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# The Use of Metaheuristics as the Resolution for Stochastic Supply Chain Design Problem: A Comparison Study

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**Abstract**

In a competitive and maintainability context, each company looks for optimizing its supply chain in order to satisfy its customers by providing the best quality products in the best delays and with the lost costs. In this sense, we are interested in a single- commodity stochastic supply chain design problem. Our supply chain is composed of suppliers and retailers. The objective is to find the best location for distribution centres (DCs) and to serve retailers from suppliers through DCs in a random supply lead time. We presented a non-linear optimization model that integrates the selection of suppliers, the location of DCs, and the retailers' allocation decisions with an oriented cost function to minimize. Note that the determination of exact solutions to this problem is a NP-hard problem. Accordingly, we proposed an optimization approach using three different metaheuristics: genetic algorithm, simulated annealing, and taboo search to solve this problem and find the best supply chain structure (location of DCs, allocation of suppliers to DCs and DCs to retailers). Computational results are presented and compared to evaluate the efficiency of the proposed approaches.

**Keywords:** Distribution network; Suppliers selection; Metaheustics; Optimization.

## 1. Introduction

A supply chain can be seen as a set of facilities provided by the producers of raw materials to the end consumer through all possible intermediates like processors, wholesalers, transporters, and distributors. The complete optimization of the supply chain is achieved by integrating strategic, tactical, and operational decision-making in terms of design, management, and control of activities (Gebennini et al., 2009). The current conditions such as product delivery by the given deadlines, product quality imposed by customers, and the after-sales service require the company to be increasingly efficient in order to remain on the market. This requires the optimization of the company's supply chain through the right choice of entities such as suppliers, distribution and storage centres, and all facilities. Rezaei and Adressi (2015) investigated seven active supply chains with similar construction in terms of supplier, producers, distributors, and customers in tile industry in Yazd province in Iran. The researchers proposed a data envelopment analysis (DEA) model with inputs and outputs and presented the obtained results for constant and variable efficiency. In this study, we address a logistics facilities design problem. Our approach consists of defining the best supply chain structure through the consideration of three decision types, i.e. DCs location, DCs to retailers' allocation, and selection of suppliers. This problem was initially addressed by Tanonokou et al. (2007). The authors integrated for the first time the three decisions in the same optimization model and solved it based on a Lagrangian relaxation method. The aim of our study is to propose other resolution methods, namely mono-objective metaheuritics to solve the problem under study and find the best structure for the studied supply chain. The objective of this study aims to find the best metaheuristic for this problem and use it for our future research studies.

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The rest of the paper is organized as follows: Section two presents the review of literature dedicated to the problems of location-allocation and supplier selection. In section three, the problems with their assumptions and their mathematical formulations are described. Then, the proposed resolution approaches are illustrated in section four. The obtained results and their analysis are given in section five. Section six concludes with future research trends.

## 2. Review of the Related Literature

This paper deals with two research areas: the problems of facility location and supplier selection that have been widely addressed. However, many studies consider the integration of strategic, tactical, and operational decisions in supply chain design problems. Many researches are still needed to integrate other concepts in order to approximate real-life problems (Melo et al. , 2009). Melo et al. (2009) present a review of facility location and supply chain management problems. The authors present different classification of many articles based on different parameters like the assumed number of location layers and commodities. The authors show the importance of location-allocation decisions in supply chain management and present a large discussion about the integration of several planning decisions in classical location-allocation decisions. They said that "It is now clear that two aspects can hardly be avoided in strategic supply chain planning: a multi-layer network and multiple commodities. Therefore, appropriate models for strategic decision-making must consider these features. A detailed literature review related to location-allocation problems has been presented by Owen and Daskin (1998). The researchers present static and deterministic problems and conclude the paper by a discussion about stochastic problems for both types based on random parameters or based on scenarios. Snyder and Daskin (2005) present location-allocation models based on the uncapacitated facility location problem (UFLP) and the P-median problem with Lagrangian relaxation for their resolution. Bischoff and Kerstin (2009) present a general class of location-allocation problems with candidate sites. Thus, a mixed integer multi-dimensional optimization model is proposed with several resolution methods. The model of joint inventory-location stochastic versions was first presented by Shen et al. (2003) and Daskin et al. (2006). Maliki et al. (2013) solve this problem for the multi-supplier multi-objective case using a multi-criteria genetic algorithm (NSGAII) minimizing relative costs. A sensitivity analysis study for this problem is presented in Maliki et al. (2011) with the consideration of an impact factors study on the supply chain performances. The authors have concluded that the opened DCs increase in line with the increase of transportation and inventory management costs and decreases when the customer's demand and supply lead time variances increase. The same problem is addressed using different inventory management policies at the DCs (Maliki & Sari, 2012).

