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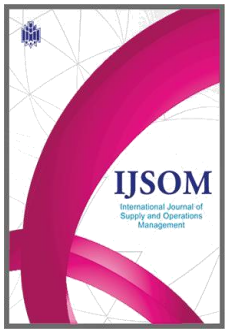

Two Meta-heuristic Algorithms for a Capacitated Inventory-location Problem in a Multi-echelon Supply Chain

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Abstract
In this study, we propose a model to minimize the inventory and location costs of a supply chain, including a production plant, warehouses and retailers. The production plant distributes a single product to retailers through warehouses. The model determines the location of warehouses, allocates retailers to the warehouses and indicates the length of order intervals at warehouses and retailers. To ensure the order quantity is lower than the warehouses' capacity, we consider the capacity constraints. Unlike the existing researches, we investigate the limitation on the number of established warehouses. We formulize the problem as a nonlinear mixed-integer model and propose two efficient meta-heuristic algorithms including a genetic algorithm (GA) and an evolutionary simulated annealing algorithm (ESA) to solve it. To improve the proposed algorithms, in generating populations, a new heuristic method which produces feasible solutions is designed. The Taquchi method is used for tuning the parameters of the proposed algorithms. The small size numerical examples are solved and sensitivity analysis is done to demonstrate the influential theoretical results. We evaluate the proposed algorithms by comparing the solutions of them with the optimal solution obtained from the Lingo 11. Further, we investigate their efficiency by solving numerical examples in different sizes and depict the percentage gaps between the best solution values and the average objective values of them. Results reveal that both the GA and ESA are efficient in solving the proposed model, but the ESA outperforms the GA on the optimal solution, computing time and stability.

Keywords: Location; Inventory; Limited capacity; Genetic algorithm; Evolutionary simulated annealing.

1. Introduction

Facility location as a strategic level decision and inventory control as a tactical level decision are two vital considerations in supply chain design. These decisions are interrelated because a change in inventory policy of warehouses or retailers can have impacts on allocation decisions and the location costs, and also a change in the number or location of warehouses can influence lead times and the inventory costs. Hence, analyzing them independently in the design of supply chain increases cost because of sub-optimally decisions. (Cavinato 1992; Chopra and Meindl 2006; Gunasekaran et al. 2001; Gunasekaran et al. 2004; Silver et al. 1998; Simchi-Levi et al. 2007; Stevens 1993). The pioneering works in joint inventory and location problems were done around 2000. Teo et al. (2001) modeled a three echelon supply chain including a supplier, warehouses and retailers. They aimed to optimize the total cost of opening warehouses and inventory holding at warehouses. Daskin et al. (2002) expanded the work of Teo et al. (2001) by considering shipping costs from the supplier to warehouses and from warehouses to retailers. Shen et al. (2003) formulated a joint location-inventory problem for a supply chain where some retailers were allowed to serve as warehouses for other retailers. The problem was formulated as a nonlinear integer-programming model to determine which retailers should serve as warehouses and how to assign the other retailers to the warehouses. They restructured the model into a set-covering integer-programming model to solve it. Shen et al. (2007) modeled a location-inventory problem with customers' random demand. They solved large-size numerical examples ranging from 40 to 320 retailers and showed the benefits of optimizing location, inventory, and routing decisions jointly. Yao et al. (2010) formulized a three echelon supply chain by considering inventory and location decisions. They assumed that retailers could be served by warehouses or production plants. The problem was presented as a mixed-integer nonlinear model, with approximation and transformation techniques being utilized to solve numerical examples.

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Jha et al. (2012) proposed a mixed-integer model for a multi-product inventory-location problem with deterministic demand, in which some retailers were considered as warehouses. They used an adaptive differential evolution algorithm to solve numerical examples. Tsao et al. (2012) investigated the problems of finding the warehouses' location, assigning retailers to warehouses, as well as determining inventory control at warehouses. They proposed a continuous approximation model and developed nonlinear programming techniques to solve it. More recently, Wheatly et al. (2015) modeled a multi-product inventory-location problem under stochastic demand and time-based service levels. The lead time assumed to be fixed and a logic-based Benders decomposition algorithm was proposed. Qu et al. (2015) used a genetic algorithm, a hybrid differential evolution algorithm and a hybrid self-adapting differential evolution algorithm to optimize the inventory and location costs at a three-level supply chain with customers' stochastic demand. They considered two replenishment policies, joint replenishment, and independent replenishment for formulating the model. Sadjadi et al. (2016) proposed a mixed-integer nonlinear programming model to address the location-inventory problem where the queueing method was utilized to determine the shortage, mean inventory, amount of annual purchase and ordering. A three-level closed-loop supply chain for location-inventory-pricing decisions was modeled by Ahmadzadeh (2017). He considered the demand of customers correlated and used periodic review (R, T) inventory control policy, and proposed three meta-heuristic algorithms including a genetic algorithm, an imperialist competitive algorithm, and a firefly algorithm for solving the model. Li et al. (2018) delt with location-inventory decisions jointly in a closed-loop system with Third-party logistics. They formulated the problem as a mixed-integer non-linear programming model and proposed a heuristics algorithm based on differential evolution and the genetic algorithm.

In line with inventory-location studies, some researchers have addressed inventory policy at retailers and warehouses, simultaneously. You et al. (2010) proposed an inventory-location model for a multi-echelon supply chain under fixed demand. Their model determines location and inventory decisions while guarantees the service time. They proposed a decomposition algorithm based on the integration of piecewise linear approximation and the Lagrangean relaxation to solve the problem in a case study from chemicals and industrial gas supply chain. A two-echelon supply chain design was studied by Romeijn et al. (2007). They formulated the problem as a set covering model to minimize location and inventory costs by considering safety stock at warehouses and retailers. A mixed-integer non-linear model for a one-product inventory problem under deterministic demand was proposed by Diabat et al. (2015). Their model determined the location of warehouses and the length of order intervals at warehouses and retailers, simultaneously. It was assumed that the inventory holding cost of warehouses is lower than retailers. Puga et al. (2017) used a genetic algorithm to minimize warehouses establishing, transportation and inventory costs. The constraint of the problem was on product shipment size. Saragih et al. (2019) dealt with a three-echelon location, inventory, and routing problem. They considered holding costs at a supplier, warehouses and retailers, simultaneously. A two-phase heuristic was proposed including a constructive stage and an improvement stage, and simulated annealing was used to improve the solutions at the improvement stage.

