JEAS
Journal of Economics and Administrative Sciences
E-ISSN: 2148-1792 P- ISSN: 1302-2024
Volume 3, Supplement Issue 3
www.jeasweb.org

Designing a resilient supply chain network for perishable products under uncertainty conditions

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ABSTRACT
The purpose of this study is to support the integrated decision-making at the strategic, tactical, and operational levels of a perishable products supply chain so that the disruption effects are diminished at the lowest cost using resilient and proactive strategies. Thus, a bi-objective mixed-integer programming model with the objective functions of cost minimization and network resilience maximization is developed to design a network for the production and distribution of perishable products under uncertainty conditions. The two strategies of resilience in this study are supplying raw materials from reliable suppliers and increasing production capacity in production facilities. In the proposed formulation, the scenario-based robust optimization approach is used to model the conditions for dealing with uncertainty. Moreover, given the lack of sufficient information in the proposed model, the demand parameter is considered as a fuzzy parameter. Given the NP-hard nature of the proposed model, the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm and the Non-dominated Sorting Genetic algorithm-II (NSGA-II) are applied to solve medium- and large-scale problems. The computational results indicate the efficiency of these methods in solving the mathematical model, especially on large scales. The validation of the proposed robust optimization approach is performed through comparing its performance against the expected value approach.
Keywords: Supply chain, location-routing-inventory, robust optimization

Introduction

Nowadays, the significance of designing and planning supply chain networks (SCNs) has attracted the attention of many scholars and decision-makers in different industries given the existing competitive market. The purpose of the supply chain is to create the maximum total value for all the elements involved in it from the customer to the first supplier. Designing a distribution network is one of the most significant issues in logistics management, involving facility location, vehicle routing problem, and inventory management. As each of these decisions affects the other decisions, introducing integrated approaches that include all decisions simultaneously, which can lead to more effective logistic network management, seems necessary. Moreover, in some industries like those related to perishable products, integrated chain activities directly affect achieving profitability of the supply chain. Thus, integrated and simultaneous planning at various levels is of paramount significance because of providing good conditions for the storage and transportation of perishable materials. In designing and planning supply chain networks, it has to be noted that because of severe environmental changes, one cannot expect that all the parameters in the problem will be available definitively (Zhen et al., 2016). Given the increasing significance and complexity of supply chain management for organizations in today's disruptive environments, it is necessary to anticipate and provide the necessary resilience capabilities to deal with or prevent disruptions in the activities of the organization (Christopher and Peck, 2004). The purpose of supply chain resilience is to stop the chain from moving into unfavorable conditions and to restore the supply chain after a disruption occurs in the shortest time and at the lowest cost possible.

De Keizer et al. (2015) showed that if products deterioration rates are excluded in the decision to design a supply chain of perishable materials, low-quality products will be delivered to customers and thus will not lead to the achievement of the desired level of service and additional waste will be produced in the network. In another study, De Keizer et al. (2017) considered the rate of gradual deterioration of the quality of perishable products and their heterogeneous nature over time in logistics planning. Yu and Nagurney (2013) included the possibility of continuous decay of products in the supply chain into a network-based food supply chain model. Given the dependence of shelf life and product quality on the storage conditions, Firoozi et al. (2013) examined the exchange relationship between inventory maintenance costs and storage conditions. Alkaabneh et al. (2020) studied a routing-inventory problem in the field of perishable products supply chain to maximize supplier profits and minimize associated costs with fuel, maintaining inventory, and greenhouse gases emission. Zulvia et al. (2020) examined a vehicle routing problem for perishable products for minimizing operating costs as well as costs associated with emissions of perished products and reaching customer satisfaction. Zahiri et al. (2014) examined designing an organ transplant network considering how long it can stay out of the body. Diabat et al. (2019) used a two-objective scenario-based model based on robust optimization to design a real blood supply chain to avoid random disturbances in facilities and routes in chain planning. Hosseini-Motlagh et al. (2020) developed a dual-purpose, two-stage model based on possible scenarios for determining location and allocation decisions as well as inventory management in the blood supply chain. Jabbarzadeh et al. (2018) proposed a two-phase approach to designing a stable and resilient supply chain. Ambrosino and Scutella (2005) studied a single-product, four-tier supply chain. In the model proposed, routing cost is assumed to be approximate and the inventory cost nonlinear. Ma and Dai (2007) studied the problem of location-routing-random inventory in logistics distribution systems. Chao et al. (2019) examined a two-stage location-routing-inventory problem with time window constraints for perishable products. The first stage of the proposed model includes a location-routing-inventory problem and the second stage, a limited-capacity transportation problem of vehicles. Considering the concept of time window requirements, Manavizadeh et al. (2020) modeled the customer satisfaction function on a location-routing-inventory problem.

According to the points raised, the most significant research gaps in the planning of supply chains of perishable items include non-addressing operational and disruptions risks simultaneously, non-use of resilience strategies against disruptive events, lack of stable and flexible supply chain design, lack of studying the relationship between total cost and level of financing and lack of integration of strategic, and tactical and operational decision-making levels. The study tries to provide a robust and flexible mathematical model for managing the flow of perishable items across a multi-level supply chain and multi-product to respond to the research gaps obtained. The model studied has two objective functions: total cost minimization and improving the level of resilience, and assumptions like the possibility of partial and complete disruptions at the suppliers, decision-making in an uncertain environment, and considering the possibility of facing shortages in different decision-making periods. The proposed model and its solution approaches will be explained in more detail in the next sections.

