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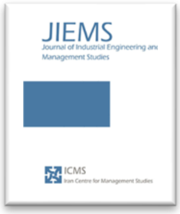

Optimal design of a multi-period supply chain network with unreliable elements: A two-stage stochastic programming approach

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Abstract

The management and design of supply chain networks in various dimensions are so critical today that managers' decisions significantly impact the configuration and flow of material in the network. Above all, supply chain management intends to reduce costs. The inability to accurately predict certain features, such as demand, can complicate the cost estimation process. To that end, an essential parameter is the reliability of supply chain networks. Considering the reliability of the supply chain network brings the model closer to reality, and the wellness or failure of its elements under different scenarios increases the enthusiasm to face unpredictable events in managers and helps network performance. Furthermore, appropriate management and design of the supply chain network can increase customer satisfaction and reduce costs in the long term. In this research, a four-tier supply chain network was designed to reduce the costs through a two-stage stochastic programming attitude. The combined metaheuristic method (genetic and simulated annealing algorithms) was used to solve the model. By treating the reliability of entities and routes and its effect on reducing cost as an essential criterion in the mentioned problem, it was showed that a reliable system has lower costs than an unreliable system.

Keywords: network design; multi-period supply chain; reliability; two-stage stochastic programming.

Paper Type: Original Research

1. Introduction

Supply chain network design and formation process are critical issues in risk control management. The supply chain risk often stems from the lack of confidence amongst its constituents. In addition to uncertainty, any manifestation of distrust in this business will lead to huge losses and eventually failure. With the recent increase in uncertainties, the importance of risk concerns has also increased (Heckmann et al., 2015). Since the need for broader development and more robust communication between all parts of the supply chain to reach the final customer is necessary, it can be claimed that rising confidence in the network reduces both risks and costs. Designing a supply chain network on the foundation of reliability is a strategic decision and assists decision-makers in setting long-term goals. It also provides better flexibility and order exchange and improves product quality (Govindan et al., 2019). Also, the higher value of network design causes healthy management of changes in supply and demand. It makes customer satisfaction and better flowing of materials in that network. A well-designed network improves the performance of entities and ensures a more efficient trade among them. Even in disasters, depending on the scale of disruptions, an appropriate network can play a vital role in enabling affected people to get back to normal. For instance, in Southeast Asia, which is a crowded region, many people have lost their lives, been hurt, or incurred financial damages because of earthquakes, floods, or tsunamis in the past years. Thus, focusing on preparedness activities like emergency planning, construction of emergency centers, and stable routes can lead to a better level of services (Abazari et al., 2021; Maharjan and Hanaoka, 2017).

The four-tier supply chain network studied in this paper includes several suppliers, manufacturers, distributors, and customers. These entities have variable cost, fixed cost, and capacity, which make the problem assumptions. The reliability parameter is one of the inputs of the studied system through Bernoulli distribution with a certain percentage of success. Unlike previous research, this criterion is obtained with a certain probability and is not a hypothetical number. Customer demand is stochastic in various scenarios and different periods along with reliability. The purpose of designing this network is to minimize the total cost. The modeling approach is two-stage stochastic programming, and the solution method involves hybrid metaheuristic algorithms (genetic and simulated annealing algorithms). In the next section, the existing literature is reviewed. The model is presented in the third section. In the Section 4, the solution approach is examined and an optimal solution is proposed, which

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includes sensitivity analysis and managerial insights too. Finally, in the last section, the results and future studies are presented.

2. Literature review

2.1. Reliability vs. Risk

Ha et al. (2018), provide a supply chain network design and risk assessment solution. They believe that it is almost impossible to estimate risk mathematically due to networks' tangled structure and operational policies. In similar studies, Samadi et al. (2020) and Fathollahi-Fard et al. (2018) challenge the financial aspects of network design risks, Govindan et al. (2019), and Goodarzian et al. (2020) assess the effects of social and environmental risk on network design by presenting a model to examine operational and strategic decisions to improve the performance of supply chain and their long-term goals. Alternatively, Gholami et al. (2019) believe that supply chain management always goes along with uncertainty, leading to increased decision-making risk. In such cases, by increasing the reliability of the supply chain, the potential risk (uncertainty) can be minimized.
Many factors can improve supply chain networks: development of entities by considering the risk and identifying it in the mentioned cases, setting objectives by defining strategic and technical plans as a goal, managing them, and preparing for suitable response in case of disruption can positively affect (Faertes, 2015). In a similar study, Hamidieh and Fazli-Khalaf (2017) define reliability as the ability of supply chain entities to cope with the adverse effects of various types of risks threatening network performance. They argue that disruptions could interrupt supply chain functioning, causing considerable damage to stakeholders, ultimately leading to market share loss and failure in customer satisfaction, thus impairing the performance of developing companies worldwide. Tolooie et al. (2020) believe that the admirable design of a secure network is one of the main priorities to protect against supply chain disruptions. The key to managing disruptions is not reducing costs or improving efficiency but creating efficient supply chains in stable and unstable situations. Yildiz et al. (2016) state that network risk control, including supply and demand, production, costs, and information risks, is critical in supply chain management. After identifying these risks, they examine their impact on navigating a four-tier supply chain network to reduce cost and increase reliability by adopting the Pareto optimization approach. They also consider the value of the objective function in three different scenarios to calculate network reliability to ensure a secure network flow. Rahmani and Mahoodian (2017) present a model to prevent uncertain events. Their model can be used with a sustainable approach. Adenso-Diaz et al. (2012) evaluate the advantages and disadvantages of supply chain networks. They report that network compactness, sensitivity, and complexity are significant factors in reducing reliability.
Pasandideh et al. (2015) propose a model to examine reliability in specific parts of the supply chain, such as warehouses. In their proposed model, managers decide the best policy to increase customer satisfaction based on fixed and variable costs in establishing an entity, existing capacities, and warehouses' reliability. Decisions that are strategic and require long-term planning and changes could prove more costly. Therefore, unplanned, impulsive decision-making is unreasonable. However, Hamidieh and Fazli-Khalaf (2017), by designing a closed-loop supply chain network, claim that reliability can lead to customer loyalty and satisfaction, increase companies' market share, and long-term planned profits to reduce costs and increase responsiveness. In a study with a similar attitude Goodarzian and Hosseini-Nasab (2021) discuss the factors concerning reducing cost and increasing reliability.