The studies we discussed above all assumed that warehouse' capacity is unlimited, which is not very practical in the real world. Miranda et al. (2004) studied a nonlinear mixed-integer inventory-location problem by regarding capacity constraints for warehouses. The model not only located warehouses and allocated retailers to them but also determined inventory policy at warehouses. A Lagrangian relaxation and subgradient methods were used to solve numerical examples. Ozsen et al. (2008, 2009) developed the problem investigated by Daskin et al. (2002) and Shen et al. (2003) by considering capacity constraints. They formulated the problem as a nonlinear integer-programming model and proposed a Lagrangian relaxation solution algorithm to solve it. A three-level supply chain for location and inventory decisions was modeled by Askin (2014) where a predetermined finite set of options was considered for warehouses' capacity. He sought to seek the warehouses' location, assigned retailers to warehouses, and determined order quantity at warehouses and retailers. A genetic algorithm was proposed to solve numerical examples. A capacitated location-allocation model by considering stochastic demands was presented by Alizadeh et al. (2015). They formulated the objective function that included fixed costs of establishing facilities, allocation costs and expected values of outsourcing and servicing costs as a mixed-integer nonlinear model. A genetic algorithm and a discrete version of the colonial competitive algorithm (CCA) were proposed, and at the end it was concluded that the CCA performs better than the genetic algorithm. Diabat et al. (2016) addressed a capacitated location and inventory problem where a genetic algorithm was used to find optimal solutions. Vahdani et al. (2017) proposed a mixed-integer non-linear model for a joint location-inventory problem under correlated demand at retailers. They considered the policy of periodic review for inventory level at warehouses. In their work, two meta-heuristic algorithms including a genetic algorithm and a simulated annealing algorithm were presented.

Today, a key factor in designing the supply chain is budget constraint. Modeling a supply chain by considering this constraint makes the problem more realistic. Adding this constraint, while making the model more practical (Lemmens et al. 2016), may increase its complexity. Snyder et al. (2005) formulated a location problem while considering the budget constraint as limiting on the number of opened warehouses. They proposed a Lagrangian relaxation algorithm to solve it. Mosavi et al. (2013) proposed a mixed binary integer program for a multi-product multi-period inventory problem in which the total budget for buying products was limited. Alikar et al. (2017) investigated a multi-product inventory system under deterministic demand. In their model, the total available budget and storage space were limited. They used a non-

dominated sorting genetic algorithm, a multi-objective particle swarm optimization, and a multi-objective harmony search to solve numerical examples. Considering budget and storage space constraints, an inventory-location problem was improved by Mousavi et al. (2019) where the demand of buyers was satisfied by vendors that stored products in their warehouses. Their model determined the optimal placement of vendors among buyers and order quantity of buyers to them. A modified genetic algorithm and a particle swarm optimization algorithm were proposed to find optimal solutions.

A review of the literature shows that each researcher has attempted to overcome the usability of inventory -location problem by breaking traditional assumptions and proposing a more realistic model. Some researches considered budget and storage space constraints and some others addressed inventory policy at retailers and warehouses, simultaneously. To the best of our knowledge, there is no inventory–location study that models inventory policy at warehouses and retailers simultaneously by regarding budget and storage space constraints. Thus, in this research, we develop a more realistic problem by filling this gap. We formulate a three echelon supply chain including one production plant, warehouses, and retailers. The production plant provides the demand of retailers through warehouses. The aim is to find the warehouses location, allocate retailers to the warehouses, and determine the length of order intervals at warehouses and retailers. We consider the budget constraint as the number of warehouses that can be opened and also assume limited capacity for warehouses. Since the model is overly NP-hard, two efficient meta-heuristic algorithms, a genetic algorithm (GA) and an evolutionary simulated annealing algorithm (ESA), are presented. In generating populations for these algorithms, a new heuristic method that produces feasible solutions is designed.

The remainder of this study is as follows: In Section 2, the problem, notations and the mathematical formulation of the model are presented. In Section 3, the solution algorithms are stated. The experimental design to tune the parameters of the proposed algorithms is explained in Section 4. In Section 5, the numerical examples are presented. Finally, in Section 6, the conclusion of the study is presented, and some suggestions for future research are proposed.

2. Problem description and notations

We consider a reliable production plant that provides the retailers' demands for a single product through warehouses. It is desired to select warehouses in candidate locations to be established, allocate retailers to established warehouses and determine the length of order intervals at the warehouses and retailers so that the operating cost of the supply chain will be minimized (Figure 1).
The assumptions, notations and decision variables will be stated as follows.

2.1 Assumptions

i. The location of the retailers is fixed and known.
ii. The demand rate of retailers is known and deterministic.
iii. Each retailer has an unlimited capacity for holding inventory.
iv. The retailer's demand must be satisfied with just one warehouse.
v. There is not any backlog at warehouses and retailers.
vi. The length of order intervals at the warehouses and the retailers is an integer power of two (Roundy 1985).
vii. The capacity of warehouses is limited (Vahdani et al. 2017; Diabat et al. 2016; Ozsen et al. 2009; Ozsen et al. 2008).
viii. The number of warehouses that can be established is limited (Li et al. 2013; Snyder et al. 2005).

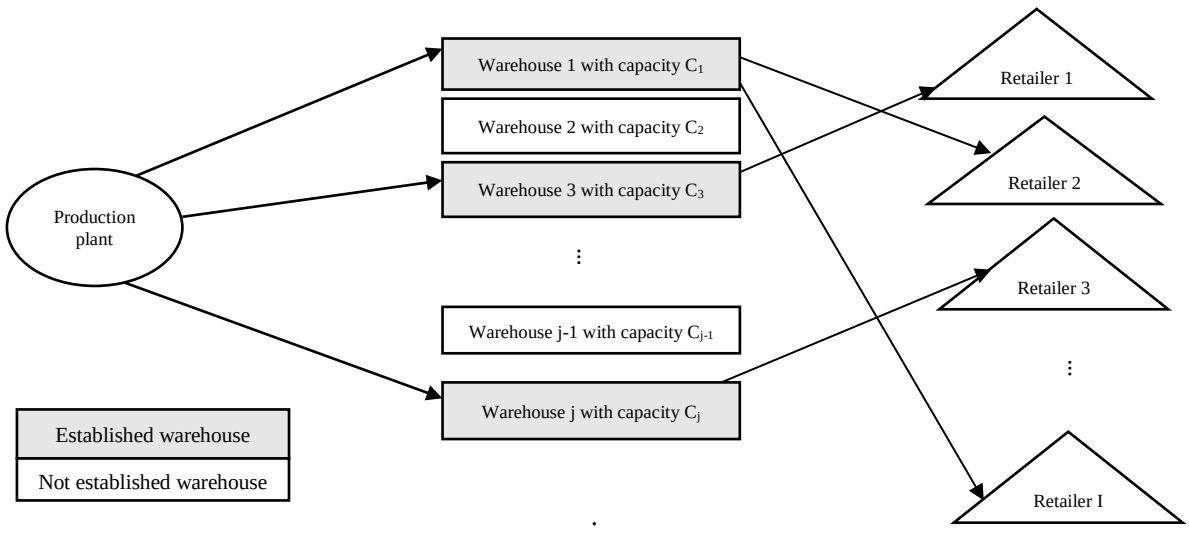

Figure 1. A potential solution for the model

2.2 Indices

$i(i= 1, . . . , I)$: Set of retailers

$j(j = 1, . . . , J)$: Set of possible warehouse' locations

2.3 Input parameters

d_i: The demand rate of retailer i

f_j: The establishing cost of a warehouse at location j

s_{ij}: The cost of shipping one unit of the product from warehouse j to retailer i