Methods

The study examined a location-routing-inventory problem of perishable products under operational and disruption risks to determine the best possible way of managing these products along the chain. In other words, the location of the supply chain network facilities, the supply policy, the inventory control in these facilities, and the route of delivery of products to customers must be determined in such a manner to ensure the resilience and stability of the chain in conditions of uncertainty.

1. Structure of the supply chain of perishable products

A four-level supply chain network is examined in this study. Such a network includes levels of raw material suppliers, production centers, product distribution centers, and end customers. Unlike previous models, besides making decisions about facility location and material flow routing, the study modeled the problem by considering inventory control decisions. We take into account the following assumptions for our proposed model to determine the study scope:

- Different supply disruption scenarios with specified occurrence probabilities are included in the problem.
- Among the suppliers, some suppliers are not affected by disruptions and can meet all their supply commitments considering the mechanisms adopted by them.
- Unlike the suppliers and production facilities, the location of distribution centers is unknown and is determined by the proposed model.
- There is the possibility to increase the capacity in the production facilities.
- Products are perishable and have a limited shelf life.
- Members of the first three levels of the chain have capacity constraints.
- Various capacity levels can be used in the construction of distribution facilities to increase their utilization rates.
- Customers' demand is uncertain and follows certain fuzzy distributions.
- There is a possibility of partial back-ordering so that if a customer's demand is not satisfied during a certain period, it will be satisfied in the next period.
- The vehicles used at each level are homogeneous in terms of capacity.

2. Robust optimization model for the supply chain of perishable items

It is necessary to first define the symbols used in the model to formulate the problem. Tables (1) to (3) introduce sets, parameters, and decision variables of the problem. It has to be noted that fuzzy parameters are distinguished from other parameters by ~. This model is formulated based on the model presented by Ghorbani and Jokar (2016).

Table 1: Mathematical model sets

Symbol	Definition
$a \in A$	Raw material suppliers
$a \in A' \subset A$	Reliable suppliers (Safe from disorders)
$m \in M$	Production centers
$d \in D$	Distribution centers
$k \in K$	Customers
$r \in R$	Types of raw materials
$p \in P$	Types of final products
$l \in L$	Facility capacity levels
$t \in T$	Periods
$v \in V$	Vehicles used to move materials between distribution centers and customers
$s \in S$	Supplier disruption scenarios

Table 2: Mathematical model parameters

Symbol	Definition
bc_{pk}	Penalty paid to the customer k because of demand backlog for the product p
ec_{dl}	Construction cost of distribution facility d with capacity level l
ac_m	Cost per unit of capacity increase in production facilitation a
hc^1_{rm}	The cost of maintaining each unit of inventory from the raw material r per unit time to facilitate production m
hc^2_{pd}	The cost of maintaining each unit of inventory of the final product P per unit time in facilitating distribution d
mc_{pm}	Production cost per unit of product P in production facilitation m
pc_{ra}	Cost per unit of raw material r provided by the supplier a
tc_{ij}	The cost of transporting products from the initial node i to the final node j
q_{pkt}	The amount of product P demand by the customer k in the period t (fuzzy parameter)
dw_{dl}	Operational capacity facilitating distribution d by capacity level l
mw_m	Production capacity facilitating production m
sw_{ra}	Maximum operating capacity of the supplier a in the supply of raw material r
lw_{as}	Coefficient of reduction of the raw material supply by the supplier a under the scenario s
vw_v	Vehicle capacity v
$D^{\max}$	Constraint on the number of distribution facilities constructed
τ^1_r	Lifespan of raw material r
τ^2_p	Final product life P
α_{rp}	The raw material r needed to produce a unit of the final product P
π	Weight ratio of long-term costs

Table 3: Mathematical model decision variables

Symbol	Definition
X_{dl}	If distribution facility d is constructed with capacity level I, it is 1 otherwise zero
Y_m	The rate of increase in capacity in facilitating production m
Z_{ijpvts}	If the communication route $i-j$ is part of the vehicle route v for the delivery of the final product P in the period t and under scenarios, it is 1 otherwise zero
U^1_{rmts}	The raw material inventory r to production facilitation m at the end of period t and under the scenario s
U^2_{pdts}	The amount of inventory of the final product P in facilitating distribution d at the end of the period t and under scenario s
W^1_{amr}	The value of the order from supplier a for raw material r by production facilitation m
W^2_{mdpts}	The amount of order from production facilitation m for the final product P by facilitation of distribution d in period t and under scenario s
W^3_{dkpts}	A part of the customer k order for the final product P that can be supplied by distribution facilitation d over the period t and under scenario s
B_{pkdts}	A part of the customer k order for the final product P that cannot be supplied by distribution facilitation d over the period t and under scenario s
E_{pkvts}	A part of the customer k order for the final product P that backlogs in the vehicle path v in the period t and under scenario s
G_{kpvts}	A non-negative auxiliary variable used to delete sub-tours