2.2. Uncertainty

In most cases, miscalculations and misjudgments lead to unpredictable developments with potentially significant consequences concerning late detection. Parameter uncertainty is an essential issue that can hinder long-term organizational decision-making by directly influencing network reliability. Tolooie et al. (2020), divide uncertainty into human and natural, occurring in the entire network. They also consider cost and demand uncertainty as factors leading to shortages of materials in many industries. Sufficient information about supply and demand can reduce uncertainty, and decreasing the volatility of either of these two criteria (supply or demand) is an outstanding achievement that prevents risk. Note that the effect of uncertainty on sales markets (Jahani et al., 2018; Zhou et al., 2019) and the value of network design (Badri et al., 2017) as well as on financial risks (Abdi et al., 2021; Fathollahi-Fard et al., 2018) have been investigated in the literature.
Two-stage stochastic programming assists efficient decision-making in uncertain environments (Dantzig, 2004). It can deal with many problems, such as logistics planning (Hsu et al., 2018), supply chain network design (Badri et al., 2017), inventory control (Dillon et al., 2017), and even air traffic management (Shone et al., 2021). There are two types of decision variables in two-stage stochastic programming models; The first type, known as "here and now," is decided before realizing the stochastic scenarios. In the discussion of network design, these variables generally relate to the initial design and construction phase. The second type of variable, known as "wait and see, " depends on the outcomes of the stochastic scenarios, which are mainly decided in more operational phases and more details. In this context, the manager seeks to make first-stage decisions that must be considered for all scenarios so that all

costs related to the first stage and the second stage decisions should be optimized. Thus, determining a reasonable scenario that ensures the solution's efficiency is vital.

Zhou et al. (2019) consider customer demand as stochastic and network design criteria insensitive to demand, such as network size, the number of constructions, and inventory of materials as first stage variables and those like purchase volume and distribution plans and production strategies in the second stage. Furthermore, Badri et al. (2017) consider the amount of demand and returned core volumes as stochastic criteria in their model and the variables related to these two, including cash flows and total contribution margin in the second stage. Wang et al. (2020) study the demand and price of materials as uncertain criteria and based on that, decisions related to network design such as establishing manufacturers' plants and assigning demand to each or sourcing as first stage variables and decisions about inventory control and product purchasing made in the second stage. Dillon et al. (2017) estimate the inventory decisions and the number of orders in each supply chain period after determining the amount of uncertain demand. Table 1 compares the present study with relevant articles. The main difference between the present research and similar articles is that it calculates the reliability index using the Bernoulli distribution function and a specific success rate. The index is used as an input parameter of the problem.

Table 1: Literature Review

Article	Subject				Uncertainty		Period		Scenarios	Solution Approach	Solving Method
	Reliability		Cost/ Profit	Network Design	Stochastic	Fuzzy	Single	Multiple			
	Entities	Routes									
(Pasandideh et al., 2015)	*		*	*				*		MILP	**Exact**
(Yildiz et al., 2016)	*	*	*	*			*			MINLP	**Metaheuristic**
(Kamalahmadi and Mellat-Parast, 2016)	*		*	*	*		*		*	SMIP	**Exact**
(Hamidieh and Fazli-Khalaf, 2017)	*		*	*		*	*		*	PP	**Exact**
(Badri et al., 2017)			*	*	*			*	*	SMILP	**Exact**
(Jahani et al., 2018)			*	*	*			*		MILP	**Exact**
(Fathollahi-Fard et al., 2018)			*	*	*		*		*	SMILP	**Metaheuristic**
(Govindan et al., 2019)			*	*			*			MIP	**Metaheuristic**
(Zhou et al., 2019)			*	*	*		*		*	SMILP	**Exact**
(Dehghani et al., 2019)		*	*	*			*			MILP	**Metaheuristic**
(Abdi et al., 2021)			*	*	*		*		*	SMILP	**Metaheuristic**
(Goodarzian et al., 2020)	*	*	*	*		*		*		MILP	**Metaheuristic**
(Tolooie et al., 2020)	*		*	*	*			*	*	SMIP	**Exact**
(Goodarzian and Hosseini-Nasab, 2021)			*	*			*			MILP	**Metaheuristic**
(Wang et al., 2020)			*	*	*			*	*	SMILP	**Heuristic**
(Goli et al., 2020)	*		*	*		*		*		PP	**Metaheuristic**
(Samadi et al., 2020)			*	*			*			MINLP	**Metaheuristic**
(Nosrati and Khamseh, 2020)	*		*	*	*		*		*	SMINLP	**Metaheuristic**
(Yolmeh and Saif, 2021)			*	*	*		*		*	MINLP	**Heuristic**
(Tirkolaee et al., 2020)	*		*	*		*		*		MILP	**Exact**
This study	*	*	*	*	*			*	*	SMIP	**Metaheuristic**

In this paper, a four-tier supply chain network was designed to study network reliability from different perspectives. The contributions of this research can be categorized as follows:

- The reliability of network elements is an input parameter for both entities and routes.
- Customers' demand has been changed based on discrete scenarios: increasing, decreasing, and constant.
- A two-stage stochastic programming model is developed to solve the problem.
- A hybrid metaheuristic method (genetic and simulated annealing algorithm) solves large-scale instances.

– The total cost of the network is calculated considering reliable and unreliable elements.

3. Model

3.1. Definitions

The defined supply chain problem involves several suppliers, manufacturers, distributors (equipped with warehouses), and customers. Customer demand is stochastic. Customers can satisfy their demand from distributors and sometimes manufacturers, although at an extra cost. The model examines several periods. Each part of this network (entities and routes) has fixed and variable costs. Therefore, suppliers' raw material extraction capacity, the production and assembly of manufacturers, and the warehouses of distributors are limited. Also, variable costs are included for the storage of materials by distributors. According to the scenarios in the problem, each entity and route has exceptional reliability.

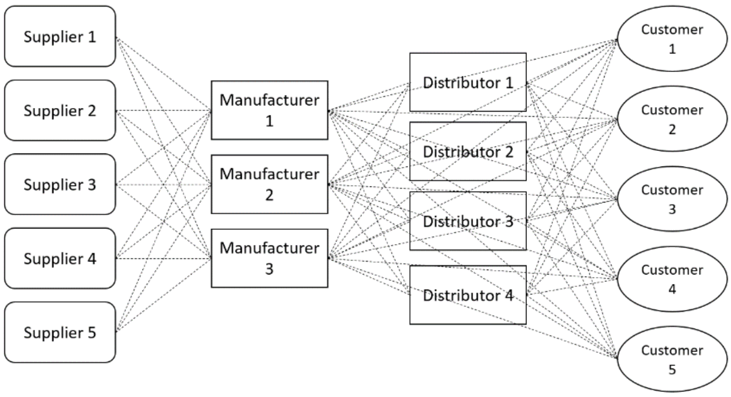


Figure. 1: The model scheme

3.1.1. Sets

I: Set of Raw Material Suppliers
J: Set of Manufacturers
K: Set of Distributors
D: Set of Customers
S: Set of Demand Scenarios
T: Set of Periods

