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Multi-stage investment planning and customer selection in a two-echelon multi-period supply chain design

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Reinvestment;
Multi-stage investment planning.

Abstract. In the supply chain of Fast-Moving Consumer Goods (FMCG), logistics costs represent a major part of total expenses. At these low-level chains, one usually faces a Vehicle Routing Problem (VRP). In practice, however, due to the high cost of service in many cases, some customers are not selected to serve. Investment-related restrictions in many cases make it impossible to serve some of the potential customers. In such conditions, designing a supply chain network, including a location-allocation problem in the warehouse, Multiple Depot Vehicle Routing Problem (MDVRP) at the distribution level, and customer selection at the retail level in several periods of time, is considered. In this respect, in addition to certain methods that can be used in small sizes, metaheuristic algorithms have been used to solve large-scale models. With the aim of improving the performance, if not improving a few diversifications, algorithms are temporarily enhanced; eventually, by using statistical approaches, it has been demonstrated that this method could have a significant impact on the quality of responses. Genetic Algorithm (GA) and Simulated Annealing (SA) algorithm have been used for this purpose.

1. Introduction

In many supply chains, logistic costs comprise a major part of the total costs. This is also true for the supply chain of fast-moving consumer goods. At the low levels of these chains, one usually faces a VRP that increases the cost of logistic drastically, because production must be distributed among mainly small customers at greater distances. In practice, due to the high service cost in many cases, some clients are not chosen for serving. Restrictions associated with the investment in many cases make it impossible to serve some potential customers. With the advent of global businesses and the development of globalization, the administration of supply chains has drawn much attention. The high complexity of the underlying acquisition, production, and delivery means, as well as the growing number of parties included, further stresses the need for effective decision support methods. Two of the major concerns of all fast-moving consumer goods organizations include (a) decreasing the total expense of administering their supply chain and (b) improving their responsiveness, i.e., attempting to deliver the goods to retailers in the assured period [1]. In the current paper, a two-echelon model of the supply chain is considered. In its first echelon, distribution warehouses are placed and, in the second echelon, customers are placed and distribution is done by designating vehicle routes. In addition, this model is able to select customers, meaning that the sale to a group of clients may not be affordable; therefore, there will not be any possibility to remove them. It is a common practice in distribution companies; they do

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not consider themselves committed to serving all of the customers and, instead, profitability indicators are the defined criteria for their decision-making. The model presented in this study considers several periods of time. Usually, demand change at different times causes problems in the form of multi-period to be modeled. In this study, however, in addition to changes in demand, financial constraints constrain the possibility of investment and, as a result, the possibility of serving potential customers. Moreover, in this model, at the end of every month, the profit earned from the sales and distribution operations is reinvested in distribution network development, and the development of infrastructures and vehicles is carried out; therefore, the number of customers increases gradually, too. Finally, potential customers for whom providing service is not cost-effective from an economic perspective are eliminated from the client list and do not receive any services. In models that have been developed for the supply chain network design, it is assumed that capital is required to start and develop a network, which may be limited or unlimited; however, in practice, multi-stage investment is conservative, and many industries, either in the medium or long run, are created over time.

In this problem, designing a supply chain network is considered including a location-allocation problem in the warehouse, MDVRP at the distribution level, and customer's selection at the retail level in some period. Selection of the warehouses, allocation of customers to the stores, selection and deletion of some customers, determining the number of required vehicles and routing vehicles are done simultaneously and in several periods in the form of a model. In this model, the proceeds of the business of the company to develop a distribution network are invested and, in any given period, in accordance with the new investments, more customers are added to the distribution network. Table 1 presents a sample of a multi-stage investment process for a two-echelon supply chain with 10 potential customers in three time periods.

GAMS software is used in small sizes for problem-solving. Metaheuristic algorithms, including GA and SA, are used in problem-solving, and the obtained results are compared with each other.

In designing the algorithms, providing a new operator and applying it to SA and GA algorithms led to the verifiable improvement of the responses.

2. Literature review

2.1. *Location-routing problem combined with the supply chain management*

The location-routing problem is at focus in logistics administration domain where the main purpose is to determine the location and the number of facilities as well as the optimum route for the vehicles. Integrated location-routing models are used for solving the Facility Location Problems (FLP) and VRP, showing a good interaction between the above two decisions [2-5].

In addition to the combination of Location and VRP, researchers have also utilized other concepts in the supply chain management and production issues in a compound form with the VRP. Schmid et al. (2013) carried out a study on the problem of access to routing issues based on a supply chain management [6]. In this paper, the classic problem of routing vehicles from different directions has been discussed. It focuses on issues such as lot-sizing, timing, packaging, sorting, inventory, and constraints. Wang and Lee (2015) studied three-echelon and two-echelon supply chain networks with the aim of optimizing the profit. The current research investigates a capacitated facility location and assignment allocation issue of a multi-echelon supply chain in risky markets. In this study, the revised ant algorithm has improved the performance of the existing ant algorithms [7]. Dondo et al. (2011) modeled and solved a VRP with temporary warehouses in the supply chain management [8]. Osman and Mojahed (2016) studied the vehicle routing problem with capacitated transport vehicle routing restrictions on distribution to different suppliers [9]. Govindan et al. (2014) investigated the problem of two-echelon multi-vehicle route selection with time window to optimize the network of a sustainable supply chain in perishable foods. In the present research, the optimization model of the multi-function integrated sustainable objective in deciding the distribution in a supply chain of perishable food is studied. This issue is summarized in a two-echelon routing in a time window for supply chain network design and optimization of environmental and

Table 1. Illustration of a problem with 10 potential customers and two warehouses.

Period of time	Number of vehicles	Number of warehouses	Number of customers	Routes
1	1	1	4	W1→C2→C7→C4→C5→W1
2	2	1	6	W1→C2→C7 →C5→W1
				W1→C3→C9→C4→ W1
3	2	2	9	W1→C2→C7→C9→C1→C5→W1
				W2→C3→C6→C4→ C10→W2

economic objectives in a sustainable supply chain network [10]. Location Routing Inventory Problem with Transshipment (LRIP-T) is a collaboration of the three parts, including vehicle routing, location-allocation, and inventory management issues, in the supply chain that would facilitate the transshipment procedure in a way that the total system expense and the consumed time are decreased [11,1].

2.2. Metaheuristic algorithms in a supply chain optimization problem

Since supply chain optimization issues include NP-hard problems, many researchers have used metaheuristic algorithms to solve large-scale problems [2,12-14]. Setak et al. (2016) used SA and GA algorithms to overcome an issue of concurrent pickup and distribution with semi-soft time windows [12-14]. Wang et al. (2016) proposed an advanced cross-entropy algorithm for solving a closed-loop supply chain planning and compared the results of the problem-solving in the three algorithms of cross-entropy, GA, and advanced cross-entropy [15]. Hassanzadeh et al. (2016) used two algorithms for solving the problem of a bi-objective supply chain management issue in a flow-shop condition. The first algorithm (HCMOPSO) is a multi-objective particle swarm optimization combined with a heuristic mutation operator, Gaussian membership function, and a chaotic sequence; the second algorithm (HBNSGA-II) is a non-dominated sorting genetic algorithm II with a heuristic criterion for the generation of initial population and a heuristic crossover operator [16]. Masoud and Mason (2016) developed a hybrid SA to overcome the automotive supply chain [17].

