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Developing location-routing-inventory model under uncertainty: A queuing-based approach

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Abstract

This study develops a mathematical model for the designing of a supply chain network. The uncertain nature of demand and lead time is incorporated into the concerned model. This motivates us to deploy the queuing concept to deal with uncertainties and analysing the number of orders, number of shortages and average of on-hand inventory. Then, in accordance with the outputs of the queuing analysis, a mixed integer nonlinear programming model is devised to design the distribution network of a supply chain. The decisions to be made are facility locations, demand allocations along with inventory management decisions. The objective function of the model aims at minimising the total supply chain costs encompassing location, transportation and inventory costs. Notably, we assume that each facility manages its inventory policy based on a $\left(S-1,S\right)$ policy and stock outs result in lost sales. Inasmuch as the developed problem is difficult to solve by means of exact methods, tailored hybrid solution algorithms based on simulated annealing and genetic algorithm are employed to overcome the computational complexity of the developed model. Finally, using the real information of the Telecommunication infrastructure company, we evaluate the proposed model and the management insights are reported.

Keywords: Supply chain network design, lost sale, inventory, queuing theory, simulated annealing, genetic algorithm.

1- Introduction and literature review

Over the past decades, wide spectrums of distribution and manufacturing companies consider the concept of supply chain (SC) management, as their main strategic discipline to benefit from competitive advantages (Ben-Daya, Hassini, and Bahroun 2019; Ross, Weston, and Stephen 2010). Broadly speaking, SCs deal with three decision-making levels:

1) Strategic level: this level comprises long-term decisions such as plant sizing, allocation decisions and products selections.
2) Tactical level: in this level, mid-term decisions such as distribution, transportation and production planning are made.
3) Operational level: this level is dedicated to short-term decisions such as delivery and production.

In the context of SCM, companies should design, manage and control the levels of SC in an integrated manner to reach better positions in today's business environment (Cárdenas-Barrón and Sana 2014, 2015; González-R, Framinan, and Ruiz-Usano 2013).

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Traditionally, inventory decisions, as tactical decisions, have been made after finalising location decisions that are known as strategic decisions (Shahabi et al. 2014). This approach may eventuate in sub-optimality and undermine the quality of the decisions since the location decisions drastically influence inventory costs (Sadjadi et al. 2016). Accordingly, most of the studies have tended to integrate inventory decisions into location models, contributing to joint location-inventory problem. To date, a considerable deal of research has been conducted in the location-inventory problem to make it more flexible and realistic. However, the existing literature suffers from some notable drawbacks. For example, most previous location-inventory models have overlooked the stochastic nature of the problem's parameters such as lead-time or demand. Likewise, they have predominantly addressed a continuous review inventory policy with backlogged shortage (Berman and Kim 1999; Gebennini, Gamberini, and Manzini 2009; Mak and Shen 2009; Sadjadi et al. 2016). In other words, scanty modelling efforts have ever attempted to take into account lost sale shortage. The lost sale conditions deal with in numerous retail institutions, wherein the violent competitions permit customers to select a new brand or use a different store. Another application can be seen in the essential spare parts, where one places emergency orders when a stock-out happens (Park, Lee, and Sung 2010).

In view of the preceding discussions, this study unveils a joint location-inventory problem to design the distribution network of a SC in an incorporated manner. The objective function aims at minimising the total SC costs comprising location, transportation and inventory costs. We suppose that the unsatisfied demands are lost and each open distribution centre (DC) manages its inventory policy based on an $(S-1,S)$ policy. A queuing approach is first adopted to derive the features of the inventory policy, viz. the number of orders, number of shortages and average of on-hand inventory. Thereafter, based on the outputs of the queuing analysis, the location-inventory model is devised to determine following decisions: (1) the number of DCs to be located; (2) the location of DCs; (3) the retailers' assignment to open DCs; as well as (4) the optimal inventory policies for established DCs. As such, in a bid to solve the model in an efficient way, tailored hybrid solution algorithms based on simulated annealing (SA) and genetic algorithm (GA) are deployed. Focus on this study can be categorised in two major classes: First, location-inventory problems and second, inventory control models with queuing theory approach. In the following, the relevant literature for each above-mentioned class is briefly reviewed and then the literature gaps addressing by this paper are offered.

1-1- Location- inventory problem

As previously noted, one of the substantial integration issues in SC is the location-inventory problem that incorporates decisions about stocks into facility location and determines location, allocation and inventory decisions concurrently. One of the earliest studies on this area was taken by Baumol and Wolfe (1958), who introduced the idea of integrating inventory costs into location models. They provided a method for locating warehouses, which comprised a sequence of transportation computations. A location-inventory problem was formulated as an mixed integer nonlinear programming model by Daskin, Coullard, and Shen (2002), where safety stock and working inventory costs at DCs were taken into account. In their research, the Poisson flow of demands was approximated by normal distributions and some heuristics were used for finding good feasible solutions. Shu, Teo, and Shen (2005) introduced a network design problem, in which lead-time was deterministic. Thereinafter, this problem was formulated as a set covering model by Shen, Coullard, and Daskin (2003). Snyder, Daskin, and Teo (2007) introduced an uncertain location-inventory problem with risk pooling. They used normal distribution as an approximation for the Poisson distribution of demands. Ozsen, Coullard, and Daskin (2008) devised capacitated versions of joint location-inventory problem. A two-level inventory system for designing a service network was analysed by Mak and Shen (2009). They assumed that when a plant or service centre is unavailable, the demand is backlogged. A stochastic SC was developed by Javid and Azad (2010) that optimised location, allocation, inventory and routing decisions simultaneously. They also introduced a hybrid algorithm based on two meta-heurist algorithms, viz. Tabu search and SA, to solve the problem. Liao, Hsieh, and Lai (2011) devised an integrated location-inventory problem and extended an evolutionary algorithm to solve the presented problem in an efficient way. Berman, Krass, and Tajbakhsh (2012) studied a stochastic location-inventory problem and considered periodic-review inventory policies for DCs. In addition, they assumed that shortages are backordered and lead-time is deterministic. Tsao (2013) developed a location-inventory problem under trade credits and used a continuous approximation approach for modelling the problem. Cárdenas-Barrón and Sana (2014) investigated a production-inventory model for a two-echelon SC, in which the procurement cost per unit was taken into account as a function of the production rate. A closed loop SC network problem was studied by Vahdani et al. (2018), where an imperialist competitive algorithm was presented to solve the problem. Recently, Manatkar et al. (2016) proposed a multi-echelon and multiple products location-inventory problem. Also, based on particle swarm optimisation and GA, they extended a novel hybrid meta-hubristic algorithm for solving the problem. Memari et al. (2017) devised a bi-objective optimization model for a three-echelon SC and employed a NSGA-II algorithm to find a set of near-optimal Pareto solutions. Vahdani et al. (2018) proposed a multi-objective location-routing model and applied two meta-heuristic algorithms to solve their model in an efficient way. Sadjadi et al. (2016) investigated a location-inventory problem in a stochastic SC. They assumed that each open DC manages its inventory using a $(S-1, S)$ policy when the unsatisfied demands are backordered. Bashiri & Hasanzadeh (2016) considered a multi-echelon location-distribution problem, where a lexicographic approach was applied to specify the most preferred distribution path. Puga and Tancrez (2017) developed a location–inventory problem for the design of large SC networks and proposed a continuous non-linear model for it. Last but not the least, Rayat, Musavi, and Bozorgi-Amiri (2017) considered a reliable model for a location–inventory problem and presented Archived Multi-Objective Simulated Annealing (AMOSA) meta-heuristic algorithm to solve it. Figure 1 displays a year-based assortment of the published papers in field of joint location-inventory problem. The evolution obviously illustrates the growing popularity of this study area, particularly after 2005.

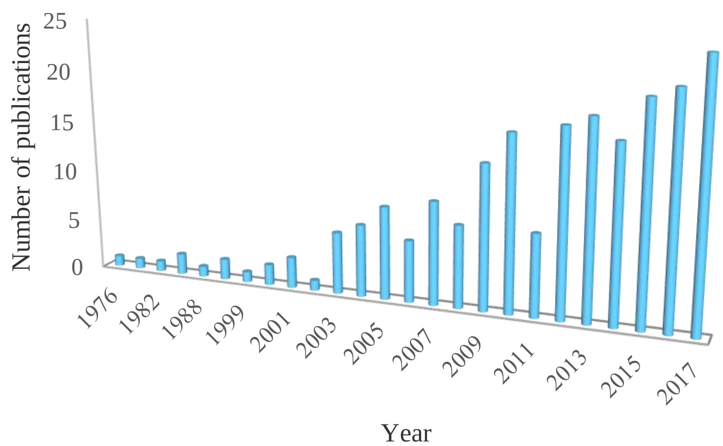


Fig 1. The evolution of the published location-inventory models (1976–2017).