3.1.2. Parameters

f_i^t: Fixed costs of establishing supplier i in period t
f_j^t: Fixed costs of establishing manufacturer j in period t
f_k^t: Fixed costs of establishing distributor k in period t
c_i^t: Variable costs of supplier i in period t
c_j^t: Variable costs of manufacturer j in period t
c_k^t: Variable costs of distributor k in period t
g_{ij}^t: Fixed costs of establishing a route between supplier i and manufacturer j in period t
g_{jk}^t: Fixed costs of establishing a route between manufacturer j and distributor k in period t
g_{jd}^t: Fixed costs of establishing a route between manufacturer j and customer d in period t
g_{kd}^t: Fixed costs of establishing a route between distributor k and customer d in period t
b_{ij}^t: Variable costs of the route between supplier i and manufacturer j in period t
b_{jk}^t: Variable costs of the route between manufacturer j and distributor k in period t
b_{jd}^t: Variable costs of the route between manufacturer j and customer d in period t
b_{kd}^t: Variable costs of the route between distributor k and customer d in period t
h_k^t : Holding and warehousing cost for distributer k in period t
sh_d^t : Shortage cost for customer d in period t
ca_i^t : Capacity of supplier i in period t
ca_j^t: Capacity of manufacturer j in period t

ca_k^t : Capacity of distributer k in period t
bn : A significant number
ds_d : Demand satisfaction for customer d
p^s : Probability of scenario s
dd_d^{ts}: Demand of customer d in scenario s and period t
L_i^{ts}: Binary parameter that Indicates supplier i is well or damaged in scenario s and period t
L_j^{ts}: Binary parameter that Indicates manufacturer j is well or damaged in scenario s and period t
L_k^{ts}: Binary parameter that Indicates distributor k is well or damaged in scenario s and period t
e_{ij}^{ts}: Binary parameter that Indicates the route between supplier i and manufacturer j is well or damaged in scenario s and period t
e_{jk}^{ts}: Binary parameter that Indicates the route between manufacturer j and distributer k is well or damaged in scenario s and period t
e_{jd}^{ts}: Binary parameter that Indicates the route between manufacturer j and customer d is well or damaged in scenario s and period t
e_{kd}^{ts}: Binary parameter that Indicates the route between distributor k and customer d is well or damaged in scenario s and period t
The binary parameters, which determine the reliability of entities and routes, are determined by the Bernoulli distribution with a success rate of p.

3.1.3. Decision variables

X_{ij}^{ts}: The flow of material between supplier i and manufacturer j in scenario s and period t
X_{jk}^{ts}: The flow of material between manufacturer j and distributor k in scenario s and period t
X_{jd}^{ts}: The flow of material between manufacturer j and customer d in scenario s and period t
X_{kd}^{ts}: The flow of material between distributor k and customer d in scenario s and period t
SH_d^{ts}: Shortage for customer d in scenario s and period t
U_k^{ts}: The amount of inventory for distributer k in scenario s at the beginning period t
Y_i^t: Binary variable of using or not using supplier i in period t
Y_j^t: Binary variable of using or not using manufacturer j in period t
Y_k^t: Binary variable of using or not using distributor k in period t
Z_{ij}^t: Binary variable of using or not using the route between supplier i and manufacturer j in period t
Z_{jk}^t: Binary variable of using or not using the route between manufacturer j and distributor k in period t
Z_{jd}^t: Binary variable of using or not using the route between manufacturer j and customer d in period t
Z_{kd}^t: Binary variable of using or not using the route between distributor k and customer d in period t
W_i^t: Binary variable for establishing or not establishing supplier i in period t
W_j^t: Binary variable for establishing or not establishing manufacturer j in period t
W_k^t: Binary variable for establishing or not establishing distributor k in period t
Q_{ij}^t: Binary variable for establishing or not establishing the route between supplier i and manufacturer j in period t.
Q_{jk}^t: Binary variable for establishing or not establishing the route between manufacturer j and distributor k in period t
Q_{jd}^t: Binary variable for establishing or not establishing the route between manufacturer j and customer d in period t
Q_{kd}^t: Binary variable for establishing or not establishing the route between distributor k and customer d in period t

Two-stage stochastic programming was used to solve the model. In this type of programming, the variables divide into two stages. In this mode, the first stage variables need to be assumed before the uncertain event occurs, and the variables of the second stage are determined after the occurrence of the uncertain event. While customer demand is not deterministic, the model should be divided into two stages. In the first stage, managers take strategic and long-term decisions such as establishing entities and routes (W and Q) and the possibility of using them (Y and Z), totally irrelevant to customer demand. Second, after the customer demand reveals (uncertain event), technical and operational decisions such as the number of materials sent from each tier to another (X), the tolerable amount of shortage (SH), or the amount of inventory at the beginning of the period with the customer (U) in terms of existing conditions and scenarios are made. The problem variables are specified separately into the first or second stage (Table 2).

Table 2: First and second stage variables

First stage variables	Definitions	Second stage variables	Definitions
W_i^t	Establishing supplier	X_{ij}^{ts}	Amount of flow between supplier and manufacturer
W_j^t	Establishing manufacturer	X_{jk}^{ts}	Amount of flow between manufacturer and distributor
W_k^t	Establishing distributor	X_{jd}^{ts}	Amount of flow between manufacturer and customer

First stage variables	Definitions	Second stage variables	Definitions
$\mathbf{Q_{ij}^{t}}$	Establishing a route between supplier and manufacturer	$\mathbf{X_{kd}^{ts}}$	Amount of flow between distributor and customer
$\mathbf{Q_{jk}^{t}}$	Establishing a route between manufacturer and distributor	$\mathbf{SH_{d}^{ts}}$	Shortage of customer
$\mathbf{Q_{jd}^{t}}$	Establishing a route between manufacturer and customer	$\mathbf{U_{k}^{ts}}$	Amount of distributor inventory at the beginning of the period
$\mathbf{Q_{kd}^{t}}$	Establishing a route between distributor and customer		
$\mathbf{Y_{i}^{t}}$	Using supplier		
$\mathbf{Y_{j}^{t}}$	Using manufacturer		
$\mathbf{Y_{k}^{t}}$	Using distributor		
$\mathbf{Z_{ij}^{t}}$	Using the route between supplier and manufacturer		
$\mathbf{Z_{jk}^{t}}$	Using the route between manufacturer and distributor		
$\mathbf{Z_{jd}^{t}}$	Using the route between manufacturer and customer		
$\mathbf{Z_{kd}^{t}}$	Using the route between distributor and customer		