$\acute{s}_j$: The cost of shipping one unit of the product from the production plant to warehouse j

h_i: The cost of holding one unit of the product in a unit time at retailer i

k_i: The cost of ordering at retailer i

$\acute{h}_j$: The cost of holding one unit of the product in a unit time at warehouse j

$\acute{k}j$: The cost of ordering at warehouse j

C_j: The capacity of warehouse j

P: The number of warehouses that can be established

β_{trn}: The transportation costs weight

β_{inv}: The inventory costs weight

2.4 Decision variables

T_j: The length of order interval at warehouse j

T_{ij}: The length of order interval at retailer i when allocated to warehouse j

$$X_j = \begin{cases} 1 & \text{If a warehouse is established at location j} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{ij} = \begin{cases} 1 & \text{If retailer i is allocated to the warehouse at location j} \\ 0 & \text{otherwise} \end{cases}$$

The objective function is defined as the total cost, which includes cost of establishing warehouses, cost of ordering for the warehouses and retailers, cost of shipping products between warehouses and retailers, cost of shipping products between the production plant and warehouses, and cost of holding inventory at the warehouses and retailers.

$$min(X_j, Y_{ij}, T_i, T_{ij}) = \sum_{j\in J}\left(f_j + \frac{\acute{k}_j}{T_j}\beta_{inv}\right)X_j + \sum_{j\in J}\sum_{i\in I}(\frac{k_j}{T_{ij}}\beta_{inv} + (s_{ij} + \acute{s}_j)d_i\beta_{trn} + \frac{1}{2}(h_i - \acute{h}_j)d_iT_{ij}\beta_{inv} + \frac{1}{2}\acute{h}_j d_i\beta_{inv} max\{T_j, T_{ij}\})\, Y_{ij} \quad (1)$$

$s.t$

$$\sum_{j\in J} Y_{ij} = 1 \qquad \forall i \in I \quad (2)$$

$$Y_{ij} \le X_j \qquad \forall i \in I, \forall j \in J \quad (3)$$

$$\frac{T_j}{T_{ij}} = 2^{N_{ij}} \qquad \forall i \in I, \forall j \in J \quad (4)$$

$$N_{ij} \in Z \qquad \forall i \in I, \forall j \in J \quad (5)$$

$$T_j \sum_{i\in I} d_i Y_{ij} \le C_j \qquad \forall j \in J \quad (6)$$

$$\sum_{j\in J} X_j \le P \quad (7)$$

$$T_j > 0 \qquad \forall j \in J \quad (8)$$

$$T_{ij} > 0 \qquad \forall i \in I, \forall j \in J \quad (9)$$

$$X_j \in \{0,1\} \qquad \forall j \in J \quad (10)$$

$$Y_{ij} \in \{0,1\} \qquad \forall i \in I, \forall j \in J \quad (11)$$

Constraint (2) assures that each retailer is allocated to only one warehouse. Constraint (3) guarantees that retailers will not be allocated to closed warehouses. The power-of-two policy is considered at constraint (4), and the integer requirement is represented at constraint (5). Constraints (6) and (7) show the warehouse's capacity and the maximum number of warehouses that can be established. The length of order intervals for retailers and warehouses that must be strictly positive are represented at constraints (8) and (9). Finally, the decision variables Y_{ij} and X_j are binary and are expressed by (10) and (11).

3. Solution approach

The literature review shows that both the location-allocation and the location-inventory problems are NP-hard (Cooper 1972; Daskin et al. 2002). Thus, our proposed model belongs to the class of NP-hard problems because it is a combination of the above problems. Therefore, exact methods cannot be efficient to solve it. In the litreture, general high-level procedures that are mostly used to find good approximate soulutions for NP-hard problems are meta-huristic alghorithms. The meta-heuristic algorithms combine simple heuristic algorithms to achieve better solutions than those obtained from a simple heuristic. The advantage of meta-heuristics over heuristic algorithms is that heuristics may trap in local optima. Also, there is a balance between diversified and intensified searches at meta-heuristic algorithms (Shiripour et al. 2017). The genetic algorithm seems to be one of the most used meta-heuristics among meta-heuristics applied in inventory-location problems (Qu et al. 2015; Ahmadzadeh 2017; Puga et al. 2017; Askin 2014; Alizadeh et al. 2015; Vahdani et

al. 2017). So, we use this algorithem in this research. Recent studies have shown that hybrid meta-heuristics are better than individual meta-heuristics to solve nonlinear models (Sadeghi et al. 2013; Chen et al. 2013; Sue-Ann et al. 2012). This algorithem is a combination of two metaheuristics. So, we also propose a hyrbid of genetic and simulated annealing algorithms (ESA). The details of these algorithms are as follows.

3.1. Genetic algorithm

GA is an evolutionary procedure for finding an approximately optimal solution. The GA starts with an initial population that is a set of solutions. Each member in the initial population is called a chromosome that involves problem variables. The chromosomes are improved by applying crossover and mutation for generating a new population. When stopping criteria are met, the algorithm terminates.

For our problem, a chromosome is described as a retailer-warehouse assignment (*Yij*). The length of the chromosome is considered as the number of retailers. Each element of the chromosome is a warehouse allocated to each retailer. For example, by considering five retailers and three possible warehouses' locations, a chromosome is depicted in Figure 2. Figure 2 shows that two warehouses should be established in locations 1 and 3 and retailers 1, 3 allocated to warehouse 1 and retailers 2, 4 and 5 allocated to warehouse 3. After determining *Xj* and *Yij*, the model is separated into multiple one-warehouse-multi-retailer problems. For each problem, the algorithm described by Roundy (1985) is used to obtain the length of order intervals at the warehouses (T_j) and retailers (T_{ij}).