The first objective function of the robust optimization model in Equation (1), to minimize the total costs in the system, is formulated through random variables, ξ_s, θ_s, δ^+_{rmts}, and δ^-_{rmts}.

$$Min\ f_1(x) = \sum_{s\in S} p_s \xi_s + \lambda \sum_{s\in S} p_s \left[\left(\xi_s - \sum_{s'\in S} p_{s'} \xi_{s'} \right) + 2\theta_s \right] + \sum_{s\in S} p_s \left(\sum_{r\in R} \sum_{m\in M} \sum_{t\in T} \delta^+_{rmts} + \delta^-_{rmts} \right) \qquad (1)$$

The second objective function in Equation (2) maximizes the level of chain resilience, which is the sum of the weight adopted by each of the three resilience strategies.

$$Max\ f_2(x) = w_1 \left(\frac{\sum_{a\in A'} \sum_{m\in M} \sum_{r\in R} W^1_{amr}}{Max\left(\sum_{a\in A} \sum_{m\in M} \sum_{r\in R} W^1_{amr} \right)} \right) + w_2 \left(\sum_{m\in M} \frac{Y_m}{Max\,(Y_m + mw_m)} \right) \qquad (2)$$

Equation (3) shows the stochastic variable ξ_s in the first objective function, which includes the costs of constructing facilities and the costs of increasing production capacity in the first component. The costs of supplying raw materials in the second component, the products production costs in the third component, inventory maintenance costs in the fourth component, fines related to the backlog of customer orders in the fifth component and material transportation costs in the sixth component.

$$\xi_s = \pi\left(\sum_{d\in D}\sum_{l\in L} ec_{dl} X_{dl} + \sum_{m\in M} ac_m Y_m\right) + \sum_{r\in R}\sum_{a\in A}\sum_{m\in M}\sum_{t\in T} pc_{ra} W^1_{amr} + \sum_{p\in P}\sum_{m\in M}\sum_{d\in D}\sum_{t\in T} mc_{pm} W^2_{mdpts} + \sum_{r\in R}\sum_{m\in M}\sum_{t\in T} hc^1_{rm} U^1_{rmts} + \sum_{p\in P}\sum_{d\in D}\sum_{t\in T} hc^2_{pd} U^2_{pdts} + \sum_{p\in P}\sum_{k\in K}\sum_{d\in D}\sum_{t\in T} bc_{pk} B_{pkdts} + \sum_{i\in(D\cup K)}\sum_{j\in(D\cup K)}\sum_{p\in P}\sum_{v\in V}\sum_{t\in T} tc_{ij} Z_{ijpvts} \tag{3}$$

Constraint (4) calculates the value θ_s.

$$\xi_s - \sum_{s'\in S} p_{s'}\xi_{s'} + \theta_s \geq 0 \quad ;\forall s \in \Omega \tag{4}$$

Constraint (5) states that a maximum of one facility can be constructed at any potential location for distribution facilities. In the case of such facilities, the capacity of the facility can only reach certain levels.

$$\sum_{l\in L} X_{dl} \leq 1 \quad ;\forall d \in D \tag{5}$$

Constraint (6) considers a high constraint on the number of distribution facilities to be constructed.

$$\sum_{l\in L}\sum_{d\in D} X_{dl} \leq D^{max} \tag{6}$$

Constraints (7) to (9) show the capacity constraints of suppliers, production centers and distribution centers, respectively.

$$\sum_{m\in M} W^1_{amr} \leq sw_{ra} \quad ;\forall a \in A, r \in R \tag{7}$$

$$\sum_{p\in P}\sum_{d\in D} W^2_{mdpts} \leq \left(mw_m + Y_m\right) \quad ;\forall m \in M, t \in T, s \in S \tag{8}$$

$$\sum_{p\in P}\sum_{k\in K} W^3_{dkpts} \leq \sum_{l\in L} dw_{dl} X_{dl} \quad ;\forall d \in D, t \in T, s \in S \tag{9}$$

Constraints (10) and (11) show the balance of input and output currents in production and distribution facilities.

$$U^1_{rmts} = U^1_{rm(t-1)s} + \sum_{a\in A} lw_{as} W^1_{amr} - \sum_{p\in P}\sum_{d\in D} \alpha_{rp} W^2_{mdpts} - \delta^+_{rmts} + \delta^-_{rmts} \quad ;\forall m \in M, r \in R, t \in T, s \in S \tag{10}$$

$$U^2_{pdts} = U^2_{pd(t-1)s} + \sum_{m\in M} W^2_{mdpts} - \sum_{k\in K} W^3_{dkpts} - \sum_{k\in K} B_{pkd(t-1)s} + \sum_{k\in K} B_{pkdts} \quad ;\forall d \in D, p \in P, t \in T, s \in S \tag{11}$$

Constraints (12) and (13) show the fact that inventory control policy in production and distribution facilities is based on the limited life of products.