1-2- Inventory control models with queuing theory approach

Conventionally, the goal of researches concerning with integrated queuing-inventory models is to earn the optimal control policy of the inventory or minimum to find the structural features of optimal strategies. Because, queuing theory method is the reaction of inventory management to queuing of demands. In addition, queuing theory method in many systems such as inventory systems, satisfying demands requires on-hand inventory and a service that takes some times has better performance than other methods (Saffari, Asmussen, and Haji 2013). The common and powerful tool for this target is to introduce a Markovian process and afterwards to exploit standard optimisation procedures (Schwarz and Daduna 2006). Several papers can be found in the literature, which address this issue. In this sense, Berman and Kim (1999) examined a queuing-inventory system under both the expected discounted and the average costs and proposed a simple heuristic policy for solving the problem. Implementing a Markov decision process, Kim (2005) modelled an inventory control problem and determined the optimal replenishment policy for it. Jain (2006) studied the scheduling problem in a make to stock (MTS) queue and compared three scheduling arrangements considering inventory cost performance. Later on, Teimoury et al. (2010) proposed a production-inventory problem with lost sales. In their problem, two types of customers were considered and a queuing approach was exploited to formulate the inventory policy. In addition, the lead-time was assumed to be imbued with uncertainty, where it had an exponential distribution. A multi-echelon inventory queuing problem was examined by Simić, Svirčević, and Simić (2015), where a manufacturer and several DCs were accounted for satisfying the demands from the sources. They considered that the lead-times and demands respectively follow exponential and Poisson distributions. Otten, Krenzler, and Daduna (2016) presented a two-echelon production-inventory system and obtained stationary distributions of inventory processes and joint queue length. Applying an M/M/1/k queuing system, Maleki et al. (2017) formulated a bi-objective remanufacturing problem.

Table 1 classifies the models of the location-inventory problem in accordance with nine criteria. The first criterion is to search about those models that exploit queuing theory. Based on the second criterion, papers are categorised into two classes: nonlinear programming (NLP) and MINLP. The third criterion, viz. the number of objective functions, divides the papers into two classes consist of single objective (SO) and multi objectives (MO). With respect to forth criterion, demand distribution, papers are classified into three groups comprising deterministic (DE), normal distribution (NO) and Poisson distribution (PO). The fifth criterion, viz. lead-time distribution, categorises the paper into three classes including deterministic, normal distribution and exponential distribution (EX). The inventory policy of facilities classifies the papers into three groups: $(R,Q),(R,T)$ and $(S-1,S)$ inventory policies. The next criterion looks for the optimal inventory policies among the mentioned papers. The next criterion considers the kinds of shortages. Based on to criterion, papers are categorised into two classes, backlogged (BA) and lost sale (LO) shortages. Eventually, according to the solution procedure, papers are categorised into three classes: Lagrangian relaxation (LA), commercial software (CO) and meta-heuristic algorithm (ME).

Regarding the literature review and table 1, this study contributes to the literature of joint location-inventory problem through the following avenues. This work is able to properly incorporate uncertain nature of parameters in the problem. Also, this is relatively one of the early attempts in the location-inventory problems that utilize the queuing concept to withstand the uncertainties as well as analysing the features of the inventory policy. It is worthy to note that as inventory models are accounted as a class of queue, they yield more practical and general models against traditional inventory models (Sadjadi et al. 2016; Saffari, Asmussen, and Haji 2013). Considering lost sales for the unsatisfied demands is the other issue that distinguishes this study from the ones existed in the literature. The proposed problem belongs to the class of NP-hard problems, owing to it is a development of the capacitated facility location problem (CFLP), as one of the most famous NP-hard problems. In addition, uncertainty of parameters adds into the complexity of model. (Diabat, Dehghani, and Jabbarzadeh 2017; Mirchandani and Francis 1990; Ramirez-Nafarrate, Araz, and Fowler 2021). Accordingly, as other innovation, we develop GA and SA embedded with direct search method (DSM) to eases the computational burden from the concerned NP-hard problem. Moreover, using the $(S-1,S)$ policy in this study for inventory control and determining the optimal inventory policy are as sub-contributions of this study. The aforementioned contributions and sub-contributions, in turn, motivate us to formulate a mathematical model for stochastic joint location-inventory problem using queuing theory with regard to $(S-1,S)$ inventory control policy and lost sales.

The remainder of the study is organised as follows. The definition and formulation of the proposed problem are given in section 2. The solving approaches are elaborated in section 3. In Section 4, the computational results and sensitivity analysis are provided. Finally, summary of the results along with conclusion remarks are offered in section 5.

Table 1. Properties of location-inventory models.

Reference	Queuing	Type of modelling	Objective function	Demand distribution	Lead-time distribution	Inventory Policy	Optimal Inventory Policy	Type of shortage	Solution procedure
(Daskin, Coullard, and Shen 2002)		MINLP	SO	NO	DE	*(R, Q)*		BA	LA
(Shu, Teo, and Shen 2005)		MINLP	SO	NO	DE	*(R, Q)*		BA	LA
(Snyder, Daskin, and Teo 2007)		MINLP	SO	NO	DE	*(R, Q)*		BA	LA
(Ozsen, Coullard, and Daskin 2008)		MINLP	SO	NO	DE	*(R, Q)*		BA	LA
(Javid and Azad 2010)		MINLP	SO	NO	DE	*(R, Q)*		BA	ME
(Liao, Hsieh, and Lai 2011)		MINLP	MO	NO	DE	*(R, Q)*		BA	ME
(Berman, Krass, and Tajbakhsh 2012)		MINLP	SO	NO	DE	*(R, T)*		BA	LA
(Tsao 2013)		NLP	SO	PO	-	-		BA	-
(Nekooghadirli et al. 2014)		MINLP	MO	NO	DE	*(R, Q)*		BA	ME
(Manatkar et al. 2016)		MINLP	MO	NO	DE	*(R, Q)*		BA	ME
(Sadjadi et al. 2016)	√	MINLP	SO	PO	EX	*(S-1, S)*		BA	CO
This study	√	MINLP	SO	PO	EX	*(S-1, S)*	√	LO	ME

MINLP: Mixed Integer Non-Linear Programming, NLP: Non-Linear Programming
SO: Single Objective MO: Multi Objectives DE: Deterministic NO: Normal Distribution
PO: Poisson Distribution EX: Exponential Distribution BA: Backlogged LO: lost sale
LA: Lagrangian Relaxation CO: Commercial Software ME: Meta-Heuristic Algorithm

2- Model development

2-1- Problem statement

Consider a multi-echelon SC network, which contains multiple retailers, multiple potential DCs, and a supplier. In general, the main objective of our problem is choosing a subset of DCs, allocating retailers to them and determining optimal inventory policy in each open DC. A graphical representation of the concerned SC is visualized in figure 2.

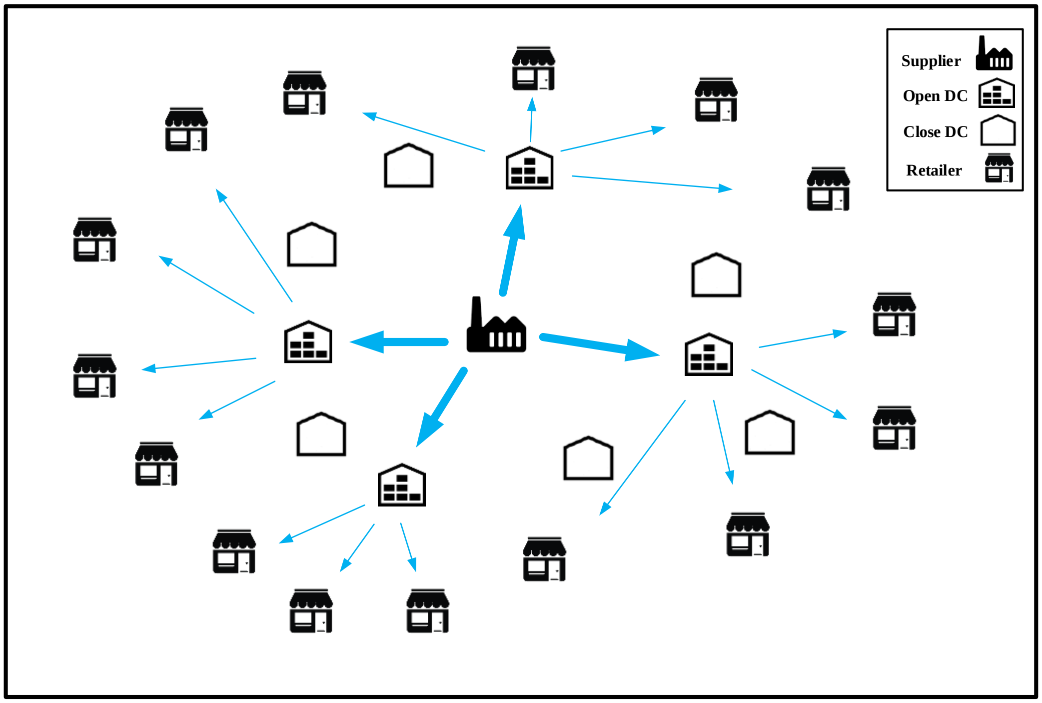


Fig 2. Graphical illustration of the concern SC

The open DCs work as the direct intermediary facilities between the retailers and supplier. Speaking intuitively, products are ordered from the opened DCs to the supplier and eventually delivered to the retailers. The objective function aims to minimize the total costs of locating DCs, transportation of products from open DCs to retailers and inventory. Single-item products are ordered from open DCs to the supplier and eventually rendered to the retailers. Each retailer is allocated to an open DC and it is supposed that each open DC manages its inventory policy based on a $(S-1, S)$ policy. In this inventory policy, an order is released when a demand or failure happens (Schmidt and Nahmias 1985). More precisely, an order will be placed when the position of inventory S (base stock level) falls down to S-1. When there is no on-hand inventory in each open DC and a demand comes from its allocated retailer(s), then it would be lost. Furthermore, the maximum inventory levels of open DCs (base stock levels) cannot exceed from the storage spaces. Each retailer has an uncertain demand with Poisson distribution, and the demands are presumed to be independent of each other. Accordingly, demands of each open DC have a Poisson distribution with rate λ, achieved through summation of its allocated retailers' demand rates. We also presume that the lead-time of supplier is hemmed in by uncertainty and is exponentially distributed with parameter μ (Following e.g., Simić, Svirčević, and Simić (2015) ; Teimoury et al. (2010) and; Given the fact that memory less property of the exponential distribution as well as constant rate of lead-time, this assumption may be acceptable).