2.3. The main innovations

In summary, the set of existing innovations in this paper includes the following cases:

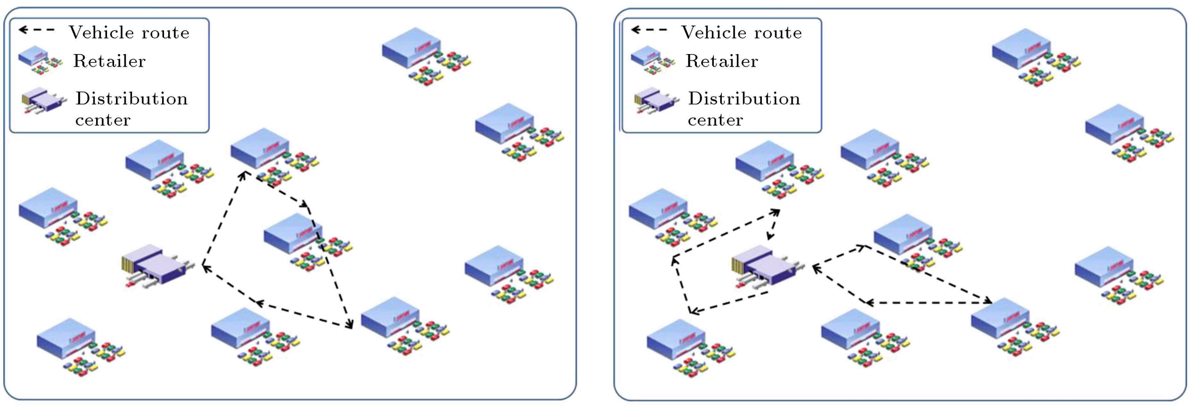
- The possibility to deselect a client for economic reasons;
- The possibility of the progressive development of the supply chain and distribution network;
- Reinvestment of profit in expanding the network of supply chain and sales;
- The possibility of customer selection, determining the warehouses, and determining the number of required vehicles and vehicle routing in a period of time, all at the same time;
- Improving the performance of metaheuristic algorithms by considering two diversification rates and activating the second rate in case of no improved answer in several successive stages and its implementation for the SA and GA algorithms.

3. Problem definition and modeling

3.1. Problem definition

In theoretical issues, it is generally assumed that necessary funds are available to develop the supply chain network and investment coherently. Once it is done in real terms, however, the investment may be made gradually and in several stages for various reasons. Lack of funds is one of the most significant influential parameters, and most of the designs created from revenues in the supply chain are funded. In such circumstances, infrastructure is developed, and the possibility of serving customers is facilitated.

This includes two levels of distribution: centers/warehouses and customers/retailers. In the warehouse, it is required to select some distribution centers/warehouses among several potential locations. Customers and vehicles are allocated to the warehouses, too. At the level of customers/retailers, the problem involves choosing the path of service and determining the number of vehicles. Cases referred to in any period are investigated, and the amount of the investment includes the initial capital and profit from the sales in the previous periods. Figure 1 provides



(a) First period (b) Second period

Figure 1. Topology of the supply chain under study.

a schematic illustration of a hypothetical answer to a problem with ten potential customers in three time periods. In the first period (Figure 1(a)), a warehouse, an auto, and four customers are selected and allocated to the warehouse, and the direction of the movement of vehicles is specified. In the second period (Figure 1(b)), profits from the sale are allocated to buy a new vehicle, and two vehicles and a warehouse are selected. In addition, during this period, six customers are served, and the movement direction of two vehicles is provided. As can be seen, some of potential customers are eliminated due to economic reasons.

Many researchers have studied location-routing problems [18-20]. Since it has been determined that this problem is of NP-hard type [21], several algorithms are suggested to solve it precisely in small dimensions, and approximation algorithms are suggested for solving it in large dimensions [7,22-26]. Given that the issue in this article is a complex form of LRP, it is an NP-hard issue.

Assumptions

- Available initial capital is determined;
- Profit from each course can be invested in other short-term activities or used to develop the business of the company;
- Short-term investments done from the profits of the business at the time of need can be invested in the activities related to the current business of the company;
- The rate of capital return expected by shareholders is known and fixed;
- Every customer demand is known and fixed;
- The capacity of warehouses is unlimited;
- The capacity of vehicles is specified and limited;
- The maximum distance that a vehicle is passing is clear and limited, and it is the same for all vehicles;
- The place of potential warehouses is clear;
- To set up each warehouse, the company pays a certain fee;
- The list and locations of potential customers are clear;
- Each vehicle route starts from a warehouse and ends in the same warehouse;
- Each customer is served exactly once by one of the autos.

Index sets

I	Set of network nodes including customers and warehouses
N	Set of customers
M	Set of warehouses
K	Set of vehicles
P	Set of time periods
i, j, h	The number of network nodes including the customer and the warehouse
p	The number of time periods
k	The number of vehicles

Parameters and notations

$bigM$	A great number
cb_{ip}	Customer demand i $(i = 1, ..., N)$ in terms of dollars in p period
q_{ip}	Customer demand i $(i = 1, ..., N)$ per unit of weight in period p
wc_i	The fixed cost of setting up warehouse i $(i = N + 1, ...N + M)$
vc_k	The expense of using vehicle k
c	The fixed expense of product displacement per km
d_{ij}	The distance between nodes i and j
NT	The maximum distance that a truck passes
Q	The maximum capacity of the vehicle by weight
capital	Initial capital available
int	Acceptable rate of return of the investment

Decision variables

SC_{ip}	If customer i is selected, it is 1; otherwise, it is 0. $(I = 1, ..., N)$
SW_{ip}	If store i is selected, it is 1; otherwise, it is 0. $(I = N + 1, ...N + M)$
x_{ijkp}	If from nodes i to j or vehicle k, a move to be done is 1; otherwise, it is 0.
AV_{kp}	If vehicle is selected k, it is 1; otherwise, it is 0.
y_i	The auxiliary variable that is defined to avoid creating the loop
cap_p	The amount of capital available in course p
inv_p	Investments in period p
return_p	Returning profit of period p
profit_p	Net profit of period p
Z	The net present value of investments (objective function)

Mathematical formulation

Objective and constraint functions of this issue are described, respectively, as follows:

$$\max: \; z = -inv_1 + \sum_{p=1}^{P} \frac{\text{profit}_p}{(1 + int)^p}, \tag{1}$$

subject to:

$$\sum_{i=1}^{N}\sum_{k=1}^{K} x_{ijkp} = SC_{jp}$$

$$(j = 1, ..., N + M;\ p = 1, ..., P), \quad (2)$$

$$\sum_{j=1}^{N}\sum_{k=1}^{K} x_{ijkp} = SC_{jp}$$

$$(j = 1, ..., N + M;\ p = 1, ..., P), \quad (3)$$

$$\sum_{i=1}^{N+M} x_{ihkp} - \sum_{j=1}^{N+M} x_{hjkp} = 0$$

$$(h = 1, ..., N + M;\ k = 1, ..., K;\ p = 1, ..., P), \quad (4)$$

$$\sum_{i=1}^{N+M}\sum_{j=1}^{N+M} x_{ijkp} \leq bigM \times AV_{kp}$$

$$(k = 1, ..., K;\ p = 1, ..., P), \quad (5)$$

$$\sum_{i=1}^{N+M}\sum_{j=1}^{N+M} d_{ij} x_{ijkp} \leq NT$$

$$(k = 1, ..., K;\ p = 1, ..., P), \quad (6)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} q_{ij} x_{ijkp} \leq Q$$