$$U^{1}_{rmts} \le \sum_{t \le \tau \le t+\tau^{1}_{r}} \sum_{p \in P} \sum_{d \in D} \alpha_{rp} W^{2}_{mdp\tau s} \quad ;\forall m \in M, r \in R, t \in T, s \in S \tag{12}$$

$$U^{2}_{pdts} \le \sum_{t \le \tau \le t+\tau^{2}_{p}} \sum_{k \in K} W^{3}_{dkp\tau s} \quad ;\forall d \in D, p \in P, t \in T, s \in S \tag{13}$$

Constraint (14) states that each customer can only be served once during each period.

$$\sum_{v \in V} \sum_{i \in (D \cup K)} Z_{ijpvts} = 1 \quad ;\forall j \in K, p \in P, t \in T, s \in S \tag{14}$$

According to constraints (15) and (16), the starting and ending points of each vehicle are a similar distribution center.

$$\sum_{i \in D} \sum_{j \in K} Z_{ijpvts} = 1 \quad ;\forall v \in V, p \in P, t \in T, s \in S \tag{15}$$

$$\sum_{j \in K} Z_{ijpvts} - \sum_{j \in K} Z_{jipvts} = 0 \quad ;\forall i \in D, v \in V, p \in P, t \in T, s \in S \tag{16}$$

Constraint (17) shows the continuity of the vehicle's trajectory, so that if a vehicle enters a node, it must leave it.

$$\sum_{i \in (D \cup K)} Z_{ijpvts} - \sum_{i \in (D \cup K)} Z_{jipvts} = 0 \quad ;\forall j \in K, p \in P, v \in V, t \in T, s \in S \tag{17}$$

Constraint (18) in the proposed model ensures the formation of sub-tours.

$$G_{ipvts} - G_{jpvts} + |K| Z_{ijpvts} \le |K| - 1 \quad ;\forall i, j \in K, p \in P, v \in V, t \in T, s \in S \tag{18}$$

Constraint (19) shows the limitation of the capacity of vehicles.

$$\sum_{i \in (D \cup K)} \sum_{k \in K} \sum_{p \in P} \sum_{j \in D} Z_{ikpvts} W^{3}_{jkpts} - \sum_{p \in P} \sum_{k \in K} E_{pkvts} + \sum_{p \in P} \sum_{k \in K} E_{pkv(t-1)s} \le vw_{v} \quad ;\forall v \in V, t \in T, s \in S \tag{19}$$

Constraint (20) states that if a customer's order is allocated by one of the distribution centers, there must be a delivery route from which the distribution center starts and includes the relevant customer.

$$W^{3}_{dkpts} \le M \sum_{i \in K} \sum_{v \in V} Z_{dipvts} Z_{ikpvts} \quad ;\forall d \in D, k \in K, p \in P, t \in T, s \in S \tag{20}$$

Constraint (21) specifies the need to meet customer demand to the end of the decision horizon.

$$\sum_{d \in D} \sum_{t \in T} W^{3}_{dkpts} \ge \sum_{t \in T} q_{pkt} \quad ;\forall k \in K, p \in P, s \in S \tag{21}$$

Constraints (22) to (24) calculate the amount of backlog orders in each period.

$$B_{pkdts} \le M \sum_{i \in K} \sum_{v \in V} Z_{dipvts} Z_{ikpvts} \quad ;\forall d \in D, k \in K, p \in P, t \in T, s \in S \tag{22}$$

$$\sum_{d\in D} B_{pkdts} = \sum_{v\in V} E_{pkvts} \quad ;\forall k\in K, p\in P, t\in T, s\in S \tag{23}$$

$$E_{pkvts} \le M \sum_{i\in(D\cup K)} Z_{ikpvts} \quad ;\forall k\in K, p\in P, v\in V, t\in T, s\in S \tag{24}$$

Constraint (25) states that the amount of decision variables related to the inventory level and the amount of backlog demand at the end of the decision horizon must be equal to zero.

$$U^1_{rmTs}, U^2_{pdTs}, E_{pkvTs} = 0 \tag{25}$$

Finally, constraints (26) and (27) specify the binary and non-negative variables of the problem.

$$X_{dl}, Z_{ijpvts} \in \{0,1\} \tag{26}$$

$$Y_m, U^1_{rmts}, U^2_{pdts}, W^1_{smr}, W^2_{mdpts}, W^3_{dkpts}, B_{pkdts}, E_{pkvts}, G_{kpvts}, \theta_s, \delta^+_{rmts}, \delta^-_{rmts} \ge 0 \tag{27}$$

3. Model linearization

By focusing on the developed mathematical model, we find that the proposed model in this study includes nonlinear expressions in the structure of the constraints (19), (20) and (22). The existence of multiplication of the problem decision variables in these constraints is the reason for the nonlinearity of this model. As the optimal solution of optimization problems in the commercial optimization software needs the presentation of a linear model, in this section, using auxiliary variables and new constraints, we linearize the model. For instance, Constraint (19) contains the term $Z_{dipvts}\times Z_{ikpvts} \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S$, which is the product of the two binary variables. The existing solution for linearizing this case is to define a new non-negative variable ($ZZ_{dikpvts} \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S$), and replace it with the product of multiplication $Z_{dipvts}\times Z_{ikpvts} \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S$ in the problem formulation. Moreover, three new constraints have to be added to the problem. Constraints (28) to (30) are used for this purpose.

$$ZZ_{dikpvts} \le Z_{dipvts} \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S \tag{28}$$

$$ZZ_{dikpvts} \le Z_{ikpvts} \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S \tag{29}$$

$$ZZ_{dikpvts} \ge Z_{dipvts} - \left(1 - Z_{ikpvts}\right) \quad ;\forall d\in D, i\in K, k\in K, p\in P, v\in V, t\in T, s\in S \tag{30}$$

Other non-linearities in the model can be linearized with a similar approach.