2-2- Problem formulation

In this section, we first implement a queuing concept to withstand the uncertainties and drive the features of the inventory policy, viz. the number of orders, number of shortages and average of on-hand inventory. Afterward, based on the outputs of the queuing analysis, a mathematical modelling is deployed to design the distribution network of the SC. The framework of the formulation procedure is depicted in figure 3.

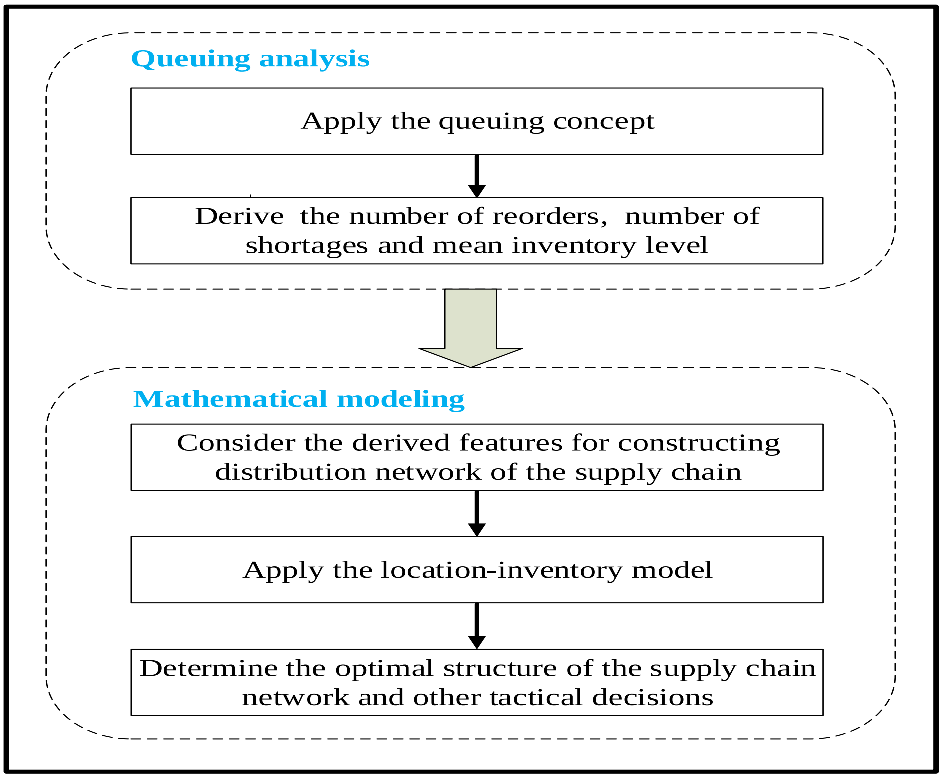


Fig 3. Framework of formulation procedure.

2-2-1- Notations

Before formulating the concerned problem, the used indexes, parameters along with decision variables are proposed in this sub-section.

Sets:

j	Index of potential DCs,
i	Index of retailers,
t	Index of time periods,
k,m	Index of Markov system states,

Parameters:

PU_j	Unit purchase cost of DC j from supplier,
SH_j	Unit shortage cost for DC j,
FI_j	Fixed (per unit time) cost for locating DC j,
TR_{ji}	Unit transportation cost from DC j to the retailer i,
OC_j	Unit ordering cost for DC j,
HC_j	Unit holding cost for DC j,
SC_j	Storage space for DC j,
$\lambda_i^{'}$	Demand rate (Poisson) at the retailer i,
μ	Parameter of exponential PDF for supplier lead-time

$LE_j(t)$	Level of inventory at DC *j* in period t,
ST_j	State space of Markov process for DC *j*,
$Q_j(m,k,t)$	Probability of being in state *m*, *t* time units from now, given the state is now *k*,
$Q_j(k)$	Steady-state probability of state *k* at DC *j*,
θ	Weight factor related to inventory costs,

Decision variables:

y_j	1 if DC *j* is opened, 0 otherwise,
x_{ji}	1 if the retailer *i* is assigned to DC *j*, 0 otherwise,
S_j	Base stock level at DC *j*,
λ_j	Demand rate (Poisson) at DC *j*,
MI_j	The amount of mean inventory at DC *j*,
RP_j	The amount of reorders at DC *j*,
LO_j	The amount of shortages at DC *j*.

2-2-2- Queuing analysis

The queuing approach is intrinsically a powerful tool for describing the behaviours of the production or inventory systems. As elucidated by Sadjadi et al. (2016) and Saffari, Asmussen, and Haji (2013), when inventory models are considered as a class of queue, they yield more general and practical models in comparison with traditional inventory ones. For the goal of deriving the features of the inventory policy, we define $\{LE_j(t); t \ge 0\}$ as a continuous time Markov process, whose state space is $ST_j = \{0, 1, \ldots, S_j - 1, S_j\}$. Let,

$$Q_j(m,k,t) = pr\left[LE_j(t) = k | LE_j(0) = m\right] \qquad m,k \in ST_j \tag{1}$$

$$Q_j(k) = \lim_{t \to \infty} Q_j(m,k,t) \tag{2}$$

The equilibrium equations of the defined Markov process are reached by equations (3)-(5).

$$\mu Q_j(0) = \lambda_j Q_j(1) \tag{3}$$

$$(\lambda_j + \mu) Q_j(k) = \lambda_j Q_j(k+1) + \mu Q_j(k-1) \qquad 1 \le k \le S_j - 1 \tag{4}$$

$$\lambda_j Q_j(S_j) = \mu Q_j(S_j - 1) \tag{5}$$

Since $\sum_k Q_j(k) = 1,$ we have:

$$Q_j(0) = \frac{\lambda_j^{S_j+1} - \lambda_j^{S_j} \mu}{\lambda_j^{S_j+1} - \mu^{S_j+1}} \tag{6}$$

$$Q_j(k) = Q_j(0) \left(\frac{\mu}{\lambda_j} \right)^k \quad 1 \le k \le S_j \tag{7}$$

In the following, the features of the inventory policy, viz. the number of orders, number of shortages and average of on-hand inventory will be determined. Since the inventory policy is $\left(S-1,S\right)$ in each open DC and unsatisfied demands are lost, so the expected amount of reorders can be achieved as follows:

$$RP_j = \lambda_j\left(1-Q_j\left(0\right)\right) = \lambda_j\,\frac{\mu(\lambda_j^{S_j}-\mu^{S_j})}{\lambda_j^{S_j+1}-\mu^{S_j+1}} \tag{8}$$

Meanwhile, due to the fact that there is no on-hand inventory in open DCs, the arriving demands are lost. Consequently, the expected amount of shortages at each open DC is acquired by equation (9).

$$LO_j = \lambda_j Q_j\left(0\right) = \lambda_j\,\frac{\lambda_j^{S_j+1}-\lambda_j^{S_j}\mu}{\lambda_j^{S_j+1}-\mu^{S_j+1}} \tag{9}$$

The mean inventory level is outlined in accordance with the expected value of inventory level, as exhibited in equation (10).

$$MI_j = \sum_k kQ_j\left(k\right) \tag{10}$$

Where, its closed form will be:

$$MI_j = \frac{\mu\left(\lambda_j^{S_j+1}-\lambda_j^{S_j}\mu\right)\left(\lambda_j^{S_j+1}-\lambda_j\mu^{S_j}-\lambda_j\mu^{S_j}S_j+\mu^{S_j+1}S_j\right)}{\lambda_j^{S_j}\left(\lambda_j-\mu\right)^2\left(\lambda_j^{S_j+1}-\mu^{S_j+1}\right)} \tag{11}$$

2-2-3- Mathematical modelling

We now aim to formulate the joint location-inventory problem to determine following decisions: (1) the number of DCs to be located; (2) the location of DCs; (3) the retailers' assignment to open DCs; as well as (4) the optimal inventory policies for established DCs.

The model of location-inventory problem can be formulated as follows:

$$\begin{aligned}\text{Min } TC = {} & \sum_j FI_j y_j + \sum_j\sum_i TR_{ji} x_{ji} \lambda_i^{'}\,\frac{\mu(\lambda_j^{S_j}-\mu^{S_j})}{\lambda_j^{S_j+1}-\mu^{S_j+1}} \\ & +\theta\left[\begin{array}{l} \sum_j HC_j y_j\left[\dfrac{\mu\left(\lambda_j^{S_j+1}-\lambda_j^{S_j}\mu\right)\left(\lambda_j^{S_j+1}-\lambda_j\mu^{S_j}-\lambda_j\mu^{S_j}S_j+\mu^{S_j+1}S_j\right)}{\lambda_j^{S_j}\left(\lambda_j-\mu\right)^2\left(\lambda_j^{S_j+1}-\mu^{S_j+1}\right)}\right] \\ +SH_j y_j\left[\lambda_j\,\dfrac{\lambda_j^{S_j+1}-\lambda_j^{S_j}\mu}{\lambda_j^{S_j+1}-\mu^{S_j+1}}\right] + y_j(OC_j+PU_j)\lambda_j\,\dfrac{\mu(\lambda_j^{S_j}-\mu^{S_j})}{\lambda_j^{S_j+1}-\mu^{S_j+1}} \end{array}\right]\end{aligned} \tag{12}$$

$$\sum_j x_{ji} = 1 \qquad \forall i\in I \tag{13}$$

$$x_{ji} \le y_j \qquad \forall i\in I, \forall j\in J \tag{14}$$

$$\sum_i \lambda_i^{'} x_{ji} = \lambda_j \qquad \forall j\in J \tag{15}$$

$$S_j \le SC_j y_j \qquad \forall j\in J \tag{16}$$

$$x_{ji} \in \left\{0,1\right\} \qquad \forall i\in I, \forall j\in J \tag{17}$$

$$y_j \in \{0,1\} \qquad \forall j \in J$$
$$S_j \geq 0 \;\; and\, integer \qquad \forall j \in J \tag{18}$$