$$(k = 1, ..., K;\ p = 1, ..., P), \quad (7)$$

$$\sum_{k=1}^{K}\sum_{j=1}^{N+M} x_{ijkp} \leq bigM \times SW_{ip}$$

$$(i = N+1, ..., N+M;\ p = 1, ..., P), \quad (8)$$

$$y_i - y_j + (M + N) x_{ijkp} \leq N + M - 1$$

$$(i = 1, ..., N;\ j = 1, ..., N;\ k = 1, ..., K;\ p = 1, ..., P), \quad (9)$$

$$SC_{ip} \leq SC_{ip+1}$$

$$(i = 1, ..., N;\ p = 1, ..., P - 1), \quad (10)$$

$$AV_{kp} \leq AV_{kp+1}$$

$$(k = 1, ..., K;\ p = 1, ..., P - 1), \quad (11)$$

$$SW_{ip} \leq SW_{ip+1}$$

$$(i = N + 1, ..., N + M;\ p = 1, ..., P - 1), \quad (12)$$

$$inv_p = \sum_{i=N}^{N+M} WC_i SW_{ip} + \sum_{k=1}^{K} VC_k AV_{kp}$$

$$(p = 1, ..., P), \quad (13)$$

$$\text{return}_p = \sum_{i=1}^{N} cb_i SC_{ip} - c\left(\sum_{i=1}^{N+M}\sum_{j=1}^{N+M}\sum_{k=1}^{K} d_{ij} x_{ijkp}\right)$$

$$(p = 1, ..., P), \quad (14)$$

$$cap_p = cap_{p-1} + \text{return}_p$$

$$(p = 2, ..., P), \quad (15)$$

$$cap_1 = \text{capital} + \text{return}_1, \quad (16)$$

$$inv_1 \leq \text{capital}, \quad (17)$$

$$\text{profit}_p = \text{return}_p, \quad (18)$$

$$\text{profit}_p = \text{return}_p + inv_p - inv_{p+1}$$

$$(p = 1, ..., P - 1), \quad (19)$$

$$\sum_{j=1}^{N+M} x_{hjkp} = \sum_{i=1}^{N+M} x_{ihkp}$$

$$(h = N+1, ..., N+K;\ k = 1, ..., K;\ p = 1, ..., P), \quad (20)$$

$$x_{ijkp} = 0$$

$$(i = N + 1, ..., N + K;\ j = N + 1, ..., N + M;$$

$$k = 1, ..., K;\ p = 1, ..., P), \quad (21)$$

$$x_{ijkp} \in \{0, 1\}$$

$$(i = 1, ..., N + M;\ j = 1, ..., N + M,\ k = 1, ..., K;$$

$$p = 1, ..., P), \quad (22)$$

$$y_i \geq 0$$

$$(i = 1, ..., N), \quad (23)$$

$$cap_p \geq 0$$

$$(p = 1, ..., P), \quad (24)$$

$$inv_p \geq 0$$

$$(p = 1, ..., P), \quad (25)$$

$$\text{return}_p \geq 0$$

$$(p = 1, ..., P), \quad (26)$$

$$SC_{ip} \in \{0,1\}$$

$$(i = 1, ..., N;\ p = 1, ..., P), \tag{27}$$

$$SW_{ip} \in \{0,1\}$$

$$(i = 1, ..., N;\ p = 1, ..., P), \tag{28}$$

$$AV_{kp} \in \{0,1\}$$

$$(k = 1, ..., K;\ p = 1, ..., P), \tag{29}$$

$$x_{ijkp} \in \{0,1\}$$

$$(i = 1, ..., N + M;\ j = 1, ..., N + M;\ k = 1, ..., K;$$

$$p = 1, ..., P). \tag{30}$$

Eq. (1) shows the objective function of the problem. In this issue, project cash flow declines in different time periods, and the resulting present value of money flow is evaluated. The objective function includes the cost of investment in the first year, which has been shown to affect the cash flow negatively, and the profits of the business in future periods that are transferred to the first year. To transfer the cash flow to the first year, each flow is divided by $(1+int)^p$. Constraints (2) and (3) ensure that if a customer is elected, the client should be provided with service. These constraints also ensure that, in case of serving, this action is only to be done by a vehicle and in one visit. Constraint (4) states that if a vehicle enters a node, it will be out of the node, too. Constraint (5) ensures that if the fixed fee of vehicles is not paid, it should not to be applied. Constraints (6) and (7) restrict the volume of vehicle load and the distance that the vehicle can move. Constraint (8) ensures that if the fixed fee of the warehouses has not been paid, the inventory should not to be out of the store. Constraint (9) is used to eliminate the sub-tours between clients and storage [15,16]. Constraint (10) ensures that if customers are selected in a course and receive services, they should also receive services in later periods. Constraint (11) guarantees that if a vehicle is used once, it should also be operated later. Constraint (12) ensures that if a warehouse is used once, it should be active in the next period, too. Constraint (13) calculates the investment needed for each period. This investment includes the cost of setting up warehouses and applying vehicles. It should be noted that this amount calculates the total capital required, not the surplus capital required in that period. Constraint (14) computes the backward business profit of the company. Returning profits in each period include the revenue from sales and logistics costs, which have been negatively imported from the cash flow. Constraint (15) shows the amount of capital available at the end of each period. This investment includes the capital available in the previous period and the returning profit in that period. It should be noted that this amount is calculated from the second period to the final period. Constraint (16) calculates the amount of capital available at the end of the first period. This investment includes the initial capital and profit returns of the first period. Constraint (17) shows that the amount of investment in the first period cannot exceed that of the initial capital. Constraint (18) shows the net income of the last period. Since no investment is done in this period, the total amount of the returned profit is considered as the net income. Constraint (19) shows the amount of net profit at the end of each period for the periods before the last period. This amount is equal to subtracting profits in each period and the amount of capital required for investment in the next period. The amount of the capital required is equal to the difference between the amount of investment at the end of the next period and investment at the end of the current period. Constraint (20) ensures that every vehicle has moved from a warehouse and returned to that warehouse. Constraint (21) restricts the movements between the warehouses. Other constraints have identified zero and one variables as well as positive variables.

4. Solution algorithms

To overcome this problem, two metaheuristic algorithms (GA and SA) are used. In each of these algorithms, the algorithm has been improved by applying changes. Therefore, if the answers do not improve in several periods, the diversification has increased.

4.1. Encoding and decoding

The coding system used in this paper is priority-based. Figure 2 presents a sample of this type of solution coding.

In this system, there are N customers and M storehouses when coding answers, and this coding produces $M + N + 1$ sequential digit randomly, whose sequence shows their service on the track. Moreover, numbers $N + 1$ to $N + M$ are dedicated to the

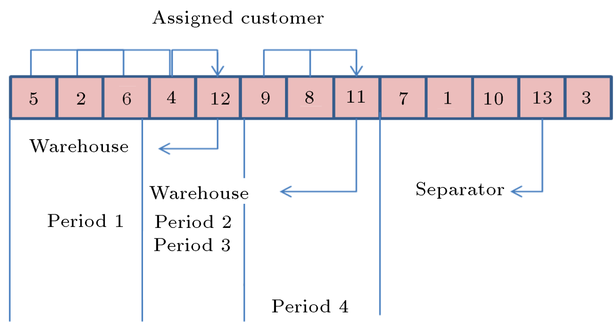


Figure 2. Illustration of the problem encoding.

storehouses. The customer's number, on the left side of each storage number left unallocated, will be allocated to this storage. The last number is also used as a separator. The number of stocks on the left side along with the clients assigned to the warehouse is selected, and other customers and stores are eliminated. For example, ten customers and two warehouses are shown in Figure 2. As is common practice in encoding this problem, 13 consecutive numbers have been used. Customers, stores, and separator numbers are marked as 1 to 10, 11-12, and 13, respectively. In this case, customers with numbers 5, 2, 6, 4 and Customers 9 are allocated to Stores 12 and 11, respectively, and Customers 3, 10, 1, 7 are eliminated and not served.

To allocate the vehicles, given that vehicles are of one kind, restrictions are used on the weight and distance of the vehicle. For this purpose, the allocation is initialized from the left side. In each allocation, the remaining weight of the truck and the distance needed to be passed are calculated. The return distance is also calculated, and if these numbers are able to cover the restrictions, the allocation is considered done; otherwise, the route is closed by calculating the distance of the returning vehicle, and another vehicle is deployed to the rest of route. This procedure continues untill achieving the total number of the warehouse. Upon arrival to each warehouse, the path is closed regardless of the remaining capacity of the vehicle. This process is repeated for all of the allocated warehouses.