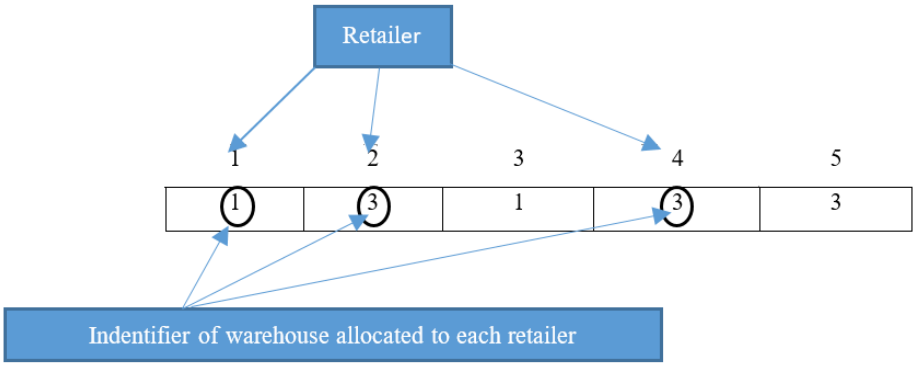

Figure 2. The defined chromosomes Y_{ij}

To prevent producing an infeasible solution in the initial population, crossover and mutation, we use a heuristic method shown in Figure 5.

3.1.1 Initial solution

Generally, one population is generated randomly and the heuristic method (Figure 5) is used to produce a feasible solution.

3.1.2 Crossover

We use the Roulette wheel selection procedure based on the fitness value of chromosomes for selecting parent chromosomes. In this method, the probability of selecting the most appropriate chromosome is greater. In this paper, appropriate chromosomes are the ones having small fitness values because of the minimization type of objective function. So, we inverse the obtained objective function for each chromosome and name it f. The probability of selecting chromosome k is $P_K = f_K \Big/ \sum_i f_i$. Then a single crossover is applied to generate new chromosomes (offsprings) (Figure 3).

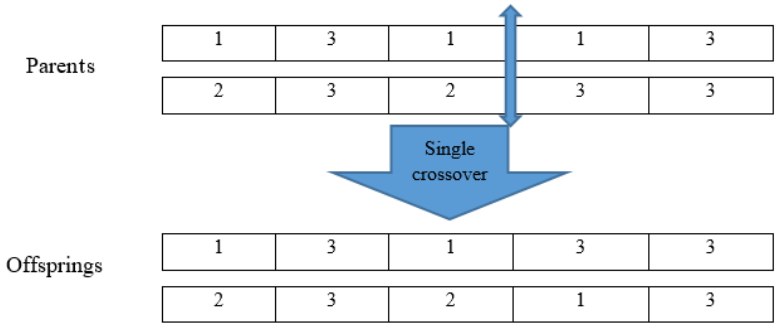

Figure 3. An example for single crossover

3.1.3 Mutation

In this paper, a chromosome (parent chromosome) is chosen randomly from the population. Then, we generate two different mutation points uniformly at random and swap the genes of their sub-strings (Figure 4).

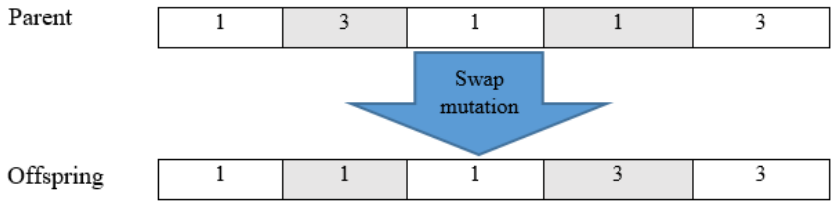

Figure 4. An example for swap mutation

3.1.4 Termination criterion

If a pre-specified maximum number of iterations are satisfied, the algorithm will stop.

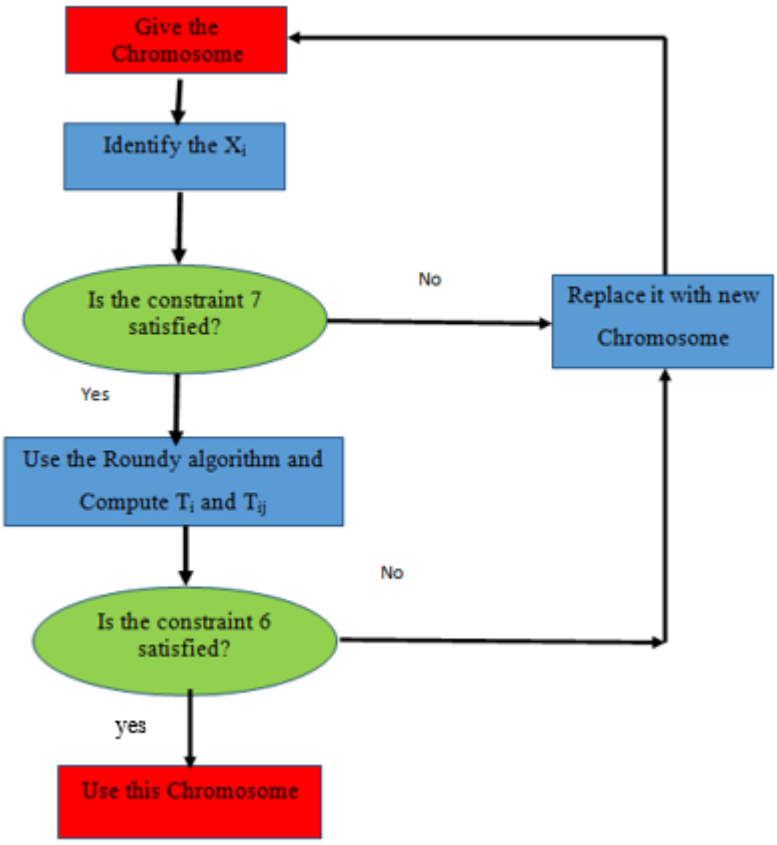

Figure 5. A flowchart of the heuristic method for selecting a feasible solution

3.2 Evolutionary simulated annealing algorithm

Kirkpatrick et al. (1983) and Gerny (1985) presented a Simulated Annealing (SA) algorithm. The SA approach works by mimicking the process of physical annealing in which a metal slowly cools down and is mostly used to solve NP-hard problems. In this algorithm, solutions and the objective values of them are equivalent to states of a physical system and the energy of the state, respectively. In this paper, we apply the evolutionary simulated annealing (ESA) algorithm proposed by Miandoabchi et al. (2011). ESA is a population-based algorithm in that SA is used as the mutation operator. The proposed ESA is described as follows:

Phase 1:

–Generate a initial population, N_p, based on the chromosome defined in Figure 2.