The objective function (12) is intended to minimise the following costs:

1- The first term computes the annual fixed costs of locating DCs, which is given by equation (19).

$$\sum_j FI_j y_j \tag{19}$$

2- The second term, shown by equation (20), calculates the annual transportation costs. Noteworthy, given the shortages are lost, the transportation costs are solely computed for satisfied demands.

$$\sum_{\mathrm{j}} \sum_{\mathrm{i}} TR_{ji} x_{ji} \lambda_i^{'} \left(1 - Q_j\left(0\right)\right) \tag{20}$$

3- Third term represents the annual inventory costs encompassing holding, shortage, ordering along with purchase costs, given by equation (21).

$$\sum_{\mathrm{j}} (HC_j MI_j + SH_j LO_j + OC_j RP_j + PU_j RP_j) y_j \tag{21}$$

Constraints (13) warrant that each retailer is allocated to precisely one DC. Constraints (14) ensure that if a DC is not open, no retailer can be assigned to it. Constraints (15) state that the demand rate of each open DC is reached through summation of its allocated retailers' demand rates. Constraints (16) imply that the maximum inventory level of each open DC must be less than storage space. Lastly, Constraints (17) and (18) introduce variables.

3- Solution method

The applications of soft computing are to solve the nonlinear models and to help the human knowledge for example learning, cognition as well as computation (Simić, Svirčević, and Simić 2015). Because of NP-hard nature of the presented problem, it is apparent that exact procedures are inefficient to solve large scale instances. In this manner, we develop two popular algorithms, viz. SA and GA, to effectively and efficiently solve large scale examples. It is worth mentioning that GA and SA are successfully implemented in the location-inventory studies (see e.g. Chew, Lee, and Rajaratnam (2007); Dalfard, Kaveh, and Nosratian (2013); Forouzanfar et al. (2016); Javid and Azad (2010); Liao, Hsieh, and Lai (2011); Nekooghadirli et al. (2014)). Also, according to the aim of the proposed problem to attain the optimal inventory policy, a DSM is embedded in the solving procedures. In the following, solution representation, solution evaluation and the solving procedures are elaborated in more details.

3-1- Solution representation

In this sub-section, we define the solution representation in the solving algorithms. In doing so, an $1 \times m$ array is created, wherein m the number of retailers is. The entry of each cell denotes which DC supplies the pertaining retailer. An example of the array is demonstrated in figure 4, where retailers 1, 2 and 3 are served through DCs 2, 3 and 4, respectively. In principle, the open DCs and allocation of retailers to them are determined by this array. Therefore, we can solely calculate the fixed costs of locating DCs at this stage.

DCs	2	3	4	…	1	2
Retailers	1	2	3	…	m-1	M

Fig 4. A sample of solution representation.

3-2- Solution evaluation

For evaluating the aforementioned array in the algorithms, the inventory decisions at the open DCs should be specified so that besides to the fixed costs of locating DCs, the transportation costs and the inventory costs are determined too. On the other hands, it should be pointed out that as the location-allocation decisions are specified, the values of the binary variables (i.e., y_j and x_{ji}) are actually determined. Thus, the origin model (12) - (18) is reduced to following model, determining the inventory policy at each open DC:

$$OF\left(S_j\right)=\theta\left[\left(OC_j+PU_j)\lambda_j+g_j\right)\left(1-Q_j\left(0\right)\right)+SH_jLO_j+HC_jMI_j\right] \tag{22}$$

$$S_j \le SC_j \tag{23}$$

$$S_j \ge 0 \quad integer \tag{24}$$

Where,

$$\sum_{\mathrm{i}} TR_{ji} x_{ji} \lambda_i^{'} = g_j \tag{25}$$

By taking into account that the objective function is nonlinear and complex, deriving the optimal solution S^* (i.e., the optimal value of base stock level) in closed form is somehow impossible. In the same fashion, we have incorporated DSM into the solving algorithms (SA and GA) to solve the above-mentioned model. For more information about the DSM, the interested readers can refer to Wright (1996). The steps of DSM are given as below. Notably, this method affords the optimal inventory policy of open DCs.

Step 1: Put $S_j=0$ and let $OF_j^*=inf$ (inf is a big number).

Step 2: Compute OF_j.

Step 3: If $OF_j-OF_j^* \le 0,$ then $OF_j^*=OF_j$.

Step 4: Let $S_j=S_j+1$.

Step 5: If $S_j > SC_j$, then stop. Otherwise, go to step 2.

Now, the total costs for evaluating the presented solution (i.e., the corresponding array) can be gained as follows:

$$TC=\sum_{j\in\Phi} FI_j + OF_j^* \tag{26}$$

Where, Φ corresponds to set of open DCs in the array.

3-3- Simulated annealing algorithm

SA was proposed by Metropolis et al. (1953). The algorithm is made based on the analogy between the annealing process of solids and the task of detecting an optimal solution in a combinatorial problem. It usually starts from a randomly created initial solution, and randomly transforms to a neighbour solution. If there is an improvement in the objective function (ΔE), transformation to a new state is accepted. Meanwhile, the algorithm escapes from a local optimal through accepting not improved solutions with probability $\exp(\frac{-\Delta E}{T})$. Temperature plays a prominent role in acceptance of not improved solutions, viz. by decreasing in temperature, then the probability of acceptance will alleviate proportionally. Likewise, by decreasing temperature with low rate, the solution space is searched better. Various methods can be used for termination of the algorithm. In the literature, methods such as reaching the pre-determined temperature, certain number of iterations, no-improvement in certain number of consensus iterations, certain run time and combination have been utilised. In this paper, we use reaching the pre-determined temperature and no-improvement in certain number of consensus iterations (NO) as stopping conditions. We also apply no-improvement in certain iterations as an equilibrium condition in each temperature (NI). Two neighbour solution generation mechanisms are implemented. In the first mechanism, the algorithm chooses a retailer accidentally and changes its DC. In the second, two retailers are randomly selected and their DCs are exchanged. The flowchart of the DSM-SA is depicted in figure 5.

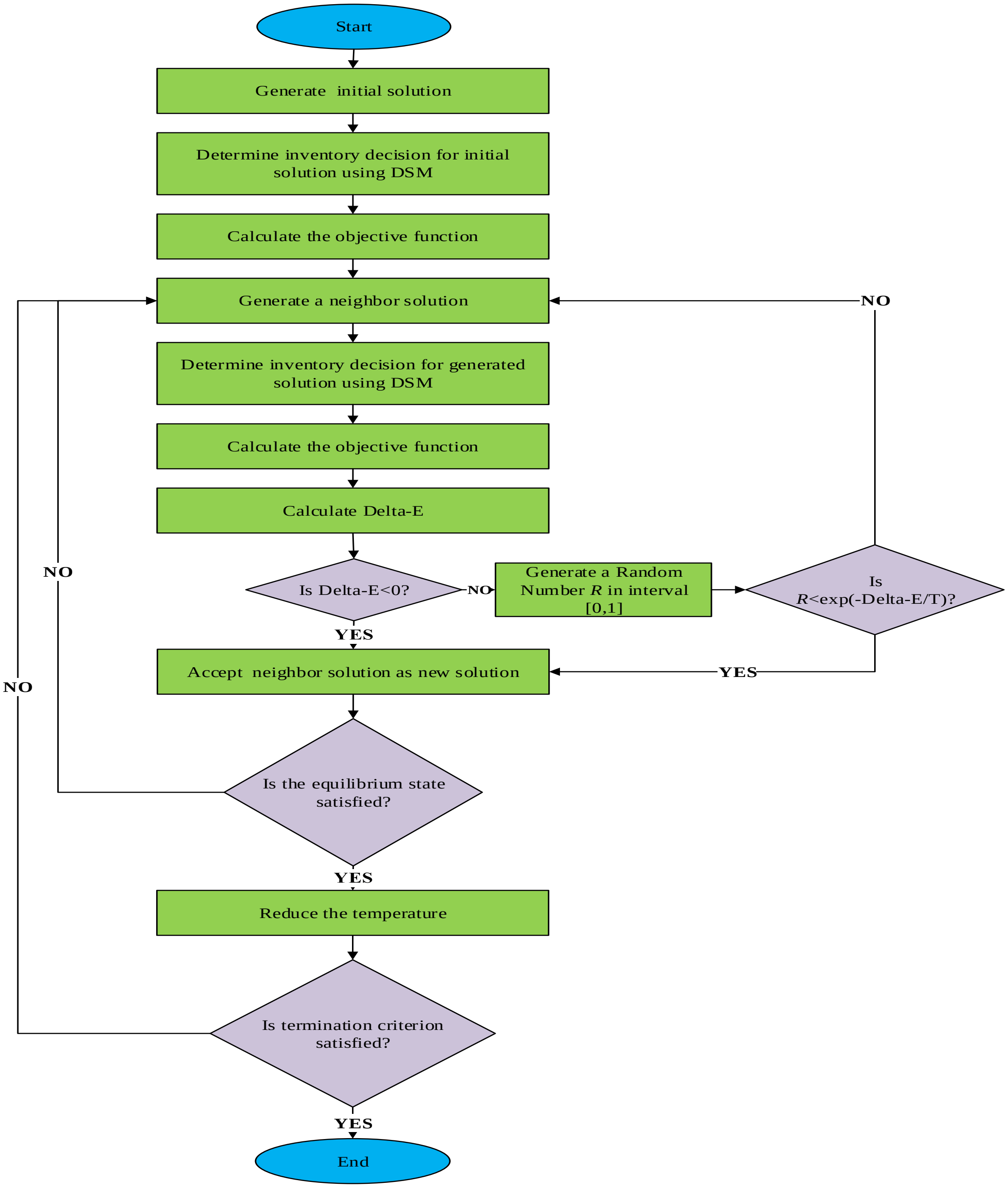


Fig 5. Flowchart of the DSM-SA.