A similar procedure is used to restrict the available capital. To distribute the product, one storage is required at least, and a vehicle regarded as sufficient initial capital is considered for it. As can be seen in Figure 2, in the first round of Store 12, a lorry is considered as the initial investment. It is also assumed that because of weight restrictions and limitations on the distance passed by any vehicle, the possibility of providing service for only three customers exists. In addition, in this period, the route of a vehicle is set as 12, 5, 2, 6, and 12. In the second round, it is assumed that profits from sales to three customers in the first round should only be provided using a new vehicle. An additional vehicle is used to serve Customer 4 in Routes 12, 4, and 12. As is specified, serving all customers requires the use of Warehouse 11, and the addition of at least one new vehicle, whose proceeds are assumed from the business in both pre-periods, fails to cover the required costs. Therefore, conditions have not changed in the third period, and four customers are served with a warehouse and two trucks. Finally, it is assumed that, in the fourth round, the possibility of using Warehouse 11 and adding one vehicle is provided; as a result, Routes 11, 9, 8 are added to the previous routes in the period.

For decoding the described code based on the method provided in the first step, it is required to determine the investment amount needed for service customers based on the order created for serving each customer. Algorithm 1 demonstrates this issue.

In addition, the instruction for calculating the objective function in Algorithm 2 is provided.

4.2. The genetic algorithm

4.2.1. Description of the algorithm

GA is a competitive evolutionary method that repeats the processes of the mechanism of natural selection and biological evolution [17,27]. This algorithm is designed on the principle that most adaptable organisms have a better chance of survival [28]. SA and GA include the most popular metaheuristic algorithms to solve large-sized problems or non-linear issues [29]. Genetic algorithms have been used by many researchers to solve problems of optimization of supply chain networks [30-33]. They are also used as combined with other algorithms by different researchers to solve optimization problems of supply chain [34-36,25]. A typical procedure of GA is illustrated in Figure 3 [37-40].

4.2.2. Natural selection

In this study, tournament selection is used as natural selection. In this method, to select each parent, two answers are selected from the population, and the top option is selected as a parent.

4.2.3. GA operators

Crossover operator

The crossover operator generates new responses based on the present responses. In this procedure, some of the features of parents' chromosomes are transmitted to children. In this article, the two-point operator is used for this purpose. Figure 4 shows an example of this operator.

Mutation operator

The mutation operator is designed and used to improve diversification in the genetic algorithm. In this paper, the shift-mutation operator is applied. Figure 5 shows the operator.

Two different mutation probabilities are used to improve the performance of this algorithm. The problem initiates with a mutation probability, and the answers improve based on GA. It is then expected that the process of achieving better solutions slows down, and the algorithm tends towards convergence. At this point, considering the output of the algorithm from possible local optimum points, if the responses are not improved within the specified number of generations, the second mutation probability is applied. This action increases diversification temporarily and leads to the production of new responses. With the first improvement of the replies, the rate of the first mutation probability is activated again. It makes the algorithm have less chance of engagement in the local optimum points

```
Inputs:
        d_ij, Q, NT, cp_ip, q_ip, WC_i, VC_k, C, solution code
Output:
        Investment (j) = an array includes each requirement for customer service investment
        Number of the warehouse (j)
        Number of the vehicle (j)
        The total distance (j)

Determining the warehouse and separator positions
Set:
    Number of warehouses = 0, number of vehicles = 0, total distance = 0
For i = 1: M
    If Warehouse position (i) = N + M + 1
        break
    else
    Number of warehouses = Number of warehouses+1
    End If
    For j = the first customer assigned to the warehouse (i): Warehouse position (i − 1)
      If j = the first customer assigned to the warehouse (i)
            total distance (i)= total distance + d_Warehouse position(i)j
            number of vehicles= Number of vehicles+1
            Vehicle total distance (number of vehicles) = d_Warehous position(i)j
       End if
       If j = the last customer assigned to the warehouse (i)
            Total distance= Total distance+ d_jWarehouse position(i)
       Vehicle total distance (number of vehicles)=vehicle total distance
      (number of vehicles)+ d_jWarehouse position(i)
       Else
       Vehicle total distance-h (number of vehicles)=Vehicle total distance (number of vehicles)
       +d_jj+1 + d_j+1Warehouse position(i)
       Total weight = SC*q
       If vehicle total distance-h <= NT and total weight <= Q
            total distance (i)= total distance (i) + d_jj+1
       Vehicle total distance (number of vehicles) = Vehicle total distance (number of vehicles)
       + d_jj+1
    Else
       total distance (i)= total distance (i)+ d_jWarehouse position(i)
       total distance (i)= total distance (i)+ d_Warehouse position(i)j+1
       Vehicle total distance (number of vehicles) = Vehicle total distance (j)+ d_Warehouse position(i)j+1
       Number of vehicles= Number of vehicles+1
       Vehicle total distance (number of vehicles) = d_Warehouse position(i)j+1
    End if
    Investment (j) = number of vehicles*CV + WC(i)*i
    Number of vehicles (j) = Number of vehicles
    Number of warehouses (j) = i
    The total distance (j) = total distance (i)
  End for
End for
```

Algorithm 1. Investment-calculating procedure.

```
        Inputs:
               cb_i, WC_i, VC_k, C, P capital, total distance (Algorithm 1), number of warehouses
                (Algorithm 1), number of vehicles (Algorithm 1), investment (Algorithm 1)
Output:
                Obj = Net present value of incomes
For j = 1 : N + M + 1
        If Capital>= Compare investment (j)
           P = 1
           Profit (p)=CS*cb_i1 - Total distance (j)*C
           Cap (1)= Capital+ Profit (1)
           Break
        End if
End For
      For p=2:P
           For j = 1 : N + M + 1
                 If Cap(p − 1) >= Compare investment (j)
                  Profit (p) = CS*cb_i2 - Total distance (j)*C
                  Cap(p)= Cap(p − 1)+ Profit (p)
        End if
      End For
End for

Obj = −inv(1) + [Profit(p) − (inv(p) − inv(p − 1))]/(1 + int)^p
```

Algorithm 2. Decoding procedure.