4. Facing the fuzzy parameters

The study uses the chance-constrained planning approach to deal with ambiguous and fuzzy parameters (Pishvaee et al., 2012). This approach can control the degree of satisfaction in chance-constrained. However, at the same time the computational complexity increases as a constraint is added to the original model for each objective function. In general, necessary size-based chance-constrained programming is an efficient fuzzy mathematical programming approach based on robust mathematical concepts. For example, the required size of a fuzzy number can support different types of fuzzy numbers such as triangles and trapezoids, as well as enable the decision maker to give minimum limits of confidence to chance-constrained. If $q_{pjt} = \left(q^{(1)}_{pjt}, q^{(2)}_{pjt}, q^{(3)}_{pjt}\right)$ is a triangular fuzzy number and a greater than 0.5, then:

$$Nec\left\{q_{pjt} \geq r\right\} \geq \alpha \Leftrightarrow r \leq \alpha\, q_{pjt}^{(1)} + \left(1-\alpha\right) q_{pjt}^{(2)} \tag{31}$$

$$Nec\left\{q_{pjt} \leq r\right\} \geq \alpha \Leftrightarrow r \geq \alpha\, q_{pjt}^{(3)} + \left(1-\alpha\right) q_{pjt}^{(2)} \tag{32}$$

As is seen from Equations (31) and (32), the necessity measurement method, whereas converting fuzzy constraints to their definite equivalent, can control the level of satisfaction. Using Equation (32), Constraint (21) can be replaced with deterministic Constraint (33).

$$\sum_{d \in D}\sum_{t \in T} W_{dkpts}^{3} \geq \sum_{t \in T} \alpha\, q_{pkt}^{(3)} + \left(1-\alpha\right) q_{pkt}^{(2)} \quad ;\forall k \in K, p \in P, s \in S \tag{33}$$

5. How to display the solutions in the meta-heuristic algorithms

A continuous solution structure is used to show the answer to the problem. The answer is shown using a matrix with $R \times C$ dimensions, so that *R* is equal to the number of chain levels minus one, and *C* is the maximum number of members in each of the first three levels. Figure (1) shows the proposed structure for displaying the answers. We will explain the extraction of the decision variables of the problem.

	Max(‖S‖, ‖M‖, ‖D‖)					
Decisions related to suppliers	0.78	0.91	0.48	…	0.30	0.85
Decisions related to manufacturers	0.93	0.11	0.19	…	0.14	0.02
Decisions related to manufacturers distributors	0.94	0.45	0.13	…	0.88	0.61

Figure 1: Displaying the answer

We select $\|D\|$ number of cells in the third row of the matrix from the left in descending order and then specify the rank of each cell to determine the location of the distribution centers and their capacity. These rankings show the number of distribution centers. For instance, the first distribution center is ranked first. We need to convert the real values inside each cell into integer variables from 1 to $\|L\|$ to determine the level of capacity proportional to each center. To this end, if the value inside a cell is in $\left(\frac{l-1}{L}, \frac{l}{L}\right]\ ; l \in \left\{1,\ldots,\|L\|\right\}$ range, the distribution center corresponding to the cell with the capacity level will be constructed. According to the capacities obtained, we estimate the minimum number of facilities required to meet customer demand during each period and show it by $D^{\min}$. Obviously, the number of facilities built must be in the range $\left[D^{\min}, D^{\max}\right]$. We use Equation (34) to establish such a condition, where ϑ is equal to the average of the cells in the third row of the response matrix.

$$D^{\min} + \left\lceil \vartheta\left(D^{\max} - D^{\min}\right)\right\rceil \tag{34}$$

We first assign the customer closest to the first facility built to this facility, delete the relevant customer from the list of customers requesting service, and do this for all distributed facilities to determine the customers assigned to each distribution center and determine the service routes to them. After assigning the first customer to all the distribution centers, we assigned the second customer to them according to the previous procedure and based on the distance factor. This process continues until all customers are assigned to the distributed distribution centers and the capacity of any of the facilities is not exceeded.

The order can be allocated up to several times this amount and use the inventory maintenance policy in future courses to determine the pattern of ordering distribution centers to production centers, based on the total demand of customers allocated to each distribution center in a period. Determining the order fulfillment coefficient is based on a random integer in the developed algorithm. Note that if the order is for three periods, the next order must be placed in the fourth period.

Decisions on the production facilities and suppliers are made in a manner similar to the approach discussed for distribution facilities. Note that these decisions are limited to allocation decisions only.

Due to the NP-hard nature of the proposed model, MOPSO and non-dominated sorting genetic algorithm-II (NSGA-II) multi-objective algorithms are used to solve medium and large-scale problems.