3-4- Genetic algorithm

GA was proposed by Holland and others (1992). It starts with a set of solutions (represented by chromosomes) called population and then establishes a new population with the aid of operators consisting selection patents, crossover, mutation and replacement. More precisely, some chromosomes are randomly chosen from the population to consider as parents and crossover combines the genes of parents and creates a new offspring. In order to retain variety, mutation changes one or more gene in a chromosome from its primary state. In addition, replacement substitutes new population with old ones. In this research, the aforementioned array (see figure 4) is used as chromosome and the first population is produced randomly. The roulette wheel/one point combination (see, An\djelić et al. (2021) and Eiben, Smith, and others (2003)) is employed for selecting parents/ crossover operator. For mutation issue, a retailer is selected randomly and then a new DC is considered for it. Furthermore, replacement is done via elitism method (see, Kumar and Kumar, (2021)). Eventually, no improvement in the objective function is made after a certain number of iterations (NG), GA terminates. The flowchart of DSM-GA is depicted by figure 6.

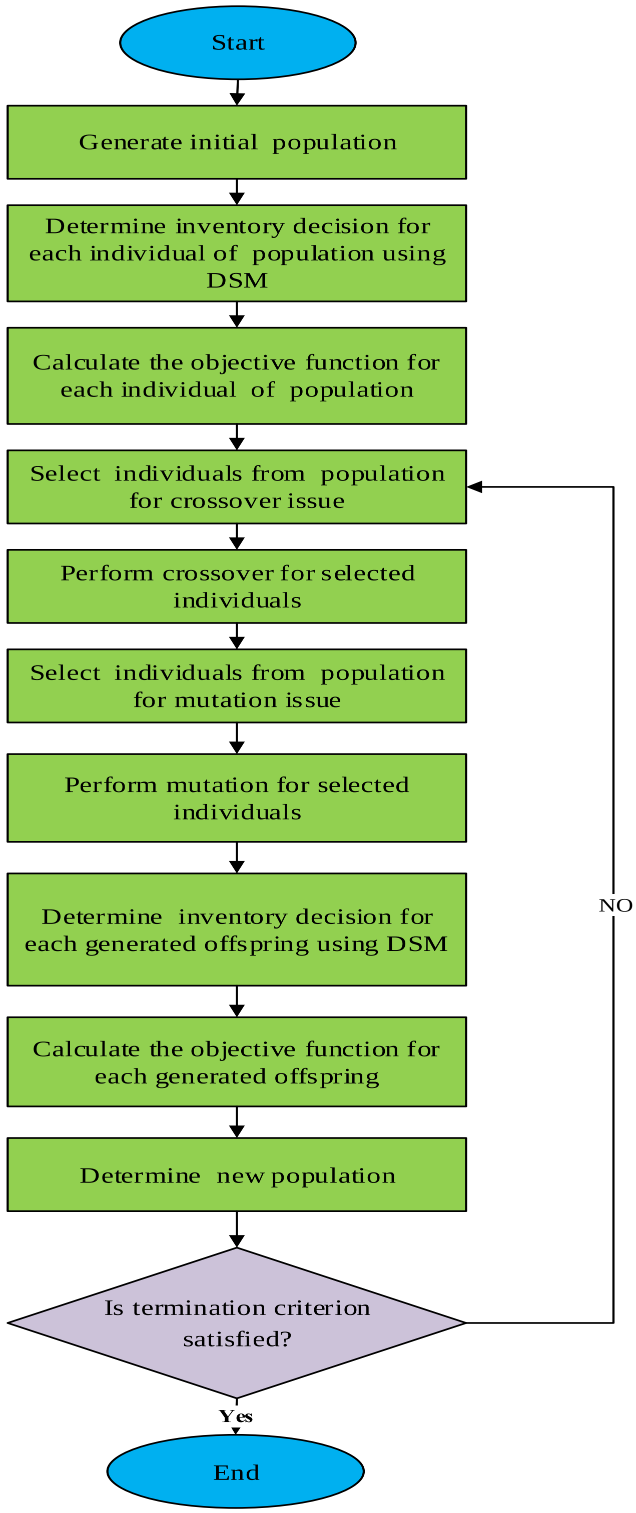


Fig 6. Flowchart of DSM-GA.

4- Computational and practical results

In this section, wide computational studies are offered to evaluate and assess the performance of the algorithms. As such, the impacts of different parameters on the number of open DCs, objective function and base stock level are studied. We coded the solving algorithms in Java programming language and run the codes on a PC with Intel five core CPU, 2.53 gigahertz computer and 4 gigabytes of RAM. The model's parameters are randomly generated. The used ranges for the parameters are reported in table 2.

Table 2. Distribution of generated parameters.

HC_j	OC_j	PU_j	SH_j	FI_j	$\lambda_i^{'}$	SC_j	μ	TR_{ji}	Θ
U[25,35]	*U[5,10]*	*U[5,10]*	*U[70,80]*	*U[5000,6500]*	*U[75,110]*	*U[15,20]*	*U[150,350]*	*N[4,10]*	1

4-1- Parameter setting

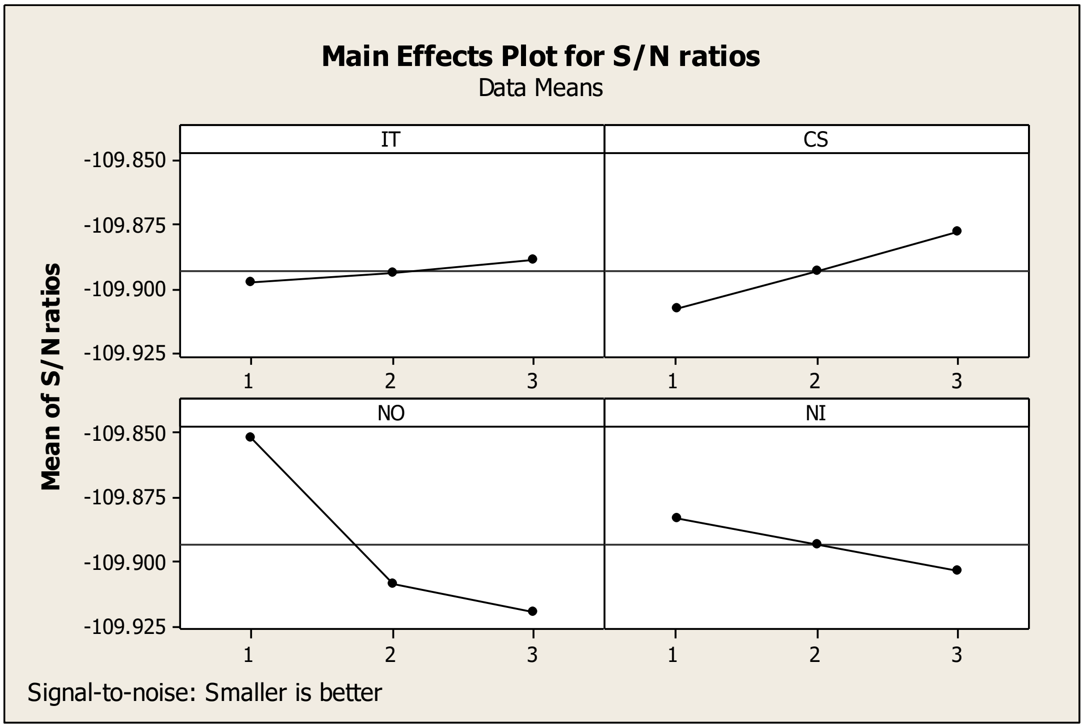
In this section, we are intended to tune the parameters of the solving algorithms applying Taguchi procedure. In principle, with tuning the parameters, we can achieve more quality and robust (i.e., with less variance) solutions (Tiwari et al. 2010). Taguchi method is an extension of fractional factorial experiment (FFE), introduced by Cochran and Cox, (1957). This method enables us to examine the effects of several factors on the response (i.e., fitness value of solution) with fewer experiments in comparison with full factorial designs (Roy 1990). That is, applying a particular design of orthogonal arrays, Taguchi method surveys the whole parameter set doing a low number of tests. In this method, the factors are classified in two categories consisting of controllable and noise factors. A major purpose of Taguchi method is to regulate the values of controllable factors so that the variability of response reduces via minimizing the impacts of uncontrollable factors. In this article, the concerned parameters for DSM-SA are initial temperature (*IT)*, cooling speed (*CS)*, certain number of consensus iterations for stopping criteria (*NO)* and certain iterations for equilibrium condition (*NI)*. Additionally, the considered parameters for DSM-GA are number of population members *(NP)*, probability of crossover *(PC)*, probability of mutation *(PM)* and the number of consensus iterations for stopping criteria (*NG)*. For each parameter, three levels are offered. The values are given in table 3. Here, we use L^9 orthogonal array for both algorithms to design the experiments. In accordance with the designed experiments, S/N ratios for each level of DSM-SA and DSM-GA parameters are illustrated by figures (7a) and (7b), respectively. The best level for each parameter is where maximizes S/N. According to this, the best values of parameters are reported in table 4.