Felfel et al. (2015) propose a two-stage stochastic programming model for a multi-site, multi-product, multi-period supply chain network of textile and apparel industry with uncertain demand. The obtained results using Lingo is presented with a robustness study of the used metrics. One of the main criteria for maintaining a business is the good selection of suppliers. To make this, several selection criteria are to be taken into consideration. Solving supplier selection problem is a critical decision. De Boer et al. (2001) affirm that for a successful supplier selection process, companies must perform the supplier selection through different steps. Many methods are presented by the authors to solve the mentioned problem. The supplier selection decision is complicated due to the existence of several qualitative and quantitative selection criteria. Jain et al. (2009) present a detailed state of the art resolution? For supplier selection problem. The authors also describe different criteria used for evaluating supplier performances during different steps of supplier selection cycle. Inemek and Tuna (2009) evaluate supplier selection strategies by examining the structure of supply relationships between Turkish automotive component manufacturers and their global buyers, global buyers' supplier evaluation and selection strategies, and the impact of global buyers' supplier evaluation and selection strategies on the supplier performance in the long run. Vijayashree and Uthayakumar (2015) develop an algorithm used to solve a two-echelon single vendor and single buyer supply chain inventory problem. A mathematical model is presented in order to optimize simultaneously the order quantity, process quality, lead time, and number of deliveries from the vendor to the buyer with minimizing total generated costs. Tanonkou (2007) addresses the unreliable facilities of single- product distribution network design problem. The researcher proposes two different design models with Monte Carlo optimization and Lagrangian relaxation approach. Two cases are considered by the authors,i.e. the first problem with unreliable DCs and single supplier distribution network (Tanonkou et al.,2006), and the second problem with unreliable suppliers and multi-supplier distribution network (Benyoucef et al.,2013). In their studies, the authors consider that the unavailable facilities are lost permanently. Shishebori and Ghaderi (2015) consider an uncapacitated facility location design problem with unreliable transportation links in a mountainous region. In this respect, a mathematical model is presented in order to find the optimum locations of new facilities regarding transportation links disruptions and the new transportation links that should be constructed in the proposed network. A hybrid algorithm using LP relaxation and variable neighbourhood search metaheuristic is developed to solve the studied problem. The obtained results are presented and compared to Cplex optimizer results showing the proposed algorithm effectiveness. Maliki et al. (2014) and Maliki et al. (2016) consider a single supplier / multi-supplier stochastic distribution network with distribution centre location (DCs) decisions and DCs' unavailability management. These problems are solved using genetic algorithm (GA) to find the best supply chain structure. The latter is simulated with the presence of DCs failures with the consideration of two different approaches, i.e. replacing each unavailable DC with the closest and performing a reallocation using the same genetic algorithm.

## 3. Problem Statement and Formulation

In this work, we consider a set of suppliers K and a set of retailers I. Each retailer location is a potential DC location. We need to locate a set of DCs noted J to satisfy the random demands generated by retailers. Note that each DC uses the economic order quantity (EOQ) for its inventory management with a safety stock avoiding the stock- out possibility during the randomly considered supply lead time from the supplier to the DC. Figure 1 presents the studied supply chain structure.

