 (↓ 5%)	4,599 (↓ 6%)	5,179 (↑ 5%)
Inventory holding costs	5,526 (↑ 72%)	4,539 (↑ 41%)	2,325 (↓ 27%)	0 (↓ 100%)
Penalty costs	3,684 (↓ 15%)	4,330 (↓ 0%)	4,702 (↑ 8%)	5,012 (↑ 15%)

5-1- Analysis on the impact of uncertainty on the planning

In order to investigate the effectiveness of the robust optimization approach on the planning of the system, we benchmark its performance against that of the expected value approach (Maggioni & Wallace, 2012). For this purpose, we use the measure of Value of the Stochastic Solution (VSS) defined as the difference between the objective values under expected value and robust optimization approaches. In the expected value approach, at first, the values of the uncertain parameters are set equal to their expected values. The optimal values of the strategic decisions are then obtained by solving the model in presence of only the new scenario (i.e., the average uncertain parameters values). Using the optimal values of the strategic decisions, the model is solved again to calculate the objective function, this time considering all the original scenarios with fixed strategic decisions. This benchmarking is conducted for the most desirable solution over a range of variability weights. Figure 4 confirms the superiority of the robust optimization approach over the expected value approach. In fact, supporting the network under higher level of uncertainties justifies the higher planning cost of the robust optimization approach than the deterministic approaches.

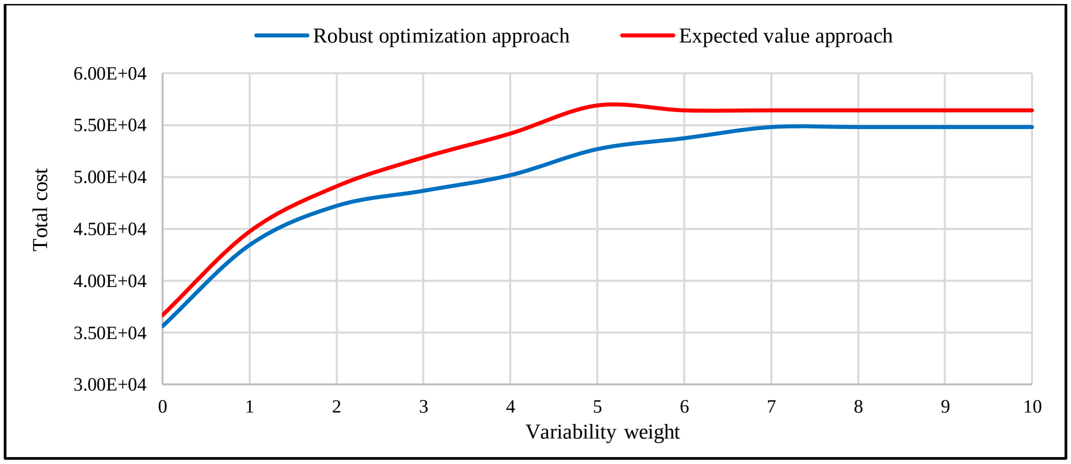

Fig. 4 The economic performance of the robust optimization approach versus the expected value approach

6- Conclusions

A key issue in supply chain management is to retain its responsiveness. Resiliency is the way to reach supply chain responsiveness in real-world situations. With this consideration, we have suggested a new two-stage stochastic optimization model for supply chain networks with perishable products taking into account both the responsiveness and resiliency. We have quantified the customer responsiveness level through the demand fill rate, which is the proportion of customers' demands met within the corresponding time period. On the other hand, the resilience concept was addressed in the configuration of the supply chain through four proactive strategies, namely signing contracts with backup suppliers, reserving extra capacity in production facilities, lateral transshipment between facilities at the same echelon, and keeping inventory. We have also employed the scenario-based robust optimization framework to capture the uncertainties are stated in the form of a finite number of possible scenarios. A small-size problem was generated to examine the validation and effectiveness of the developed model. We have studied the behavior of the cost function versus the acceptable service levels and found a direct relationship between them. Moreover, it is observed that all the resilience strategies are effective in achieving cost-efficiency at a pre-specified service level. Finally, the robust optimization approach was compared with the expected value approach. The obtained results support the accuracy of the stochastic programming approach. As a future research direction, it would be worth to examine the influence of other resilience strategies in designing a supply chain network. In addition, machine learning techniques can open new perspectives in preparing for supply chain disruptions. The authors also highlight the need for updating the dataset with information associated with a real-world case study.

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