Table 3. Level values of DSM-SA and DSM-GA parameters.

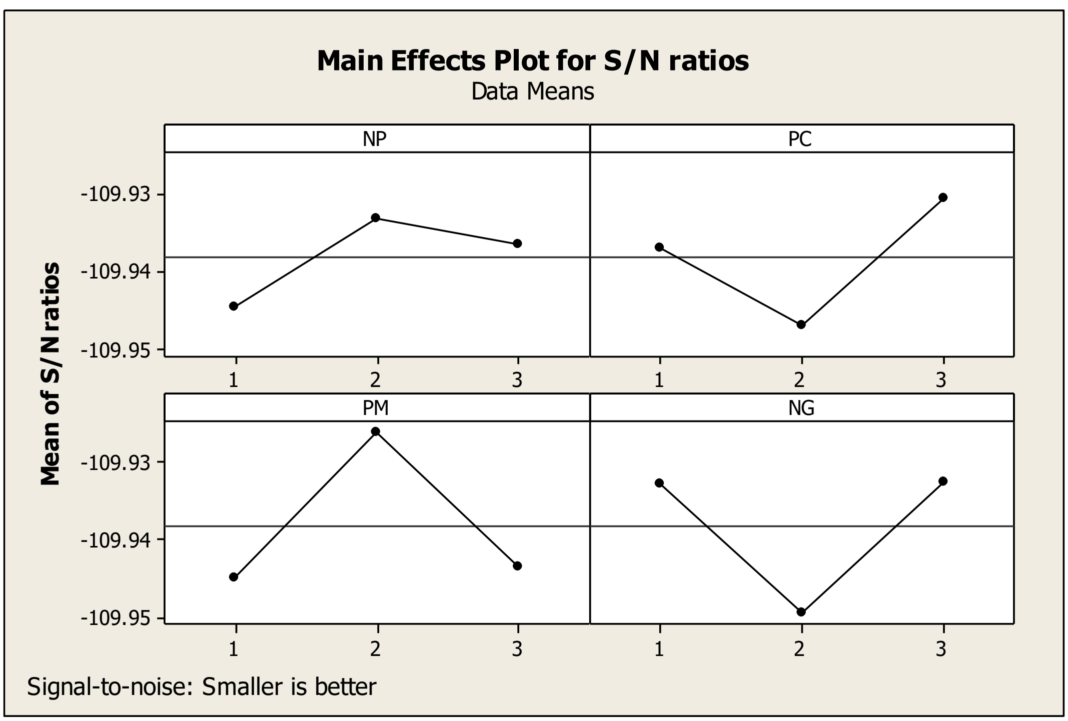
	DSM-SA				DSM-GA			
	IT	*CS*	*NO*	*NI*	*NP*	*PC*	*PM*	*NG*
Level 1	900	0.9	15	60	90	0.65	0.1	50
Level 2	1000	0.95	20	65	100	0.7	0.15	55
Level 3	1100	0.99	25	70	110	0.75	0.2	60

Table 4. Best values of DSM-SA and DSM-GA parameters.

DSM-SA parameter	*IT*	*CS*	*NO*	*NI*
Value	1100	0.99	15	60
DSM-GA parameter	*NP*	*PC*	*PM*	*NG*
Value	100	0.75	0.15	50



(a) DSM-SA



(b) DSM-GA

Fig 7.a, b. The mean S/N chart for different levels of DSM-SA and DSM-GA parameters.

4-2- Validation of the solving algorithms

A full enumeration method (FEM) is implemented to assess the performance of the meta-heuristic algorithms. FEM seeks all possible solutions of the array proposed in section 3.1, viz. for a problem with m potential DCs and n retailers, all m^n possible solutions are tested and the best value of the objective function is reported. The corresponding results containing the objective functions, CPU times and the gap between objective functions of FEM and meta-heuristic algorithms are summarised in table 5. It should be pointed out that the gap is calculated as follow:

$$Gap(\%) = \frac{TC_{EN} - TC_{ME}}{TC_{ME}} \times 100 \tag{27}$$

Where, TC_{EN} and TC_{ME} are attributed to objective functions reached by FEM and corresponding meta-heuristic algorithm, respectively. In other words, Gap_1 and Gap_2 are interrelated with DSM-SA and DSM-GA, respectively. It should be pointed out that the CPU time is confined to 24 hours in FEM. For instances 1, 2 and 3, FEM is terminated less than 24 hours and consequently the obtained solutions are optimal. According to the results presented in this table, it can be seen that the maximum gaps between the optimal solution and the solutions of DSM-SA and DSM-GA are 0.313% and 0.049%, respectively. This connotes that the proposed meta-heuristic algorithms reach optimal or near-optimal solutions. Also, the best-found solutions of FEM for instances 4 and 5 in 24 hours run-time are reported. It is apparent that in both terms of quality of solutions and CPU times, the meta-heuristic algorithms solutions are considerably better than those in FEM. All in all, it can be concluded that the solving algorithms perform efficiently.

Table 5. Comparison between full enumeration and meta-heuristic algorithms.

NO.	# Retailers	# Potential DCs	FEM		DSM-SA		DSM-GA		GAP$_1$ (%)	GAP$_2$ (%)
			Cost	CPU Time(s)	Cost ($)	CPU Time(s)	Cost ($)	CPU Time(s)		
1	4	2	15592.99	0.014	15592.99	0.96	15592.99	2.3	0	0
2	10	4	34388.75	1071.58	34388.75	3.49	34388.75	12.02	0	0
3	11	5	407297.35	46969.48	408574.8	4.23	407497.59	27.24	-0.31	-0.04
4	15	6	50434.238	24h limit	`48794.91	5.29	48437.61	45.63	3.2	4.09
5	20	8	71359.47	24h limit	65321.13	7.26	65026.12	68.56	8.46	9.6

4-3- Comparison of meta-heuristic algorithms in larger instances

The meta-heuristic algorithms are utilised for larger instances of the problem and their performances are compared. The results including the objective functions, CPU times and the gap between two meta-heuristic algorithms are summarised in table 6. The gap is calculated as follows:

$$Gap = \frac{TC_{SA} - TC_{GA}}{TC_{SA}} \times 100 \tag{28}$$

Where, TC_{SA} and TC_{GA} are pertaining to the objective functions of DSM-SA and DSM-GA, respectively. From table 6, one can see that with respect to quality of the solutions, DSM-GA predominantly outperforms DSM-SA, whilst DSM-SA dramatically performs better than DSM-GA in term of CPU time. Not surprisingly, it can be also seen with increase in the sizes of instances, CPU times of algorithms increase.

Table 6. Comparison between meta-heuristic algorithms in larger instances.

NO.	# Retailers	# Potential DCs	DSM-SA Cost ($)	DSM-SA CPU Time(s)	DSM-GA Cost ($)	DSM-GA CPU Time(s)	Gap (%)
1	35	12	110990.6	31.409	111439.7	165.421	-0.404
2	45	15	144286.3	40.842	143017.6	193.314	0.879
3	55	17	177283.6	49.792	175320.8	226.457	1.107
4	70	19	233780.9	70.896	232291.5	285.359	0.637
5	80	21	274548.3	92.974	271648.6	320.337	1.056
6	95	28	311909.5	355.186	314571.5	484.71	-0.85
7	100	35	335854.5	432.689	328990.4	577.7036	2.043
8	110	40	368131.9	554.8366	362657.5	770.054	1.487
9	140	45	464955.3	832.324	455983.9	1519.351	1.929
10	150	50	502710.1	902.477	493789.6	1634.331	1.77

4-4- Sensitivity analysis

We survey the effects of retailers' demand rates and exponential distribution parameter of lead-time on the number of open DCs and the objective function in this sub-section. This study is carried out for three instances with size of $4\times10, 12\times35$ and 28×95 ($m\times n$ means that the instance includes m potential DCs and n retailers). For the convenience's sake, we term them instances 1, 2 and 3, respectively. Moreover, the influences of different parameters on the value of base stock level will be investigated too.

4-4-1- Number of open DCs

Here, we investigate the impact of the demand rates and exponential parameter of lead-time on number of open DCs. The achieved results are given in table 7. What is apparent from this table is that thought raising the retailers' demand rates, the SC tends to establish more DCs for the purpose of preventing the shortage costs. This happens for all instances. Additionally, the results highlight that the number of open DCs tend to decrease with increase in the value of μ. In fact, increased the value of μ eventuates in decreased the expected lead-time and the supplier delivers the orders in less time. That is, at higher value of μ, the probability of facing the shortage in open DCs is small. In this manner, each DC can cover more demands and the SC can satisfy the demands of retailers with a smaller number of DCs. The results also manifest that by increasing the instance size, the number open DCs raises.

Table 7. Impacts of the retailers' demand rates and exponential parameter of lead-time on the number of open DCs for different instances.