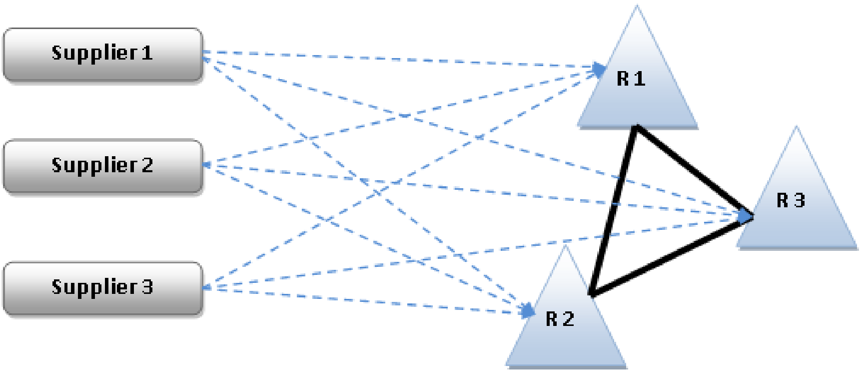


**Figure 1.** The studied supply chain model

We aim to find the best location of DCs (each DC is identified by its location zone), and the best allocation of DCs to retailers and of selected suppliers to DCs. Note that the DCs and the supplier numbers and locations are not known a priori. So, three different metaheuristics are used to determine the structure of the studied supply chain minimizing the total generated cost. In our approach, a proposed solution is composed of binary value 0 or 1 with three parts, the first one concerns DCs location decisions, the second is reserved to the assignment of retailers to DCs, and the third shows the different allocations of suppliers to DCs.

### 3.1 Notations and Assumptions

The following variables and notations are used for the considered problem mathematical formulation:

***The used notations are:***

$\boldsymbol{I}$: Retailers set indexed by i;
$\boldsymbol{K}$: Suppliers set indexed by k;
$\boldsymbol{DC_j}$: Distribution centre DC located at retailer j;
$\boldsymbol{\mu_i}$: Retailer i global demand;
$\boldsymbol{D_j}$: $\boldsymbol{DC_j}$ daily demand;
$\boldsymbol{\sigma_i^2}$: Retailer i global demand variance;
$\boldsymbol{f_j}$: Locating $\boldsymbol{DC_j}$ fixed annual cost;
$\boldsymbol{d_{ij}}$: Per-unit shipement cost from $\boldsymbol{DC_j}$ to retailer i;
$\boldsymbol{h_j}$: Per- unit per year $\boldsymbol{DC_j}$ Inventory holding cost;
$\boldsymbol{F_{jk}}$: Fixed distribution cost from supplier k to $\boldsymbol{DC_j}$;
$\boldsymbol{a_{jk}}$: Per-unit transportation cost from supplier k to $\boldsymbol{DC_j}$;
$\boldsymbol{L_{jk}}$: Mean distribution time in days from supplier k to $\boldsymbol{DC_j}$;
$\boldsymbol{\lambda_{jk}^2}$: Lead-time Variance from supplier k to $\boldsymbol{DC_j}$;
$\boldsymbol{\alpha}$: DCs desired service level;
$\boldsymbol{Z_\alpha}$: Standard normal variate such that $P(Z \leq z_\alpha)$;

***The decision variables are:***

$\boldsymbol{X_j}$= {1 if $\boldsymbol{DC_j}$ is located; 0 otherwise};
$\boldsymbol{Y_{ij}}$ = {1 if retailer i is served by $\boldsymbol{DC_j}$; 0 otherwise};
$\boldsymbol{Z_{jk}}$ = {1 if supplier k is selected to supply$\boldsymbol{DC_j}$; 0 otherwise};

### 3.2 Mathematical Model

We propose the following non-linear mixed-integer mathematical problem formulation; this model is obtained based on the study of Tanonkou et al. (2007). The problem resolution allows us to determine the decision variables $X_j$, $Y_{ij}$ ,and $\boldsymbol{Z_{jk}}$:

$$(MF) J^* = \min_{X,Y,Z} \boldsymbol{J}(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Z})$$

