ABSTRACT

Supply-chain network design is a fundamental problem for most organizations. The optimization of the network allows for efficient management of operations in the entire supply chain. The supply chain involves all activities concerning the flow of goods from raw material to delivery to the consumer, as well as the flow of information throughout the process. This study investigates a three-level supply chain with a single-period model comprising a number of manufacturers and a set of distributors and consumers. A novel methodology was presented to limit the random behavior of genetic operators in solving the problem. The problem was modeled aiming to minimize the total cost of the system. Moreover, the production capacity was considered limited and insufficiency was assumed unacceptable. Given their inherent complexity, this category of problems is recognized as NP-hard type. Therefore, this study employed an improved genetic algorithm to solve the problem that—according to the results—was found to be highly effective.

Keywords: *Supply Chain, Production–Distribution Planning, Genetic Algorithm, Optimization.*

1. INTRODUCTION

Supply chain management is a constrained problem that relates all production and supply processes, from raw materials to the consumer, and may involve several organizations. Supply chain management focuses on processes, technologies, and the potentials of suppliers to build competitive advantages. A supply chain is a network of distribution equipment and facilities responsible for the supply of materials, their transformation into semi-finished and final products, and delivering the products to the consumers. Overall, logistics costs account for a large portion of firms' budget. Such costs can be considerably reduced by a precisely-designed supply chain. The objective in urban logistics is to optimize the logistics and freight activities of transportation services in urban areas. Supply chain management helps logistics directors manage the relationship between suppliers and consumers and establish a coherent and optimal supply chain to fulfill the consumers' demands. Given the rapid technological progress in recent years and correlations between different branches of science, nature-inspired methods, known as metaheuristic algorithms, have been proposed for solving optimization problems. Metaheuristic algorithms are today commonly employed to solve optimization problems in different fields of application with an extensive search space. Without them, the search for the optimal solutions is extremely time-consuming and somehow impossible.

2. LITERATURE REVIEW

Today, the need for supply chain management has become increasingly important with the advent of novel technologies in recent years and major breakthroughs in global markets. The supply chain is a gathering of facilities, inventories, customers, goods, and control methods for inventory, procurement, and distribution that connects suppliers to consumers, starting with the production of raw materials by the supplier and ending with consumption by the customer [1].

Lee and Billington investigated most of the supply chain management problems [2]. Pagel also compared inventory management in the past with today's conditions and facilities [3]. Lawrence and Warma proposed a framework that allocates customer inventory management to the main supplier that is responsible for integrating the supplier–customer relationships. However, inventories are held at customer sites, thus dismissing a large portion of holding costs [4]. Landsam designed a framework for material supply management that allows suppliers to store goods in a central warehouse in convenient quantities. This approach reduces lead time for all stored goods, as well as the transportation time [5].

Vehicle routing is considered an NP-hard problem. Therefore, the inventory-routing problem, an extension of the routing problem, is also considered to be of the same type, for which several studies have employed metaheuristic algorithms to develop approximate solution methods. In 2011, Young et al. [6] investigated the robustness of different supply chain strategies under different conditions. For this purpose, the Beer Game simulation, Taguchi method, multi-criteria decision analysis, and the GRA method, as well as the multi-criteria ranking technique and TOPSIS were employed. In 2011, Chen Sebli [7] modeled the reverse logistics network design along with collection, inspection, refurbishment, and disposal by mixed integer programming. A heuristic solution method was proposed for this problem given that the problem is of NP-hard type. Then, the results were compared with the case of adopting a Genetic Algorithm (GA) approach, proving the superiority of the proposed algorithm. The objective of the problem is to minimize the total cost of the proposed reverse logistics network. In 2010, Kanan et al. [8] presented a closed-loop, multi-level, multi-product, supply-chain network model to optimize the usage of remanufactured products by making decisions on the logistics, production, distribution, recycling, and disposal. The model was developed by Mixed-Integer Linear Programming (MILP), aimed to minimize the total cost, and was solved using a heuristic GA. In 2007, Aziz and Moin [9] investigated a multi-product and multi-period problem with several suppliers and an assembly plant with the aim of minimizing the total transportation and inventory holding costs. By investigating two solution representations, they developed a mixed GA based on an "allocation first, routing second" approach. In a similar study, Moin et al. presented an improved hybrid GA in 2010. In 2007, by studying an inventory-routing problem that included production planning, Bodia et al. [11] developed solution algorithms which were based on the greedy randomized adaptive search. In 2009, Bodia and Prinz carried out a similar study based on the memetic algorithm with population management. In 2008, Zhao et al. [13] proposed an integrated model for the inventory–routing problem in a three-level supply chain and developed a large variable neighborhood search algorithm. In another study in 2007, Zhao et al. [14] presented a new approach based on the metaheuristic tabu search algorithm to solve the problem in a two-level supply chain. In 2007, Asparchi-Alkasar et al. [15] adopted a GA approach to solving a multi-product inventory-routing problem and evaluated the impacts of the GA inputs to obtain the best total. In 2005, Rasdiansia and Sao [16] developed a model for the inventory-routing–problem with vending machines and presented a two-stage algorithm based on merge and tabu search algorithms.