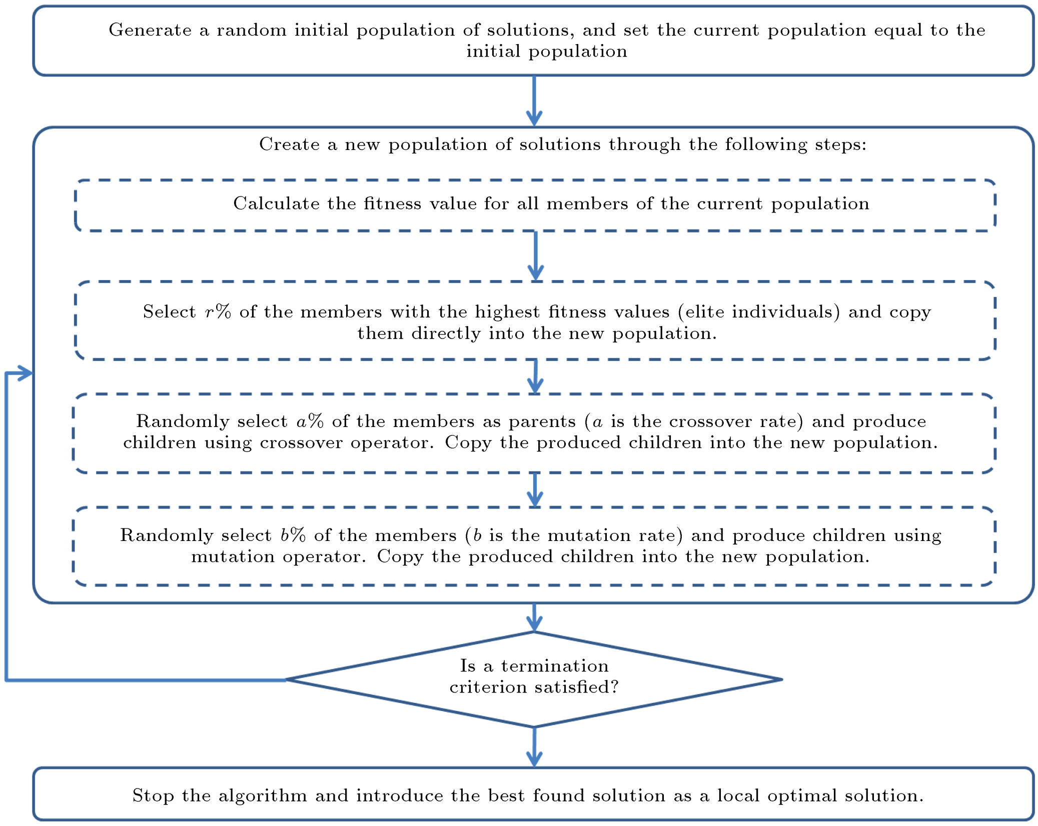


Figure 3. The standard GA procedure.

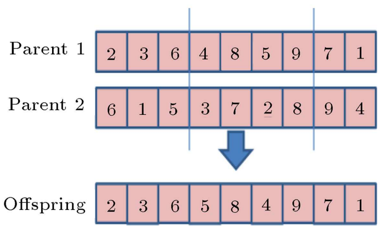


Figure 4. A schematic of the two-point crossover operator.

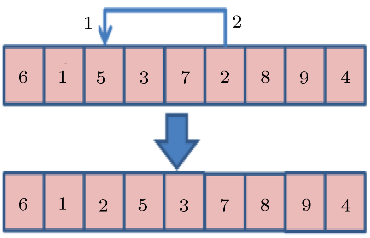


Figure 5. An illustration of the shift mutation operator.

while maintaining its convergence. Another important point is that increasing the mutation probability can lead to an increase in calculations; as a result, the speed of the algorithm and the quality of the final answer are reduced. Since two mutation probabilities are included in this algorithm, the initial mutation probability can be reduced as much as possible. It also increases the speed of improving answers in early diversifications.

Figure 6 compares the result of solving a problem using genetic algorithms with that of genetic algorithms with two mutation probabilities.

4.3. SA algorithm

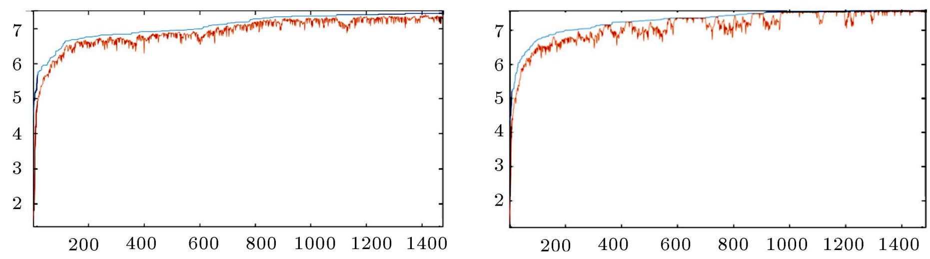
4.3.1. Description of SA algorithm

SA is a metaheuristic algorithm used to overcome large-sized problems that have a large solution space and produce results close to the global optimum amount in a short amount of time. The SA algorithm was first created by Metropolis et al. in 1953 to generalize the Monte Carlo method to determine the equations of state and, also, frozen states of n-body systems in the field of metallurgy [3-5]. A typical procedure of SA is illustrated in Figure 7

4.3.2. Operators of SA algorithm

Cooling scheme

In the cooling scheme, an exponential approach is used and, in each diversification, the temperature is multiplied in a fixed number smaller than one. In this method, since there are only two temperatures in the algorithm, only one of the temperatures decreases and the other temperature is fixed with the aim of



(a) Diagram of GA performance

(b) Diagram of GA performance with 2 mutation probabilities

Figure 6. Comparison of the performances of GA and the two GAs in this paper.

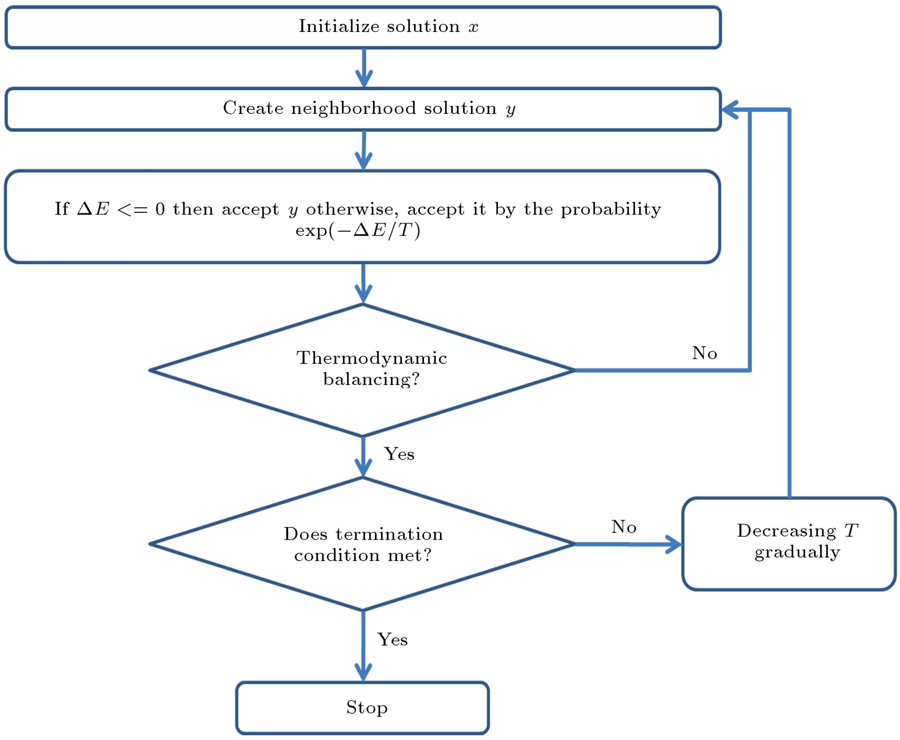


Figure 7. The standard SA procedure.

increasing diversification in the whole process of solving the algorithm.

Acceptance probability
The possibility of selecting an inferior solution (X_{new}) is provided by the next equation, where T_i and X_i are the temperature and the real solution amounts in iteration i.

$$p(T_i, X_{\text{new}}, X_i) = exp^{(-\frac{\Delta}{T_i})},$$

where $\Delta = (f(X_{\text{new}}) - f(X_i)/f(X_i)) \times 100$ is a dimensionless parameter; it shows the relative rate of deviation of the perturbed solution (X_{new}) from the real one (X_i) [6].

Temperature settings
The temperature controls the diversification of the algorithm. In SA, the standard of temperature was great at first (diversification was high) and gradually decreased with the continuation of the solution. In this paper, two different SA algorithms are designed, and the results obtained by solving the problem using these two algorithms are compared with each other. In the first algorithm, a standard SA is considered, and the initial temperature is determined according to the conventional methods of setting parameters. The second algorithm is designed with the aim of increasing diversification at times when the algorithm cannot improve the answer in several consecutive times. For this reason, two temperatures are considered in this algorithm. The first temperature is reduced continuously based on the cooling scheme in different solving stages, and the chance of accepting bad answers and diversification reduces proportionately. If the algorithm is not able to improve the best answer

Table 2. Other statuses of the examined problems.