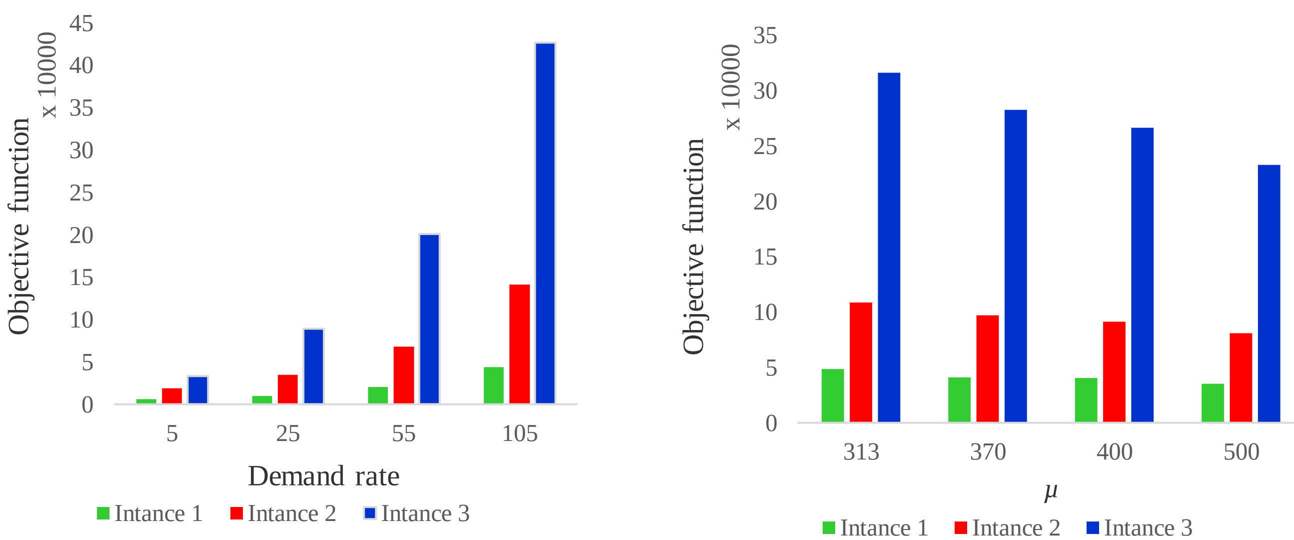
	Demand rates				exponential parameter of lead-time			
	50	60	80	100	300	350	400	450
Instance 1	2	2	3	4	4	3	3	3
Instance 2	7	10	12	12	11	11	9	9
Instance 3	21	23	27	28	28	27	25	23

4-4-2- Objective function

The sensitivity of the objective function with regard to changes in demand rates is plotted in figure 8(a). As this figure shows, there is a direct relation between the demand rates of retailers and the objective function. The rationale behind this is that through raising the values of demand rates, inventory costs increase. Moreover, based on table 7, the SC tends to serve demands with more numbers of DCs, yielding to increase the fixed costs too. The relationships between the objective function and exponential distribution parameter of lead-time are displayed in figure 8(b). The results underscore that by increasing the value of μ, the total cost reduces. Furthermore, by further increasing of this parameter, no additional changes in the objective function would be imposed. This fact is consistent with the literature (see,).

4-4-3- Base stock level

Here, we aim to evaluate the effect of the parameter on the value of base stock level. For this particular experiment, we suppose that $\lambda = 110, \mu = 200, SH = 75, HC = 30, \ PU = 5, \ OC = 5$ and $g = 400$. The relevant results are demonstrated in figure 9. From figure 9(a), we see that at the higher value of unit shortage cost, the value of base stock level rises. Indeed, increased the value of base stock levels results in reduced the probability of facing shortage. Accordingly, the shortage cost term in the objective function would diminish. Figure 9(b) also evinces that at higher values of the demand, the value of base stock level tends to increase. This can be mainly imputed to the fact that through increasing the value of the demand rate, the losses increase. Therefore, the value of base stock level rises to alleviate the unsatisfied demands. Additionally, at the higher value of μ, the expected lead-time and probability of losing decrease. Hence, the value of base stock level alleviates, eventuating in more savings in the inventory costs. The results are depicted in figure 9(c).



(a) The effect of demand rate on the total SC costs

(b) The effect of supplier lead-time on the total SC costs

Fig 8. The impact of parameters on the total SC costs.

4-5- Case study

The development of the digital economy in the world and on the other hand the high penetration rate of mobile phones and people's lifestyles have made the approach of governments to the IT as a driver of economic progress. Undoubtedly, the transformation resulting from the development of the digital economy will increase productivity, greater transparency and less corruption, promote innovation and creativity, reduce inequality, improve the quality of government services, reduce bureaucracy, improve public welfare. Of course, achieving this requires that the important roles of governance in the IT, including the establishment of national information network, the development of communication and information infrastructure, regulating relationships between different actors, and supporting start-ups and domestic producers, be seriously pursued. Among the countries of the Middle East, the highest growth and use of IT services, including mobile services, landlines and the Internet is related to Iran, which can be boldly introduced it as one of the leading countries in the IT industry (Badri Ahmadi, Hashemi Petrudi, and Wang 2017). On the other hand, owing to the rapid expansion of the information and communication technology industry and its key role in improving business and daily life, operators and service providers also expect to receive secure and appropriate communication (Büyüközkan and şakir Ersoy 2009). One of the most important companies that has a key role in creating communication and information infrastructure in Iran is the Telecommunications Infrastructure Company (TIC). The TIC Participates in the communication infrastructure in the fields of core network bandwidth development, development of Internet connection ports, development of traffic transit network and in the field of information infrastructure.

4-5-1- Data gathering

The TIC has established a network by constructing about 360 main centres in all parts of Iran and also by establishing 7 entrance ports in border areas, through which all communication services reach customers safely. As mentioned in this section, establishing secure communication is one of the most important tasks of companies in charge of IT services, which in Iran is the responsibility of the TIC. Due to the complexity of the company's network, the existence of problems such as cooling equipment and racks, outages in the network for reasons such as fibre outages can be predicted, but the short time to solve these problems is one of the priorities of senior managers. The reason of this issue is that e-mail services, banking services and similar items depend on communication in the network, which in case of disruption in the network, all services will be out of reach. Therefore, it can be concluded that if any of the 360 main centres have a problem, they should be solved in the shortest possible time.

In the TIC, the procedure is to solve network problems through outsourcing, which has problems such as increasing costs and increasing the time to solve the problem. Due to the problems raised and the opinion of senior management, the procedure has changed and the goal is to establish a number of warehouses in parts of Iran that can solve network problems in the shortest possible time. For this purpose, due to the importance of inventory control in the warehouse, space constraints and determining the optimal location of the proposed locations for the establishment of the warehouse, the location-inventory model has been used. It is necessary to mention that the cost of building warehouse in different parts of the country is different, so that the cost of building a 10,000-meter warehouse in "Sistan and Baluchestan province" requires twice the budget than building a similar warehouse in "Tehran province". Also, due to the fact that the demand of existing centres is uncertain, queueing theory has been used to deal with this problem. Owing to the complexities of the model, the hybrid genetic algorithm and simulated annealing algorithm, have been used to solve the model, and the relevant results will be reported in the following sections.

In this research, it has been tried to consider a number of TIC centres that are more important from the point of view of senior management as demand points. Some of the criteria that senior management has considered to prioritize the TIC centres, can be the impact of the centre on the company's stable network and taking into account the technical considerations of the centre. Therefore, out of 360 of the TIC centres, 10 important centres in the cities of "Tabriz", "Kermanshah", "Isfahan", "Bushehr", "Kerman", "Zahedan", "Bandar Abbas", "Tehran", "Mashhad" and "Gorgan" are considered as warehouse demand centres and out of 150 Proposed location for the establishment of the warehouse, 7 proposed locations in the cities of "Tabriz", "Tehran", "Ahvaz", "Shiraz", "Birjand", "Mashhad" and "Semnan" have been selected on which the senior management has a more favourable opinion than other places.

Figure 1 shows the location of 10 TIC centres and 7 proposed locations for the establishment of warehouses.