3.2. Objective function

$$\begin{aligned}
\min \mathrm{cost} = &\left(\sum_{i\in I,t\in T} f_i^t w_i^t + \sum_{j\in J,t\in T} f_j^t w_j^t + \sum_{k\in I,t\in T} f_k^t w_k^t\right) + \left(\sum_{i\in I,j\in J,t\in T} g_{ij}^t Q_{ij}^t + \sum_{j\in J,k\in K,t\in T} g_{jk}^t Q_{jk}^t + \sum_{j\in J,d\in D,t\in T} g_{jd}^t Q_{jd}^t + \sum_{k\in K,d\in D,t\in T} g_{kd}^t Q_{kd}^t\right)\\
&+ \sum_{s\in S} p^s \left\{\left(\sum_{i\in I,j\in J,t\in T} c_i^t X_{ij}^{ts} + \sum_{j\in J,k\in K,t\in T} c_j^t X_{jk}^{ts} + \sum_{j\in J,d\in D,t\in T} c_j^t X_{jd}^{ts} + \sum_{k\in K,d\in D,t\in T} c_k^t X_{kd}^{ts}\right)\right.\\
&+ \left(\sum_{i\in I,j\in J,t\in T} b_{ij}^{ts} X_{ij}^{ts} + \sum_{j\in J,k\in K,t\in T} b_{jk}^{ts} X_{jk}^{ts} + \sum_{j\in J,d\in D,t\in T} b_{jd}^{ts} X_{jd}^{ts} + \sum_{k\in K,d\in D,t\in T} b_{kd}^{ts} X_{kd}^{ts}\right) + \sum_{k\in K,t\in T} h_k^t u_k^{ts}\\
&\left.+ \sum_{d\in D,t\in T} sh_d^t SH_d^{ts}\right\} \qquad (1)
\end{aligned}$$

In the first line of the objective function (1), the fixed costs of establishing entities (suppliers, manufacturers, and distributors), and in the second line, the establishment costs of the routes among these entities are calculated. Then, in the third and fourth lines, which show events after the scenario, fixed and variable costs of flowing materials in each period are investigated. Finally, the storage cost of the materials by distributors' warehouses and the cost of the customers' shortage with the customer are calculated in the last line.

$$\sum_{j\in J} X_{ij}^{ts} \le ca_i^t Y_i^t L_i^{ts} \qquad \forall i\in I, s\in S, t\in T \qquad (2)$$

$$\sum_{k\in K} X_{jk}^{ts} + \sum_{d\in D} X_{jd}^{ts} \le ca_j^t Y_j^t L_j^{ts} \qquad \forall j\in J, s\in S, t\in T \qquad (3)$$

$$\sum_{d\in D} X_{kd}^{ts} \le ca_k^t Y_k^t L_k^{ts} \qquad \forall k\in K, s\in S, t\in T \qquad (4)$$

Constraints (2) to (4) ensure that the flow of materials cannot exceed capacity if they are flowing through well entities.

$$\sum_{i\in I} X_{ij}^{ts} - \left(\sum_{k\in K} X_{jk}^{ts} + \sum_{d\in D} X_{jd}^{ts}\right) \ge 0 \qquad \forall j\in J, s\in S, t\in T \qquad (5)$$

Constraint (5) ensures that incoming flow to the manufacturer entity cannot exceed the outcoming flow.

$$\sum_{j\in J} X_{jk}^{ts} + U_k^{ts} - \sum_{d\in D} X_{kd}^{ts} = U_k^{t+1,s} \qquad \forall k\in K, s\in S, t\in T \ge 1, t \le |T|-1 \qquad (6)$$

Constraint (6) calculates the inventory at the beginning of each period (except period one) with the distributor.

$$U_k^{t,s} = 0 \qquad \forall k\in K, s\in S, t=1 \qquad (7)$$

Constraint (7) ensures that amount of inventory with the distributor in period one is zero.

$$X_{ij}^{ts} \le bnZ_{ij}^t E_{ij}^{ts} \qquad \forall i\in I, j\in J, s\in S, t\in T \qquad (8)$$

$$X_{jk}^{ts} \le bnZ_{jk}^t E_{jk}^{ts} \qquad \forall j\in J, k\in K, s\in S, t\in T \qquad (9)$$

$$X_{jd}^{ts} \le bnZ_{jd}^t E_{jd}^{ts} \qquad \forall j\in J, d\in D, s\in S, t\in T \qquad (10)$$

$$X_{kd}^{ts} \le bnZ_{kd}^t E_{kd}^{ts} \qquad \forall k\in K, d\in D, s\in S, t\in T \qquad (11)$$

Constraints (8) to (11) ensure the route is selected if a flow goes through that route.

$$\sum_{j\in J} X_{jd}^{ts} - \sum_{k\in K} X_{kd}^{ts} = dd_d^{ts} - SH_d^{ts} \qquad \forall d\in D, s\in S, t\in T \qquad (12)$$

Constraint (12) ensures the incoming flow to customers equals demand minus shortage.

$$\frac{SH_d^{ts}}{dd_d^{ts}} \leq 1 - ds \qquad \forall d \in D, s \in S, t \in T \tag{13}$$

Constraint (13) calculates the limit for the maximum amount of shortage.

$$Y_i^t = W_i^t \qquad \forall i \in I, t \in T = 1 \tag{14}$$
$$Y_j^t = W_j^t \qquad \forall j \in J, t \in T = 1 \tag{15}$$
$$Y_k^t = W_k^t \qquad \forall k \in K, t \in T = 1 \tag{16}$$

Constraints (14) to (16) ensure that a fixed cost must be paid for establishing if an entity selects in the first period.

$$Y_i^{t+1} - Y_i^t = W_i^{t+1} \qquad \forall i \in I, t \in T \geq 1, t \leq |T| - 1 \tag{17}$$
$$Y_j^{t+1} - Y_j^t = W_j^{t+1} \qquad \forall j \in J, t \in T \geq 1, t \leq |T| - 1 \tag{18}$$
$$Y_k^{t+1} - Y_k^t = W_k^{t+1} \qquad \forall k \in K, t \in T \geq 1, t \leq |T| - 1 \tag{19}$$

Constraints (17) to (19) ensure that if any entity establishes each period, that must be ready to use in the following periods.

$$Z_{ij}^t = Q_{ij}^t \qquad \forall i \in I, j \in J, t \in T = 1 \tag{20}$$
$$Z_{jk}^t = Q_{jk}^t \qquad \forall j \in J, k \in K, t \in T = 1 \tag{21}$$
$$Z_{jd}^t = Q_{jd}^t \qquad \forall j \in J, d \in D, t \in T = 1 \tag{22}$$
$$Z_{kd}^t = Q_{kd}^t \qquad \forall k \in K, d \in D, t \in T = 1 \tag{23}$$