3. NUMERICAL MODEL

The assumptions made in supply chain management are as follows:
The number of manufacturers: k
The number of distributors: j
The number of consumers: i
Goods transported from the manufacturer to the distributor: y_{kj}
Goods transported from the distributor to the consumer: x_{ji}
Demand by the consumer: R_i
Distribution capacity of the distributor: D_j
Production capacity of the manufacturer: p_k
Cost of transportation of a unit of goods from the manufacturer to the distributor: b_{kj}
Unit goods transported from the distributor to the consumer: a_{ji}
The constraints assumed in supply chain management are as follows:
Consumption constraint: Total goods received by the ith consumer is equal to the demand by the ith consumer.

$$\sum_j x_{ji} = R_i \quad (\forall\, i) \tag{1}$$

Two constraints are assumed at the distribution level.
The first distribution constraint: Total goods sent by the jth distributor is less than or equal to the distribution capacity of the jth distributor.

$$\sum_i x_{ji} \le D_j \quad (\forall\, j) \tag{2}$$

The second distribution constraint: Total goods received by the jth distributor is equal to the total amount of goods sent by the jth distributor (nothing is stored).

$$\sum_k x_{kj} = \sum_i x_{ji} \quad (\forall\, j) \tag{3}$$

Production constraint: Total goods sent by the kth manufacturer is less than or equal to the distribution capacity of the kth manufacturer.

$$\sum_j y_{kj} \le p_k \quad (\forall\, k) \tag{4}$$

The aim in this problem is to minimize total costs, including the costs of transportation from the manufacturer to the distributor, and from the distributor to the consumer. The numerical relation for the target function is as follows:

$$Z = \sum_{i,j} a_{ji} x_{ji} + \sum_{j,k} b_{kj} y_{kj} \quad (x_{ji}, y_{kj} \geq 0) \tag{5}$$

4. GENETIC ALGORITHM

The Genetic Algorithm is a general metaheuristic optimization method. The simulation method—which is readily discussed—was introduced in 1975 by Holland and in 1989 by Goldberg [17, 18]. In the natural world, evolution takes place when the following four conditions are satisfied:
a) The creature is capable of replication (for example by reproduction);
b) There is a population of the replicating creatures;
c) There is diversity;
d) The creatures are separated by some life possibilities.
Different species of the same creature exist in the natural world with some differences in chromosomes that lead to diversity. Creatures that exhibit more capability in activities will have a higher rate of reproduction. The standard GE operates as follows:
1. Select a correct chromosome structure—that is, a solution;
2. Form the initial population by generating a random set of solutions;
3. Randomly select a set of solutions—chromosomes—as parents;
4. Through such operations as crossover, and mutation, generate offsprings from parents;
5. Replace parents with offsprings in the population;
6. Repeat steps 3 through 5 until the population has evolved.