Phase 2:

- Repeat if the high temperature (T) is lower than a specified value.
- Select one chromosome from the population randomly
- Initialize Temperature (T_f and T_0)
  - Repeat if r is smaller than R.
    - Repeat if n is smaller than N.
    - Generate a random neighbor by applying perturbation in the allocations.
    - Check the feasibility of the generated neighbor (Figure 5).
    - Compare the current solution and generated neighbor based on SA as follows:

If the current solution is better than the offspring, we replace it; otherwise, replace it with the probability *exp (-ΔE/T$_r$)* (the difference between the objective function of the offspring and the current solution is considered as *ΔE*)

- Set the T_r as follows

$$T_r = \frac{1}{2}(T_0 - T_f).\left(1 - tanh\left(\frac{10.r}{R} - 5\right)\right) + T_f$$

– Return the best solution

– If the best solution is not the same to any individual of the population and is better than the worst individual, join it to the population and eliminate the worst case; otherwise, reject it.

Also in this algorithm, to prevent producing an infeasible solution in the initial population and mutation, we use a heuristic method described in Figure 5.

4. Experimental design

The metaheuristics used in this paper are parametric algorithms. Therefore, choosing the best values for their parameters have an impressive effect on the performance of them. We use the Taguchi method for tuning the parameters. The Taguchi is one of the most widely used methods for tuning the parameters of metaheuristic algorithms (Talbi, 2009).
In the Taghchi as an experimental design method, the factors (process inputs) which affect the efficiency of a process output are classified into two types: controllable factors (factors S) and uncontrollable factors (noise factors N). In the meta-heuristic algorithm, parameters are controllable factors and fitness function is the process output. Taguchi method builds a design by employing an approach to control N based on the number of parameters that need to simultaneously tuned and the number of levels for each parameter.

In this paper, we extract three initial values for each unknown parameters of the GA algorithem from the literature. For the GA, the four parameters that are tuned are population size (N_P), maximum number of iterations (M_{it}), probability of mutation (P_m), and probability of crossover (P_c). Employing Minitab software a L9 Taguchi design is used. Table 1 shows the used values for each parameter in the GA.

For the ESA meta-heuristic algorithm, 6 parameters are calibrated. Similar to the case of GA parameter tuning, three levels of value for each parameter are obtained from the literature. As a result, a L27 Taguchi design is utilized to tune the parameters. The parameters of interest are: population size (N_P), high temperature (T), initial temperature (T_0), final temperature (T_f), and the number of iteration in inner loops (R and N). The values for these parameters are shown in Table (1). We use Relative Percent Deviation (RPD) for scalling the resuts of proposed algorithms in each design.

Table 1. The parameters levels of the algorithms

Algorithm	Parameter	Low (1)	Medium (2)	High (3)
GA	N_p	50	100	200
	M_{it}	100	200	500
	P_m	0.1	0.2	0.3
	p_c	0.5	0.6	0.7
ESA	N_p	50	100	200
	T	100	200	300
	T_0	50	100	200
	T_f	1	2	3
	R	15	20	25
	N	10	15	20

The standard approach and the signal to noise ratio (S/N) approach can be utilized to analyze the results of Taguchi. The standard approach is employed for experiments with only one replication and signal to noise ratio is used for experiments with more than one replication. In the proposed algorithms in this paper, we use the signal to noise ratio (S/N) since we need more than one iteration. Based on the signal to noise ratio, a good condition is seen if the signal is more than noise. We aim to gain a condition that optimizes the signal to noise ratio. There are three classes of characters in the Taguchi, “bigger is better”, for which the objective function is of a maximization type, “smaller is better” where the objective function is of a minimization type and “nominal is the best” for which the objective function has modest variance around its target. In these three class, the signal to noise ratio is formulated as follows (Roy, 1990):

$$(S/N)_B = -10\log\left(\frac{1}{n}\sum_{m=1}^{n}\frac{1}{a_m^{\,2}}\right)$$

$$(S/N)_S = -10\log\left(\frac{1}{n}\sum_{m=1}^{n}a_m^{\,2}\right)$$

$$(S/N)_N = -10\log\left(\frac{1}{n}\sum_{m=1}^{n}(a-a_m)^2\right)$$

where a_m is the objective function in the mth iteration, n is the number of iteration, and a is the average of objective function. We use "smaller is better" because our problem is minimization.

The mean S/N ratio plot for different parameter levels of the GA and ESA are displayed in Figures 6 and 7. Figures show that the best parameter values of the GA are N_p= 200, M_{it}= 200, P_m=0.2 and P_c= 0.5, the best parameters of ESA are Np= 100, T=200, T_0= 50, T_f=2, R=25 and N=10. We employ these values for solving numerical examples and algorithms comparison.

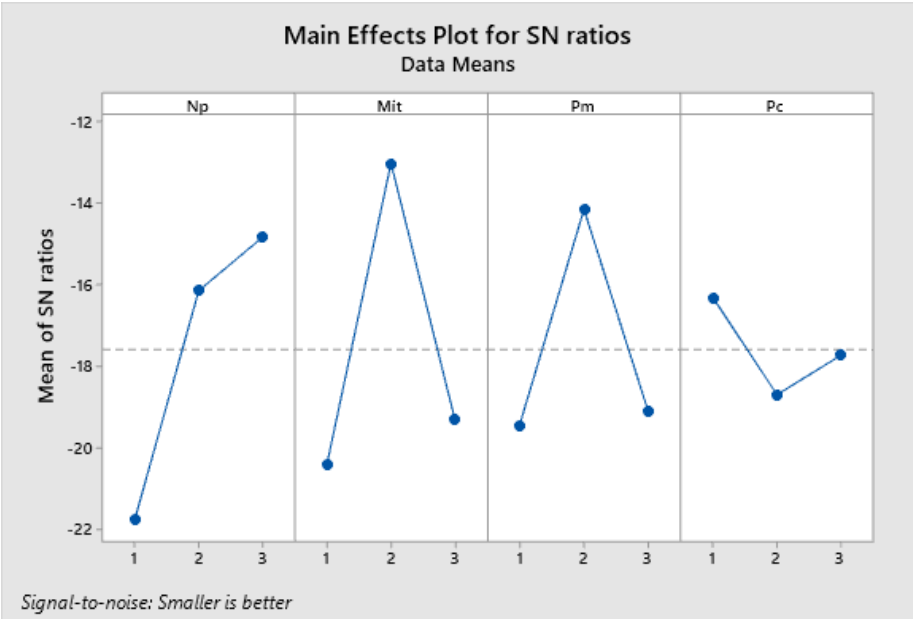

Figure 6. The mean S/N ratio plot for different levels of the parameters of the GA