Constraints (20) to (23) ensure that a fixed cost must be paid for establishment in the first period if a route is selected.

$$Z_{ij}^{t+1} - Z_{ij}^t = Q_{jk}^{t+1} \qquad \forall i \in I, j \in J, t \in T \geq 1, t \leq |T| - 1 \tag{24}$$
$$Z_{jk}^{t+1} - Z_{jk}^t = Q_{jk}^{t+1} \qquad \forall j \in J, k \in K, t \in T \geq 1, t \leq |T| - 1 \tag{25}$$
$$Z_{jd}^{t+1} - Z_{jd}^t = Q_{jd}^{t+1} \qquad \forall j \in J, d \in D, t \in T \geq 1, t \leq |T| - 1 \tag{26}$$
$$Z_{kd}^{t+1} - Z_{kd}^t = Q_{kd}^{t+1} \qquad \forall k \in K, d \in D, t \in T \geq 1, t \leq |T| - 1 \tag{27}$$

Constraints (24) to (27) ensure that they must be ready to use in the following periods if any routes establish in each period.

$$Y_i^{t+1} \geq Y_i^t \qquad \forall i \in I, \in T \geq 1, t \leq |T| - 1 \tag{28}$$
$$Y_j^{t+1} \geq Y_j^t \qquad \forall j \in J, \in T \geq 1, t \leq |T| - 1 \tag{29}$$
$$Y_k^{t+1} \geq Y_k^t \qquad \forall k \in K, \in T \geq 1, t \leq |T| - 1 \tag{30}$$
$$Z_{ij}^{t+1} \geq Z_{ij}^t \qquad \forall i \in I, j \in J, t \in T \geq 1, t \leq |T| - 1 \tag{31}$$
$$Z_{jk}^{t+1} \geq Z_{jk}^t \qquad \forall j \in J, k \in K, t \in T \geq 1, t \leq |T| - 1 \tag{32}$$
$$Z_{jd}^{t+1} \geq Z_{jd}^t \qquad \forall j \in J, d \in D, t \in T \geq 1, t \leq |T| - 1 \tag{33}$$
$$Z_{kd}^{t+1} \geq Z_{kd}^t \qquad \forall k \in K, d \in D, t \in T \geq 1, t \leq |T| - 1 \tag{34}$$

Constraints (28) to (34) ensure that if any locations or routes establish in period t, they can be used in the following periods.

$$\sum_{t \in T} W_i^t \leq 1 \qquad \forall i \in I \tag{35}$$
$$\sum_{t \in T} W_j^t \leq 1 \qquad \forall j \in J \tag{36}$$
$$\sum_{t \in T} W_k^t \leq 1 \qquad \forall k \in K \tag{37}$$
$$\sum_{t \in T} Q_{ij}^t \leq 1 \qquad \forall i \in I, j \in J \tag{38}$$
$$\sum_{t \in T} Q_{jk}^t \leq 1 \qquad \forall j \in J, k \in K \tag{39}$$
$$\sum_{t \in T} Q_{jd}^t \leq 1 \qquad \forall j \in J, d \in D \tag{40}$$
$$\sum_{t \in T} Q_{kd}^t \leq 1 \qquad \forall k \in K, d \in D \tag{41}$$

$$\sum_{t \in T} Q_{ij}^t \leq 1 \qquad \forall i \in I, j \in J \tag{38}$$
$$\sum_{t \in T} Q_{jk}^t \leq 1 \qquad \forall j \in J, k \in K \tag{39}$$
$$\sum_{t \in T} Q_{jd}^t \leq 1 \qquad \forall j \in J, d \in D \tag{40}$$
$$\sum_{t \in T} Q_{kd}^t \leq 1 \qquad \forall k \in K, d \in D \tag{41}$$

Moreover, Constraints (35) to (41) ensure the fixed cost paid for establishing locations and routes within period t.

4. Experimental analysis

This section tries to estimate the optimal answer to the problem by explaining it. In that regard, many solutions, including exact, heuristic, and metaheuristic methods, are applicable. Exact solving methods are considerably time-consuming but highly accurate. In contrast, heuristic and metaheuristic algorithms are more time-efficient, generating more errors. This section evaluated the model in terms of time and dimensions to determine the appropriate solution. The problem design had three dimensions. Each dimension was tested to determine how long it took to solve the problem. The tests were classified into small (S), medium (M), and large (L) in each level (Table 3).

Table 3: Test Problem

Instances		Suppliers	Manufacturers	Distributors	Customers	Periods	Scenarios
Small	S1	2	2	2	2	4	4
	S2	2	2	2	3	8	8
	S3	5	5	5	5	4	4
	S4	2	2	3	3	12	12
	S5	5	5	5	6	8	8
	S6	2	3	3	3	15	15
Medium	M1	10	10	10	10	4	4
	M2	3	3	3	3	20	20
	M3	5	5	6	6	12	12
	M4	3	3	3	3	25	25
	M5	10	10	10	10	8	8
	M6	5	6	6	6	15	15
Large	L1	6	6	6	6	20	20
	L2	10	10	10	10	12	12
	L3	6	6	6	6	25	25
	L4	10	10	10	10	15	15
	L5	10	10	10	10	20	20
	L6	20	20	20	20	20	20
	L7	20	20	20	20	25	25

These dimensions of the problem were implemented in GAMS CPLEX MIP SOLVER and under the specifications of a computer system with a 5 GHz CPU and 8GB of memory (for results, see Table 4).

Table 4: Computational results

Instances		Equations	Variables	Discrete Variables	CPU Time (s)
Small	S1	625	497	176	0.313
	S2	2,529	2,017	416	0.532
	S3	3,001	2,681	920	2.641
	S4	6,529	5,233	768	0.969
	S5	10,801	10,168	3,440	8.578
	S6	11,025	9,745	2,000	21.985
Medium	M1	12,481	10,006	1230	7.938
	M2	23,401	18,601	1,800	85.891
	M3	25,465	22,441	3,288	260.218
	M4	36,001	28,501	2,250	405.25
	M5	36,321	33,761	6,880	1181.968
	M6	43,576	38,401	4,650	1278.281
Large	L1	75,401	66,201	6,200	>5000
	L2	78,001	70,801	10,320	>5000
	L3	116,401	107,401	12,900	>5000
	L4	120,601	105,601	8,100	>5000
	L5	201,201	185,201	17,200	>10000
	L6	754,401	722,401	66,400	>10000
	L7	1,158,001	1,108,001	83,000	>10000