5. THE PROPOSED METHOD

In this method, to keep the best solutions while maintaining the diversity of the population, the generated offsprings were made close to their parents if the parents were fit on their own, but dissimilar to the parents otherwise. In this case, a single-point crossover was used to create similar offsprings to parents while more distant offsprings were generated by a computational crossover. To maintain solutions in different parts of the search space, the distance between uniform initial solutions was investigated and the median cost was used to categorize solutions, and the fitness of each group was used to apply the best crossover. The proposed GA-based algorithm is as follows:
1. Select a correct chromosome structure;
2. Form the initial population by generating a random set of solutions;
3. Select a set of chromosomes as parents by roulette wheel selection;
4. Categorize the selected parents into four sub-populations based on the cost function, which is the sum of two distances (distances between the producer and distributor, and between the distributor and the consumer).
Group 1: Both distances are small.
Group 2: The first distance is small, but the second is large.
Group 3: The first distance is large, but the second is small.
Group 4: Both distances are large.
(Whether a distance is large or small is determined based on the median of the categorized distances)
5. Generate offsprings by crossover considering to which category the population belongs;
6. Generate offsprings from the selected parents by crossover;
5. Add the offsprings produced by genetic operators to the population;
6. By simple elitism, the most unfit members are eliminated until reaching the initial population size;
7. Repeat Steps 3 through 7 until the population has evolved.

Proposed Algorithm
Begin
$t = 0$

```
Initialize P (t)
Evaluate P (t)
While not finished do
Begin
t = t + 1
Made p1, p2, p3, p4 from P(t)
Select pair P (t) from P (t − 1)
Set flag base on pair P (t) & p1 to p4
Crossover (pair P (t))
Select P (t) from P (t − 1)
Mutate (P (t))
Evaluate P(t)
End
End
```

6. SIMULATION

To simulate the problem, first a suitable model is developed that involves determining the number of manufacturers and the capacity of each, the number of distributors and the capacity of each, and the number of consumers and the capacity of each.

Then, the initial solutions—chromosomes—were generated. Chromosomes were the arrays $\hat{x}$ and $\hat{y}$ in this problem, and $\hat{x}$ is a j*i array and $\hat{y}$ is a k*j array of uniformly-distributed random numbers ranging between 0 and 1. The two variables $\hat{x}$ and $\hat{y}$ are used to generate x_{ji} and y_{kj}.

To satisfy the consumption constraint (1), the sum of j x_is must be R_i.

Mathematically speaking, for the sum of n numbers to be a fixed number, we have:

$$x_1 + x_2 + \cdots + x_n = C \quad (6)$$

$$0 \leq \hat{x}_i \leq 1 \rightarrow x_i = \frac{c\hat{x}_i}{\hat{x}_1 + \hat{x}_2 + \cdots + \hat{x}_n} \ (i = 1, \dots, n) \quad (7)$$

$$0 \leq \hat{x}_{ji} \leq 1 \rightarrow x_{ji} = \frac{R_i \hat{x}_{ji}}{\sum_j \hat{x}_{ji}} \quad (8)$$

According to Eqs. 6 and 7, j number of xs were created from the randomly-chosen $\hat{x}$s that sum up to R_i—which is, again, random.

Fully satisfying the first distribution insofar as possible.

$$\sum_j x_{ji} = D'_j \quad (9)$$

Given the x_{ji}s determined in when satisfying the consumption constraint, the sum can be assumed fixed at 1.

$$v_j = \max\left(\frac{D'_j}{D_j} - 1, 0\right) \quad (10)$$

$$\overline{v_1} = \frac{1}{j} \sum_j v_j \quad (11)$$

Satisfying the second distribution constraint (3) is similar to the consumption constraint.

$$0 \leq \hat{y}_{kj} \leq 1 \rightarrow y_{kj} = \frac{D'_j \hat{y}_{kj}}{\sum_k \hat{y}_{kj}} \quad (12)$$

It is concluded from the consumption constraint (1) and the second distribution constraint (3) that:

$$\sum_k y_{kj} \leq D_j \quad (13)$$

Therefore, either of two cases can take place:
First, if $D'_j \leq D_j$, it is concluded from Eqs. 3, 9, and 13 that:

$$\sum_k y_{kj} = D'_j \leq D_j \quad (14)$$

First, if $D'_j > D_j$, it is concluded from Eqs. 3, 9, and 13 that:

$$\sum_k y_{kj} = D'_j = D_j \quad (15)$$

From Eqs. 14 and 15, we have:

$$\sum_k y_{kj} = \min (D'_j, D_j) \quad (16)$$

Therefore, according to Eqs. 12 and 16, the second distribution constraint (3) is satisfied by the following equation:

$$0 \leq \hat{y}_{kj} \leq 1 \rightarrow y_{kj} = \frac{\min (D'_j, D_j) \hat{y}_{kj}}{\sum_k \hat{y}_{kj}} \quad (17)$$