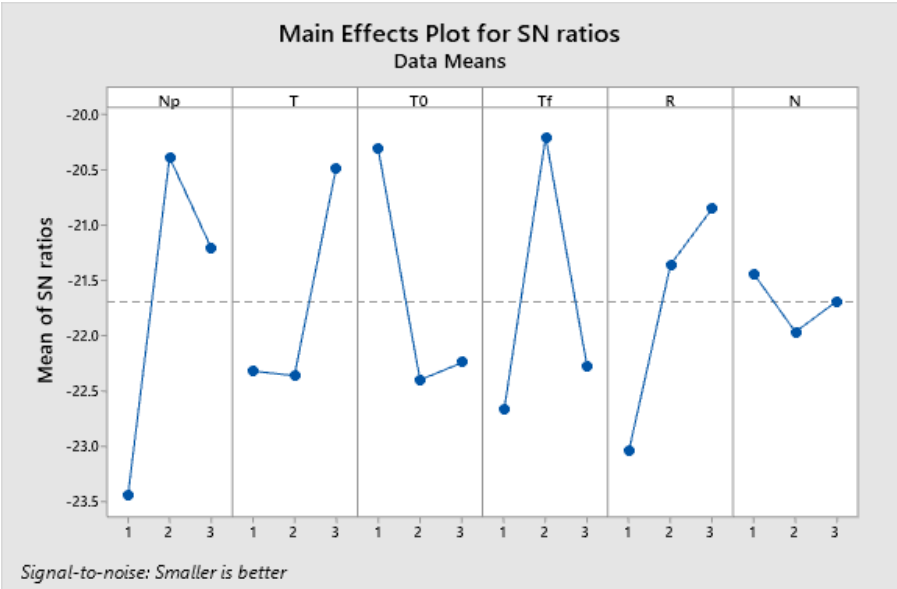

Figure 7. The mean S/N ratio plot for different levels of the parameters of the ESA

5. Computational results

In this section, to investigate the application of the two proposed algorithms to solve our model, first, the accuracy of the algorithms are tested by comparing their solutions to those obtained from Lingo 11 software. Then, the sensitivity analysis with respect to cost parameters is done. Finally, we apply algorithms to large-size numerical examples of the problem to compare their efficiency.

5.1. Testing the accuracy of algorithms

We use the parameters of Diabat et al. (2016) that are shown in Tables 2, 3 and 4. There are two possible warehouses' location and three retailers. We set β_{inv} and β_{trn} to 1.5 and consider one warehouse that can be opened (P=1).

Table 2. Parameters of warehouses

parameters	Warehouse1	Warehouse2
$\acute{k}_j$	200	400
$\acute{s}_j$	7	9
$\acute{h}_j$	4	5
f_j	6000	5100
C_j	700	600

Table 3. Parameters of retailers

parameters	Retailer 1	Retailer 2	Retailer 3
k_i	24	34	20
h_i	14	12	15

Table 4. Unit shipping cost between warehouses and retailers

s_{ij}	**Warehouse** 1	**Warehouse** 2
Retailer 1	34	43
Retailer 2	55	51
Retailer 3	39	30

Under the given values of the parameters and according to five demand scenarios displayed in Table 5, numerical examples are solved by Lingo, GA and ESA. Table 5 shows that the results of the proposed algorithms are the same as the solution obtained via exact method using Lingo11.

Table 5. Comparing GA and ESA algorithms with Lingo

scenario	Demand of retailers			Lingo objective function	GA objective function	ESA objective function
	1	2	3			
S-1	61	89	69	24958	24958	24958
S-2	52	48	50	18929	18929	18929
S-3	77	17	71	19405.47	19405.47	19405.47
S-4	60	12	45	15690.97	15690.97	15690.97

5.2. Sensitivity analysis

To get a deeper insight into the proposed model and algorithms, we do the sensitivity analysis with respect to cost parameters of the model by changing the value of one parameter by +50% and -50% at a time and keeping the other parameter values unchanged (Tables 6 and 7). On the basis of the results of Tables 6 and 7, the following observations can be made.

- If the values of parameters h'_j and h_i enhance, the optimal length of order intervals of warehouse and retailers will decrease. It is reasonable that by increasing the holding cost, warehouses and retailers keep lower inventory.
- In the case in which the values of parameters k'_j and k_i increase, the optimal length of order intervals of warehouse and retailers will increase. This means that the retailers and the warehouses will order more quantity when the order cost is high.
- If the value of the parameter s'_j increases, the nearest warehouse to production plant is chosen. By increasing s_{ij}, the optimal length of order intervals doesn't change. The corresponding managerial insight is that we consider the unit-shipping cost as a function of demand.
- When the values of cost parameters increase, the optimal total cost will increase. This indicates that increases in costs adversely affect the total cost.

Table 6. Sensitivity analysis with respect to warehouses' parameters

Parameter	% Change	Decision variables				Objective function
S_j'	+50	X_1=1	X_2= 0	Y_{11}= 1	Y_{12}=0	Lingo= 26841.21
		Y_{21}=1	Y_{22}=0	Y_{31}=1	Y_{32}= 0	GA=26841.21
		T_1=0.61	T_2= 2.103	T_{11}=0.305	T_{21}=0.305	ESA=26841.21
		T_{12}=2.103	T_{22}=2.103	T_{31}=0.305	T_{32}=0.526	
	0	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo= 24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24134.09
		T_1=3.343	T_2=0.803	T_{11}=0.418	T_{21}=3.343	ESA= 24134.09
		T_{12}=0.400	T_{22}=0.401	T_{31}=1.672	T_{32}=0.201	
	-50	X_1= 0	X_2=1	Y_{11}=0	Y_{12}=1	Lingo = 22655.84
		Y_{21}=0	Y_{22}=1	Y_{31}=0	Y_{32}=1	GA = 22655.84
		T_1=2.498	T_2=0.804	T_{11}=2.498	T_{21}=1.249	ESA = 22655.84
		T_{12}=0.401	T_{22}=0.401	T_{31}=1.249	T_{32}=0.205	
h_j'	+50	X_1=0	X_2=1	Y_{11}=0	Y_{12}=1	Lingo=24402.51
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24402.51
		T_1=1.285	T_2=0.598	T_{11}=1.285	T_{21}=1.285	ESA=24402.51
		T_{12}=0.598	T_{22}=0.598	T_{13}=0.643	T_{23}=0.299	
	0	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24134.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA=24134.09
		T_{12}=0.401	T_{22}=0.401	T_{31}=1.672	T_{32}=0.201	
	-50	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=23823.93
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=23823.93
		T_1=3.632	T_2=1.113	T_{11}=0.908	T_{21}=3.632	ESA=23823.93
		T_{12}=0.278	T_{22}=0.278	T_{31}=1.816	T_{32}=0.278	
K_j'	+50	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24698.91
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24698.91
		T_1=2.037	T_2=1.194	T_{11}=1.019	T_{21}=0.509	ESA=24698.91
		T_{12}=0.298	T_{22}=0.298	T_{31}=0.509	T_{32}=0.298	
	0	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24134.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA=24134.09
		T_{12}=0.401	T_{22}=0.401	T_{13}=1.672	T_{23}=0.201	
	-50	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=23706.07
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=23706.07
		T_1=1.314	T_2=0.593	T_{11}=0.657	T_{21}=1.314	ESA=23706.07
		T_{12}=0.296	T_{22}=0.296	T_{13}=1.314	T_{23}=0.296	