With $\boldsymbol{J}(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Z})$ defined by

$$\mathbf{J}(\mathbf{X},\mathbf{Y},\mathbf{Z}) = \sum_{j\in I} \mathbf{f_j X_j} + \sum_{j\in I}\sum_{i\in I} \boldsymbol{\mu}_\mathbf{i} \mathbf{d_{ij} Y_{ij}} + \sum_{j\in I}\sum_{i\in I}\sum_{k\in K} \boldsymbol{\mu}_\mathbf{i} \mathbf{a_{jk} Y_{ij} Z_{jk}} + \sum_{j\in I}\sum_{k\in K}\sqrt{\mathbf{2 h_j F_{jk}} \sum_{i\in I} \boldsymbol{\mu}_\mathbf{i} \mathbf{Y_{ij}}}\, \mathbf{Z_{jk}}$$

$$+ \sum_{j\in I}\sum_{k\in K} \mathbf{Z}_{\boldsymbol{\alpha}} \mathbf{h_j} \sqrt{\mathbf{L_{jk}} \sum_{i\in I} \boldsymbol{\sigma}_\mathbf{i}^2 \mathbf{Y_{ij}} + \boldsymbol{\lambda}_\mathbf{jk}^2 \mathbf{D_j^2}}\, \mathbf{Z_{jk}} \qquad (\mathbf{1})$$

Subject to

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

$$\sum_{k\in K} \mathbf{Z_{jk}} = \mathbf{X_j} \qquad \forall\ \mathbf{j} \in \mathbf{I} \qquad (\mathbf{3})$$

$$\mathbf{Y_{ij}} \le \mathbf{X_j} \qquad \forall\ \mathbf{i},\mathbf{j} \in \mathbf{I} \qquad (\mathbf{4})$$

$$\mathbf{X_j}, \mathbf{Y_{ij}}, \mathbf{Z_{jk}} \in \{\mathbf{0},\mathbf{1}\} \qquad \forall\ \mathbf{i},\mathbf{j} \in \mathbf{I}\ \forall\ \mathbf{k} \in \mathbf{K} \qquad (\mathbf{5})$$

The objective function (1) minimizes total cost which represented the sum locating facilities with fixed cost, the costs of shipment, and transportation from DCs to retailers and from suppliers to DCs. By assuming that each DC uses an EOQ policy, the total inventory costs at the DCs are represented by the third term. Further, the last term is reserved for the presentation of the costs of holding safety stock at the DCs in order to maintain a service level $\boldsymbol{\alpha}$. Constraint (2) is used to guarantee that each retailer is assigned to a single located DC. Constraint (3) ensures that each open DC is supplied only by one supplier. Constraint (4) states that retailers can be only assigned ($\mathbf{Y_{ij}} = \mathbf{1}$) to opened DCs ($\mathbf{X_j} = \mathbf{1}$). Constraints (5) are standard integrity constraints.

## 4. Resolution Approaches

The present integer programming model is non-linear and the determination of its exact solution depends on NP-hard problem (Tanonokou et al., 2007). We have implemented three different algorithms to solve it in order to determine the best supply chain structure. In the present approach, a candidate solution is presented using binary values 0 or 1, where each one is divided into three parts. The first one is allowed to the DCs location, the allocation of retailers to DCs is shown in the second part, and the last one is reserved for the assignment of the different DCs to suppliers. Each candidate solution fitness is evaluated based on the total generated cost according to equation (1) (see section 3.2).

Therefore, each solution representing a structure of a supply chain is composed of three parts, each one corresponds to one variable decision $\mathbf{X_j}$ or $\mathbf{Y_{ij}}$ or $\mathbf{Z_{jk}}$ (see section 3.2). Thus, an integer representation is used by assigning to each gene a binary value (0 or 1). A chromosome representation example corresponding to a problem with 4 retailers (There are only 4 candidates DCs because the DCs are located in the same regions as retailers) and 3 potential suppliers are shown in Figure 2.