The production constraint (4) is treated similar to the first distribution constraint—using a penalty function.

$$v_k = \max (\frac{\sum_j y_{kj}}{p_k} - 1,0) \quad (18)$$

$$\overline{v_2} = \frac{1}{k} \sum_k v_k \quad (19)$$

The penalty functions $\overline{v_1}$ and $\overline{v_2}$ are added to the target function to determine the cost of the possible solution.
In the proposed method, for the crossover to operate, depending on to which category each of the parents belong, the single-point crossover or the computational crossover are used on $\hat{x}$, $\hat{y}$, or both (it was mentioned earlier that the single-point operator is used to generate close offsprings to the parents, while the computational crossover is used to generate more distant ones).

7. CROSSOVER

In the single-point crossover, one point is selected from the parents from which they are halved. The first offspring inherits its first half from the first parent and the second from the other parent, while inverse applies to the second offspring.

In computational crossover, the parents are modified by a computational process.

$$\alpha = unifrnd\left(-\gamma, 1+\gamma, Size(\text{parent})\right) \tag{20}$$

The larger the selected gamma, the more notable the variations. After calculating alpha, the offsprings are calculated from the following equation:

$$\begin{cases} child1 = \alpha.* (parent1) + (1-\alpha).* (parent2) \\ child2 = \alpha.* (parent2) + (1-\alpha).* (parent1) \end{cases} \tag{21}$$

8. RESULT

Three datasets of different sizes—small, medium, and large—were used to evaluate the proposed method. Table 1 presents the specifications of the dataset.

Table 1. *Dataset specifications*

Number of manufacturers	Number of distributors	Number of consumers	Dataset size
2	5	40	Large
2	5	20	Medium
2	5	10	Small

The results of solving the supply chain problem with the GA approach are presented in Table 2 using the method proposed in Table 3.

Table 2. *Results for 50 runs on each dataset using the basic genetic algorithm*

Standard deviation	Average Cost	Best Cost	dataset
263.97	32728	32310.132	Large
106.01	19476	19357.503	Medium
105.6	10753	10617.0379	Small

Figure 1 illustrates the variations of costs by running the GA on a large dataset, while Figure 2 illustrates the variations of costs with the proposed method on the same dataset.

Table 3. *Results for 50 runs on each dataset using the proposed method*

Standard deviation	Average Cost	Best Cost	dataset
256.85	31913	31615.2539	Large
53.443	19239	19185.2857	Medium
63.513	10617	10496.9037	Small

Figure 1 illustrates the variations of costs by running the GA on a large dataset, while Figure 2 illustrates the variations of costs with the proposed method on the same dataset.
Similarly, Figures. 3, 4, 5, and 6 illustrate cost variations in both methods using the other two datasets.

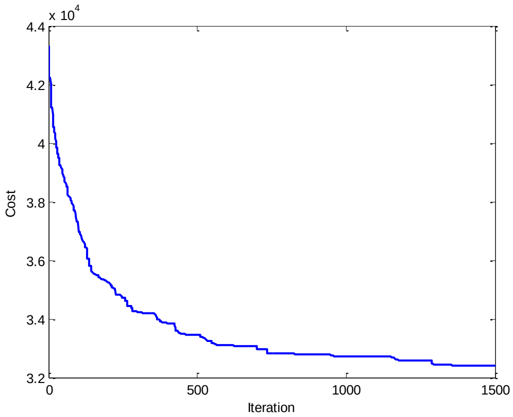

Fig. 1. *Best response from the genetic algorithm for large data*

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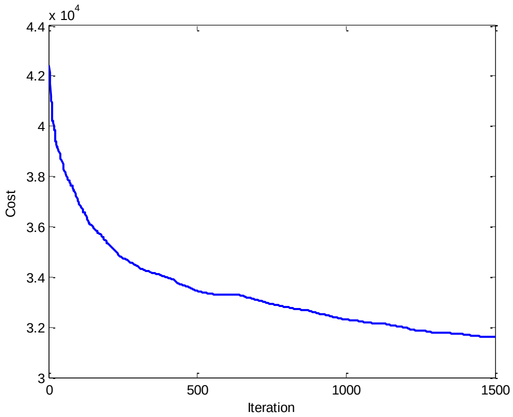