Parameter	Description	Distribution
Lo_i	The area longitude ($i = 1, ...N + M$)	$U[50, 100]$
Wi_i	The area width ($I = 1, ...N + M$)	$U[50, 100]$
d_{ij}	Distance between node I to node j	Sum(absolute($Lo_i - Wi_i$))
NT	Vehicle capacity (kilometer)	$U[250, 350]$
Q	Vehicle capacity (ton)	$U[30, 60]$
q_i	The demand of customer, $i = 1, ..., N$ weight unit	$U[5, 10]$
cb_i	Customer demand	$U[1500, 2500]$
c	Fixed cost of product displacement per km	30
wc_i	Fixed cost of setting up warehouse i ($i = N + 1, ...N + M$)	$U[2000, 3000]$
vc_k	Kth the cost of using vehicle	$U[300, 700]$

obtained during several periods (N), the second temperature is activated, which leads to the increase of the diversification algorithm. If the answer is improved, the first temperature is activated again, and this process continues.

Termination condition
In this paper, since the findings of the algorithms of the solution are compared with each other, the stoppage condition of the algorithms implies reaching a pre-specified time. This method facilitates the comparison of algorithms only through the investigation of the quality of their answers.

Producing vicinity answer
The shift operator that is introduced in Section 4.2.3 is used to produce the vicinity answer.

5. Numerical examples

To determine the performance of the algorithms, producing numerical examples is common [41]. In this section, the performance of the algorithms presented through numerical examples is shown. GAMS software is used for problem-solving in small sizes, and GA and SA are used for medium- and large-sized problems. The coding of metaheuristic algorithms is done by Matlab software.

5.1. Producing random responses

Two groups of random problems are used in this research. The first group, containing 15 problems, includes small-scale numerical problems that have been used to verify the authenticity of the results of metaheuristic algorithms. The second group, which includes 21 medium- and large-scale problems, has been solved by metaheuristic algorithms, and responses are produced to assess the effectiveness of the changes created by the algorithms. The algorithms are also compared with each other.

The parameters of numerical examples were produced through the production of random data in MATLAB software. The method of producing the parameters of the problems is presented in Table 2.

5.2. Tuning the parameters of algorithms

In this section, the set of parameters of the algorithms is considered. One of the common approaches in this regard is the use of numerical examples and Design of Experiments methods [7]. Central Composition Design (CCD) method is selected for this purpose, and MINITAB software is used for calculations. In this approach, five levels are considered for each factor and, by considering the midpoints, the possibility of detecting the curve is provided. To provide numerical examples based on common methods, random numbers are generated. The production of numerical examples is described in Section 4.1. In this section, a mathematical model with 50 customers and five warehouses is used, and the problem is solved in 20 time periods.

Normally, in GA, the parameters of mutation probability, the population size (pop) that ranges in [25 100] (Pm) in [0.1 0.4], and the maximum number of generations in various articles are intended to set the parameters [37,32]. Since the GA in this research is executed at a fixed time, the number of generations deemed not necessary will be deleted from this group. Therefore, these two parameters have been considered in GA. Regarding the GA with two mutation probabilities in addition to nPop, the two amounts intended for the mutation probability are [0.05 0.1] and [0.3, 0.5]. The parameter of the number of generations that reduces with non-improvement in response to mutation probability (N) in the range [4, 10] has been considered. The output of software in GA with two

Table 3. Coded coefficients table (proposed GA).

Term	Effect	Coef.	SE Coef.	T-value	P-value	VIF
Constant		721061	4309	167.33	0.000	
psize	-15896	-7948	2327	-3.42	0.001	1.00
N	5612	2806	2327	1.21	0.232	1.00
$MP1$	9346	4673	2327	2.01	0.048	1.00
$MP2$	-2418	-1209	2327	-0.52	0.605	1.00
psize*psize	-4767	-2384	2132	-1.12	0.267	1.03
N^*N	1090	545	2132	0.26	0.799	1.03
$MP1^*MP1$	-1823	-911	2132	-0.43	0.670	1.03
$MP2^*MP2$	-709	-354	2132	-0.17	0.868	1.03
psize*N	-900	-450	2850	-0.16	0.875	1.00
psize*$MP1$	-5567	-2784	2850	-0.98	0.332	1.00
psize*$MP2$	1540	770	2850	0.27	0.788	1.00
N*$MP1$	14798	7399	2850	2.60	0.011	1.00
N*$MP2$	11828	5914	2850	2.07	0.041	1.00
$MP1^*MP2$	-8101	-4051	2850	-1.42	0.159	1.0

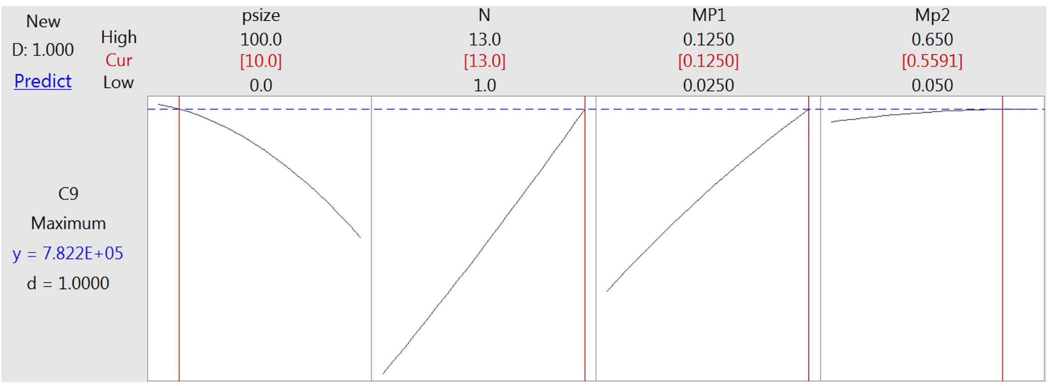


Figure 8. Optimization plot of the objective function (the proposed GA).

mutation probabilities is offered in Eq. (31):

$$\begin{aligned}\text{Result} = {} & 742943+368\ \text{psize}-11612\ N+315838\ MP1\\ & -18282\ MP2-3.81\ \text{psize}^*\text{psize}+61\ N^*N\\ & -1458325\ MP1^*MP1-15750\ MP2^*MP2\\ & -6.0\ \text{psize}^*N-4454\ \text{psize}^*MP1\\ & +205\ \text{psize}^*MP2+98653\ N^*MP1\\ & +13142\ N^*MP2-1080167\ MP1^*MP2. \quad (31)\end{aligned}$$

In Table 3, the testing hypothesis and the coefficients of this problem are provided, and the output results of optimization of parameters of this algorithm are provided in Figure 8. Accordingly, the size = 10, N = 13, $MP1$ = 0.125, and $MP2$ = 0.56 are considered. The output of analysis presented in the GA algorithm parameters in Eq. (32) is provided:

$$\begin{aligned}\text{Result} = {} & 779412-1578\ \text{psize}-107645\ \text{MP}\\ & +5.04\ \text{psize}^*\text{psize}-145689\ \text{MP}^*\text{MP}\\ & +1868\ \text{psize}^*\text{MP}. \qquad (32)\end{aligned}$$

The optimal parameter values of the algorithm are 40 upsize = and MP = 0.138. The optimization plot of the algorithm is presented in Figure 9.