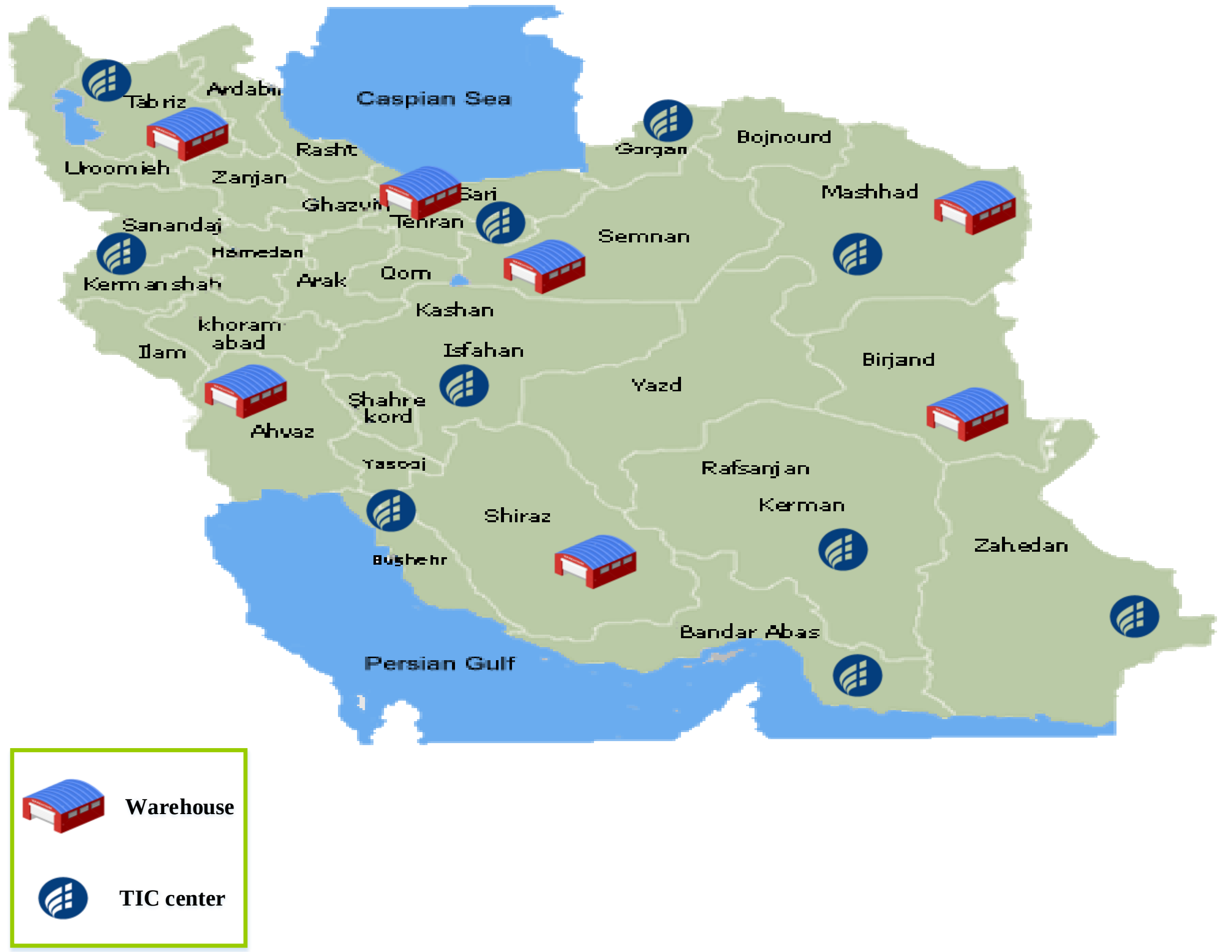


Fig 9. Location of TIC centre and warehouse

It should be noted that the proposed model can be generalized to the whole problem and the problem can be solved on a large scale and the results can be analysed.

One of the parameters that the model needs to solve is to determine the transportation cost between the TIC centres and the proposed locations for the establishment of the warehouse. Due to the fact that a number of centres are located out of reach, so the distance between the warehouses to the city is calculated and the distance from the city to the exact location of the centre is converted to a normal distance and finally the exact distance from the proposed location to Establishment of warehouse to company centres is calculated. The transportation cost between the TIC centres and the proposed locations for the establishment of the warehouse are reported in table 8:

Table 8. Transportation cost between TIC centre and Warehouse (Km)

TIC centre	Warehouse						
	Tehran	Tabriz	Semnan	Mashhad	Birjand	Ahvaz	Shiraz
Tabriz	625	10	845	1530	1770	1142	1376
Tehran	15	627	223	1050	1150	823	981
Kermanshah	515	600	721	1391	1491	489	982
Gorgan	400	1052	351	582	984	1199	1312
Mashhad	1050	1530	690	15	505	1652	1360
Esfahan	450	895	591	1262	880	520	490
Bushehr	1072	1520	1199	1600	1432	465	320
Bandar Abas	1290	1805	1420	1400	1060	1220	591
Zahedan	1500	2010	1372	965	470	1705	1081
Kerman	995	1551	1130	948	572	1210	582

Another parameter that must be determined is the level of demand of the TIC centres, which has already been discussed about its uncertainty. Given that the queueing theory has been used to deal with the uncertainty, it is necessary to determine the value of λ of the Poisson distribution. For this purpose, the value of parameter λ for each of the TIC centres is considered in table 9:

Table 9. λ of TIC centre

TIC centre	λ
Tabriz	150
Tehran	320
Kermanshah	100
Gorgan	88
Mashhad	150
Esfahan	189
Bushehr	90
Bandar Abas	75
Zahedan	250
kerman	150

4-5-2- Validation the proposed model with Case study

In this section, according to the case study, we evaluate the proposed model. According to the information provided in figure 9, 10 centers of TIC are considered as points of demand and 7 locations as proposed locations for the establishment of warehouses. The results of solving the model show that among the proposed locations for the establishment of the warehouse, the provinces of "Ahvaz", "Tehran" and "Birjand" have been selected. The results also demonstrate that the centers of "Mashhad", "Zahedan", "Bandar Abbas" and "Kerman" provinces are allocated to warehouses established in "Birjand province", the centers of "Isfahan", "Kermanshah" and "Bushehr" provinces to "Ahvaz province" warehouses and the centers of "Tehran", "Tabriz" and "Golestan" provinces to "Tehran province" warehouses. Finally, the relationship between the centers of TIC and the locations selected for the establishment of the warehouse is shown in figure 10.

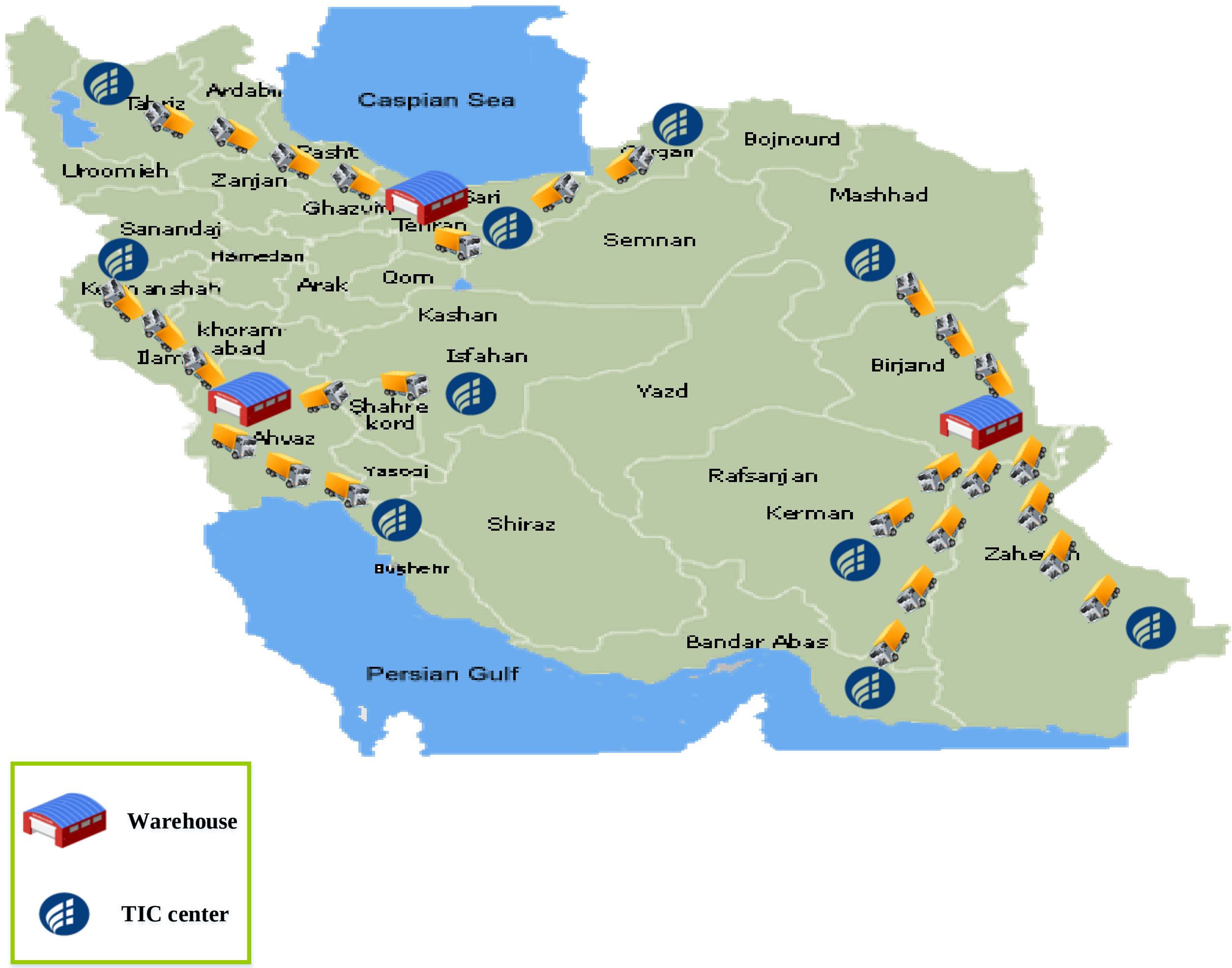


Fig 10. Results of case study

5- Conclusion

In this study, we have investigated a mathematical model for stochastic network design problems with regard to inventory decisions when the lost sale is possible. According to the best of our knowledge and the related literature, this is the first study that incorporates $(S-1, S)$ inventory policy with regard to lost sales in joint location-inventory problem. Likewise, in a bid to withstand the uncertain nature of retailer's demands and supplier's lead-time and analysing the feature of inventory policy, viz. the number of orders, number of shortages and the mean inventory, a queuing theory was adopted. Thereafter, the concerned problem was formulated in term of an MINLP model based on the outputs of the queuing theory. Meanwhile, DSM-GA and DSM-SA were deployed to circumvent the computational burden from the concerned NP-hard problem. DSM was used to realize the aim of determining the optimal policy for inventory. To validate the derived solutions of the solution algorithms, the results were compared with the FEM. The computational results corroborated that the solution algorithms are capable of solving the model in an efficient way. Moreover, some useful output analyses were drawn in accordance with the real information of the TIC. For example, our analyses revealed that that the number of DCs and the total costs are sensitive in small values of μ; viz. if the supplier reduces its lead-time in these rages, the costs and required facilities are dramatically deducted. As such, the rates of demands have substantial effects on the objective function and the number of open DCs.

The current paper can be developed in a number of promising avenues to enrich this context. Addressing a sustainable location-inventory problem considering the environmental and social impacts in addition to the economic aspects is an interesting future research direction with salient practical relevancies. Incorporating disruption of facilities in the proposed problem can be taken into account as another appealing avenue. Eventually, in view of computational complexity of the proposed model, future studies could be aimed at extending new algorithms for solving it.

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