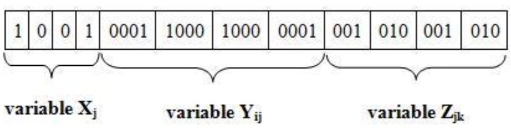


**Figure 2.** A candidate solution example

### 4.1 Genetic Algorithm

The first developed approach is based on a genetic algorithm (GA). The steps are as follows:

**Step 1** (initial population generation):
**1:** The initial population P with size N is generated randomly (each individual represents a solution $\mathbf{X_j}$, $\mathbf{Y_{ij}}$, $\mathbf{Z_{jk}}$).
**2: For** each individual from population P
**3: If** the generated solution is infeasible * **then** execute the correction procedure.
**4:** Evaluate the fitness of this individual (Using equation (1) section **3.2**).
**5: If** the objective function is lower than the best solution **then** update the best solution.
**6: End For**
**7: While** (has not meet stop criterion)

**Step 2** (Selection):
**8:** Select the individuals for reproduction using the « binary tournament selection ». This step is performed by selecting randomly two solutions of the current population P and choosing the solution having the lowest fitness value.

**Step 3** (Crossover):
**9:** Apply the operator of crossing using single point crossover with probability $0.25 \leq Pc \leq 0.95$ (to obtain a population G of N new individual).

**Step 4** (Mutation):
**10:** Apply the operator of mutation on the new individuals based on a deterministic mutation with probability *Pm* between 0.05 and 0.1.

**Step 5** (Evaluation of the individuals):
**11: For** each individual from population G
**12: If** the solution is infeasible * **then** execute the correction procedure.
**13:** Evaluate the fitness of this individual (Using equation (1) section **3.2**).
**14: If** the objective function is lower than the best solution **then** update the best solution.
**15: End For**

**Step 6**(Constitution of the next generation)
**16:** The elements of the next generation are the N best solutions from P and G (elitism)
**17: End While**

### 4.2 Simulated Annealing

In the second proposed approach, we use a simulated annealing based on algorithm which is a method developed by physics specialists in 1983 in a study by Kirkpatrick et al. The principle of this algorithm is simple. It starts with a high initial temperature T and an initial solution which may be selected randomly. For each iteration of the algorithm, a new solution is generated by a random elementary modification of the current solution, which causes a variation of the energy ($\Delta$E) of the system and therefore of the objective function. According to these movements, two scenarios can be considered:

- If there is an objective function improvement, the latter solution is automatically saved;
- If this movement degrades the objective function, the new solution may not be rejected, and can be accepted with a probability dependent on the variation of the objective function and temperature. The solution acceptance peculiarity allows us to better explore the search space and the probability of finding satisfactory solutions.

Once the thermodynamic equilibrium is reached slowly, we decrease the system temperature before moving on to the next iteration. The temperature reduction function is very important because a small decrease in the temperature can cause a slow convergence of the algorithm, while leading to a sharp decrease risk of trapping algorithm in a local minimum. The process iterates until the stopping criterion is reached. The principle of this algorithm is simple. It starts with an initial solution; its iterative process tries to converge to the optimum solution for each iteration by replacing the current solution by means of the best solution found in its neighbourhood.

In our case, we start with a temperature equal to 10 degrees. This temperature is decreased passing from one iteration to the other multiplied by a parameter α equal to 0.5. The pseudo code of the used simulated annealing algorithm is as follows:

**Step 1**(The initial configuration built):
**1:** Build the initial state (Generate $\mathbf{X_j}$, $\mathbf{Y_{ij}}$and $\mathbf{Z_{jk}}$ randomly).
**2: If** the generated solution is infeasible * **then** execute the correction procedure.
**3:** Evaluate the objective function (Using equation (1) section **3.2**).
**4: While** (has not meet stop criterion)

**Step 2** (The solution update):
**5:** Modify the value of a position selected randomly from the generated solution.
**6: If** the obtained solution is infeasible * **then** execute the correction procedure.
**7:** Evaluate the objective function (Using equation (1) section **3.2**).
**8: If** the objective function is lower than the best solution **then** update the best solution (elitism).