5.3. Comparison of the two algorithms

After verifying the algorithms' solutions, they can now be used to solve the large-size problems. We test the performance of the solution algorithms on one dataset containing 30 nodes (LiQ et al. 2011). Demands (d_i) are taken from Snyder et al. (2005). For *I* and *J* greater than 30, we generate data randomly. The Euclidean distance among nodes i and j is defined as the cost of shipping one unit (s_{ij}). The other parameters are randomly generated.

We consider the objective function and CPU time (t) to compare the performance of the algorithms. The results of these two measures are presented in Table 8. The optimal solutions are not known in large-size problems. So, it is necessary to achieve good lower bounds to evaluate the quality of the solutions obtained from the GA and ESA in these scales. We consider the minimum of the objective function obtained from the GA and ESA at ten runs as the best function value, f_{best}. The main finding based on Table 8 is that the best objective function obtained belongs to ESA. To analyze the variation of the obtained objective function values of the GA and ESA over ten runs, we compute the relative differences between the best objective function value and the average objective function values for all the instances as follows:

$$\%Gap = \frac{average\ objective\ function\ value - best\ objective\ function\ value}{best\ objective\ function\ value} \times 100$$

Table 7. Sensitivity analysis with respect to retailers' parameters

Parameter	% Change	Decision variables				Objective function
S_{ij}	+50	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo= 37982.09
		Y_{21}=0	Y_{22}=1	Y_{31}=0	Y_{32}= 1	GA=37982.09
		T_1=3.234	T_2= 0.802	T_{11}=0.808	T_{21}=1.617	ESA=37982.09
		T_{12}=0.401	T_{22}=0.401	T_{31}=1.617	T_{32}=0.201	
	0	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo= 24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA= 24134.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA= 24134.09
		T_{12}=0.401	T_{22}=0.401	T_{31}=1.672	T_{32}=0.201	
	-50	X_1= 0	X_2= 1	Y_{11}= 0	Y_{12}= 1	Lingo = 17210.09
		Y_{21}= 0	Y_{22}=1	Y_{31}=0	Y_{32}= 1	GA = 17210.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA = 17210.09
		T_{12}=0.401	T_{22}=0.401	T_{31}=1.672	T_{32}=0.201	
h_i	+50	X_1=0	X_2=1	Y_{11}=0	Y_{12}=1	Lingo=24618.98
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24618.98
		T_1=2.201	T_2=0.787	T_{11}=0.550	T_{21}=0.550	ESA=24618.98
		T_{12}=0.197	T_{22}=0.197	T_{13}=2.201	T_{23}=0.197	
	0	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24134.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA=24134.09
		T_{12}=0.401	T_{22}=0.401	T_{13}=1.672	T_{23}=0.201	
	-50	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=23670.86
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=23670.86
		T_1=0.586	T_2=0.846	T_{11}=0.586	T_{21}=0.586	ESA=23670.86
		T_{12}=0.846	T_{22}=0.846	T_{31}=0.293	T_{32}=0.423	
K_i	+50	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24452.30
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24452.30
		T_1=1.487	T_2=0.838	T_{11}=0.743	T_{21}=1.487	ESA=24452.30
		T_{12}=0.419	T_{22}=0.419	T_{31}=0.743	T_{32}=0.419	
	0	X_1= 0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=24134.09
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=24134.09
		T_1=3.343	T_2=0.802	T_{11}=0.418	T_{21}=3.343	ESA=24134.09
		T_{12}=0.401	T_{22}=0.401	T_{13}=1.672	T_{23}=0.201	
	-50	X_1=0	X_2=1	Y_{11}= 0	Y_{12}= 1	Lingo=23880.45
		Y_{21}= 0	Y_{22}= 1	Y_{31}= 0	Y_{32}= 1	GA=23880.45
		T_1=1.658	T_2=0.844	T_{11}=0.414	T_{21}=0.414	ESA=23880.45
		T_{12}=0.211	T_{22}=0.211	T_{13}=0.414	T_{23}=0.211	

Table 8. Results for the large-size problems

Instance			Algorithms								
			GA					ESA			
I	*J*	*P*	f_{best}	f_{low}	f_{ave}	t_{ave}(s)	Gap	f_{low}	f_{ave}	t_{ave}(s)	Gap
4	4	2	25185.45	25185.45	25185.45	12.99	0	25185.45	25185.45	9.52	0
5	5	2	27466	27466	27466	15.91	0	27466	27466	11.9	0
7	7	3	25940.07	27197	27883.2	22.36	7.49	25940.07	26225.06	17.29	1.10
10	5	3	30647	30842	31187	21.08	1.76	30647	30874.6	22.84	0.74
10	7	3	31300.95	31329	31954	34.49	2.09	31300.95	31758	31.06	1.46
10	10	3	30764	31694.71	32649	28.94	6.13	30764	32894	26.91	6.92
12	10	3	31720	35581	36217	82.33	14.18	31720	32362	76.83	2.02
12	12	3	33925	36409.06	37556.7	99.06	10.71	33925	34938.6	101.24	2.99
15	10	4	35837	38493	39426	68.24	10.01	35837	36167.2	53.92	0.92
15	15	4	39400	40042.19	42371	86.29	7.54	39400	40297	72.5	2.28
17	12	5	40378	41124	41635	110.37	3.11	40378	40421.2	92.53	0.11
17	17	5	40801	41480.87	42617	162.44	4.45	40801	40998	142.5	0.48
20	12	7	41954.75	44055	45751	139.5	9.05	41954.75	42218.8	136.82	0.63
20	15	7	41920.52	43475	43994	148.02	4.95	41920.52	43267	139.21	3.21
20	17	10	41638	45764	46138	179.47	10.81	41638	42191	154.52	1.33
20	20	10	41726.26	44132	45246	138.52	8.43	41726.26	42364	139.33	1.53