In SA algorithm, two parameters of temperature [100 200] and the number of vicinity solutions created in each temperature It-num [30 50] to set the parameters have been considered. The method used to set the

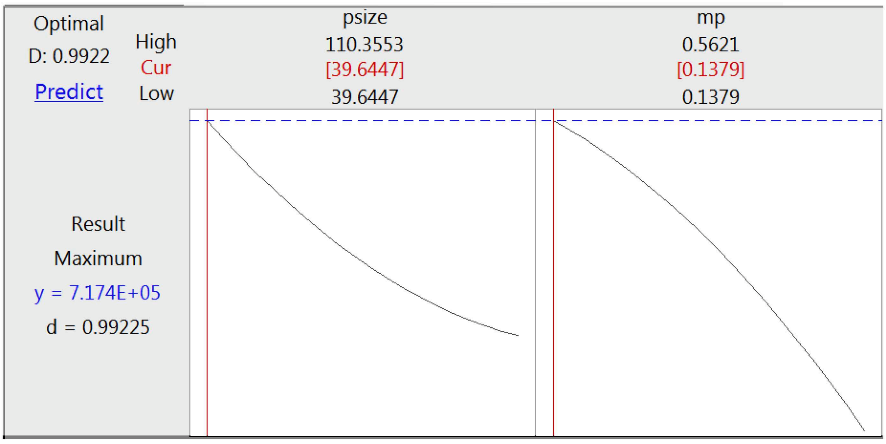


Figure 9. Optimization plot of the objective function (GA).

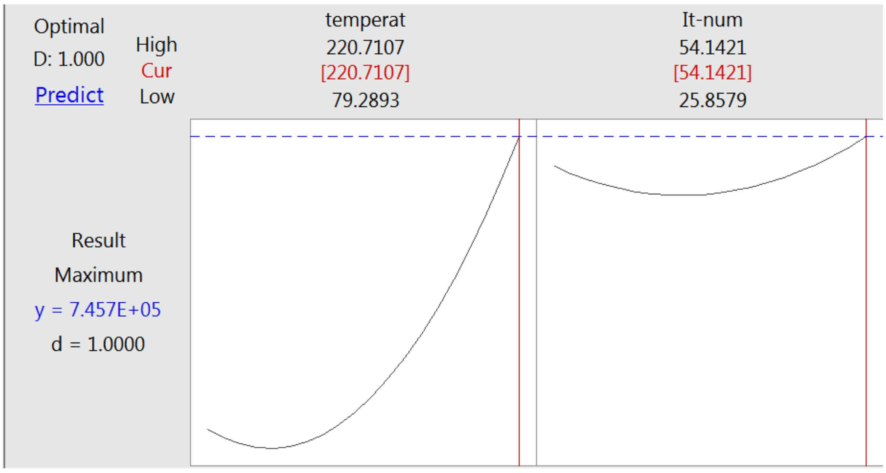


Figure 10. Optimization plot of the objective function (SA).

parameters is similar to other algorithms. The result is provided in Eq. (33), and the optimization plot of this algorithm is presented in Figure 10.

$$\begin{aligned}\text{Result} =&774039 - 500 \text{ temperature} - 1568 \text{ It-num}\\&+ 2.11 \text{ temperature}^*\text{temperature}\\&+ 18.4 \text{ It-num}^*\text{It-num}\\&+ 0.8 \text{ temperature}^*\text{It-num} .\end{aligned}\tag{33}$$

On this basis, the optimum values are calculated as equal to 221 degrees for the temperature and equal to 54 for It-num. Regarding the SA algorithm considered in this article, two values are created for Temperature 1 [100 200] and Temperature 2 [150 300]. The number of vicinity solutions created in each degree It-num [30 50] and the number of successive answers are considered in case of failure to improve the optimal answer and the temperature range changes N [100 200]. The results of Eq. (34) and the optimization plot of this algorithm are presented in Figure 11.

$$\begin{aligned}\text{Result} =&653913 + 139 \text{ temp1} + 62 \text{ temp2}\\&+ 3427 \text{ It-num} - 132 \text{ N} + 0.061 \text{ temp1}^*\text{temp1}\\&- 0.378 \text{ temp2}^*\text{temp2} - 43.7 \text{ It-num}^*\text{It-num}\\&- 0.789\ N^*N - 0.505 \text{ temp1}^*\text{temp2}\\&- 5.71 \text{ temp1}^*\text{It-num} + 1.218 \text{ temp1}^*N\\&+ 3.15 \text{ temp2}^*\text{It-num} + 0.572 \text{ temp2}^*N\\&+ 2.05 \text{ It-num}^*N.\end{aligned}\tag{34}$$

On this basis, the optimal amounts of Temperature 1 and Temperature 2 are calculated as equal to 50 degrees and 375 degrees. It-num equals 53 and N equals 159.

5.3. Solving numerical problems in small sizes

Model verification and validation have been among the concerns of researchers in the field of mathematical

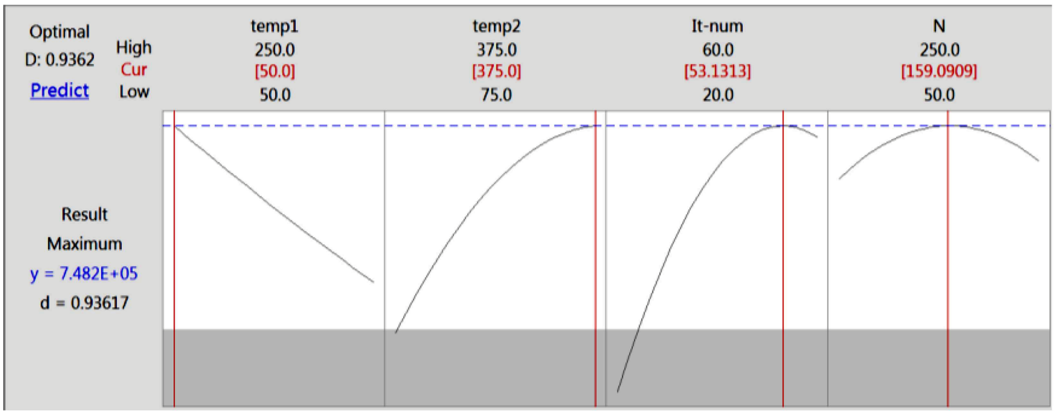


Figure 11. Optimization plot of the objective function (the proposed SA).

Table 4. The results of numerical examples for validation analysis.

Test problem	Number of customers (N)	Number of warehouses (M)	Number of periods (P)	GAMS answer			GA	
				Final solve	Best possible	Time	Final solve	Time
1	4	1	2	8350	9184	2.46	8350	5
2	4	1	4	17604	19363	43.84	17731	5
3	4	1	6	25483	27583	910.8	25483	5
4	5	2	1	4745	5164	2.53	4800	7
5	5	2	2	11786	12930	26.94	11891	7
6	5	2	3	18088	19897	98.31	18264	7
7	5	2	4	24007	26197	36.93	24197	7
8	6	2	1	4527	4972	14.62	4527	8
9	6	2	2	12140	13354	242.96	12140	8
10	6	2	3	19128	21106	1000.01	19128	8
11	6	2	4	25479	29274	1000.01	25480	8
12	7	3	1	8127	8939	75.51	8127	10
13	7	3	2	18243	19647	991.53	18243	10
14	7	3	3	27274	29865	208.76	27439	10
15	7	3	4	32734	38354	1000.03	35799	10

models [42-44]. Verification ensures that the conceptual description and the solution of the pattern are employed truly so that the real condition can be presented. In the validation process, the numerical simulation is associated with the experimental data, and the precision of the simulation is determined [45]. Simple examples, with predetermined answers, are used to investigate the verification of algorithms. The answer obtained from problem-solving is compared with the predetermined answers to investigate the verification of the model. The validity of algorithms is investigated through 15 numerical examples. For this purpose, 15 numerical examples with small dimensions are solved simultaneously using GAMS and metaheuristic algorithms, and the results are compared with each other. Table 4 presents the outcomes of this analysis for GA and GAMS. It should be noted that the results of other algorithms used are similar to those obtained from the GA. The termination condition of solution algorithm through GAMS software is satisfied by achieving an optimal algorithm and an answer with a 10% difference from that with high limits, or by the passage of 1000 seconds as of the time of solution. A number of nodes have been considered for solving the problem of time by metaheuristic algorithms. According to the results obtained and the minuscule difference between them, the responses obtained from metaheuristic algorithms can be regarded as valid.