**Step 3** (The next solution acceptance):
**9: If** the objective function is decreased **then** this solution is accepted.
**10: Else** generates a random number between 0 and 1.
**11: If** the generated number is lower or equal to $exp\left(-\Delta \mathrm{E}/_{\mathrm{T}}\right)$**then** this solution is accepted.
**12: End If**

**Step 4** (The temperature updating)
**13:** Slow decrease of *T*.
**14: End While**

### 4.3 Taboo Search

Our last used optimization approach is based on a taboo search algorithm. The taboo search is formalized by Glover in 1986. This method is particularly based on mechanisms inspired by human memory. The taboo method uses the memory Principe for overcoming local optima.

As simulated annealing, the taboo search is a solution-based metaheuristic. Otherwise, this method provides a set of the current solution **S** neighbours **V(S)** that is examined to select the best next solution unlike simulated annealing that generates one neighbour solution randomly in each iteration. This transition from a solution to another is done in two stages, the first is to generate a set of the current solution neighbours in one elementary movement, and then select the best one after evaluating the objective function of the studied problem for each built configuration. This choice is adopted even if it is worse than the current solution. So thanks to this mechanism of accepting the objective function deterioration, the taboo search avoids local minima.

The problem is to return to an already chosen configuration or cycles between two solutions. To avoid this, the mechanism is to prohibit, hence the name taboo, access to the latest solutions through information stored in a taboo list that is a short memory that will be used to prevent movements to the last visited solutions.

In this work, we generate three neighbours and we use a taboo list of three elements. The steps of this algorithm are summarized as follow:

**Step 1** (The initial configuration built):
**1:** Build the initial state S (Generate $\mathbf{X_j}$, $\mathbf{Y_{ij}}$and $\mathbf{Z_{jk}}$ randomly).
**2: If** the solution S is infeasible * **then** execute the correction procedure.
**3:** Evaluate the objective function (Using equation (1) section **3.2**).
**4:** Initialize the parameters (taboo list size, number of neighbours,...)
**5: While** (has not meet stop criterion)

**Step 2** (Neighbours generation):
**6: For** t = 1 **to** number of neighbours
**7:** Modify the value of a position selected randomly from the solution S according to no-taboo moves (Modification of S).
**8:If** the obtained solution is infeasible * **then** execute the correction procedure.
**9:** Evaluate the objective function for each neighbour (Using equation (1) section **3.2**).
**10: End For**

**Step 3** (Select the next neighbour or the next configuration):
**11:** Select the best neighbour T.
**12:** Insert movement *T->S* in the taboo list

**13: If** the objective function of $T$ is lower than the best solution **then** update the best solution.
**14:** New current configuration $S=T$
**15: End If**
**16: End Whi le**

* If a solution is infeasible, we execute a correction procedure after mutation to verify the following constraints:

- We need to open one DC at least;
- Each retailer must be affected to one DC;
- Each open DC must be supplied by one supplier;
- A retailer cannot be served by a closed DC.

## 5. Obtained Results and Comparison Study

In order to evaluate the proposed approach performance, it is necessary to take into account different supply chain instances of different sizes. These instances can be generated by varying retailer number who represents the candidates' DCs number and the suppliers number. We consider five different scenarios for each instance. The simulations are performed using a Pentium Core *i5* 2.3 GHZ and 4 GB of RAM. It is also noted that the used metaheuristics are implemented in "VBA" language. The considered parameters can be presented as follows:

- **The retailer location number (#RL):** the studied problem is considered with 10, 15, 20, 30, 40 and 60 retailers (each one can be selected to host a DC).
- **The supplier number (#F):** the studied problem is considered with 4, 6, 8, 12, 15 and 18 suppliers.
- **Retailer demands:** the mean demand $\boldsymbol{\mu_i}$ for each retailer is discredited through time t, this parameter is assumed to be randomly generated with $\boldsymbol{\mu_i(t) \sim U[100,\ 1600]}$.
- **Supply lead times:** for each potential location, this parameter is assumed to be randomly generated with $\boldsymbol{L_{jk} \sim U[10,\ 30]}$.
- **The demand and supply lead time standard deviations:** the former is randomly generated with $\boldsymbol{\sigma_i \sim U[50,\ 100]}$and the latter is generated according to $\boldsymbol{\lambda_j \sim U\ [5,\ 10]}$.
- **Fixed facility location cost($\boldsymbol{f_j}$), transportation cost ($\boldsymbol{a_{jk}}$) and shipment cost ($\boldsymbol{d_{ij}}$):** are randomly generated with respect to $\boldsymbol{f_j \sim U[4500,\ 10000]}$, $\boldsymbol{a_{jk} \sim U[2,\ 10]}$ and $\boldsymbol{d_{ij} \sim U[1, 5]}$.
- **Desired service level:** $\boldsymbol{\alpha = 97.5}$% for $\boldsymbol{Z\alpha = 1.96}$ for all the studied problems.
- **Inventory holding costs($\boldsymbol{h_j}$):** all DCs constant value is set to be 25.
- **Fixed distribution costs($\boldsymbol{F_{jk}}$):** all suppliers to DCs constant value, is set to be 50.
- **Working days Number:** 250 working days have been considered.

Table 1 illustrates results the supply chain structure (located DCs and selected suppliers) and the global generated cost obtained for six different case simulations for each instance of the studied problem.

**Table 1.**Obtained results

| | | ***Genetic algorithm*** | | | ***Simulated annealing*** | | | ***Tabu search*** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***#RL*** | ***#F*** | ***#DC*** | ***#S*** | ***Cost*** | ***#DC*** | ***#S*** | ***Cost*** | ***#DC*** | ***#S*** | ***Cost*** |
| 10 | 4 | ***3*** | ***2*** | ***115.025*** | ***5*** | ***4*** | ***179.537*** | ***3*** | ***2*** | ***122.620*** |
| 15 | 6 | ***5*** | ***2*** | ***193.050*** | ***6*** | ***3*** | ***191.052*** | ***8*** | ***5*** | ***206.453*** |
| 20 | 8 | ***8*** | ***5*** | ***276.708*** | ***9*** | ***6*** | ***344.186*** | ***8*** | ***6*** | ***285.071*** |
| 30 | 12 | ***12*** | ***8*** | ***432.390*** | ***12*** | ***8*** | ***482.945*** | ***11*** | ***7*** | ***442.583*** |
| 40 | 15 | ***15*** | ***9*** | ***590.146*** | ***16*** | ***10*** | ***681.031*** | ***17*** | ***11*** | ***631.177*** |
| 60 | 18 | ***23*** | ***13*** | ***910.689*** | ***25*** | ***15*** | ***978.915*** | ***24*** | ***13*** | ***940.655*** |

- ***#DC***: Number of located DCs.
- ***#S***: Number of selected suppliers.
- The costs are presented in millions money unit.

From Table 1, it is shown that globally generated cost increases compared to the located DCs number and selected suppliers. It is also clear that the costs obtained by the genetic algorithm are better than the ones obtained by the other metaheuristics showing the effectiveness of the developed genetic algorithm. So, we can conclude that mataheuristics with population get better results compared to metaheuristics using one solution for this problem resolution.

## 6. Conclusions and Perspectives

In this paper, we have studied a location-allocation integrated supplier selection problem. We have proposed three metaheuristics-based optimization approaches to solve a stochastic distribution network problem design by integrating the strategic decisions of supplier selection, location of DCs, and retailer allocation. We have also presented a non-linear integer-programming model which determines all the decisions considered in our study in order to minimize both the location of DCs, shipment and transportation costs, the total inventory cost at the DCs, and the holding safety stock cost at the DCs. The incorporation of these costs leads to NP-hard problem. Three mono-objective metaheuristics are used to solve this problem. The comparison between the three approaches through total generated costs has shown that the genetic algorithm- based strategy provides better performance.

This work has identified a research for several future directions. The most immediate one is to consider other metaheuristics. It is also possible to consider suppliers with limited supply capacities. We also aim to perform a sensitivity parameter study to confirm the obtained results. We can also consider other extensions for the multi-product case.

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