Results

First, a number of sample problems are randomly generated in different dimensions and the results of the implementation of MOPSO and NSGA-II meta-heuristic algorithms are reported on these problems. These algorithms are coded in MATLAB (R2015a) in a PC with Intel Corei7 PC specifications with 8 GB of RAM and over 2 GHz CPU. The results obtained are compared with the results of the exact solution based on complex integer programming implemented in GAMS 24.1.3 software environment for sample problems with small dimensions to evaluate the validity of the proposed models and algorithms.

The problem in question is discussed in different dimensions of small, medium and large, and the data related to the supply chain network in the sample problems are presented in Table (4).

Table 4: Dimensions of sample problems

Problem dimensions	Sample	Set							
		Supplier	Manufacturer	Distributor	Customer	Period	Product		Scenario
							Raw	Final	
Small	1	2	2	2	5	3	2	2	2
	2	2	2	2	8	3	2	2	2
	3	3	3	3	10	4	3	3	2
	4	3	3	3	12	4	3	3	2
	5	3	3	3	15	4	3	3	2
Medium	6	4	4	4	20	5	4	4	3
	7	4	4	4	25	7	4	4	3
	8	5	5	5	30	8	5	5	4
	9	6	6	6	40	9	5	5	4
	10	6	6	6	50	10	5	5	4
Large	11	7	7	7	60	15	6	6	5
	12	8	8	8	70	20	6	6	5
	13	8	8	8	80	20	7	7	5
	14	9	9	9	90	25	7	7	5
	15	10	10	10	100	30	7	7	5

It has to be noted that the number of vehicles to deliver products to customers is determined based on the mathematical expectation of demand values and therefore we do not need to randomly generate this parameter in the problems based on the assumptions made in the modeling of the problem. Given the lack of sufficient information in the subject literature and the lack of a model similar to the proposed model, a uniform distribution in different intervals has been used to produce the rest of the required information in the problems. The intervals needed for uniform distribution to produce model parameters are presented in Table (5).

Table 5: Uniform distribution intervals to generate model parameters

Distribution intervals	Parameter	Distribution intervals	Parameter
□ 105 Uniform [1, 15] ($)	ec_{dl}	□ Uniform [0.5, 0.9] ($)	bc_{pk}
□ Uniform [0.4, 0.8] ($)	hc^2_{pd}	□ Uniform [0.3, 0.6] ($)	hc^1_{rm}
□ 102 Uniform [1, 9] ($)	ac_m	□ Uniform [1, 3] ($)	mc_{pm}
□ Uniform [5, 40] ($)	tc_{ij}	□ Uniform [3, 5] ($)	pc_{ra}
□ 102 Uniform [10, 15] (ton)	dw_{dl}	□ Uniform [10, 40] (ton)	q_{pkt}
□ 103 Uniform [0.5, 10] (ton)	sw_{ra}	□ 102 Uniform [10, 15] (ton)	mw_m
□ 10 Uniform [9, 12] (ton)	vw_v	□ Uniform [0.1, 0.5] (ton)	lw_{ra}
□ Uniform [1, 2.5] (ton)	α_{rp}	□ Uniform [2, 5] (day)	τ^1_r , τ^2_p

The uniform distributions specified in Table (5) are used to simulate the values of the problem parameters in the sample problems. Concerning the uncertain parameters (demand parameter) we first obtain the most probable value of this parameter based on the information in Table (5). Then two random coefficients are selected from the intervals [0.9 and 0.4] and [1.5 and 1.1], respectively, and by multiplying these coefficients in the probable value, the optimistic and pessimistic values of the parameter are obtained.

Computational results of small sample problems

We must first have a normalized weight combination of the objective functions to solve the problem in GAMS software. Figure (2) shows the optimal values for the objective functions in the form of a Pareto curve.

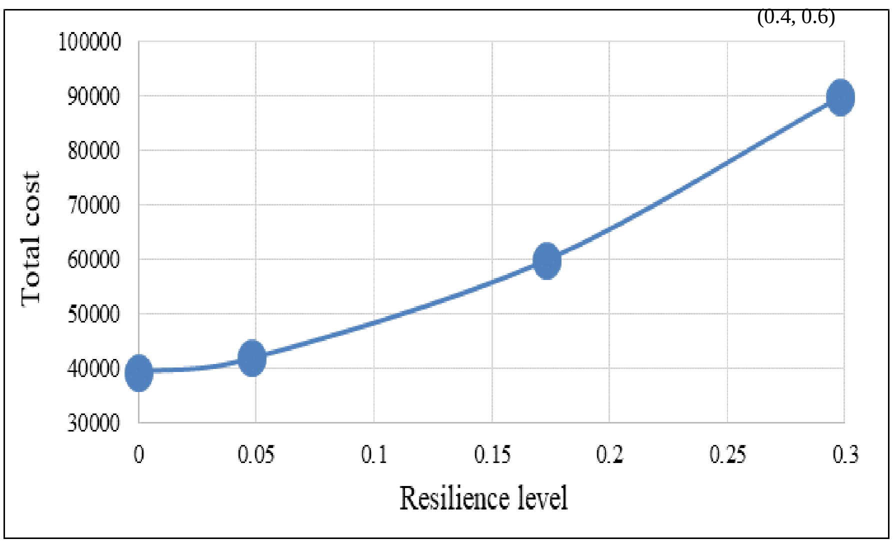

Figure 2: Pareto curve obtained from solving problem instance 2 in GAMS software

As Figure (2) shows, four Pareto solutions are obtained using different weighting coefficients.