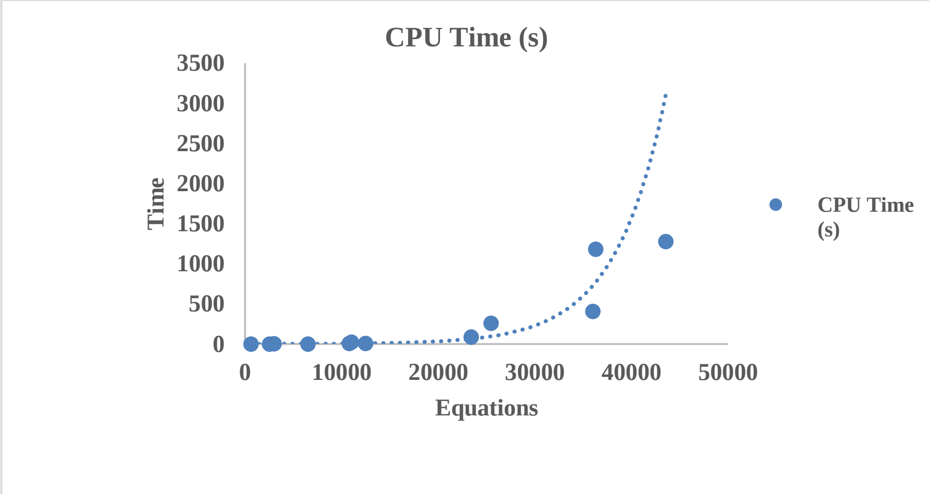
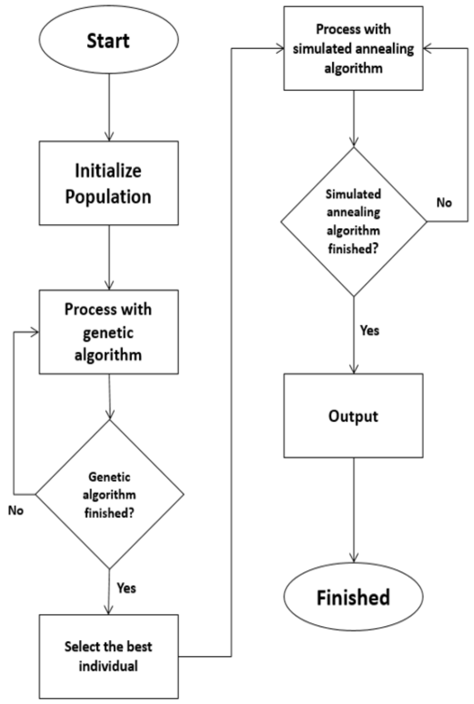


Figure. 2: CPU time

As shown in Fig. 2, increasing the solution time relative to the dimensions of the problem seems nonlinear, hence the necessity to use other methods. The proposed solution is the metaheuristic method that uses genetic and simulated annealing algorithms.

4.1. Solution approach

The genetic algorithm is inspired by Darwin's theory of evolution, in which the survival of more suitable organisms and their genesis are simulated. It is a population-based algorithm. Each answer corresponds to a chromosome, and each parameter represents a gene. It assesses each individual's fitness using fitness functions. The operators are applied to the current generation to improve the quality of genes in the next generation. Genetic algorithms are often known as performance optimizers. Implementing a genetic algorithm begins with a population of chromosomes (randomly) and gives reproductive opportunities at each stage to better species in line with the problem(Goldberg and Holland, 1988; Whitley, 1994). Simulated annealing is created by simulating the process of physical cooling in metals. The principle of the annealing process is to heat the solid-state metal to a high temperature so that the metal atoms are in a random state and then cool it very slowly. If the initial heating temperature is high enough and the cooling process slows, the atoms set themselves in a regular pattern. The patterns of the atoms define the state of the metal in the annealing process, and the particles arrive at an organized structure with minimal energy. The solid-state can only be achieved in a significantly slow cooling process. Otherwise, the particles are not organized, and the minimum energy is not obtained. This heating and cooling process (e.g., glass or metal) increases the strength and improves the material's properties (Siddique and Adeli, 2016; Van Laarhoven and Aarts, 1987).
Genetic algorithm specializes in exploring the global area and finding an optimal overall solution. In contrast, simulated annealing is a skill in the local area and can be used to exploit local search space around a global solution found by genetics. The combination of genetics and simulated annealing creates an efficient search strategy so that the best global ultimate solution found through genetics can be the primary solution for simulated annealing. In recent years, combining these two algorithms has performed better in finding optimal solutions (Bank et al., 2020; Fatyanosa et al., 2017; Li et al., 2013).




```
Initialize parameters;
    Initialize MaxIteration, Npop, Pc, Pm, Gamma, Beta, Alpha, Mu, Temp;
Iteration=0;
Initialize population;
Evaluate fitness of individuals;
Sort individuals;
Select best individual;
While iteration< MaxIteration;
    Calculate selection probabilities;
    For i from 1 to number of offspring's;
        Select parents by roulette wheel selection;
        Apply crossover operator;
        Evaluate fitness of offspring's;
    End for;
    For i from 1 to number of mutants;
        Select parents by uniform random;
        Apply mutation operator;
        Evaluate fitness of mutant's;
    End for;
    Select best individual;
    Evaluate fitness of individual;
        Create a neighbor;
        Evaluate fitness of neighbor;
        Compare fitness of individual and neighbor and keep better one;
    Decrease temperature;
    Iteration=iteration+1;
End while;
```

Figure. 3: Flowchart and pseudocode of the hybrid algorithm

Tuning the proposed problem for the metaheuristic method is better done in each problem dimension separately. Many researchers have also proposed a separate parameter setting to improve the quality of metaheuristic solutions. However, due to the lack of case studies in this article and relatively large parameters and stochastic variables, reviewing similar articles to set the parameter requires little expertise or trial and error. Generally, in our research, this issue has been solved (Table 5) (Diabat et al., 2017; Fathollahi-Fard et al., 2019; Khalifehzadeh et al., 2019; Sahebjamnia et al., 2018)

Table 5: Parameters setting

Instances		Parameters				
		Npop	**CP**	**MP**	**T**	**Alpha**
	S1	50	0.2	0.5		
	S2	60	0.2	0.5		
Small	S3	70	0.2	0.6	100	0.9
	S4	80	0.3	0.7		
	S5	90	0.4	0.7		
	S6	100	0.5	0.8		
	M1	150	0.5	1		
	M2	170	0.5	1		
Medium	M3	190	0.6	1	100	0.9
	M4	210	0.7	1.2		
	M5	230	0.8	1.2		
	M6	250	0.8	1.2		
	L1	300	1.2	1.2		
	L2	340	1.3	1.3		
	L3	380	1.4	1.4		
Large	L4	420	1.5	1.5	100	0.9
	L5	480	1.6	1.6		
	L6	500	1.7	1.7		
	L7	500	1.8	1.8		

Npop: Initial population, CP: Crossover percentage, MP: Mutation percentage, T: Initial temperature, Alpha: Cooling percentage

Table 6 displays the values and solution time differences in both exact and metaheuristics.