5.4. Solving numerical problems

5.4.1. Solving test problems

In this section, 21 problems in medium and large sizes are randomly generated and explained five times by four algorithms and are resolved each time over a period of ninety $(M + N)$. The values of the best answer and the average of 5 answers to the problem are extracted and compared with each other by statistical methods. Table 5 shows a summary of the results obtained in the two GAs. The results obtained by problem-solving by two SA algorithms are presented in Table 6. For this purpose, statistical analysis of the priority of the considered operator, a difference of the best answers, and the average of answers generated by the two algorithms are calculated in each of the problems, and the test $H0$: $\mu \geq 0$ against $H1$: $\mu < 0$ is tested for them through the t-statistic at a 5% level of significance. The results obtained from two GA algorithms and SA considered by this article are deducted from each other, and the above test is done for them. MINITAB software is used for this purpose. The results of software output are presented in Table 7. In this study, the following results were obtained:

- At a 5% level of acceptance, the hypothesis of the higher best answer than the conventional GA produced by the GA considered in this paper is not rejected (P-value = 0.002);
- At a 5% level of acceptance, the hypothesis of the higher best answer than the conventional GA produced by the GA considered in this paper is not rejected (P-value = 0.003);
- At a 5% level of acceptance, the hypothesis of the higher best answer than the conventional GA produced by the GA considered in this paper is not rejected (P-value = 0.000);
- At a 5% level of acceptance, the hypothesis of the higher best answer than the conventional GA produced by the GA considered in this paper is not rejected (P-value = 0.000);
- At a 5% level of acceptance, the hypothesis of the higher best answer than the GA considered in this

Table 5. The results of numerical examples (GA and the proposed GA).

				GA		Proposed GA		Deviation (GA- proposed GA)	
TP	***M***	***N***	***P***	**Best**	**Average**	**Best**	**Average**	**Best**	**Average**
1	2	30	3	129600	125678	130550	125062	−950	616
2	2	30	4	170830	164480	170200	164362	630	118
3	2	30	7	260050	252608	259430	254334	620	−1726
4	3	40	3	143270	136614	139630	132200	3640	4414
5	3	40	5	229330	226904	233140	229062	−3810	−2158
6	3	40	10	394740	383708	398780	385316	−4040	−1608
7	4	50	5	303040	289144	292470	282152	10570	6992
8	4	50	10	507610	491236	499350	491952	8260	−716
9	4	50	15	608510	604358	635390	614698	−26880	−10340
10	5	60	5	366010	352692	362380	357976	3630	−5284
11	5	60	10	601020	596160	606600	596022	−5580	138
12	5	60	15	744190	739688	773160	758496	−28970	−18808
13	5	70	5	448830	439790	453780	437584	−4950	2206
14	5	70	10	741880	734660	752430	734950	−10550	−290
15	5	70	15	904670	896278	941040	919170	−36370	−22892
16	6	80	10	805780	794812	823440	817676	−17660	−22864
17	6	80	15	1012100	994820	1022900	1003120	−10800	−8300
18	6	80	20	1128200	1114440	1160500	1146180	−32300	−31740
19	6	90	10	902840	886194	908730	887288	−5890	−1094
20	6	90	15	1128600	1111980	1162200	1129400	−33600	−17420
21	6	90	20	1250800	1230700	1272100	1262440	−21300	−31740

Table 6. The results of numerical examples (SA).

				SA		Proposed SA		Deviation (SA- proposed GA)	
TP	***M***	***N***	***P***	**Best**	**Average**	**Best**	**Average**	**Best**	**Average**
1	2	30	3	129450	124488	129570	126064	−120	−1576
2	2	30	4	163110	160922	167580	162860	−4470	−1938
3	2	30	7	256890	253870	262880	258578	−5990	−4708
4	3	40	3	140230	133874	138600	130938	1630	2936
5	3	40	5	232290	222634	235180	226814	−2890	−4180
6	3	40	10	398420	391344	408660	398212	−10240	−6868
7	4	50	5	293040	284102	297360	293424	−4320	−9322
8	4	50	10	505200	499448	507380	501752	−2180	−2304
9	4	50	15	630700	623570	638270	632148	−7570	−8578
10	5	60	5	361040	351332	367140	360212	−6100	−8880
11	5	60	10	614960	603178	624260	613004	−9300	−9826
12	5	60	15	768820	757702	796400	785202	−27580	−27500
13	5	70	5	439890	430446	450740	446008	−10850	−15562
14	5	70	10	738460	730264	771690	750610	−33230	−20346
15	5	70	15	932820	927292	945900	933406	−13080	−6114
16	6	80	10	824400	806942	838360	829922	−13960	−22980
17	6	80	15	1029100	1016060	1061100	1039720	−32000	−23660
18	6	80	20	1172800	1158940	1197900	1183840	−25100	−24900
19	6	90	10	904450	892660	927530	907728	−23080	−15068
20	6	90	15	1130900	1124940	1171600	1147320	−40700	−22380
21	6	90	20	1268300	1260440	1310100	1296460	−41800	−36020

Table 7. The results of statistical analyses.

	Test	***H*0**	***H*1**	***N***	**Mean**	**St Dev**	**SE mean**	**95% upper Boun**	***T***	***P***
Best	GA- proposed GA	$\mu = 0$	$\mu < 0$	21	–10300	14408	3144	–4877	–3.28	0.002
Average	GA- proposed GA	$\mu = 0$	$\mu < 0$	21	–7738	11728	2559	–3324	–3.02	0.003
Best	SA- proposed SA	$\mu = 0$	$\mu < 0$	21	–14901	13513	2949	–9816	–5.05	0.000
Average	SA- proposed SA	$\mu = 0$	$\mu < 0$	21	–12846	10393	2268	–8935	–5.66	0.000
Best	Proposed GA-proposed SA	$\mu = 0$	$\mu < 0$	21	–11905	13206	2882	–6935	–4.13	0.000
Average	Proposed GA-proposed SA	$\mu = 0$	$\mu < 0$	21	–14037	12069	2634	–9495	–5.33	0.000

paper produced by the SA algorithm considered in this paper is not rejected (P-value = 0.000);

- At a 5% level of acceptance, the hypothesis of the higher best answer than the SA considered in this paper produced by the SA algorithm considered in this paper is not rejected (P-value = 0.000).

The idea proposed to improve the performance of GA and SA algorithms managed to improve the performance of both algorithms considerably. In addition, according to the statistical tests of the four algorithms investigated, the SA algorithm considered by this paper showed better performance than the other algorithms.

6. Conclusion and future research

In this problem, designing a supply chain network, including a location-allocation problem in the warehouse, VRP in distribution, and customer selection at the retail level in some periods of time is considered. Selection of warehouses, allocation of customers to the warehouse, selection and deletion of some customers, determining the number of required vehicles and routing vehicles, is done simultaneously and in one period in the form of a model. In this model, the proceeds of the business of the company are invested to develop a distribution network and, in any period, more customers are added to the distribution network by the new investments. A coding system of responses is proposed to this problem, and the problem is solved through GAMS software and metaheuristic algorithms. Two algorithms of SA and GA are used for this purpose, and a number of ways are offered to improve them. Finally, it was shown that the results obtained by implementing these methods improved considerably. In GA, this change led to 1.2 percent and 1.6 percent improvement in the average of solutions and the best answer; in SA algorithm, this change led to 2.1% and 2.4% improvement in the average of solutions and the best answers.

In future researches of this problem, the number of levels can be increased or parameters such as demand can be certainly considered. Moreover, since the proposal of two existing diversifications on both SA and GA algorithms could lead to improvement in the solutions, this idea can be applied to other algorithms.

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