The results show that the increase in the level of resilience in the supply chain needs additional costs. Now the question is "What effect does addressing resilience have on supply chain network design?" A detailed study of Pareto solutions shows that increasing the level of resilience of the supply chain reduces the amount and costs of shortages in the system. Figure (3) shows that the shortages in the system decreases to zero, as the level of resilience increases.

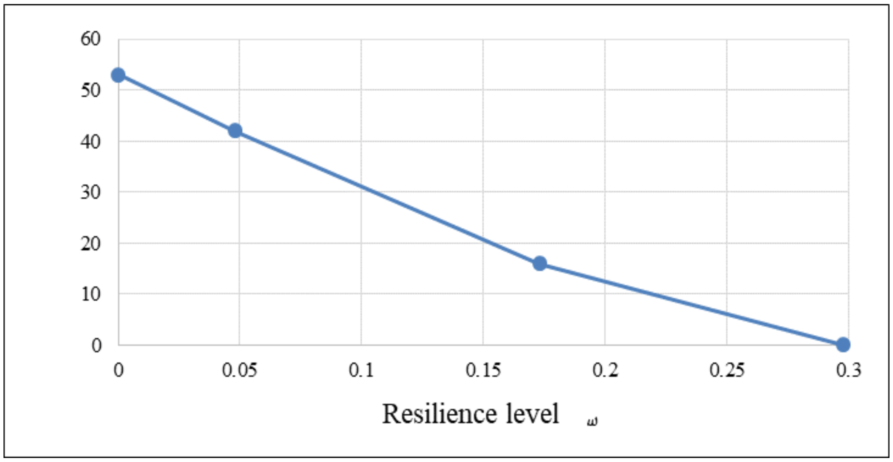

Figure 3: Conflicting relationship between resilience level and deficit level corresponding to sample problem 2

Table (4) reports the values obtained for the normalized objective function of small-scale problem instances obtained from the exact integer programming approach as well as the MOPSO and NSGA-II algorithms. It has to be noted that the meta-heuristic algorithms are run ten times for each problem instance and the average values obtained are used to compare their performance given the randomness of the initial population selection in the meta-heuristic algorithms.

Table 4: The value of the normalized weight objective function and the computational time for small sample problems

Sample problem	GAMS		MOPSO		NSGA-II	
	Objective function	Time (s)	Objective function	Time (s)	Objective function	Time (s)
1	0.249	2.37	0.250	25.18	0.252	28.37
2	0.389	3076	0.395	35.52	0.392	36.33
3	0.343	33734	0.351	52.79	0.347	57.60
4	0.283	62009	0.294	62.81	0.297	71.26
5	0.341	196028	0.350	75.64	0.360	83.59

As Table (4) shows, the results of meta-heuristic algorithms are not optimal compared to the output of GAMS software. The results show that with increase in the dimensions of the location-routing-inventory problem, the average deviations from the optimal value increase. However, the NP-hard nature of the problem justifies the use of meta-heuristic algorithms. The computational time needed to solve the problem with GAMS software increases exponentially with increasing dimensions of the problem, whereas the computational complexity in the meta-heuristic algorithms increases based on a linear function which is one of the consequences of the NP-hard problem.

Computational results of sample problems with medium and large dimensions

We will continue to solve medium- and large-scale problems using MOPSO and NSGA-II algorithms given the proven efficiency of the proposed algorithms in solving small-scale problems. Table (5) shows that the two algorithms are evaluated based on two measures of number of Pareto solutions and Spacing Metric (SM) for medium- and large-scale problems. In addition, Table (6) compares the two algorithms based on Diversity Metric (DM) and Mean Ideal Distance (MID). Finally, Table (7) is the computational time needed for these algorithms.

Table 4: Number of Pareto optimal solutions and spacing metric for medium- and large-size problems

Problem no.	Number of Pareto solutions		Spacing Measure (SM)	
	MOPSO	NSGA-II	MOPSO	NSGA-II
6	3	5	0.4625	0.4328
7	3	4	0.2802	0.1345
8	4	5	0.8535	0.2286
9	5	6	0.4245	0.3897
10	4	5	0.4589	0.3549
11	6	6	0.9825	0.8631
12	8	8	0.8215	0.6617
13	5	8	0.7448	0.6569
14	9	10	0.6911	0.6562
15	5	7	0.7389	0.7305

Table 5: Diversity and mean ideal distance metrics for medium- and large-size problems

Problem no.	Diversity Metric (DM)		Mean Ideal Distance (MID)	
	MOPSO	NSGA-II	MOPSO	NSGA-II
6	0	0.5612	0.8477	0.8931
7	0.2001	0	0.9277	0.9987
8	0.2748	0.6804	0.7505	0.7341
9	0.4656	0.4578	0.8226	0.8995
10	0.4532	0.6348	0.9575	0.9824
11	0.7548	0.7984	0.8919	0.9357
12	0.7456	0.8145	0.8321	0.8817
13	0.6015	1	1	1
14	0.6923	0.7997	0.7177	0.7506
15	0.6610	0.6984	0.8025	0.8543