Table 6: Exact and Metaheuristic solutions

Instances	objective Exact function	Metaheuristic objective function	Gap	solving time Exact	solving Metaheuristic time
S1	7,772,072	7,965,432	2.49%	0.313	15.348
S2	23,840,186	25,447,340	6.74%	0.532	22.669
S3	18,110,106	18,108,200	0.01%	0.969	37.048
S4	29,911,775	29,829,744	0.27%	2.641	39.574
S5	40,646,979	40,326,511	0.79%	7.938	59.15
S6	44,897,079	46,230,555	2.97%	8.578	62.143
M1	35,872,215	37,187,322	3.67%	21.985	99.682
M2	50,005,794	53,058,002	6.10%	85.891	138.632
M3	56,374,625	58,681,231	4.09%	260.218	148.223
M4	65,246,949	68,002,524	4.22%	405.25	203.778
M5	79,321,998	81,369,415	2.58%	1181.968	358.558
M6	83,305,493	89,533,255	7.48%	1278.281	465.392
L1	103,509,360	114,041,239	10.17%	>5000	586.79
L2	96,801,972	101,998,780	5.37%	>5000	660.24
L3	151,889,360	166,437,777	9.58%	>5000	811.644
L4	142,526,000	159,601,250	11.98%	>5000	1067.735
L5	169,545,670	183,402,110	8.17%	>10000	2559.262
L6	211,104,402	232,007,651	9.90%	>10000	3882.23
L7	271,754,900	303,363,303	11.63%	>10000	5990.89

4.2. Sensitivity analysis

To have a sensitivity analysis for the model, we solve it in a small size, for example, by considering two suppliers, two manufacturers, two distributors, and one customer (as in Fig. 4) in different scenarios by Bernoulli distribution and the probability of 90% being well and 10% damaged (those with dashed lines are probable and those with straight lines are Deterministic with a 100% probability of being well as mentioned in Fig. 4). Since it is necessary to have a supplier in this network, we have reduced the probability of their failure to zero. Also, customer demand in three periods is considered decreasing, constant or increasing. As shown in Table 7, the scenario occurrence probability is obtained by multiplying the probabilities in each equivalent row, indicating network elements' construction and establishment.

Table 7: Scenarios Calculations

Establishment of entities scenarios				Construction of routes scenarios										Customer demand scenario		Scenario occurrence probability
$L^{t,s}_{j=2}$		$L^{t,s}_{k=2}$		$e^{t,s}_{k=1,j=2}$		$e^{t,s}_{k=2,j=1}$		$e^{t,s}_{k=2,j=2}$		$e^{t,s}_{k=1,d=1}$		$e^{t,s}_{k=2,d=1}$				
p	Value	p	Value	p	Value	p	Value	p	Value	p	Value	p	Value	p	Type	
0.9	1	0.9	1	0.9	1	0.9	1	0.9	1	0.9	1	0.9	1	0.333333	Constant	0.159432
0.9	1	0.1	0	0.9	1	0.1	0	0.9	1	0.9	1	0.9	1	0.333333	Increasing	0.001968
0.9	1	0.9	1	0.1	0	0.9	1	0.1	0	0.1	0	0.9	1	0.333333	Decreasing	0.000219
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.1	0	0.1	0	0.1	0	0.1	0	0.9	1	0.9	1	0.9	1	0.333333	Constant	0.000024
0.1	0	0.1	0	0.1	0	0.1	0	0.1	0	0.9	1	0.9	1	0.333333	Increasing	0.000003
0.1	0	0.1	0	0.1	0	0.1	0	0.1	0	0.1	0	0.1	0	0.333333	Decreasing	0.000000

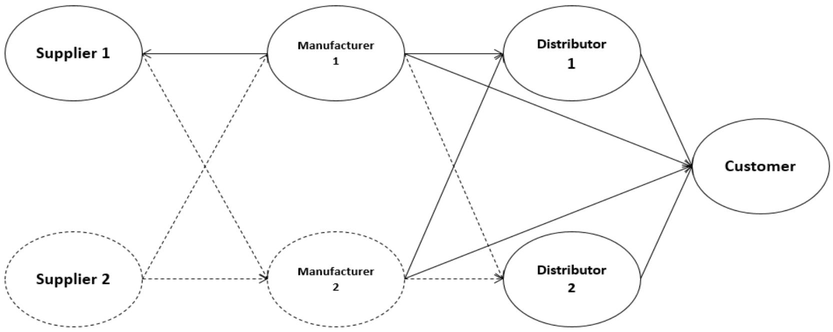


Figure. 4: Hypothetical network structure

An important parameter to be considered is the capacity of the locations shown by the Ca^{t} in the model. The observations are summarized in Table 8.

Table 8: Analysis of Capacity

$\Delta \mathbf{Ca}^{t}$	T	$W^{t}_{i=1}$	$W^{t}_{i=2}$	$W^{t}_{j=1}$	$W^{t}_{j=2}$	$W^{t}_{k=1}$	$W^{t}_{k=2}$	Objective function
+20%	1		1	1		1		5012644
0%	1		1	1		1		5379419
	2						1	
-20%	1	1	1	1	1	1		5524444
	2						1	

Table 8 shows that when the capacity decreases, most entities are established in the first period because they seek to function with maximum efficiency in delivering materials to the customer in the network. However, the network formation changes slightly, and the final cost of the network significantly increases over time, hence the importance of the location's capacity as it significantly impacts both the final objective function and the establishment and even sending of materials. Table 8 does not include the periods in which the establishment of the entities did not exist.

The following parameter checks the shortage penalty cost, displayed with the symbol sh^{t}_{d} in the model. The observations are summarized in Table 9.

Table 9: Analysis of Shortage

$\Delta \mathbf{sh}^{t}_{d}$	T	$W^{t}_{i=1}$	$W^{t}_{i=2}$	$W^{t}_{j=1}$	$W^{t}_{j=2}$	$W^{t}_{k=1}$	$W^{t}_{k=2}$	Objective function
+20%	1		1	1		1		5782112
	2						1	
0%	1		1	1		1		5379419
	2						1	
-20%	1		1	1				4989264
	2					1		
	3						1	

When the shortage penalty cost decreases, some parts of the network are changed to counterbalance the penalty cost as much as possible in the earliest periods (Table 9). Usually, it is more economical for the whole network to keep some items in the distributor warehouses than to send them away in these situations. Conversely, when the amount of inventory and shortage variable decreases, the whole network uses its maximum power to reduce transportation costs, but naturally, other criteria and parameters increase the total cost. The efficiency of the network will increase by establishing all entities and routes, thus indicating that the penalty cost is effective in the model and the final costs and the network formation depend on this parameter. It should be noted that the periods in which the establishment of the entities did not exist are not listed in Table 9.