Table 8. Continued

Instance			Algorithms								
			GA					ESA			
I	*J*	*P*	f_{best}	f_{low}	f_{ave}	t_{ave}(s)	Gap	f_{low}	f_{ave}	t_{ave}(s)	Gap
25	20	13	42641	52185.45	53568	194.72	25.62	42641	43291	182.66	1.52
25	25	13	42252.01	52204	54021	253.04	27.85	42252.01	43563.06	229.48	3.10
30	25	15	45132.75	56252.5	57596	194.2	27.61	45132.75	47720.69	189.64	5.73
30	30	15	42212.8	57837	58324	204.14	38.17	42212.8	44052	202.61	4.36
35	30	17	45431	59340	60454	210.29	33.07	45431	48032	206.22	5.72
35	35	17	45768	60441.2	61988	256.54	35.44	45768	48329	241.37	5.59
40	35	20	48246	62627	63375	198.97	31.36	48246	50564	204.97	4.80
40	40	20	50533	61284	63087	252.76	24.84	50533	52921	234.19	4.73
45	40	23	51954	63465	65212	241.75	25.52	51954	53264	240.45	2.52
45	45	23	53076	65824	66945	257.03	26.13	53076	55824	251.52	5.18
50	45	25	52148	69322	72625	276	39.27	52148	54968	268.01	18.69
50	50	25	54766	70999	72843	282.5	33	54766	58920	276.94	20.20

Based on Table 8 and Figure 8, the relative differences between the best objective function values and the average objective function values over ten runs of the ESA are smaller than the ones for GA. Therefore the ESA is more robust than the GA. It is noticeable that by increasing the number of I and J, the difference between the values of percentage gaps of the ESA and GA increases. This may confirm that the ESA is more efficient than the GA in large-size numerical examples. Moreover, according to Table 8 and Figure 9, it can be said that by increasing the size of the problem, the CPU time increases too. This possibly confirms that by increasing the number of warehouses and retailers, the computational effort to indicate the best locations of warehouses, allocate retailers to them by considering constraints, and determine inventory policy of warehouses and retailers is much more; the algorithms also need more time to solve them. The result shows that the proposed ESA works faster than the GA algorithm except for two instances.

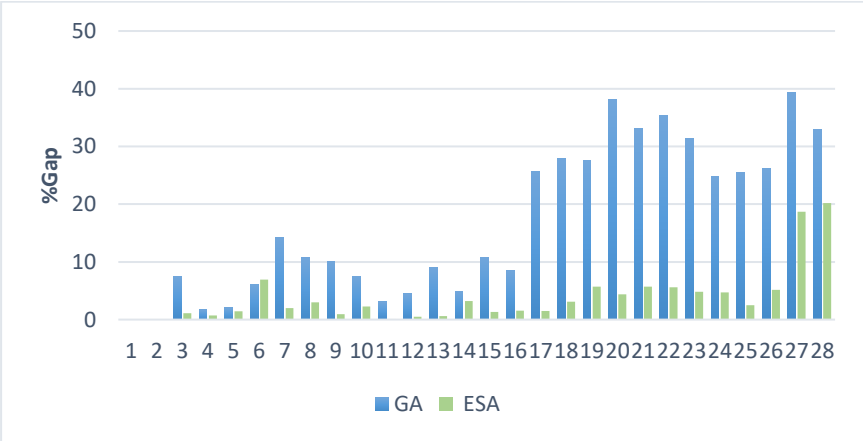

Figure 8. The percentage gaps between the best function value (f_{best}) and average function value (f_{ave}) obtained from the GA and ESA for large-size numerical examples

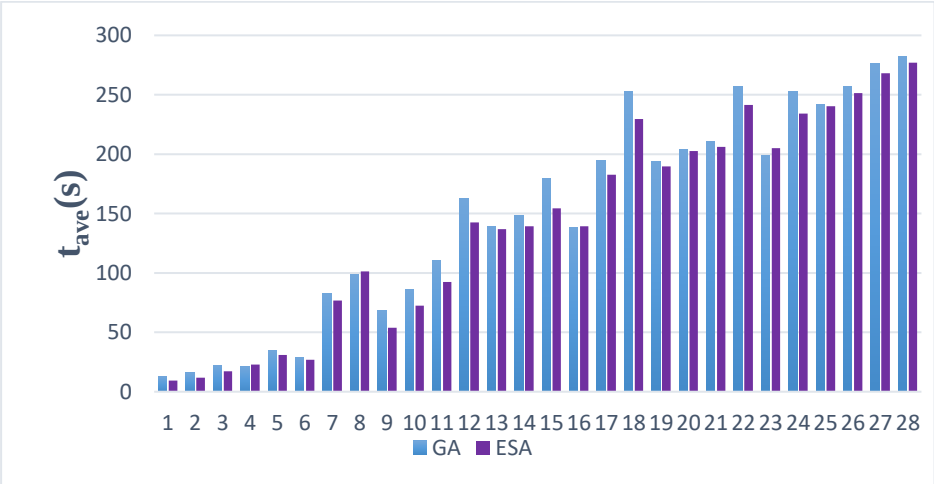

Figure 9. The average time for running the GA and ESA for large-size numerical examples

6. Conclusion

We propose a multi-echelon joint inventory-location model for a three-level supply chain. This supply chain includes one production plant that distributes products to retailers through warehouses. The proposed model decides on the optimal location of warehouses, allocates retailers to warehouses, and determines inventory policies at the warehouses and retailers, simultaneously. Here, the number of warehouses that can be opened and their capacity are limited. We propose two efficient algorithms: a genetic algorithm (GA) and an evolutionary simulated annealing algorithm (ESA). We use the Taguchi method for tuning the parameters of the proposed algorithms. The small size problems are solved by Lingo11 software package, the GA and ESA. Then numerical examples verify the accuracy of our algorithms. Also, the sensitivity analysis with respect to the main parameters of the model is carried out. The large-size numerical examples are provided to investigate the efficiency of the proposed solution algorithms. The average of computing time and the percentage gaps between the best solution values and the average objective values of the GA and ESA are calculated for comparing the algorithms. The results indicate that the two algorithms are efficient in solving the proposed model but the ESA outperforms the GA on the optimal solution, computing time, and stability. Broad scopes can expand this research. For instance, we consider the demand of retailers deterministic; even though there is a certain population in each retailer location for the product, all of them may not intend to buy the product. So, considering stochastic demand makes the problem more practical. In this research, we model a single product with unlimited shelf-life, another possible extension to the problem would be to develop this problem toward considering multi products and perishable products. Also, investigation of other meta-heuristics or hybrid meta-heuristics such as particle swarm optimization algorithm may be useful in a future research.

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