Table 6: Computational time needed to solve medium- and large- size problems

Problem no.	Computational time (s)	
	MOPSO	NSGA-II
6	130	152
7	151	171
8	163	186
9	182	206
10	196	229
11	213	248
12	231	232
13	250	287
14	284	317
15	309	337

As is seen from the tables, NSGA-II performed better than MOPSO algorithm in three metrics of number of Pareto solutions, diversity, and spacing. In terms of MID and computational time complexity, the MOPSO algorithm performed better overall than the NSGA-II algorithm. However, there are no significant differences between the two algorithms in terms of computational time, and in some cases, NSGA-II has performed equally and even better than the MOPSO algorithm.

Validation of scenario-based robust planning model

Value of the Stochastic Solution (VSS) method will be used to evaluate the scenario-based robust optimization model in this study. The expected value of correct information shows the value of knowing the future. In this method, assuming that exactly a certain scenario occurs for each scenario, the objective function resulting from the application of that scenario is calculated. The objective function is then calculated according to the probability of encountering supply disruptions other than the predicted scenario. After considering all the scenarios, the expected value for the mentioned objective functions is calculated. Finally, the difference between the value obtained from the total cost objective function with random solution and the total cost obtained from above shows the "expected value of correct information."

The total cost in the scenario-based robust optimization approach compared to the expected value approach in problem instance 2 is shown for the various weights of variability (λ) in Figure (4). The results show the superiority of a robust approach. This advantage can bring about an eight percent improvement in total supply chain costs in λ = 8. It has to be noted that these results are based on solving the problem in GAMS software and weight coefficients of (0.5, 0.5).

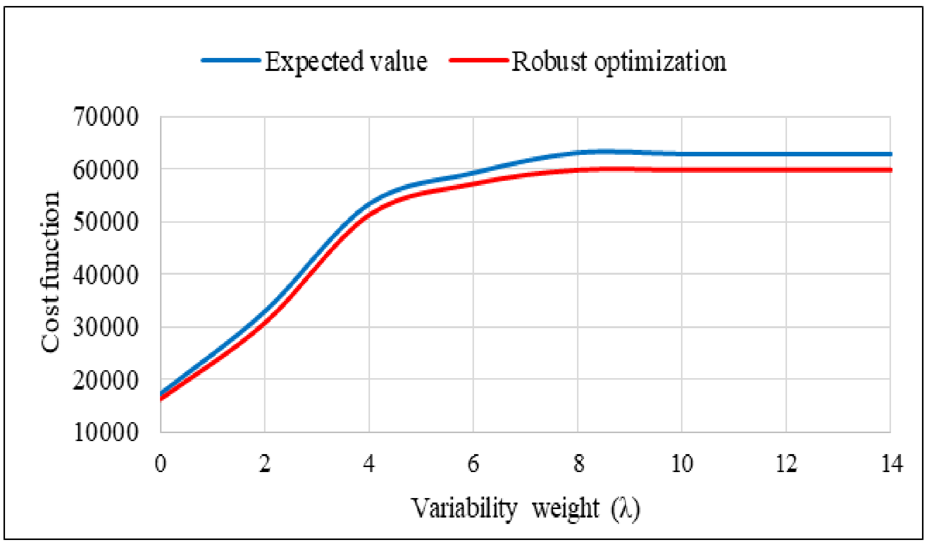

Figure 4: Cost performance of the robust approach compared to the expected value approach for different variability weights

Conclusions

he study examined the challenges like the significance of resilient supply chain structures against operational and disruption risks, integrated decision-making on location, inventory control, and routing problems, and many realistic assumptions about perishable products to make advances in research and implementation in supply chain management. A mathematical formulation was developed for periodic planning for perishable products in the context of supply chain network design. The developed model with a bi-objective structure is trying to increase the level of network resilience. The model was developed to determine decisions related to (1) the location of distribution facilities, (2) the level of inventory in the facilities, and (3) routing and volume control planning in a decision-making environment with uncertainty. In the proposed model, the scenario-based robust optimization approach was used for modeling the problem in conditions of uncertainty. Given the NP-hard nature of the problem, two meta-heuristic algorithms, namely Multi-Objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) were developed to deal with high-dimensional problems.

NSGA-II performed better than the MOPSO in three metrics of the number of Pareto solutions, diversity, and spacing in the majority of problem instances from various sizes. In terms of MID and computational time complexity, the MOPSO algorithm performed better overall than the NSGA-II algorithm. Then, the expected value approach was compared with the solutions obtained from solving the model with the robust optimization approach to evaluate the performance of the proposed robust model. The results show that the robust approach performs better than the other method. Moreover, we examined the existence of a trade-off relationship between the level of resilience and supply chain costs to identify opportunities to enhance chain performance while maintaining cost-effectiveness.

In spite of the focus of the study on supply-related disruptions, supply chain networks not only face this type of disruptions but also production and transportation disruptions are a part of the chain uncertainties. To overcome such limitations, future studies should consider such issues.

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