The last parameter analyzed in this section is reliability. Table 10 summarizes the observations of the objective function.

Table 10: Analysis of Reliability

$L^{t,s}, e^{t,s}$	Objective function
%80	5472718
%90	5379419
%95	5227817

Table 10 shows that increasing the reliability of entities and routes reduces the costs of the supply chain network. Due to the small size of the study network, there has been no change in structure and the number of materials flowing. It can be seen that by increasing reliability, the final cost from suppliers to the customer has decreased. It can be inferred from this issue that the reliability criterion in this model acts as a complement to reduce costs. Furthermore, in this paper, it is estimated that more confidence in the system results in less financial loss. Therefore, the best advice to network managers is to find reliable entities and routes to set up the network in the first step.
The parameter setting can be tested in three modes, including optimistic, realistic, and pessimistic (Table 11), for in-depth analysis and validation of the study model results, to increase robustness, and expand the decisionmaker's view on any good or bad event. When the parameters are at their most optimistic level, the least number of locations and routes in the network will be established: Adding 20% of the shortage cost, 20% more capacity to the problem elements, and considering the full reliability for them, the costumer's lack of demand and the objective function will decrease. However, as long as the studied parameters are pessimistic; That is, about 20% of the capacity and the shortage cost is reduced, and the reliability is estimated to be 80%. Naturally, the trend of the objective function will be increasing in the pessimistic state.

Table 11: The best and the worst case

Case	T	$W_{i=1}^{t}$	$W_{i=2}^{t}$	$W_{j=1}^{t}$	$W_{j=2}^{t}$	$W_{k=1}^{t}$	$W_{k=2}^{t}$	Objective function
Optimistic	1		1		1			**4594973**
	2							
	3					1		
Realistic	1		1	1		1		**5379419**
	2						1	
Pessimistic	1	1	1	1	1	1		**564232**
	2						1	
	3							

In this section, we examined some parameters that seemed to be essential and observed their impact on the model's objective function and network structure. However, in completing this section, one of the most critical parameters that need to be analyzed from another perspective is the consequences of a manager not considering reliability for network design. Suppose all entities and routes are safe (ideal state of reliability), the value of the objective function reaches its minimum, and some elements establish and operate according to customers' demands. Nevertheless, some elements may get damaged in specific periods and cannot be used in the supply chain network. For example, the supplier suffers from a shortage of raw materials, the producer's machine suffers from failure, the material delivery route to the customer is temporarily blocked, and similar elements. In case a manager does not predict such events and implements all inputs and processes without considering system reliability, events occur: Compensating for these events imposes more cost on the whole system. In this way, after solving the model in a small format and considering the 100% reliability, the value of the objective function reached 5,141,325 units. However, the objective function of the same system with the same number and considering the reliability of 90% of the costs reaches 5,554,455 units with a value of 80% reliability; it incurs costs amounting to 5,859,897 units.
As you can see, the objective function of the model increases, which is due to the establishment of elements that are not necessary, and only fixed costs are paid for them, as well as some entities or routes that were assumed to be well. However, they were accidentally damaged, which could lead to customer shortage. This difference seems to be a small number in the analyzed network, but in reality, and considering an extensive supply chain system, it causes a significant loss.

4.2. Managerial insights

Despite the dependent variables and parameters and the objective function to minimize costs, a supply chain network problem has unique complexities. Some parameters do not have much effect on network structure; some cause considerable change. The parameters used in this model, including fixed and variable costs, holding costs, and shortage costs, directly impact the number of materials sent to the customer. Naturally, more establishment and use of entities increase the final cost.
The existence of a reliability criterion that is effective in the objective function of the problem (total cost) and the sensitivity analysis found that the wellness percentage of the elements increases, and the total cost decreases. Correct predictions in designing a network are the primary input of managers' planning and decision-making in the supply chain. Predicting future demand resource needs and correctly identifying reliable elements play essential roles in helping network performance. It can also be argued that the quality of managers' decisions and their results contribute to greater trust in the network and more excellent compatibility and cooperation of its entities, finally reducing risk. Admittedly considering the reliability of the supply chain network brings the model closer to reality, and the wellness or failure of its elements under different scenarios increases the enthusiasm to face unpredictable events in managers.
Notably, the capacity of the locations and the percentage of customer satisfaction are the most critical parameters impacting network configuration. If production and storage capacities of materials are insufficient, but the need

for the requested materials from customers is high, the network managers should seek other parallel entities to respond to customer demand. Thus, it is recommended that system managers first design a network with elements that can respond to customer demand.

5. Results and future study

The results indicated that while some researchers examined cost in managing a supply chain network, others studied reliability. For some, the type of product and the way of sending materials were essential, and for others, the problem-solving attitude was critical. However, in this article, a four-tier supply chain network was considered that included suppliers, manufacturers, distributors, and customers. The network considered several vital factors, such as cost and reliability, type of customer demand in several periods, and capacity of locations. The proposed model expressed the importance of network management and design. It aimed to reduce total costs and limitations in different situations. The approach to solving the problem was two-stage stochastic programming considering scenarios for customer demand. It was found that designing a model with the exact solution was considerably time-consuming and inefficient. The proposed hybrid metaheuristic solution solved the model in different dimensions. Also, various parameters were analyzed in another part, and their sensitivity to the objective function and network structure were investigated. In this article, an attempt was made to determine the effects on the flowing of materials and network costs by considering reliability through Bernoulli distribution with a certain percentage of success. Furthermore, it was indicated how different parameters, such as the capacity of locations, cost of shortage, and customer demand satisfaction, affect the network structure and decrease or increase the value of the objective function. In different periods, the type of demand (increasing, decreasing, or constant) was examined, and its effect on the probability of scenarios was determined to identify the answer to the variables. It can be said that accurate prediction of a supply chain network can reduce costs. Managers should accurately predict stochastic events, such as customer demand, and properly understand the trend of some vital parameters. Also, they must be aware of the latest status of each entity in the network and put them together so that their capacities meet the needs of customers. Finally, it is possible to upgrade this model with a multi-stage stochastic programming approach, price-related demand, or add other levels to the network for future study. Moreover, the proposed model can contain production and transportation planning issues.

Declaration of interest statement

I hereby and on behalf of my co-authors announce that there is no conflict of interests related to this submission.

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