Fig. 2. *Best response from the proposed algorithm for large data*

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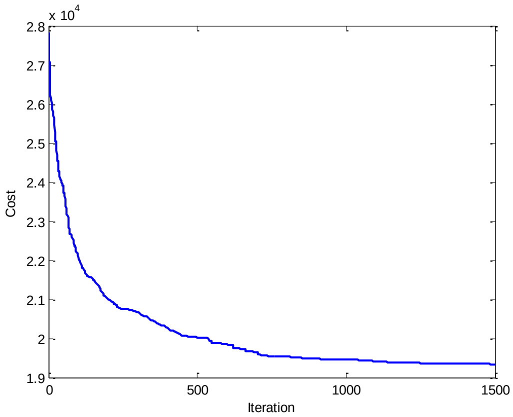

Fig. 3. *Best response from the genetic algorithm for average data*

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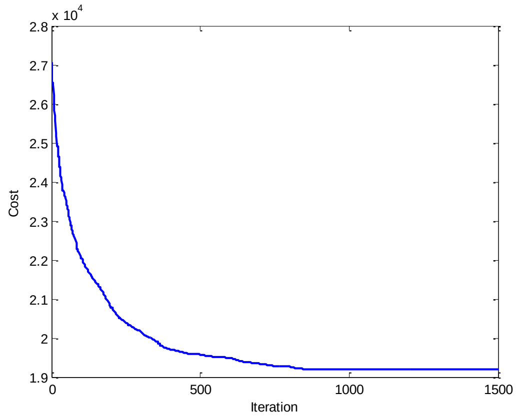

Fig. 4. *Best response from the proposed algorithm for average data*

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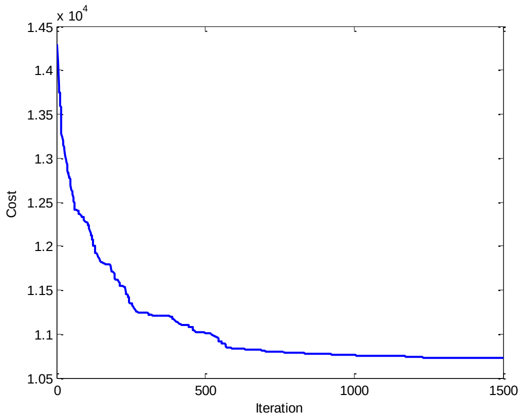

Fig. 5. *Best response from the genetic algorithm for small data*

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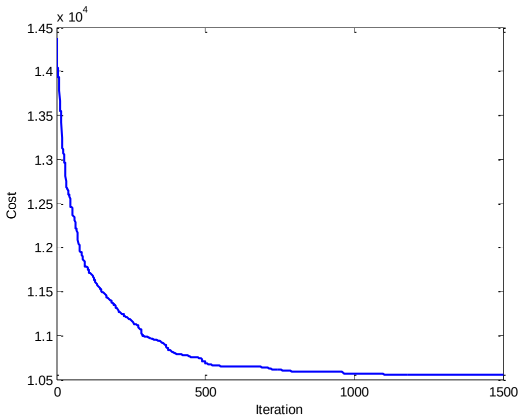

Fig. 6. *Best response from the proposed algorithm for small data*

9. CONCLUSION

A novel genetic-algorithm-based method was proposed to solve the problem of optimizing a three-level supply chain in a forward logistics network. The aim of the problem was to minimize transportation costs. This study attempted to reduce the randomness of the crossover operator and direct it accordingly based on the target function and the cost of each chromosome. The results of all three datasets are suggestive of the superior performance of the proposed method.

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